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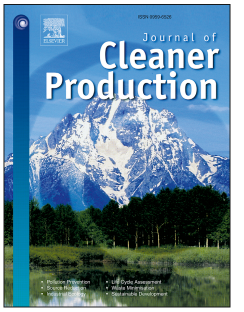

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Mind the Gap: Developments in Autonomous Driving Research and the Sustainability Challenge

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Mind the Gap: Developments in Autonomous Driving Research and the Sustainability Challenge

Scientific knowledge on autonomous-driving technology is expanding at a faster-than-ever pace. As a result, the likelihood of incurring information overload is particularly notable for researchers, who can struggle to overcome the gap between information processing requirements and information processing capacity. We address this issue by adopting a multi-granulation approach to latent knowledge discovery and synthesis in large-scale research domains. The proposed methodology combines citation-based community detection methods and topic modeling techniques to give a concise but comprehensive overview of how the autonomous vehicle (AV) research field is conceptually structured. Thirteen core thematic areas are extracted and presented by mining the large data-rich environments resulting from 50 years of AV research. The analysis demonstrates that this research field is strongly oriented towards examining the technological developments needed to enable the widespread rollout of AVs, whereas it largely overlooks the wide-ranging sustainability implications of this sociotechnical transition. On account of these findings, we call for a broader engagement of AV researchers with the sustainability concept and we invite them to increase their commitment to conducting systematic investigations into the sustainability of AV deployment. Sustainability research is urgently required to produce an evidence-based understanding of what new sociotechnical arrangements are needed to ensure that the systemic technological change introduced by AV-based transport systems can fulfill societal functions while meeting the urgent need for more sustainable transport solutions.

Keywords: autonomous vehicle; research developments; text mining; topic modeling; sustainability; knowledge gap

1. Introduction

The first motor vehicle that pioneering mechanical engineer Karl Benz invented in 1885 has escalated into a global fleet of approximately one billion cars and trucks, which constantly transport flows of people and goods (Burns, 2013). The existing transportation system is an essential enabler of social and economic interactions, yet its multifaceted negative impacts (Santos et al., 2010) are turning society away from meeting its sustainable development goals. Public transport services and private mobility solutions have become unaffordable for a growing share of the world population (Mullen et al., 2020). In addition, with an overall production of energy-related greenhouse gas emissions of approximately 25%, transportation represents one of the most carbon-intensive sectors (Creutzig et al., 2015; Edenhofer et al., 2014). Being heavily dependent on fossil fuels (Ahmed et al., 2016), the transportation systems are also responsible for releasing a vast amount of air pollutants and harmful levels of noise, causing environmental degradation and acute effects on public health (Nicoletti et al., 2015). Not to mention the concerns generated by safety and security risk factors, with road traffic crashes which give rise to approximately 1.25 million deaths annually (Bartolomeos et al., 2013).

Decoupling the provision of transport services and infrastructure assets from the detrimental consequences that the sector is imposing on society is key to attaining sustainable development objectives. In response to this call for a radical shift (Stephenson et al., 2018), multi-disciplinary research efforts are being made to assemble cross-cutting strategies in which diversified mitigation measures and sustainable transport solutions are combined (Xenias and Whitmarsh, 2013; Zawieska and Pieriegud, 2018).

A growing body of research suggests autonomous-driving technology has the potential to radically reshape the future of transportation (Al-Kanj et al., 2020) and help generate the system innovation required to support the transition to fully sustainable sociotechnical transportation systems (Whitmarsh, 2012). Advancements in self-driving-vehicle technology promise to make urban environments more sustainable by reducing fuel consumption (Chehri and Mouftah, 2019), carbon emissions (Burns, 2013), air and light pollution (Dean et al., 2019; Stone et al., 2020), congestion-related productivity losses (Fagnant and Kockelman, 2015), and the risk of driving crashes (Duarte and Ratti, 2018; Grace and Ping, 2018). In addition, the global AV market is expanding and expected to generate a global revenue of 173 billion dollars by 2023. Leading tech firms have already joined this expanding market, together with large vehicle manufacturers and related industries. Notable examples include the Intel company Mobileye, Uber, Waymo, Microsoft, and Tesla (Birdsall, 2014; Dagan et al., 2004; Stringham et al., 2015; Xu and Fan, 2019). Yet the commercial availability of self-driving vehicles is still far from becoming a reality (Hemphill, 2020). Despite the growing investments and interest, making self-driving vehicles penetrate into the mainstream market still needs substantial research and development efforts.

With the volume of research on autonomous vehicles (AVs) on the rise, more and more knowledge is becoming available at a remarkably fast pace. This fast knowledge production process opens up significant development opportunities, but researchers can struggle with managing and exploring the large quantity of information which is constantly made available. In order to avoid information overload issues, research efforts are required to organize this information into an easy to interpret style.

This paper contributes to meet such an objective by reporting on the results of a multi-method bibliometric study which offers a synthetized view of the scientific knowledge produced during the last five decades of AV research (1970-2019). Citation-based community detection methods and topic modeling based on exploratory factor analysis are combined to extract the relevant semantic structures (i.e. main keywords, central topics, and core research themes) hidden in this complex data-rich environment. These sub-information systems of latent variables are then analyzed to give a full account of how the intellectual structure of the AV research field is conceptually shaped.

The paper is structured in four main sections. After presenting the growth rate of the AV research domain, the paper goes into the rationale behind its call for a more consistent effort to reach knowledge summarization in the large network of AV-related scientific publications released during the period under investigation. The introductory discussion ends by focusing on the challenges affecting large-scale exploratory text analytics and the role that digitally-induced text mining techniques play in facilitating knowledge discovery processes. The paper continues with a detailed description of the methodology adopted to conduct the bibliometric analysis. This second section is followed by a discussion on the latent knowledge extracted during the analytical process, which is used to convey core knowledge from a large volume of scientific publications in a concise but comprehensive way. The paper concludes with a final section in which the insights captured through the analysis is summarized and used to offer recommendations on future research directions. The analysis demonstrates that AV research is not paying sufficient attention to the environmental consequences and socio-economic, cultural, political, institutional, and organizational implications that a mass market for autonomous driving technology can generate. After elaborating on this evidence-based statement, the conclusive section also reports on the limitations of the study and details its contribution.

2. Latent knowledge discovery in AV research: a multi-granulation perspective

Branches of science resemble living organisms and are subject to the evolutionary nature of scientific discovery. Since its inception, a field of scientific research progressively develops through knowledge production mechanisms, facilitated by open discussion amongst scholars. Formalized through academic publications, this debate progressively frames the overall intellectual structure of the research area. During this co-production process, however, it is easy for scholars to experience information overload and lose sight of how their fields of study have conceptually evolved (Roetzel, 2019). The likelihood of incurring information overload is particularly notable in an era where scientific knowledge is produced and accumulated at a faster-than-ever pace (Thananusak and Ansari, 2019; Valdez et al., 2018), in particular when dealing with research domains where a strong and fast-growing interest generates a sudden increase in the amount of available scientific information (Mora et al., 2017). This event can cause a potential gap between information processing needs and the existing capability to process such information (Eppler and Mengis, 2004).

Recent developments in AV have raised information overload concerns (Cavazza et al., 2019; Gandia et al., 2019; Rashidi et al., 2020). The interest of research institutions in examining the largely unknown socio-cultural, environmental, economic, and technological implications of vehicle automation has grown conspicuously over the years, especially during the last decade. This trend can be observed in Figure 1, where Scopus data is used to show the annual production volume of peer-reviewed scientific outputs focusing on AV research. Conducted at the end of January 2020, this publication search covers a 50-year timespan and has resulted in the identification of 18,153 publications. Approximately 80% of these knowledge items have been published during the period 2010-2019 and the majority has been accumulated between 2017 and 2019. These three years account for 55% of the Scopus-indexed scientific publications on autonomous driving released in the last five decades. The production peak was reached in 2019, with 4,841 publications (26.7%).

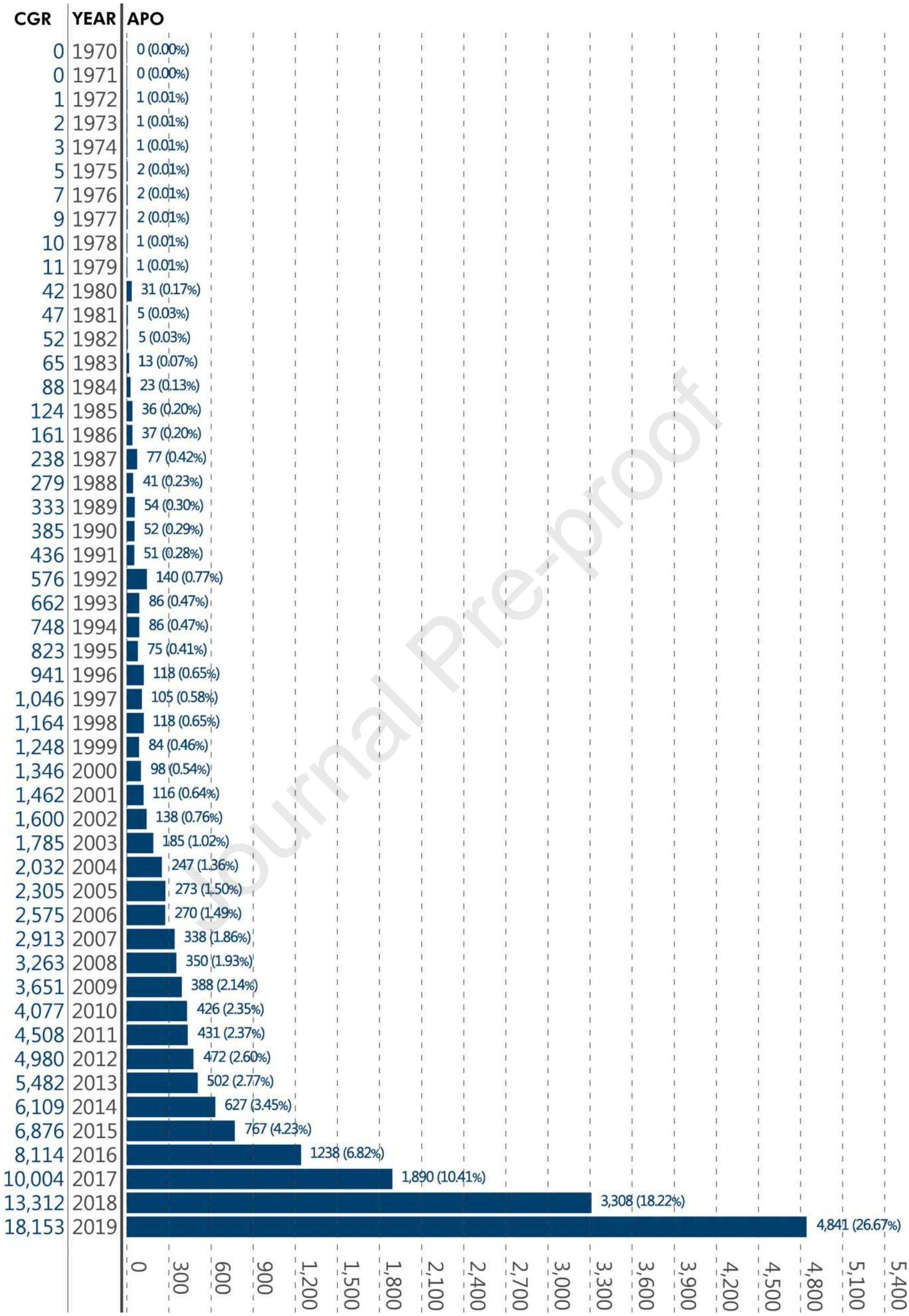

Figure 1. Five decades of AV research (Scopus data). APO: Annual publication output; CGR: Cumulative growth.

Scopus data confirms that autonomous driving has become a prominent topic of investigation in the scientific debate on transportation futures. Aware of the difficulties that researchers may experience when attempting to grasp the rapidly expanding intellectual structure of the AV research field, two initial studies have been conducted which attempt to guide summarization by means of knowledge maps. These studies combine knowledge domain visualization and bibliometric techniques to identify relevant semantic links between natural language representation components, whose visualization facilitates the understanding of core concepts embedded in large-scale collections of AV-related bibliographic data sources.

The first study is conducted by Gandia et al. (2019), who focus on the WoS-indexed literature published between 1969 and 2018. The selection of this timeframe leads to the identification of 10,580 publications, from which two groups of items are extracted: a set of “research-front concepts” (Chen, 2006, p. 359) and a number of emergent research categories. The extraction process is conducted by using the software CiteSpace, where the burst detection algorithm designed by Kleiberg (2003) allows the authors to estimate the burst of each emergent concept and research category. When comparing the results, evidence of a trend change surfaces. According to the findings, AV research shows an initial techno-centric focus, with subject areas belonging to engineering and technology disciplines dominating the scientific debate. Research trends begin to evolve around 2015, when a more holistic research environment starts to develop as a result of the growing scientific contribution offered by studies in the social sciences.

The investigation into the conceptual shifts describing the evolutionary nature of the AV research field continues with Rashidi et al. (2020). CiteScape remains the main supporting tool, but unlike the previous study, this second bibliometric analysis: (1) relies on a smaller bibliographic record composed of Scopus-indexed publications, rather than WoS data; (2) narrows the timeframe, covering the years between 1999 and 2018; and (3) excludes conference papers and a series of subject areas from the analysis which are considered irrelevant in the framework of the study. After dividing the 20-year timeframe of the analysis in 2-year time slices, Rashidi and colleagues use the 50 most co-cited publications of each slice to develop a document co-citation network, which is split into thematic clusters. Each cluster is then assigned a keyword that best synthesizes its underlying thematic focus. While the citation-based clustering analysis has been automated, the authors have conducted the labelling process manually, by reviewing titles, abstracts, and keywords of the publications in each cluster. The result of this task is a list of thirteen themes, which are visualized on a timeline tracing their evolution.

The abovementioned studies offer an initial overview of the AV research field, but the insight they produce does not provide sufficient granularity to determine how this knowledge domain is conceptually structured. As Gandia et al. (2019) observe, additional research is needed to complement their findings by increasing the level of detail. This requires looking over the too wide approximation of concepts resulting from their initial lists of emergent thematic areas and deepening the current understanding of the latent knowledge that each thematic area is shaped by. However, fulfilling this refined knowledge extraction process requires coping with the "curse of dimensionality" (Verleysen and François, 2005, p. 761).

By adopting metrics of proximity or distances (Glänzel et al., 2019), community detection algorithms can be used to split a research field into clusters of thematically related publications (Panori et al., 2019). Thematic clusters are high-dimensional knowledge spaces in which huge amounts of textual data is gathered and connected by an intricate network of semantic links (Mora et al., 2019). As basic entities of natural languages, words offer an initial level of language-dependent understanding of the clusters' contents. However, the presence of meaningless textual components generate noise, making it difficult to extract core information. Reducing the volume of the input variable space is indispensable, by removing as much irrelevant textual components as possible. During the dimensionality reduction process, depending upon the extent of the synthesis and degree of approximation (Yao, 2004), different levels of knowledge granulation can be reached.

Given the limitations of manual coding techniques in large-scale exploratory text analyses (Kobayashi et al., 2018), the discovery of latent knowledge patterns requires examining thematic clusters by means of text mining techniques, which make it possible to automatically reduce dimensionality by filtering quality information from high-dimensional sets of textual data. The core knowledge embedded in a large-scale dataset can be expressed as the sum of three complementary sub-information systems (Jing et al., 2017) of latent variables: main keywords, central topics, and core research themes[1]. Sourcing and connecting the different levels of knowledge which are rooted in these subsystems is key to produce a condensed but thorough representation of the intellectual shape of a research area. As a result, a comprehensive knowledge discovery process entails a multi-granulation perspective (Roslovtsev and Marenkov, 2018; Thijs, 2019).

Topic modeling is one of the most frequently used computer-assisted text data mining applications for knowledge discovery. Its usage makes it possible to automatically identify and look into sub-information systems of latent variables in high-dimensional collections of textual data, producing "insight in properties underlying those knowledge structures" (Tijssen, 1993, p. 111). Given a collection of unstructured textual data extracted from a cluster of thematically related publications, topic modeling combines a probabilistic approach to unsupervised learning and co-occurrence measures to: extract the words and phrases of

[1] The groups of variables are listed in ascending order of knowledge granularity.

greatest significance (Level 1: Keywords); arrange these text elements into groups of core topics (Level 2: Topics); and, facilitate the identification of the foremost thematic area emerging from each group of topics (Level 3: Research themes).

Topic modeling allows the integration of latent knowledge sourced from multiple analytical levels (Valdez et al., 2018), moving from individual keywords to collections of textual components delineating relevant topics and core themes. With researchers selecting from a wide range of different topic modelling techniques and heterogenous data sources, this multi-granulation perspective to large-scale exploratory text analyses has proven successful in examining knowledge structures in different application domains. For example, by progressively increasing the granularity of the analysis, Valdez et al. (2018) surveyed the transcripts of 2016 US presidential debates to detect the main differences between the political views of the two candidates. With a content analysis of some 900 articles published in regional and national newspapers, Chandelier et al. (2018) assessed the printed media coverage of wolf recolonization in France during the period 1993–2014. Kuhn (2018) sourced textual data from 25,706 publicly available records to map recurrent topics within aviation incident reports. Talavera et al. (2020) discovered behavioral habits by translating the visual content of 100,000 images into textual data. Roy et al. (2012) offered insights into the environmental contributions to early lexical development by examining more than 200,000 hours of audio and video recordings. This data captures the day-to-day linguistic environment in which a newborn child has been immersed during the first three years of life.

3. Data and methods

The abovementioned studies demonstrate that topic modelling has been successful in replacing laborious manual coding exercises in which the volume of data would have made the analysis impossible to complete without a computer-assisted approach. In addition, this research shows that different types of objectives call for different approaches to topic modelling and variations in the techniques, yet the analytical stages tend to remain the same. Three main phases can be identified, which have been considered in the framework of this study: preparation, topic modelling, and post-processing (Asmussen and Møller, 2019; Kobayashi et al., 2018).

3.1. Preparation

The preparation phase begins with the identification of the peer-reviewed literature which forms the intellectual structure of the AV research area. Considering that Scopus represents one of the most comprehensive databases indexing scientific literature (Gomez-Jauregui et al., 2014), the exploratory text-data mining analysis was conducted using the Scopus-indexed scientific literature on autonomous driving as data sources. The analysis covers a 50-year timespan, between 1970 and 2019. As shown in Figure 1, these five decades account for 18,153 publications, which were retrieved from the results of a keyword search. The search was conducted in January 2020 by using the following combination of terms and Boolean operators: TITLE-ABS-KEY (“autonomous car*” OR “autonomous vehicle*” OR “autonomous automobile*” OR “driverless car*” OR “driverless vehicle*” OR “driverless automobile*” OR “self-driving car*” OR “self-driving vehicle*” OR “self-driving automobile*”).

After manually checking for errors in the dataset, citation data was used to build a document citation network which comprises 6,970 of the initial 18,153 bibliographic references. Only AV-related intellectual work which has been cited by or has cited other AV publications has been included. This methodological approach considers citations as a similarity measure and a mean for connecting publications dealing with a mutual intellectual interest (Fitzpatrick et al., 2018), and it indicates that central topics and core research themes of a research field are rooted in its highly cited publications and the chain of publications which have subsequently built on their contents (Panori et al., 2019).

The Louvain modularity algorithm implemented in Gephi was then used to measure the strength of division of the large network of publications into clusters of thematically related items. Several algorithms can be found in the available literature, which are adopted for network modularity optimization, but most of them are unsuitable for finding communities in large networks. The Louvain algorithm, a large-scale modularity optimization algorithm designed by Blondel et al. (2008), is the most commonly used option for such purposes (Glänzel and Thijs, 2017; Yu et al., 2017).

During the clustering process, 13,397 citations were considered, and each publication was assigned to a thematic cluster. The publications belonging to each thematic cluster were subsequently assigned a Rich Text Format (RTF) file containing the following textual data: the publication title, abstract, and keywords. The RTF files were then uploaded onto the content analysis software WordStat (Version 8.0.21), which converted the thematic clusters into high-dimensional sets of unstructured textual data and to semi-automatize the data preparation and cleaning process. For each cluster, the textual data extracted from its RTF files was organized in a tabulated form, in which all words were listed together with their raw frequency and co-occurrence. Stop words were subsequently filtered out to eliminate noise. In addition, acronyms were substituted with their extended forms, common misspellings were corrected, and variant forms of the same word were grouped together (lemmatization).

3.2. Topic modelling

To reduce dimensionality and better filter quality information describing the intellectual structure of the AV research field, topic modelling was used to analyze each thematic cluster. WordStat's topic modelling function was selected, which is performed on factor analysis with varimax rotation (Péladeau and Davoodi, 2018). Multiple levels of analysis were combined during the examination, making it possible to progressively source different types of latent knowledge. By considering co-occurrence values, the software was instructed to detect groups of interrelated keywords and assign a topic to each group. The topics represent a set of underlying variables called factors.

Scree plots (Cattell, 1996) and parallel analyses (Horn, 1965) were used for factor retention purposes, to determine the number of topics to consider for each cluster. In an exploratory factor analysis, a scree plot is a line chart which displays the eigenvalues of all the factors identified during the analytical process in a downward curve (Nebel-Schwalm and Davis, 2011). The inflection point where the slope of the curve levels off divides the factors, revealing those which can be discarded as irrelevant to the analysis (Jany et al., 2020). If considered in the profile of the thematic cluster, these factors "would add relatively little to the information already extracted" (Woods and Edwards, 2011, p. 373). A number of experiments demonstrate that scree plot tests are easily manageable and tend to produce accurate results (Cattell and Vogelmann, 1977; Linn, 1968; Zwick and Velicer, 1982). However, reliability issues can surface, leading to an overestimated number of salient topics (Crawford and Koopman, 1979; Zwick and Velicer, 1986). Aware of the potential bias that the "subjective quality" (Hoyle and Duvall, 2004, p. 305) of this technique can generate, the examination of the patterns of decreasing eigenvalues was conducted by overlapping the results of both scree plot tests and parallel analysis (Ledesma et al., 2015; Nebel-Schwalm and Davis, 2011).

The topic modelling phase concludes with the identification of the core research themes, which were derived by inductive reasoning. This task was completed by examining the groups of keywords and topics of each cluster, as well as their top ten core documents. The core documents of a thematic cluster are the publications with the highest level of centrality. The centrality of a document in a cluster is directly proportional to its in-degree value, a social network analysis measure which is calculated by combining the number of citations they have received from other publications belonging to the network. Due to their high connectivity, core documents are the main cognitive nodes of a thematic cluster (Meyer and Beiker, 2014; Mora and Deakin, 2019) and provide most of the information describing its contents. In this investigation, core documents are deployed as a form of data triangulation to improve construct validity.

3.3. Post-processing

The last phase of the knowledge discovery process involved interpreting the results of the topic modelling and validating the proposed observations (Kobayashi et al., 2018). A concise review of each thematic cluster was proposed, in which the three complementary sub-information systems of latent variables identified during the topic modelling phase were linked (i.e. keywords, topics, and research themes).

Finally, four independent experts were tasked with verifying the validity of the extracted knowledge patterns and significance of the contents used to present them. In this study, domain experts are representatives of public or private organizations who have been actively engaged with research activities in the AV sector and have accumulated at least five years of professional experience. This selection criteria made it possible to ensure that the selected experts had a proven knowledge background in AV research. Each domain expert was invited to undertake a one-hour interview. During the interview, they were initially introduced to the analysis and were then asked to provide feedback on the results. A yes/no binary system was adopted to evaluate the extent to which the experts were in agreement with the proposed overall structure and the contents of each cluster. In case of disagreement, comments motivating the answer were collected and used to refine the topic modelling output. When changes were proposed, before being processed, their validity was checked with all other reviewers.

4. Results

The network graph in Figure 2 is a document citation network which shows how the AV research field is structured by considering the last five decades of scientific publication output and its main thematic research areas. The network is a combination of edges and nodes. The nodes are Scopus-indexed publications. Each node has a diameter proportional to its in-degree centrality. Therefore, the higher the number of citations received by a publication, the larger its diameter in the graph. The citations are represented as edges, whose weight is directly proportional to the number of citations connecting two nodes.

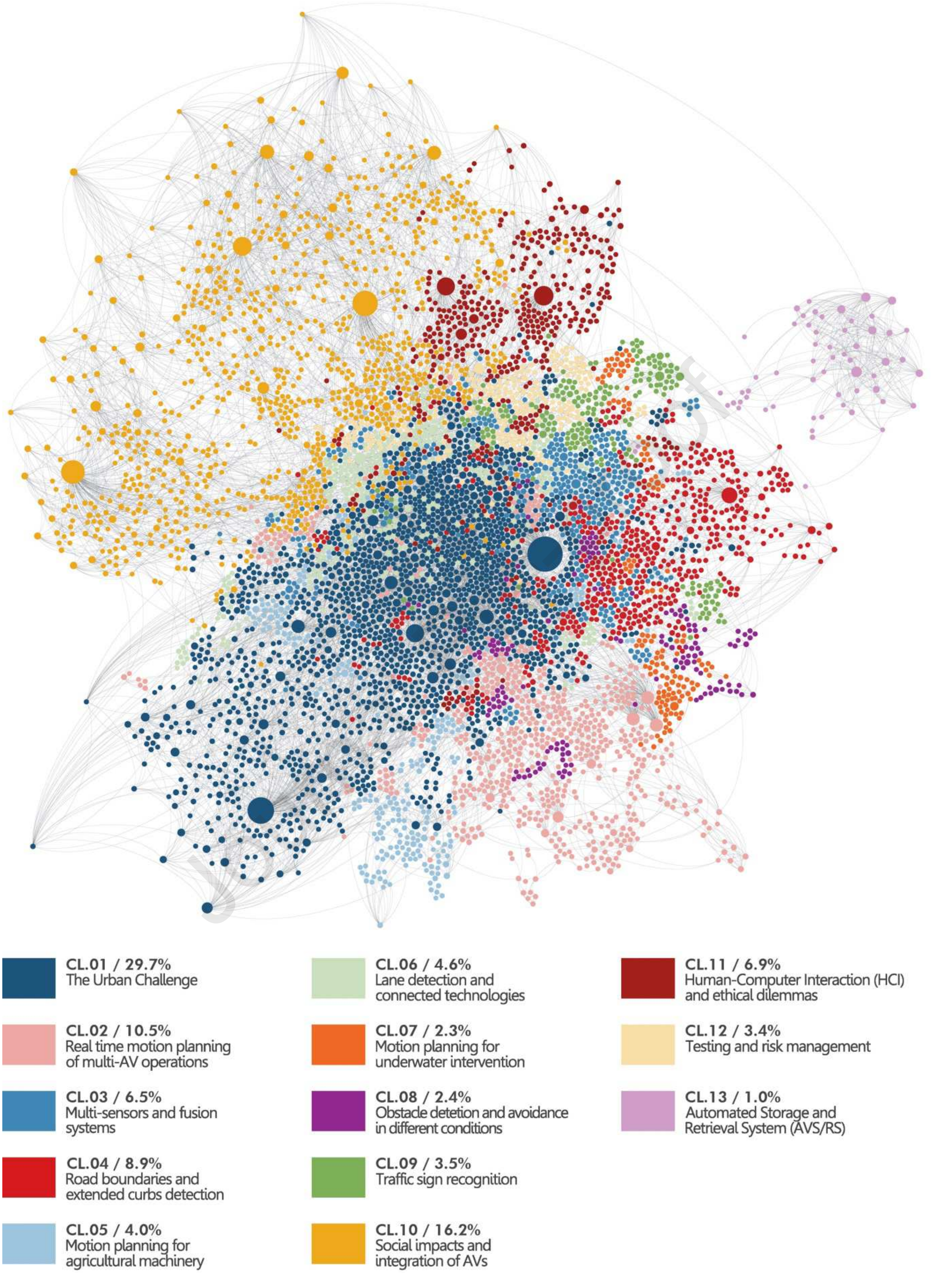

Figure 2. Document citation network and thematic clusters. The size of each cluster is expressed in percentage of publications.

The analysis of the document citation network uncovered 13 clusters of thematically related publications. The core literature of each cluster is listed in Appendix A, while the results of the topic modelling phase are presented in Appendix B, in which the main keywords, emergent topics, and core research themes are organized. The following sub-sections draw a connection between these knowledge items in order to provide a concise written account of the semantic structure of each thematic cluster.

This activity has been implemented by using the core literature as the main reference source, together with the data in Table 1, which visualizes the temporal evolution of the core research themes and shows how their intensity has evolved over the years. The intensity is a measure of the annual publication output of each cluster. The higher the number of publications added to a thematic cluster during a specific year, the higher its intensity.

During the validation process, all reviewers agreed with the conceptual structure of the AV research field. As a result, only a few changes were suggested, but at the cluster level. These changes aimed at enhancing clarity in the discussion phase. Therefore, the input collected during the validation process has not only generated construct validity evidence, but it has also helped refine the description of the thematic clusters.

Year	Thematic clusters												
	CL.01	CL.02	CL.03	CL.04	CL.05	CL.06	CL.07	CL.08	CL.09	CL.10	CL.11	CL.12	CL.13
1970-85	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.7%	0.0%	0.0%	0.0%	0.0%	0.0%
1986	0.0%	0.0%	0.3%	0.0%	0.0%	0.0%	0.0%	1.4%	0.0%	0.0%	0.0%	0.0%	0.0%
1987	0.0%	0.0%	0.0%	0.2%	0.0%	0.0%	0.0%	0.7%	0.5%	0.0%	0.0%	0.0%	0.0%
1988	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.7%	0.0%	0.0%	0.0%	0.0%	0.0%
1989	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	2.1%	0.0%	0.0%	0.0%	0.0%	0.0%
1990	0.0%	0.0%	0.0%	0.2%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
1991	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.7%	0.0%	0.0%	0.0%	0.5%	0.0%
1992	0.2%	0.0%	0.3%	0.2%	0.0%	0.0%	0.7%	3.5%	3.4%	0.1%	0.0%	0.0%	0.0%
1993	0.1%	0.0%	0.3%	0.2%	0.0%	0.0%	0.0%	0.7%	0.0%	0.1%	0.0%	0.0%	0.0%
1994	0.1%	0.2%	0.5%	0.0%	0.0%	0.7%	0.0%	1.4%	0.0%	0.0%	0.0%	0.0%	0.0%
1995	0.1%	0.0%	0.3%	0.0%	0.0%	0.0%	0.0%	2.1%	0.0%	0.0%	0.0%	0.0%	0.0%
1996	0.1%	0.3%	0.3%	0.2%	1.3%	0.7%	0.0%	2.8%	0.0%	0.0%	0.0%	0.0%	1.7%
1997	0.2%	0.5%	0.3%	0.4%	1.3%	1.1%	0.0%	1.4%	1.5%	0.0%	0.0%	0.0%	0.0%
1998	0.4%	0.3%	0.8%	1.0%	2.5%	0.0%	0.0%	2.8%	1.5%	0.3%	0.0%	0.5%	0.0%
1999	0.0%	0.3%	0.3%	0.0%	0.4%	0.4%	0.0%	2.1%	2.0%	0.0%	0.0%	0.5%	0.0%
2000	0.3%	0.8%	0.3%	0.2%	0.8%	0.7%	0.7%	0.0%	0.5%	0.0%	0.0%	0.0%	0.0%

2001	0.1%	2.2%	0.8%	0.8%	0.8%	1.8%	0.0%	5.6%	0.0%	0.0%	0.2%	0.0%	0.0%
2002	0.2%	3.0%	0.8%	1.0%	3.4%	1.5%	0.0%	1.4%	0.5%	0.0%	0.0%	0.0%	1.7%
2003	0.3%	4.0%	1.3%	1.0%	3.0%	0.4%	0.0%	2.8%	2.4%	0.0%	0.0%	0.0%	1.7%
2004	0.5%	4.0%	1.3%	1.1%	5.9%	1.1%	2.9%	5.6%	2.9%	0.0%	0.0%	0.5%	1.7%
2005	0.6%	5.1%	2.6%	1.0%	7.6%	1.5%	1.5%	4.2%	0.5%	0.1%	0.5%	0.5%	0.0%
2006	1.2%	5.3%	0.5%	2.1%	3.4%	1.1%	2.9%	4.2%	0.5%	0.2%	0.0%	1.0%	0.0%
2007	1.8%	3.7%	1.6%	1.7%	3.4%	0.7%	4.4%	4.9%	2.0%	0.6%	1.0%	1.0%	1.7%
2008	2.8%	5.8%	1.0%	2.1%	5.1%	1.8%	0.7%	5.6%	1.5%	0.6%	0.7%	2.0%	6.8%
2009	2.4%	5.1%	1.6%	2.7%	5.5%	1.5%	2.9%	4.2%	1.5%	0.4%	0.0%	0.5%	10.2%
2010	3.3%	4.7%	3.1%	2.9%	4.7%	1.5%	4.4%	9.7%	1.0%	0.8%	1.0%	2.0%	6.8%
2011	3.4%	4.0%	4.1%	5.7%	3.0%	1.5%	2.2%	2.1%	3.9%	1.8%	0.7%	2.0%	11.9%
2012	4.7%	6.3%	2.1%	3.2%	3.4%	1.5%	3.7%	3.5%	3.9%	2.4%	1.2%	3.9%	6.8%
2013	4.8%	5.3%	4.7%	3.4%	6.4%	3.3%	5.1%	3.5%	2.4%	2.2%	1.0%	3.4%	5.1%
2014	6.6%	5.3%	5.2%	6.3%	5.5%	5.9%	6.6%	1.4%	4.4%	3.0%	3.6%	5.4%	11.9%
2015	7.9%	5.1%	6.2%	7.6%	5.5%	6.6%	8.1%	2.1%	9.3%	5.2%	5.8%	4.9%	5.1%
2016	10.0%	5.5%	8.8%	10.8%	5.9%	8.4%	8.1%	3.5%	9.3%	11.3%	13.6%	8.9%	8.5%
2017	13.1%	7.2%	16.8%	13.3%	6.4%	13.6%	6.6%	2.8%	17.6%	16.3%	19.0%	9.9%	5.1%
2018	21.6%	9.1%	19.4%	21.3%	8.9%	27.1%	22.8%	8.3%	16.6%	28.2%	29.2%	31.0%	11.9%
2019	13.2%	6.7%	15.0%	9.7%	5.9%	15.8%	15.4%	2.1%	10.7%	26.4%	22.4%	21.7%	1.7%

Table 1. Temporal evolution of the core research themes: intensity of the publication output by year

4.1. CL.01: The Urban Challenge

The first cluster mainly focuses on the 2007 DARPA Urban Challenge[2] (Broggi et al., 2016). This driverless car race has triggered a significant number of studies that build on its outcome to examine the complexity of AV operation in urban environments and propose approaches to modelling, as well as motion planning, for improving AV operations in uncertain, dynamic and un/semi-structured environments. For example, Urmson et al. (2008) introduce the three-layer planning system of Boss, the driverless vehicle which won the first place of the challenge. The Boss is a 2007 Chevy Tahoe with an artificially intelligent mixed-mode system combining: (1) a mission planning layer, which creates various options of

[2] The Defense Advanced Research Projects Agency (DARPA) sets competitions with millions of dollar awards to encourage the development of AVs, and the Urban Challenge is the third one of the Grand Challenge series. It took place in November 2007, in California, where the Carnegie Mellon University's vehicle named Boss reached the first place.

trajectories towards the destinations; (2) a behavioral layer that decides the moment for lane-changing and simulates error recovery, and; (3) a layer of motion planning to avoid obstacles.

Lessons learned from Boss are deployed by Ferguson et al. (2008) to design a motion planning framework that improves AV's navigation in urban environments. This framework combines three components: the first component is an algorithm that generates accurate trajectories and dynamically feasible actions, the second component is a lane-based planner for real-time road situations, and the third one is a 4D lattice planner that tackles unstructured areas. By gathering insight from other prototypes presented during the challenge, Campbell et al. (2010) examine the status of the AV research and further highlight the technological challenges of introducing autonomous driving into urban environments. Kuwata et al. (2009) and Dolgov et al. (2010) report on two novel path planning approaches which they have deployed during the challenge. The first team of researchers proposes a system that deploys the Rapidly-exploring Random Tree (RRT) algorithm to manage motion planning. The second one consists of a two-phase procedure in which the variant of the A* search is used to obtain feasible trajectories.

Borrelli et al. (2005) and Falcone et al. (2007) both look at how the Active Front Steering (AFS) systems functioned for AVs in the challenge. They expand this subject area by proposing a new Model Predictive Control (MPC)-based approach, which can effectively enhance AV's stability of predictive active steering, barking, and driving performance in general.

4.2. CL.02: Real-time motion planning of multi-AV operations

Planning the real-time motion of multi-AV operations is a key challenge (Frazzoli et al., 2002). This cluster focuses attention on this subject matter of investigation and introduces various control systems and techniques for multi-AV operations in dynamic road environments, such as sensor network and position measurement for collision avoidance. For example, based on mathematical programming formulations, Schouwenaars et al. (2001) present an approach to planning the trajectories of multiple vehicles to avoid collisions. In addition, Leonard and Fiorelli (2001) contribute with a framework that coordinates a fleet of vehicles by modelling the vehicles as point masses that contain full actuation. The approach stabilizes flocking motions with vehicles' prescribed group geometry and controls the inter-vehicle spacing by using artificial potentials and virtual beacons.

Advancements in real-time motion planning of multi-AV operations continue with Olfati-Saber and Murray (2002). The framework proposed by Leonard and Fiorelli seeks a distributed control law that works for the scenario of multi-AVs' operation. Olfati-Saber and Murray provide two examples of structural formation stabilization which demonstrate such a framework, involving 3 vehicles and 6 vehicles respectively. Similarly, Olfati-Saber (2006) introduces a theoretical framework that can generate and analyze the distributed flocking algorithms for multi-vehicle networked systems. It addressed not only the cases of free-flocking but also the cases of flocking with obstacle avoidance. Comparative studies of three flocking algorithms contributed to the future research of collision avoidance. Similarly, Cortes et al. (2004) present an approach that focuses on multi-vehicle networks.

Inspired by the DARPA Urban Challenge, Wongpiromsarn et al. (2012) put forward an approach that can synthesize control protocols automatically. It ensures system correctness for its specification expressed in linear temporal logic in any operational conditions. Besides, a receding-horizon based framework was presented, which can simplify a computational synthesis problem and divide it into smaller, easy-to-solve problems. Further investigation of the robustness of this framework is expected.

4.3. CL.03: Multi-sensors and fusion systems

Seeing and understanding road conditions is crucial for AV detection and navigation, which depend on the interaction between sensors and AI-empowered systems. This cluster looks at virtual-based techniques and tests for automated driving.

Sensor devices, processing, and fusion algorithms are crucial components of a data fusion system. Important probabilistic modelling and fusion techniques as well as nonprobabilistic data fusion methods are reviewed by Durrant-Whyte and Henderson (2016). Their research outlines key principles in data fusion architectures from a hardware perspective as well as an algorithmic perspective. It also reports on two examples of applications: (1) a self-tracking application for AV navigation and (2) an application in mapping and environment modelling.

Pioneering research on multi-sensor data fusion first appears in the late 90s (Hall and Llinas, 1997). The experiment-based studies, however, emerge only in recent times. Cho et al. (2014) design an object-detection and tracking system based on the old version implemented during the DARPA Urban Challenge in 2007. The vision module in this system detects vehicles, cyclists, and pedestrians to generate vision targets accordingly, which improves the capabilities of movement classification and data association for sensors' measurement. The major downsides of this system are identified as the errors caused by: (1) the perceptions of new areas and (2) the inaccurate pose estimation and noise measurements (Moras et al., 2011).

Research belonging to this cluster also examines various approaches to implementing navigation systems for AVs. For example, using evidential reasoning, Pagac (1998) analyses the issues of building and maintaining a map of the AV environments to improve its navigation performance. The implemented approach allows support for multiple propositions at a time, which differs from the Bayes approach as it only allows a single hypothesis. Building upon such studies, Desjardins and Chaib-Draa (2011) propose a method for designing AV controllers with machine learning techniques, while Häne et al. (2015) present an approach to drawing out static obstacles from depth maps that are computed from multi-consecutive images. With the support of monocular fisheye cameras, this system enables a wider view to detect obstacles. Other novel approaches to the implementation of AV navigation systems include focusing on image processing and vision abilities (Menze and Geiger, 2015), designing driving behavior models (Al-Shihabi and Mourant, 2003), and simulators (Pereira and Rossetti, 2012).

4.4. CL.04: Road boundaries and extended curbs detection

This cluster focuses on developing sensors and algorithms for AV real-time detection of road boundaries and extended curbs. Improvements in stereo image processing, localization, and mapping techniques are key topics.

Bertozzi et al. (1998) discuss the possibility of extending an inverse perspective mapping geometrical transformation to a stereo image procession and present a calibration method for autonomous vehicles. As an example of an application in the field of AVs, it explicates the efficiency of an inverse perspective mapping. This work contributes to the development of various sensors and cameras for operating AVs. For example, Davison et al. (2007) developed an algorithm called MonoSLAM that uses real-time data to playback the 3D trajectories of a monocular camera that moves at high speed in unfamiliar scenes. based on real-time data. Furthermore, this work is expected to be extended for AV's real-time localization and mapping. With the development of Lidar, IMU, and GPS techniques, collected data can be applied to build a high-resolution infrared remittance ground map and this improvement supports AV navigation in dynamic urban environments (Levinson and Thrun, 2010). An extension to this approach can generate higher precision, improve the ability to understand and learn maps continually, and increase the robustness to the diversification of environments. Following this stream of research, Mutz (2016) introduced an end-to-end framework that can enhance the precision of large-scale mapping for autonomous driving. The large-scale mapping system was evaluated, and the experiment suggests it has the potential to support AV operations.

By adopting different approaches, Huang et al. (2009) demonstrate a system that uses calibrated video imagery plus laser range data to detect and predict the multiple travel lanes on city roads. This system successfully guides an AV through a 90km long course at speeds up to 40km/h in dynamic environments during the 2007 DARPA Urban Challenge. Similar systems that use vision data and Lidar emerge in the following years (Han et al., 2012; Hata et al., 2014; Li et al., 2014; Wijesoma et al., 2004). Numerous experiments are conducted for map-based visual localization and the results suggest the possibility and feasibility of using a single monocular camera to produce data for visual localization in a 3D Lidar map that contains surface reflectivity (Wolcott and Eustice, 2014).

4.5. CL.05: Motion planning for agricultural machinery

This cluster investigates motion planning for autonomous wheeled vehicles, especially addressing maneuver issues by means of fussy systems and other methods, and with a predominant focus on autonomous driving systems for agricultural machinery.

Gómez-Bravo et al. (2001) present a method to generate real-time operation strategies for wheeled vehicles, which uses artificial intelligence techniques, namely, fuzzy logic. A fuzzy system helps select strategies from the set of maneuvers based on the environments. It is associated with the optimization of path-selection, the performance of path tracking and collision avoidance. The proposed method contains three advantages: (a) it includes maneuvers for parallel parking as well as diagonal parking; (b) it obtains a set of maneuvers for collision avoidance and suggestions for viable starting points; and (c) it can define several optimal maneuvers for consideration.

Fuzzy systems are applied to address specific car maneuvers. For example, the Autonomous Fuzzy Behavior Control (AFBC) approach is introduced to simulate human's driving techniques and behaviors, especially parallel parking skills (Li et al., 2003). This method is developed based on the driving experiences, sensor-based behaviors, and Fuzzy Logic Control (FLC) techniques. Similarly, a fuzzy control system is developed to tackle issues associated with the diagonal parking of AVs in the narrow space, which is a common challenge in motion planning of wheeled systems (Baturone et al., 2004). A wide collection of experimental results from Cuesta et al. (2004), including different vehicles, environments and control architectures, suggests the robustness and flexibility of the proposed fuzzy systems.

In terms of testing, Kelly et al. (2006) investigated the architecture of the system in the DARPA PerceptOR program. The DARPA PerceptOR project enforces a strict test that accelerates the development of mobile robots and other applications in the field. By demonstrating the challenges and lessons learned from the testing, this study contributes to enhanced motion planning in various challenging environments.

To increase the productivity of specialty crops and reduce the human-labor cost, the Autonomous Prime Movers (APMs) is designed (Bergerman et al., 2012). The three-year experiment proves the ability to create cost-effective orchard AVs that can automate tree pruning, mowing, spraying, fruit harvesting, and other daily orchard tasks. Likewise, Subramanian et al. (2006) discussed the design and development of an autonomous guidance system that can be potentially used in a citrus grove and Cariou et al. (2009) address the problem of path tracking for mobile robots that move on the slippery ground.

4.6. CL.06: Lane detection and connected technologies

This cluster focuses on two major technologies for autonomous driving-lane detection based on visual abilities and connected technologies. The recent development of connected technologies enables vehicle-to-vehicle communication, vehicle-to-infrastructure communication, and vehicle-to-everything communication, which benefits lane detection and can be expanded to broad functional areas.

Ünyelioğlu et al. (1997) designed a constant steering controller for lane following by measuring the look-ahead point’s deviation. This study lays a foundation for lane-keeping and detection research. Building upon such research, a real-time algorithm for AV lane detection is proposed (Assidiq et al., 2008), which uses the video data captured by a vehicle driving on the highway. This algorithm can be applied to AV’s operation on various roads, including unpainted roads and roads with slight curves. Using both a linear algorithm and a non-linear algorithm, Törő et al. (2016) present the lane-keeping design and implementation of an automated and electric go-cart. Focusing on AV visual abilities, Batista et al. (2015) come up with a novel method to detect and estimate lanes, which relies on the road image captured by a monocular camera. In other words, the key to the success of this algorithm is the robustness of image processing, which deploys techniques such as Probabilistic Hough Transform, vehicle lateral localization, road marker estimation. This study thus offers a robust system that takes the perspective image as the only data source. Another example is the system designed in the Blind Driver Challenge[3] (BDC), which allows the safe operation of a vehicle by the visually impaired (Hong et al., 2008). This system shows the potential to enhance mobility for visually impaired people. It can also be extended to assist in driving for other groups of people.

Having benefited from the advancement of the internet and connected technologies, vehicles became connected. The development of intelligent vehicles based on different technologies such as grid, automation, connectivity, and vehicular cloud starts being explored (Gerla et al., 2014), as well as its potential impact on the market (Pearmine, 2017). Meanwhile, Amoozadeh et al. (2015) propose a critical view of the vulnerability of connected

[3] BDC was launched in 2009 by the National Federation of the Blind Jernigan Institute. This initiative aimed to support the creation of a vehicle that blind persons can operate independently.

AVs by looking at the potential attacks on communication channels that may threaten AV security. This investigation points out a future research direction of AV security.

4.7. CL.07: Motion planning for underwater intervention

The cluster CL.07 investigates the deployment of collaborative/multi autonomous vehicles in dynamic environments, especially focusing on their underwater operation.

Automation technologies enable the exploration of dangerous environments, such as the deep ocean. An overview of the development of automated technologies that enable various aerial and sea applications is offered by Steinberg (2006), while Marani et al. (2009) present one of the first approaches that involve the development of a robust autonomous manipulation. Some live experiments and trials are conducted. For example, during the Adaptive Sampling and Prediction (ASAP) experiment in California in 2006, a full-scaled ocean sampling network is implemented (Leonard et al., 2010), demonstrating new techniques designed to coordinate environmental sensor-empowered AVs to conduct sampling tasks in the ocean. Likewise, other research (Nađ et al., 2015) presents an experiment of AV's navigation, guidance and control (NGC), which suggests the robustness of motion of all directions for an autonomous marine vessel. These practices enrich theoretical discussions and technological approaches. The Underwater Systems and Technology Laboratory (LSTS), which creates sensing devices, various types of AV applications, and networked AV systems with human operators, lead the way to develop and evaluate approaches to underwater automation technologies. A layered control architecture invented at LSTS is introduced along with a demonstration of its deployed software (Pinto et al., 2012), and a C3I infrastructure (Communications, Command, Control, and Intelligence/Information), i.e. the Neptus framework, is also developed by LSTS (Dias et al., 2005). This framework supports the coordinated operation of multiple types of AVs, including the fully automated vehicles and the semi-automated ones.

Studying the evolutionary history of autonomous underwater vehicles (AUVs) also helps improve the understanding of coastal dynamics and further contributes to its characterization. Galceran et al. (2012) assess the relatively mature Remote Environmental Monitoring Units (REMUS) of an AUV system. Based on data collected from a 750km long underwater operation, the study demonstrates the REMUS as a feasible underwater platform that can operate automatically. Furthermore, it implies the importance of adopting suitable sampling methods and the parameterization of model domains.

The prospects of using collaborative autonomous vehicles in mine countermeasures (MCM) scenarios are also explored (Djapic and Nađ, 2010), where this technology can reduce the workload while improving the safety of operators.

4.8. CL.08: Obstacle detection and avoidance in different conditions

This cluster looks at different approaches to lane detection based on vision systems and algorithms. AV obstacle detection and avoidance abilities are explored in different conditions.

In 1985, a pioneering computer-vision system was built by the University of Maryland's computer vision lab (Davis and Kushner, 1986) for AV's road and road network navigation, wherein the image processing component along with the implementation of a set of algorithms were investigated. Inspired by this work, a cruise control system is created for AV guidance on the German highway system (Maurer et al., 1996) and image sequences techniques are implemented (Enkelmann, 1991; Suzuki et al., 1992), laying the foundations for AV detection and navigation studies.

Equally important to road recognition, efficient obstacle detection on roads within a short time helps trigger appropriate reactions to road situations. Apart from the slow changes in aspect conditions caused by long translation processes, there exist fast changes generated by rotational motion components. Research by Dickmanns (2007) mainly focuses on this subject matter of investigation.

AV's lane detection technique becomes mature under certain conditions in terms of speed and accuracy. Additional research was conducted, tackling challenging conditions, for instance, night-time operations. A lane detection algorithm implemented by Lipski et al. (2008), which is tested on an AV that participated in the 2007 Urban Challenge, has achieved satisfying experimental results as it can robustly detect and track multiple lane markings simultaneously. The algorithm, in combination with Lidar, radar, and other sensors, empowers the autonomous vehicles to drive in cities at the maximum speed of 15 mp/h. Similarly, the Springrobot prototype, which adopts a novel algorithm for lane-marking detection, uses a driver assistance system with the safety warning and an autopilot system for traffic in both rural and urban environments (Li et al., 2004). The prototype is demonstrated along with its lane-detecting tasks, and the experiment suggests that the accuracy and robustness of detecting road boundaries are challenging for AVs under different road conditions or during different periods of a day with changing light-conditions. It also points out that future studies should aim to reduce the running time in lane detection and improve machine learning's role in such a domain.

4.9. CL.09: Traffic sign recognition

Traffic sign recognition for AV is the main focus of this cluster, with cybersecurity concerns briefly mentioned. A vision-based smart vehicle has three roles, including road detection, obstacle detection as well as sign recognition. De la Escalera et al. (2003; 1997) introduced algorithms to improve the detection and classification of signs. Fairfield and Urmson (2011) proposed a novel method to automatically map the 3D positions of traffic lights and detect traffic light state onboard vehicles. In addition, Levinson et al. (2011) presented a passive camera-based pipeline that can detect the traffic light state. It uses vehicle localization techniques and assumes a prior knowledge of traffic light location. The latter study shows that multi-lights detection for each intersection improves the robustness to noise. The performance of single-light detection is also improved. Algorithms for traffic light recognition that use machine learning and computer vision techniques are further introduced in the following years. For instance, traffic light recognition algorithm presented by John et al. (2014) used a neural network to detect and draw out images features.

After recognizing traffic signs, AVs need to make decisions. Regele (2008) proposes a modelling method to improve the decision-making process for autonomous vehicles. Applying a hierarchical world model, it distinguishes a low-level model from a high-level model as the former one plans vehicle trajectories while the latter one coordinates road traffic. The traffic model is expected to be integrated into traffic management.

4.10. CL.10: Social impacts and integration of AVs

This cluster gathers social-oriented research on AVs and its attention is focused on the social effects and public acceptance of AV technology. The publications in this cluster also provide an overview of the potential benefits of AV developments to road safety and driving environments, and they point out the challenges that AV integration brings. Although covering many aspects at a high level, in-depth investigations are less diffused.

For instance, Fagnant and Kockelman (2015) draw a brief overview of the technology and the potential social impacts of AVs, and they discuss the challenges for social deployment. Their study focuses on aspects such as safety, congestion and traffic operation, travel behavior, vehicle ownership, and parking. Barriers to implementation, which are associated with vehicle cost, AV certification, litigation, liability and public perception, security, and privacy are also discussed. Fagnant and Kockelman (2014) continue the analysis by exploring an agent-based model regarding the implementation of shared AVs (SAV), which as a basic framework, can extract travel features of an SAV fleet. Furthermore, their work estimates the waiting time for customers based on the analysis of AV's relocation maneuver and its operational conditions. AV's and SAV's impacts on the broader driving environment also raise research attention (Talebpour and Mahmassani, 2016).

Another important aspect of AV societal research is acceptability, which is closely related to people's opinions on AV technology and SAV service. By means of a survey with 5,000 responses from 109 countries, people's preferences and willingness to different types of AV regarding the level of automation are studied by Kyriakidis et al. (2015). The results show that nearly 69% of people believe AVs with full automation will reach half of the market share between now and 2050, however, various concerns are revealed at the same time. These concerns are related to aspects such as safety, data privacy, and AV legislation. It enriches stakeholders' understanding of public opinions on AVs and contributes to market strategies. Likewise, user preference is widely studied and analyzed in multiple regions and cultures, for instance, regional differences between Israel and North America (Haboucha et al., 2017) are explained through the study of user preference of AVs, which may inspire regional policy making in the future.

Some researchers also look at the willingness to pay for AV/SAV services (Bansal et al., 2016; Krueger et al., 2016). For example, a survey conducted in Austin indicates that people perceive a decrease in car accidents to be the primary benefit and equipment failure as the top concern. The study also finds that participants are more willing to pay for the service that can add a higher level (level 4) of automated technology to their current car than adding comparatively lower automation (level 3).

However, apart from discussing broad social impacts and challenges, these studies are mainly centered around evaluating and improving social acceptance. The marketing strategies and implications from such studies thus imply a research driven out of commercialization. In-depth investigations of other non-technical implications of autonomous-driving technology, such as accessibility, affordability and liability, are largely missing.

4.11. CL.11: HCI and ethical dilemmas

This cluster explicates different types of challenges of human-robot (automated vehicles) interaction and discusses some ethical dilemmas.

Five major challenges of human factors research on automated vehicles are pointed out by Sheridan (2016): (1) a task analysis that considers environmental, economic and other potential factors; (2) the avoidance of accidental consequences; (3) the mutual models and shared features between robots and humans; (4) robotic applications for education; and (5) strategies for managing users' concerns and considerations caused by cultural or value difference. In the context of automated driving, complex situations are discussed such as pedestrian behavior (Chang et al., 2017; Rothenbucher et al., 2016), challenges that a driver with autopilots experience on the roads (Brown and Laurier, 2017), and moral dilemmas in vehicle crash scenarios (Lin, 2015).

Goodall (2014) and Lin (2015) suggest that, even in ideal conditions, automated vehicles cannot always avoid being involved in crashes, and the AV decision that precedes certain crashes has a moral and ethical component. Lin introduces scenarios such as the trolley problem that implicate ethics and illustrate the complexity of AV decision making since this process goes beyond mechanically obeying the existing traffic rules. These studies highlight the importance of ethics for AVs and encourage methods from various disciplines to tackle these challenges.

Gerdes and Thornton (2015) attempted to find a mathematical way to pin down the philosophical ethical considerations of AV and address them accordingly by offering better choices of steering, braking, or accelerating under certain circumstances. Efforts on translating between philosophical concepts and mathematical equivalents contribute to simple implementations of ethical rules, however, they simplify the real-world complexity. As suggested by Goodall (2014), human morality can hardly be encoded into AVs.

To understand and increase users' acceptance and adoption, Pettersson and Karlsson (2015) introduced two methodologies to explore the user's reaction and expectation. The first one encompasses techniques such as interviews while the second one mediates a shift of views over time through setting expectations of the AV use. For a similar purpose of studying pedestrian's reaction and expectation, a breaching experiment was designed and conducted at Stanford (Rothenbucher et al., 2016), which used a faux driverless car as an intervention in the real-world setting. This study contributed to a new method to investigate interactions between pedestrians and driverless vehicles, and it provided insights on pedestrian behavior and pedestrians' expectations of encountering driverless vehicles.

4.12. CL.12: Testing and risk assessment

This cluster mainly discusses testing methods of autonomous driving and cybersecurity risks, which are introduced in an overview by Huang et al. (2016). Their work also covered topics such as the functional testing and verification of AVs and the validation of AV systems.

The core literature also demonstrates some novel ideas and methods. For example, Kalra and Paddock (2016) call for adaptive policies, by pointing out that AVs need to be driven up to billions of miles to demonstrate their functional feasibility. In addition, Huang et al. (2017) applied the Satisfiability Modulo Theory (SMT) and developed an AV verification system, which focuses on making safe decisions based on image management.

Testing the vision-based control systems of AV is a complicated task. To tackle this, Abdessalem et al. (2018) designed and demonstrated an AV testing algorithm that builds upon the learnable evolutionary algorithms. The core technologies for this algorithm to generate new sets of solutions are machine learning and a mix with Darwinian genetic operators. The proposed algorithms show accuracy in evaluations. Aiming to solve the ADAS's time testing issue in simulated environments, Abdessalem et al. (2016) proposed a neural network-based approach that combines a multiobjective search with alternative models. They evaluate the robustness of this method through an industrial application.

Behere and Törngren (2016) described a functional reference architecture for AV operation and explicate several considerations that may affect it. The functions of such architecture do not rely on specific implementation technologies, rather, they are logistically described. The study investigates two aspects, first, how do implementation technologies affect functional architectures, and second, how does the fact of replacing human drivers with computers affect the architectures. Furthermore, the study suggests that to incorporate the processes of such deployment, it is essential to speed up the testing and verification.

Some types of risks around AV operation also trigger discussions. For instance, Sharif et al. (2016) looked at cybersecurity issues. In particular, they aim to design facial biometric systems that can identify certain attacking behaviors and attackers who try to evade recognition. These systems have been widely applied for surveillance and regulation.

4.13. CL.13: Automated Storage and Retrieval System (AVS/RS)

Autonomous Vehicle Storage and Retrieval System (AVS/RS) represents an advanced alternative to the traditional automated storage and retrieval systems. AVs operate as storage or retrial devices while also being able to transfer loads out of the storage racks. The superiority of this new system is that AV systems can match the size of vehicle fleets as well as the number of lifts to the storage system's transaction demand. This cluster focuses on the development and evaluation of AVS/RS, which shows a constant effort in enhancing the technological feasibility of AVs.

Through opportunistic interleaving, a network queuing model was used to evaluate the AVS/RS performance measures (Fukunari and Malmborg, 2009). This model contains the potential to provide an important component of a decision support system to conceptualize AVS/RS. At the same time, it can combine modelling of cost and resource requirements. Taking inspiration from the network queuing models, Roy et al. (2012) designed a semiopened system to estimate one AVS/RS layer's design trade-offs. After testing, the model was proven to help quantify the trade-offs and such a result further implies its impact on reducing transaction time of AVS/RS. The computationally efficient cycle time model (Fukunari and Malmborg, 2008) is essential in an AVS/RS as it is proved to be useful for the accurate system conceptualization. The model also enables a comparison between the performances of AVS/RS and the traditional AS/RS (Kuo et al., 2007).

Simulation-based experimental designs were further conducted for AVS/RS studies (Ekren et al., 2010) and strategies are tested in practical projects, for example, a regression analysis of an AVS/RS rack configuration is demonstrated to build warehouse configurations that deploy AVS/RS and AS/RS alternately (Ekren and Heragu, 2009; Zhang et al., 2009). Likewise, a state equation model was introduced by Malmborg (2002, 2003) to estimate the usage of dual command cycles in an AVS/RS. Using interleaving, it empowers users with a clear understanding of the computational complexity as well as a rational consideration of the model's accuracy in an early stage of its development.

5. Discussion and conclusion

Autonomous-driving technology has the potential to radically change the automotive industry and generate the system innovation which is needed to boost sociotechnical transitions to a sustainable transportation sector. Driven by the desire to unleash its innovation potential, a fast-growing interest in AV research has manifested across academic disciplines, which has resulted in a sudden increase in the volume of scientific publications. AV-related scientific knowledge is produced and accumulated at a very fast pace. As a consequence, the likelihood of incurring information overload is particularly notable for AV researchers, who can struggle to overcome the gap between requirements for and capacity of information processing.

Inspired by information granularity studies and mixed-methods bibliometric investigations, this paper suggests addressing this issue by adopting a multi-granulation approach to latent knowledge discovery and synthesis in large-scale research domain. The proposed methodology combines citation-based community detection methods and topic modeling techniques to: (1) extract the relevant semantic structures (i.e. main keywords, emergent topics, and core research themes) hidden in large data-rich environments; and (2) use these sub-information systems of latent variables to give a concise account of how the intellectual structure of research field is conceptually structured.

The proposed methodological approach has been successful in providing a synthetized view of the scientific knowledge produced during five decades of AV research (1970-2019). Starting from 18,153 publications, 13 clusters of thematically related publications were detected, which are complementary to each other in terms of developing the insight needed for enabling AV operations. The clusters CL.01, CL.02, CL.04, CL.05, CL.06, CL.08, and CL.13 all discuss the technical developments related to AV detection and navigation, with each group of publications representing different techniques and approaches. CL.03 and CL.09 both focus on the importance of AV multi-sensors and discuss image recognition and processing techniques. In consideration of the literature belonging to these clusters, the findings of the bibliometric analyses show advancements in different AV-related technological domains. This collective research efforts are making it possible to shine light onto the unknowns and uncertainties surrounding complex tasks that AVs are expected to implement in real-life environments. The analysis also shows that automated technologies have been applied to different fields, such as agriculture (see CL.05), underwater operations, and unmanned aerial vehicles (see CL.07).

However, despite the development of various technologies that can empower AV operations, which been developing at high-speed, most of the research is experimental in nature. As a result, large-scale deployment of AVs remains undeveloped. Pioneering experiments have led to an exploration of the broader uses of AV technology. Numerous models, algorithms, and methods have been proposed since the 1970s to develop automated technologies. But laboratory-based experiments remain the core component of AV deployment, with only some initial and quite recent small-scale testing in urban environments. In fact, evaluation and verification methods for moving to real-world trials have started emerging only during the past decade (see CL.12).

Finally, CL.10 and CL.11 concentrate on Human-Computer-Interaction (HCI). In addition to introducing the ethical dilemma of AV technology, CL.11 literature reports on the technical aspects of HCI, examining the rollout of neural networks and deep learning. The former is instead mainly focused on public acceptance and the overall social impacts and challenges. Out of thirteen clusters, CL.10 is the only group of publications which identify the non-technical implications of AVs as a core topic.

By defining each thematic cluster and presenting its content, this paper produces a synthesized view of the most relevant AV-related thematic areas which expands the list of research-front concepts proposed by Gandia et al. (2019), providing a more information-rich understanding of how the AV research field is conceptually structured. In addition, the analysis has made it possible to cluster these concepts in groups of thematically related keywords, helping researchers to grasp the bigger picture. The higher level of detail that this paper offers also becomes evident when comparing the keyword-topic-theme correlations embedded in each thematic cluster with the manually labelled co-citation clusters identified by Rashidi et al. (2020), whose thematic focus is defined by using single keywords rather than a group of complementary sub-information systems of latent variables. Supported by the use of core literature, the latter approach has offered a broader understanding of how thematic areas are conceptually shaped and improved the contextualization process required to comprehensively communicate the core knowledge included in each cluster. For example, the proposed cluster analysis details the differences between AV core control systems and techniques and their progressive development, whereas Rashidi and colleagues generalize this knowledge area under abstract themes, such as *Algorithm*, *Control strategy*, and *Controller*.

In addition, this study has made it possible to discover that AV research has seriously overlooked the wide-ranging sustainability implications of autonomous-driving technology. As a result, "the discussions and studies extrapolating AVs technical aspects, by inserting them in a dynamic environment with several agents and implications, are far from being exhausted" (Gandia et al., 2019, p. 22).

5.1. The sustainability challenge

Overall, the findings of this study show that AV research is mainly technology-driven and is much more oriented towards examining the technological developments needed to enable the widespread rollout of AVs, rather than exploring the socio-economic, environmental, cultural, political, institutional, and organizational dimensions of a future sociotechnical transition to sustainable transport systems. The research investigating the non-technical aspects of AVs is significantly underdeveloped when compared to technology-related dimensions. As a result, the current status of AV research exposes a serious lack of attention to the sustainability of large-scale AV deployment. This gap probably explains why no thematic clusters strongly related to sustainability research have been identified. During the last fifty years, little research has been conducted which attempts to assess the sustainability implications of AVs, and this limited effort represents an exclusion of the utmost importance.

When looking at the annual intensity of each core theme, the findings show that the thematic clusters CL.10 and CL.11, which are mainly associated with social sustainability aspects, have grown significantly during the last four years, especially in comparison to the technology-related clusters of the network, where it is possible to assume that a higher degree of maturity has been reached. But the content analysis demonstrates that most of the research is only focused on user experience studies exploring market dynamics and how public acceptance of AV solutions can be enhanced. This suggests that the research focusing on the social and economic sustainability of a potential sociotechnical transition to AVs is not only scarce, but it is also mainly driven by a market-oriented approach. Despite being pivotal in the search for a sustainable approach to AV deployment in urban environments, broader topics such as accessibility, affordability, liability, trust, business models, travel behavior, political and cultural implications, and socio-economic impacts remain unexplored. The solutions to some of the most relevant barriers to AV implementation and mass-market penetration relate to these unexplored areas of research (Fagnant and Kockelman, 2015; Hess, 2020).

In addition, the analysis shows that social and economic implications are not the only sustainability dimensions which have been largely overlooked in the 50 years of AV research under investigation. Not enough consideration has been given to environmental consequences. Autonomous-driving solutions are expected to introduce the systemic technological changes required to provide society with environmentally sustainable transportation systems. The frequently claimed benefits notwithstanding, only a few academic publications attempt to evaluate the potential impacts that AVs can have on environmental sustainability (Martin, 2019) and green city making (Chehri and Mouftah, 2019; Vleugel and Bal, 2018), and a full environmental assessment of AVs is still missing (Gawron et al., 2018). This lack of evidence creates uncertainty in relation to what the ecological impacts of AVs will be and the real role that newly introduced travel behavior patterns will play. As Miller and Heard (2016) note, not all the AV-induced behavioral shifts will introduce environmentally favorable changes, because the approach to usage may worsen already existing ecological conditions (Ryan, 2020). For example, "additional vehicle miles traveled may be incurred due to unoccupied travel miles where the vehicle is moving without passengers" and "the reduced aggravation associated with commuting may lead to an increased acceptable commuting radius, increasing overall vehicle miles traveled and inducing additional GHG emissions related to urban sprawl" (Miller and Heard, 2016, p. 6119).

A major lesson from transitions studies is that sustainability transitions do not only involve major shifts in technological systems fulfilling societal functions. They also imply co-evolutionary changes of non-technological assets, which give meaning and purpose to the newly introduced artefacts (Naor et al., 2015; Smith et al., 2010). These changes are strictly interconnected and relate to the socio-economic, cultural, political, institutional, environmental, and organizational dimensions of sustainability transitions (Geels et al., 2016). Sustainability transitions require finding a new equilibrium between innovative technological trajectories and these non-technical dimensions. A stable match is needed, which can be found through experimenting with new structural arrangements. AV research seems still far from finding this equilibrium and additional sustainability-oriented research is required in order to shed light on what new sociotechnical arrangements can ensure that the systemic technological change introduced by AV-based transport systems will fulfill societal functions while meeting the urgent need for more sustainable transport solutions.

For example, cultural inclinations are well entrenched in urban environments, but a shift is essential to cultivating the new set of desired behaviors and virtues which is needed to underpin autonomous-driving technology and the improved sustainability that this transition promises to deliver (Castán Broto and Dewberry, 2016; Throop and Mayberry, 2017). Negative cultural perceptions are hard to replace and can prevent innovative practices and technologies. When looking at transport-related sustainability issues, for instance, it is widely acknowledged that cycling can substitute many short- and medium-distance trips, making the transport sector more environmentally friendly (Pucher and Buehler, 2017). Whilst the Amsterdam cycling transition was backed by a strong sociocultural connection between the bicycle and the Dutch national identity, conversely, a culturally negative image of cyclists has become an obstacle to the cycling niche which is opposing the regime of motorized trans-ports in London (Marije De Boer and Caprotti, 2017).

The politics of regime change is an additional factor that plays a major role in building the institutional and regulatory systems needed to sustain sustainability transition contexts (Gonzalez de Molina, 2013), but it also represents an explored area of research when observing the AV research field. Sociotechnical transitions require political action to readjust public policies, so that they reflect more sustainable trajectories (Goyal and Howlett, 2020) and arbitrate when competing propositions, resistance, and powers struggles hinder the transformation (Wironen and Erickson, 2020). As a result, formal institutional frameworks are modified by setting and enacting new laws, guiding principles, norms, and procedures which regulate power relations in niche-regime interactions (López-García et al., 2019) and facilitate the development of multi-actor networks, protecting and deepening the reach of sustainability transitions (Brown et al., 2013).

The project Aramis is emblematic of the importance that the politics of regime change has in sustainability transitions. Launched in the 1970s, Aramis attempted to introduce a revolutionary Personal Rapid Transit (PRT) system in Paris. This government-funded experimental project was expected to improve road capacity by placing small cars on an automated highway system and using them as trains. The system was never completed, and research investigating the development process has proved that inconsistent political support was one of the major failure-causing issues, together with a serious lack of strategic planning (Latour, 1996).

Sustainability transitions also require changes in organizational settings (Bögel et al., 2019). By replacing existing values, norms, infrastructure components, services, and routines, transition processes alter the way in which local communities are organized. Transition management research has shown that pursuing sustainability transitions requires democratic governance arrangements (Jhagroe and Loorbach, 2015) based on inter-organizational collaboration and co-creation principles (Cohendet et al., 2014). New alliances between heterogeneous actors and social groups emerge which are tasked with developing the pathway leading to the envisioned sustainable future, while overcoming the resistance of existing regimes (Köhler et al., 2019). As a result, roles and responsibilities of individuals and communities are subject to modifications, generating empowering and (dis)empowering effects (Hölscher et al., 2019). However, relevant questions have yet to be answered in relation to what organizational settings should be enacted to facilitate the sustainable widespread of AV solutions and how these settings modify due to geographical differences.

In addition, when looking at changes in organizational settings regulating the functioning of transport systems, it is also important to highlight that AV-related sustainability studies are also required for exploring how AV development will be affected by the Covid-19 pandemic and what new barriers and opportunities have been brought to light. For example, while people are forced to observe social distancing measures to prevent the virus for spreading, AVs have been deployed for non-contact, low-speed delivery services, in particular in areas that were subject to lockdown measures (Okyere et al., 2020). This approach to deployment shows that driverless technology may provide an opportunity to reduce biosafety risks. In addition, the pandemic has caused a drop in transit ridership, making it difficult for public transport systems to address transport needs in some urban areas (Short et al., 2020; Wang et al., 2020). The pressure exerted by this unfortunate event may help accelerate the development of mass autonomous transit systems, by lowering the existing resistance to change (Zeng et al., 2020). However, shrinking economies and health concerns may also challenge the AV industry, by reducing funding opportunities and slowing down real-world testing. How self-driving technology development and deployment will be reorganized in the post Covid-19 era is another subject matter worthy of investigation.

5.2. Limitations

This methodological approach has been effective in achieving the proposed research objectives, but it is important to acknowledge the presence of a number of methodological limitations, which themselves present future research opportunities.

First, the use of a single database to gather the source literature may have resulted in some relevant academic publications on AV being undetected. Scholarly databases retrieve different sets of publications when the same search query is processed and their level of coverage tends to change depending upon the subject under investigation (Martín-Martín et al., 2018). Mindful of this limitation, Scopus and Web of Science, two of the main sources of bibliometric data currently available (Mongeon and Paul-Hus, 2016), were both tested to establish their coverage of AV research. The initial keyword search was performed in both databases and Scopus was found to offer a broader coverage of literature, sourcing 6,626 additional titles.

Second, this study only focuses attention on peer-reviewed publications. Therefore, AV-related grey literature was not taken into account. It would be interesting to evaluate whether this type of literature, which is not subject to a formal peer-review process, has influenced the academic debate and the shaping of the intellectual structure of the AV research field.

Finally, the evaluation phase of the topic modelling output can be further enhanced. This phase of the analytical process has proven successful in generating construct validity evidence and input for refining the description of the thematic clusters. However, due to resource constraints, validity was ascertained by means of a limited number of domain experts and the interrater reliability was measured by considering qualitative rather than qualitative approaches, which would provide more robust measures. Therefore, additional research involving large-scale data collection tools would be beneficial for further testing and refining the results of the topic modelling.

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APPENDIX A

CLUSTER	IN-DEGREE CENTRALITY	AUTHORS	YEAR	TITLE	TYPE
CL.01	212	Urmson C., Anhalt J., Bagnell D., Baker C., Bittner R., Clark M.N., Dolan J., Duggins D., Galatali T., Geyer C., Gittleman M., Harbaugh S., Hebert M., Howard T.M., Kolski S., Kelly A., Likhachev M., McNaughton M., Miller N., Peterson K., Pilnick B., Rajkumar R., Rybski P., Salesky B., Seo Y.-W., Singh S., Snider J., Stentz A., Whittaker W., Wolkowicki Z., Ziglar J., Bae H., Brown T., Demitrish D., Litkouhi B., Nickolaou J., Sadekar V., Zhang W., Struble J., Taylor M., Darms M., Ferguson D.	2008	Autonomous driving in urban environments: Boss and the urban challenge	AR
	151	Falcone P., Borrelli F., Asgari J., Tseng H.E., Hrovat D.	2007	Predictive active steering control for autonomous vehicle systems	AR
	92	Kuwata Y., Teo J., Fiore G., Karaman S., Frazzoli E., How J.P.	2009	Real-time motion planning with applications to autonomous urban driving	AR
	66	Dolgov D., Thrun S., Montemerlo M., Diebel J.	2010	Path planning for autonomous vehicles in unknown semi-structured environments	AR
	58	Broggi A., Zelinsky A., Özgüner Ü., Laugier C.	2016	Intelligent vehicles	BC
	58	Naranjo J.E., González C., García R., De Pedro T.	2008	Lane-change fuzzy control in autonomous vehicles for the overtaking maneuver	AR
	46	Ferguson D., Howard T.M., Likhachev M.	2008	Motion planning in urban environments	AR
	46	Ferguson D., Howard T.M., Likhachev M.	2009	Motion planning in urban environments	BC
	43	Campbell M., Egerstedt M., How J.P., Murray R.M.	2010	Autonomous driving in urban environments: Approaches, lessons and challenges	AR
	43	Borrelli F., Falcone P., Keviczky T., Asgari J., Hrovat D.	2005	MPC-based approach to active steering for autonomous vehicle systems	AR
CL.02	57	Frazzoli E., Dahleh M.A., Feron E.	2002	Real-time motion planning for agile autonomous vehicles	AR
	57	Frazzoli E., Dahleh M.A., Feron E.	2000	Real-time motion planning for agile autonomous vehicles	CP
	57	Frazzoli E., Dahleh M.A., Feron E.	2001	Real-time motion planning for agile autonomous vehicles	CP
	43	Leonard N.E., Fiorelli E.	2001	Virtual leaders, artificial potentials and coordinated control of groups	CP
	37	Schouwenaars T., De Moor B., Feron E., How J.	2001	Mixed integer programming for multi-vehicle path planning	CP
	32	Cortés J., Martínez S., Karataş T., Bullo F.	2004	Coverage control for mobile sensing networks	AR
	31	Olfati-Saber R.	2006	Flocking for multi-agent dynamic systems: Algorithms and theory	AR
	23	Olfati-Saber R., Murray R.M.	2002	Distributed cooperative control of multiple vehicle formations using structural potential functions	CP
	18	Wongpiromsarn T., Topcu U., Murray R.M.	2012	Receding horizon temporal logic planning	AR
	16	Cochran J., Krstic M.	2009	Nonholonomic source seeking with tuning of angular velocity	AR
CL.03	31	Cho H., Seo Y.-W., Kumar B.V.K.V., Rajkumar R.R.	2014	A multi-sensor fusion system for moving object detection and tracking in urban driving environments	CP
	30	Durrant-Whyte H., Henderson T.C.	2016	Multisensor data fusion	BC
	22	Menze M., Geiger A.	2015	Object scene flow for autonomous vehicles	CP
	18	Desjardins C., Chaib-Draa B.	2011	Cooperative adaptive cruise control: A reinforcement learning approach	AR
	14	Pagac D., Nebot E.M., Durrant-Whyte H.	1998	An evidential approach to map-building for autonomous vehicles	AR
	11	Hall D.L., Llinas J.	1997	An introduction to multisensor data fusion	AR
	10	Pereira J.L.F., Rossetti R.J.F.	2012	An integrated architecture for autonomous vehicles simulation	CP
	10	Häne C., Sattler T., Pollefeys M.	2015	Obstacle detection for self-driving cars using only monocular cameras and wheel odometry	CP
	10	Al-Shihabi T., Mourant R.R.	2003	Toward more realistic driving behavior models for autonomous vehicles in driving simulators	AR
	9	Moras J., Cherfaoui V., Bonnifait P.	2011	Credibilist occupancy grids for vehicle perception in dynamic environments	CP
CL.04	77	Levinson J., Thrun S.	2010	Robust vehicle localization in urban environments using probabilistic maps	CP

	24	Li Q., Chen L., Li M., Shaw S.-L., Nüchter A.	2014	A sensor-fusion drivable-region and lane-detection system for autonomous vehicle navigation in challenging road scenarios	AR
	23	Davison A.J., Reid I.D., Molton N.D., Stasse O.	2007	MonoSLAM: Real-time single camera SLAM	AR
	21	Mutz F., Veronese L.P., Oliveira-Santos T., De Aguiar E., Auat Cheein F.A., Ferreira De Souza A.	2016	Large-scale mapping in complex field scenarios using an autonomous car	AR
	18	Huang A.S., Moore D., Antone M., Olson E., Teller S.	2009	Finding multiple lanes in urban road networks with vision and lidar	AR
	18	Hata A.Y., Osorio F.S., Wolf D.F.	2014	Robust curb detection and vehicle localization in urban environments	CP
	17	Han J., Kim D., Lee M., Sunwoo M.	2012	Enhanced road boundary and obstacle detection using a downward-looking LIDAR sensor	AR
	17	Wijesoma W.S., Kodagoda K.R.S., Balasuriya A.P.	2004	Road-boundary detection and tracking using ladar sensing	AR
	15	Bertozz M., Broggi A., Fascioli A.	1998	Stereo inverse perspective mapping: Theory and applications	AR
	15	Wolcott R.W., Eustice R.M.	2014	Visual localization within LIDAR maps for automated urban driving	CP
CL.05	16	Gómez-Bravo F., Cuesta F., Ollero A.	2001	Parallel and diagonal parking in nonholonomic autonomous vehicles	AR
	15	Li T.-H.S., Chang S.-J., Chen Y.-X.	2003	Implementation of human-like driving skills by autonomous fuzzy behavior control on an FPGA-based car-like mobile robot	AR
	13	Subramanian V., Burks T.F., Arroyo A.A.	2006	Development of machine vision and laser radar based autonomous vehicle guidance systems for citrus grove navigation	AR
	12	Baturone I., Moreno-Velo F.J., Sánchez-Solano S., Ollero A.	2004	Automatic design of fuzzy controllers for car-like autonomous robots	AR
	10	Kelly A., Amidi O., Bode M., Happold M., Herman H., Pilarski T., Rander P., Stentz A., Vallidis N., Warner R.	2006	Toward reliable off road autonomous vehicles operating in challenging environments	AR
	10	Kelly A., Stentz A., Amidi O., Bode M., Bradley D., Diaz-Calderon A., Happold M., Herman H., Mandelbaum R., Pilarski T., Rander P., Thayer S., Vallidis N., Warner R.	2006	Toward reliable off road autonomous vehicles operating in challenging environments	CP
	9	Reina G., Johnson D., Underwood J.	2015	Radar sensing for intelligent vehicles in urban environments	AR
	8	Cuesta F., Gómez-Bravo F., Ollero A.	2004	Parking maneuvers of industrial-like electrical vehicles with and without trailer	AR
	8	Bergerman M., Singh S., Hamner B.	2012	Results with autonomous vehicles operating in specialty crops	CP
	7	Bakker T., Wouters H., van Asselt K., Bontsema J., Tang L., Müller J., van Straten G.	2008	A vision based row detection system for sugar beet	AR
CL.06	46	Pearmine A.	2017	Connected vehicle	BC
	40	Gerla M., Lee E.-K., Pau G., Lee U.	2014	Internet of vehicles: From intelligent grid to autonomous cars and vehicular clouds	CP
	17	Amoozadeh M., Raghuramu A., Chuah C.-N., Ghosal D., Michael Zhang H., Rowe J., Levitt K.	2015	Security vulnerabilities of connected vehicle streams and their impact on cooperative driving	AR
	16	Assidiq A.A.M., Khalifa O.O., Islam Md.R., Khan S.	2008	Real time lane detection for autonomous vehicles	CP
	10	Behere S., Törngren M.	2015	A functional architecture for autonomous driving	CP
	8	Töro O., Bécsi T., Aradi S.	2016	Design of lane keeping algorithm of autonomous vehicle	AR
	7	Shi W., Alawieh M.B., Li X., Yu H.	2017	Algorithm and hardware implementation for visual perception system in autonomous vehicle: A survey	AR
	6	Ünyelioğlu K.A., Hatipoğlu C., Özgüner Ü.	1997	Design and stability analysis of a lane following controller	AR
	6	Batista M.P., Shinzato P.Y., Wolf D.F., Gomes D.	2015	Lane detection and estimation using perspective image	CP
	5	Petrillo A., Pescapé A., Santini S.	2018	A collaborative approach for improving the security of vehicular scenarios: The case of platooning	AR
	5	Najada H.A., Mahgoub I.	2016	Autonomous vehicles safe-optimal trajectory selection based on big data analysis and predefined user preferences	CP
	5	Hong D., Kimmel S., Boehling R., Camoriano N., Cardwell W., Jannaman G., Purcell A., Ross D., Russel E.	2008	Development of a semi-autonomous vehicle operable by the visually-impaired	CP

	5	Tassi A., Egan M., Piechocki R.J., Nix A.	2017	Modeling and design of millimeter-wave networks for highway vehicular communication	AR
CL.07	26	Rudnick D.L., Davis R.E., Eriksen C.C., Fratantoni D.M., Perry M.J.	2004	Underwater gliders for ocean research	AR
	11	Marani G., Choi S.K., Yuh J.	2009	Underwater autonomous manipulation for intervention missions AUVs	AR
	10	Pinto J., Calado P., Braga J., Dias P., Martins R., Marques E., Sousa J.B.	2012	Implementation of a control architecture for networked vehicle systems	CP
	6	Leonard N.E., Paley D.A., Davis R.E., Fratantoni D.M., Lekien F., Zhang F.	2010	Coordinated control of an underwater glider fleet in an adaptive ocean sampling field experiment in Monterey Bay	AR
	6	Dias P.S., Gomes R.M.F., Pinto J., Fraga S.L., Gonçalves G.M., Sousa J.B., Pereira F.L.	2005	Neptus - A framework to support multiple vehicle operation	CP
	5	Galceran E., Djapic V., Carreras M., Williams D.P.	2012	A real-time underwater object detection algorithm for multi-beam forward looking sonar	CP
	5	Moline M.A., Blackwell S.M., von Alt C., Allen B., Austin T., Case J., Forrester N., Goldsborough R., Purcell M., Stokey R.	2005	Remote environmental monitoring units: An autonomous vehicle for characterizing coastal environments	AR
	4	Nad D.D., Mišković N., Mandić F.	2015	Navigation, guidance and control of an overactuated marine surface vehicle	AR
	4	Djapic V., Nad D.	2010	Using collaborative autonomous vehicles in mine countermeasures	CP
	3	Steinberg M.	2006	Intelligent autonomy for unmanned naval vehicles	CP
CL.08	13	Li Q., Zheng N., Cheng H.	2004	Springrobot: A prototype autonomous vehicle and its algorithms for lane detection	AR
	11	Maurer M., Behringer R., Fürst S., Thomanek F., Dickmanns E.D.	1996	A compact vision system for road vehicle guidance	CP
	8	Davis L.S., Kushner T.R.	1986	Road boundary detection for autonomous vehicle navigation	AR
	7	Enkelmann W.	1991	Obstacle detection by evaluation of optical flow fields from image sequences	AR
	6	Dickmanns E.D.	2007	Dynamic vision for perception and control of motion	BO
	6	Dickmanns E.D.	2002	Vision for ground vehicles: History and prospects	AR
	5	Lipski C., Scholz B., Berger K., Linz C., Stich T., Magnor M.	2008	A fast and robust approach to lane marking detection and lane tracking	CP
	5	Suzuki A., Yasui N., Nakano N., Kaneko M.	1992	Lane recognition system for guiding of autonomous vehicle	CP
	4	Wu B.-F., Lin C.-T.	2005	A fuzzy vehicle detection based on contour size similarity	CP
	4	Watanabe M., Takeda N., Onoguchi K.	1996	A moving object recognition method by optical flow analysis	CP
	4	Kuan D., Phipps G., Chuan Hsueh A.	1988	Autonomous Robotic Vehicle Road Following	AR
	4	Wu C.-J., Tsai W.-H.	2009	Location estimation for indoor autonomous vehicle navigation by omni-directional vision using circular landmarks on ceilings	AR
	4	Holzapfel W., Sofsky M., Neuschaefer-Rube U.	2003	Road profile recognition for autonomous car navigation and Navstar GPS support	AR
	4	Charnley D., Blissett R.	1989	Surface reconstruction from outdoor image sequences	AR
CL.09	31	Fairfield N., Urmson C.	2011	Traffic light mapping and detection	CP
	24	Levinson J., Askeland J., Dolson J., Thrun S.	2011	Traffic light mapping, localization, and state detection for autonomous vehicles	CP
	17	De La Escalera A., Moreno L.E., Salichs M.A., Armingol J.M.	1997	Road traffic sign detection and classification	AR
	16	Regele R.	2008	Using ontology-based traffic models for more efficient decision making of autonomous vehicles	CP
	15	John V., Yoneda K., Qi B., Liu Z., Mita S.	2014	Traffic light recognition in varying illumination using deep learning and saliency map	CP
	13	De la Escalera A., Armingol J.M., Mata M.	2003	Traffic sign recognition and analysis for intelligent vehicles	AR
	10	Alheeti K.M.A., Gruebler A., McDonald-Maier K.D.	2015	An intrusion detection system against malicious attacks on the communication network of driverless cars	CP
	8	Pollard E., Morignot P., Nashashibi F.	2013	An ontology-based model to determine the automation level of an automated vehicle for co-driving	CP
	7	Mu G., Xinyu Z., Deyi L., Tianlei Z., Lifeng A.	2015	Traffic light detection and recognition for autonomous vehicles	AR
	6	Alheeti K.M.A., Gruebler A., McDonald-Maier K.	2016	Intelligent intrusion detection of grey hole and rushing attacks in self-driving vehicular networks	AR
	6	Alheeti K.M.A., Gruebler A., McDonald-Maier K.D.	2015	On the detection of grey hole and rushing attacks in self-driving vehicular networks	CP
	6	Provine R., Schlenoff C., Balakirsky S., Smith S., Uschold M.	2004	Ontology-based methods for enhancing autonomous vehicle path planning	AR

CL.10	143	Fagnant D.J., Kockelman K.	2015	Preparing a nation for autonomous vehicles: Opportunities, barriers and policy recommendations	AR
	131	Dresner K., Stone P.	2008	A multiagent approach to autonomous intersection management	AR
	97	Fagnant D.J., Kockelman K.M.	2014	The travel and environmental implications of shared autonomous vehicles, using agent-based model scenarios	AR
	65	Krueger R., Rashidi T.H., Rose J.M.	2016	Preferences for shared autonomous vehicles	AR
	63	Kyriakidis M., Happee R., De Winter J.C.F.	2015	Public opinion on automated driving: Results of an international questionnaire among 5000 respondents	AR
	51	Haboucha C.J., Ishaq R., Shiftan Y.	2017	User preferences regarding autonomous vehicles	AR
	48	Talebpour A., Mahmassani H.S.	2016	Influence of connected and autonomous vehicles on traffic flow stability and throughput	AR
	40	Carlino D., Boyles S.D., Stone P.	2013	Auction-based autonomous intersection management	CP
	35	Bansal P., Kockelman K.M., Singh A.	2016	Assessing public opinions of and interest in new vehicle technologies: An Austin perspective	AR
	29	Levin M.W., Boyles S.D.	2016	A multiclass cell transmission model for shared human and autonomous vehicle roads	AR
CL.11	102	Sheridan T.B.	2016	Human–Robot Interaction: Status and Challenges	AR
	92	Bonnefon J.-F., Shariff A., Rahwan I.	2016	The social dilemma of autonomous vehicles	AR
	44	Goodall N.	2014	Ethical decision making during automated vehicle crashes	AR
	32	Lin P.	2015	Why ethics matters for autonomous cars	BC
	27	Rothenbucher D., Li J., Sirkin D., Mok B., Ju W.	2016	Ghost driver: A field study investigating the interaction between pedestrians and driverless vehicles	CP
	13	Gerdes J.C., Thornton S.M.	2015	Implementable ethics for autonomous vehicles	BC
	11	Pettersson I., Karlsson I.C.M.	2015	Setting the stage for autonomous cars: A pilot study of future autonomous driving experiences	AR
	10	Brown B., Laurier E.	2017	The trouble with autopilots: Assisted and autonomous driving on the social road	CP
	9	Alahi A., Goel K., Ramanathan V., Robicquet A., Fei-Fei L., Savarese S.	2016	Social LSTM: Human trajectory prediction in crowded spaces	CP
	8	Mahadevan K., Somanath S., Sharlin E.	2018	Communicating awareness and intent in autonomous vehicle-pedestrian interaction	CP
	8	Chang C.-M., Toda K., Sakamoto D., Igarashi T.	2017	Eyes on a car: An interface design for communication between an autonomous car and a pedestrian	CP
	8	Rausch V., Hansen A., Solowjow E., Liu C., Kreuzer E., Hedrick J.K.	2017	Learning a deep neural net policy for end-to-end control of autonomous vehicles	CP
	8	Möller L., Risto M., Emmenegger C.	2016	The social behavior of autonomous vehicles	CP
CL.12	39	Kalra N., Paddock S.M.	2016	Driving to safety: How many miles of driving would it take to demonstrate autonomous vehicle reliability?	AR
	18	Huang X., Kwiatkowska M., Wang S., Wu M.	2017	Safety verification of deep neural networks	CP
	13	Wurman P.R., D'Andrea R., Mountz M.	2008	Coordinating hundreds of cooperative, autonomous vehicles in warehouses	AR
	13	Wurman P.R., D'Andrea R., Mountz M.	2007	Coordinating hundreds of cooperative, autonomous vehicles in warehouses	CP
	12	Behere S., Törngren M.	2016	A functional reference architecture for autonomous driving	AR
	10	Huang W.L., Wang K., Lv Y., Zhu F.H.	2016	Autonomous vehicles testing methods review	CP
	9	Abdessalem R.B., Nejati S., Briand L.C., Stifter T.	2016	Testing advanced driver assistance systems using multi-objective search and neural networks	CP
	8	Abdessalem R.B., Nejati S., Briand L.C., Stifter T.	2018	Testing vision-based control systems using learnable evolutionary algorithms	CP
	7	Sharif M., Bhagavatula S., Bauer L., Reiter M.K.	2016	Accessorize to a crime: Real and stealthy attacks on state-of-the-art face recognition	CP
	6	Jana S., Tian Y., Pei K., Ray B.	2018	DeepTest: Automated testing of deep-neural-network-driven autonomous cars	CP
	6	Pathak P.M., Samantaray A.K., Merzouki R., Ould-Bouamama B.	2008	Reconfiguration of directional handling of an autonomous vehicle	CP
CL.13	40	Malmborg C.J.	2002	Conceptualizing tools for autonomous vehicle storage and retrieval systems	AR
	31	Kuo P.-H., Krishnamurthy A., Malmborg C.J.	2007	Design models for unit load storage and retrieval systems using autonomous vehicle technology and resource conserving storage and dwell point policies	AR
	24	Zhang L., Krishnamurthy A., Malmborg C.J., Heragu S.S.	2009	Variance-based approximations of transaction waiting times in autonomous vehicle storage and retrieval systems	AR
	23	Fukunari M., Malmborg C.J.	2009	A network queuing approach for evaluation of performance measures in autonomous vehicle storage and retrieval systems	AR
	23	Fukunari M., Malmborg C.J.	2008	An efficient cycle time model for autonomous vehicle storage and retrieval systems	AR
	23	Malmborg C.J.	2003	Interleaving dynamics in autonomous vehicle storage and retrieval systems	AR
	18	Ekren B.Y., Heragu S.S., Krishnamurthy A., Malmborg C.J.	2010	Simulation based experimental design to identify factors affecting performance of AVS/RS	AR

	14	Kuo P.-H., Krishnamurthy A., Malmborg C.J.	2008	Performance modelling of autonomous vehicle storage and retrieval systems using class-based storage policies	AR
	9	Roy D., Krishnamurthy A., Heragu S.S., Malmborg C.J.	2012	Performance analysis and design trade-offs in warehouses with autonomous vehicle technology	AR
	8	Marchet G., Melacini M., Perotti S., Tappia E.	2012	Analytical model to estimate performances of autonomous vehicle storage and retrieval systems for product totes	AR
	8	Ekren B.Y., Heragu S.S.	2009	Simulation based regression analysis for rack configuration of autonomous vehicle storage and retrieval system	CP

Table A.1. Thematic clusters: top-10 core publications by cluster. AR: Journal article; BO: Book; BC: Book chapter; CP: Conference paper

APPENDIX B

CLUSTER	THEME	TOPIC	KEYWORDS	EI	FR	CO
CL.01	The Urban Challenge	Motion planning	Planning; Motion; Planner; Generate; Trajectory; Feasible; Plan; Path; Free; Motion Planning; Trajectory Planning; Planning Algorithm	11.00	4452	62.51%
		Automobile steering equipment	Steering; Equipment; Wheel; Angle; Automobile; Front; Active; Tire; Brake; Desire; Automobile Steering Equipment; Steering Control; Steering Angle; Steering Wheel; Front Steering; Wheel Steering; Steering Controller; Steering System; Vehicle Wheels; Vehicle Dynamics; Automobile Parts and Equipment; Active Steering; Vehicle Steering	3.83	2423	45.11%
		Human behavior and decision making	Decision; Behavioral; Make; Human; Interaction; Behavior; Research; Action; Decision Making; Behavioral Research; Human Driver; Markov Decision Process; Driver Behavior	3.30	1785	53.92%
		Computer vision and image processing	Image; Vision; Processing; Camera; Detection; Computer; Computer Vision; Image Processing; Object Detection; Obstacle Detection; Optical Radar; Vision System; Detection and Tracking; Obstacle Detector; Stereo Vision; Lane Detection; Computer Graphic; Object Recognition; Image Segmentation	2.94	970	28.10%
		Control system	Control; Controller; Lateral; Design; Track; Simulation; Predictive; Steering; Control System; Simulation Results	2.71	8856	79.75%
		Obstacle avoidance	Assistance; Driver; Advance; Automobile; Accident; Driver Assistance; Automobile Driver; Advanced Driver Assistance; Driver Assistance System; Human Driver; Driver Model; Driver Behavior	2.59	1334	39.42%
		Uncertainty analysis	Uncertainty; Disturbance; Robustness; Robust; Uncertainty Analysis; Robust Control; Disturbance Observer; Disturbance Rejection; External Disturbance; Robust Controller; Robust Tracking; Parametric Uncertainty	2.43	538	21.44%
		DARPA	Urban; Advanced; Challenge; Research; Describe; Environment; Urban Environment; Urban Challenge; DARPA Urban Challenge; Urban Planning; Grand Challenge; Urban Traffic	2.26	1441	55.69%
		Optimization problem	Problem; Solve; Optimization; Optimal; Programming; Solution; Optimization Problem; Optimal Control; Control Problem; Optimal Trajectory; Planning Problem; Optimal Path	2.24	1397	44.14%
CL.02	Real-time motion planning of multi-AV operations	Position, velocity and convergence	Convergence; Constant; Seek; Velocity; Local; Numerical; Modeled; Position; Signal; Position and Velocity; Angular Velocity; Convergence of Numerical Methods; Numerical Simulations; Position Measurement	14.93	486	55.06%
		Motion planning	Planning; Trajectory; Path; Motion; Constraint; Programming; Compute; Optimization; Planner; Optimal; Motion Planning; Path Planning; Motion Control; Trajectory Planning; Planning Problem	3.49	1630	64.85%
		Stability analysis	Loop; Lyapunov; Stability; Close; Law; Stability Analysis; Control Law; System Stability; Closed Loop; Lyapunov Method; Control Theory; Closed Loop Control; Graph Theory; Loop System; Lyapunov Function; Ensure Stability	3.18	304	30.34%
		Unmanned aerial vehicle	Unnamed; Aerial; Unmanned; Aircraft; Air; Flight; Unmanned Aerial Vehicle; Unmanned Vehicle; Aerial Vehicle; Aircraft Control; Air Navigation; Unmanned Autonomous Vehicles; Unmanned Air Vehicle; Autonomous Unmanned Vehicle; Fixed Wing	3.07	730	33.71%
		Intelligent Vehicle-Highway System	Traffic; Highway; Transportation; Intelligent; Safety; Road; Drive; Intelligent Vehicle; Intelligent Vehicle Highway; Intelligent Transportation; Intelligent Robot; Roads and Streets; Traffic Control; Vehicle Platoon	2.89	390	29.05%
		Sensor network	Detection; Data; Sensor; Environmental; Map; Search; Development; Sensor Network; Environmental Monitoring	2.80	412	40.77%
		Collision avoidance	Avoidance; Collision; Obstacle; Avoid; Free; Collision Avoidance; Obstacle Avoidance; Avoid Obstacle; Avoidance Problem; Avoiding Obstacle; Collision with Obstacle	2.68	564	26.00%
CL.03	Multi-sensors and fusion systems	Road	Road; Street; Lane; Transportation; Traffic; Road and Street; Traffic Control; Intelligent Transportation System; Lane Detection; Road Traffic	17.69	483	46.51%
		Lidar	Lidar; Optical; Radar; Cloud; Point; Optical Radar; Point Cloud; Lidar Data; Optical Flow; Lidar Sensor; Light Detection and Ranging; Detection and Tracking	3.97	497	32.56%
		Neural networks and deep learning	Neural; Convolutional; Network; Deep; Train; Learning; Dataset; Neural Network; Deep Learning; Convolutional Neural Network; Machine Learning; Learning System; Deep Neural Network; Learning Algorithm; Learning Approach	3.73	672	33.85%
		Stereo image processing	Stereo; Image; Camera; Processing; Dense; Estimate; Estimation; Map; Vision; Visual; Compute; Match; Image Processing; Computer Vision; Stereo Image Processing; Stereo Vision; Optical Flow	3.41	806	59.95%
		Global positioning system (GPS)	Global; Localization; Location; Trajectory; Positioning; System; Position; Mobile; Estimation; Mobile Robot; Motion Estimation; Autonomous Mobile; Global Navigation; Vehicle Location	3.33	325	44.44%
		Virtual-based testing	Virtual; Reality; Agent; Behavior; Rule; Modeled; Coordinate; Surface; Virtual Reality; Autonomous Agent; Virtual Environment; Behavioral Research; Urban Traffic	3.10	228	30.75%
		Motion planning	Planning; Path; Motion; Avoidance; Collision; Compute; Constraint; Obstacle; Motion Planning; Path Planning; Collision Avoidance; Obstacle Detection; Obstacle Avoidance; Obstacle Detector; Motion Estimation; Robotic Vehicle	3.05	422	43.67%
		Autonomous car drive	Car; Drive; Driverless; Driving; Autonomous Car; Driverless Car	2.74	547	52.45%

CL.04	Road boundaries and extended curbs detection	Deep neural network	Neural; Deep; Network; Train; Learning; Dataset; Neural Network; Deep Learning; Convolutional Neural Network; Deep Neural Network; Learning System; Machine Learning; Learning Algorithm; Semantic Segmentation	15.13	671	31.94%
		Liadar	Radar; Optical; Lidar; Cloud; Point; Light; Optical Radar; Point Cloud; Light Detection and Ranging; Lidar Data; Lidar Sensor	3.80	789	38.40%
		Simultaneous localization and mapping	Slam; Simultaneous; Mapping; Localization; Robotic; Vehicle Localization; Localization and Mapping; Simultaneous Localization and Mapping; Localization Method; Localization Accuracy; Localization System; Localization Algorithm; Localization Error; Monte Carlo Method; Particle Filter; Visual Localization	3.41	641	46.77%
		Road marking detection	Marking; Street; Road; Mark; Lane; Road and Street Marking; Lane Marking; Road Surface; Road Marking	3.21	1222	47.72%
		Safety	Technology; Future; Development; Develop; Safety; Research; Accident Prevention; Automobile Manufacture; Automotive Industry; Research and Development	3.04	281	44.11%
		Global positioning system (GPS)	Global; Inertial; Positioning; System; Position; Accurate; Global Positioning System; Inertial Navigation System; Vehicle Position; Global Navigation Satellite System; Inertial Measurement; Inertial Sensor; Position Estimation; Inertial Measurement Unit; Navigation Systems	2.87	605	45.63%
		Autonomous car drive	Driver; Assistance; Advance; Automobile; Advanced Driver Assistance System; Automobile Driver; Driving Assistance System	2.74	320	24.14%
		Stereo image processing	Vision; Image; Camera; Computer; Monocular; Visual; Stereo; Processing; Computer Vision; Image Processing; Image Segmentation; Stereo Vision	2.67	1326	65.59%
		Motion planning	Planning; Path; Motion; Motion Planning; Path Planning; Motion Estimation; Path Planner; Highway Planning; Local Path; Path Tracking; Control System; Autonomous Parking; Tracking Error	2.51	334	28.71%
		Experimental results	Result; Experimental; Show; Method; Propose; Experimental Result; Proposed Method; Detection Method	2.41	775	87.83%
		Odometry	Scale; Large; Odometry; Outdoor; Collect; Visual Odometry; Large Scale; Outdoor Environment; Monocular Visual	2.37	181	29.47%
CL.05	Motion planning for agricultural machinery	Scene segmentation	Segmentation; Classification; Scene; Outdoor; Visual; Ground; Terrain; Perception; Natural; Feature; Selection; Unmanned; Operating; Outdoor Environment; Perception System; Unmanned Vehicle; Image Segmentation; Road Vehicle; Autonomous Ground Vehicle; Natural Environment	22.01	242	48.73%
		Image processing	Image; Vision; Camera; Detect; Processing; Detection; Stereo; Detector; Computer; Machine; Row; Computer Vision; Machine Vision; Image Processing; Stereo Vision; Autonomous Navigation	4.12	544	62.71%
		Path tracking	Straight; Average; Curve; Steering; Proportional; Guidance; Angle; Error; Equipment; Path; Successfully; Develop; Path Tracking; Automobile Steering Equipment; Guidance System; Automatic Guidance; Steering Angle	3.91	348	70.76%
		Control	Velocity; Orientation; Adaptive; Relative; Nonlinear; Linear; Feedback; Trajectory; Curvature; Distance; Follow; Feedback Control; Autonomous Vehicle; Control Approach; Tracking Control; Control System; Control Law; Nonlinear Control; Control Method	3.72	234	53.39%
		Agricultural machinery	Agricultural; Agriculture; Precision; Machinery; Increase; Farm; Agricultural Machinery; Agricultural Vehicle; Precision Agriculture; Agricultural Robotics; Agricultural Environment; Agricultural Field; Agricultural Operation	3.59	298	44.92%
		Vehicle behavior	Behavior; Solve; Problem; Plan; Nonholonomic; Mobile; Practical; Constraint; Deal; Robot; Mobile Robot; Fuzzy Controller	3.30	265	65.25%
		Advanced driver-assistance systems	Assistance; Driver; Advance; Advanced; Automobile; Technology; Case; Advanced Driver Assistance System; Automobile Driver; Human Driver	3.19	140	33.90%
		Fuzzy control	Controller; Fuzzy; Logic; Simulation; Design; Proportional; Tune; Fuzzy Control; Control System; Fuzzy Controller; Fuzzy Set; Simulation Result; Fuzzy Logic Control; Controller Design; Autonomous Vehicle Control	3.18	532	50.42%
CL.06	Lane detection and connected technologies	Edge computing	Cloud; Distribute; Computation; Edge; Complexity; Unit; Computing; Require; Assist; Edge Computing; Distributed Computer System; Driverless Vehicle	21.51	171	42.49%
		Vehicular ad-hoc networks (VANETs)	Hoc; Ad; Vehicular; Network; Communication; Lead; Vehicle to Vehicle Communication; Vehicular Ad Hoc Network; Network Security; Millimeter Wave; Short Range Communication; Mobile Communication System	4.60	506	40.66%
		Lane detection	Image; Detection; Lane; Detect; Camera; Vision; Transform; Condition; Line; Extract; View; Edge; Road; Computer Vision; Road and Street; Lane Detection; Vision System; Hough Transform; Road Condition	3.89	582	61.90%
		Internet of things and smart cities	Thing; Internet; Service; Smart; Quality; Cloud; Life; City; Internet of Things; Internet of Vehicles; Smart City; Base Station; Connected Vehicle	3.65	422	31.14%
		Control	Verify; Lateral; Angle; Controller; Introduce; Reference; Modeled; Track; Good; Follow; Lane; Side; Steering; Comfort; Automobile Steering Equipment; Lane Detection; Lateral Control; Computer Vision; Hough Transform; Lane Tracking; Vision System	3.50	338	58.61%
		Cybersecurity	Security; Cyber; Attack; Cooperative; Safety; Secure; Physical; Connect; Network Security; Cyber Physical System; Cyber Security; Embedded System	3.36	337	42.86%
		Kalman filter	Filter; Kalman; Estimation; Estimate; Method; Image; Kalman Filter; Kalman Filtering; Image Processing; State Estimation; Feature Extraction; Image Segmentation; Road and Street	3.12	223	39.93%

		Traffic control	Traffic; Behavior; Transportation; Street; Safety; Capability; Traffic Control; Traffic Congestion; Transportation System; Road Traffic; Autonomous Car; Traffic Information; Traffic Sign	2.97	269	58.61%
CL.07	Motion planning for underwater intervention	Spatio-temporal scale of oceanographic sampling	Spatial; Temporal; Sample; Resolution; Sampling; Oceanography; Scale; Data; Observation; Spatial and Temporal; Autonomous Underwater	30.95	140	49.26%
		Underwater intervention	Manipulator; Intervention; Recovery; Submersibles; Man; Knowledge; Object; Project; Learning; Class; Equip; Demonstration; Dock; Highlight; Open; Recent; Exist; Float; Free; Human; Address; Survey; Task; Capability; Future; Underwater Intervention	5.55	243	72.06%
		Mixed initiative planning and control	Mix; Initiative; Support; Team; Laboratory; Heterogeneous; Operational; Command; Type; Air; Include; Number; Infrastructure; Technology; Management; Framework; Requirement; Command and Control; Underwater System	5.17	160	62.50%
		Motion planning	Numerical; Derive; Drive; Modeled; Wind; Efficient; Scheme; Methodology; Speed; Level; Finally; Dynamic; Method; Energy; Presence; Path; Motion Planning; Path Planning	5.09	206	69.12%
		Model predictive control	Formation; Decentralize; Predictive; Nonlinear; Action; Constrain; Operative; Local; Computational; Model; Avoid; Strategy; Constraint; Formation Control; Operative Control; Control System; Cooperative Control	4.65	168	48.53%
		Kalman filtering	Filter; Localization; Kalman; Position; Accuracy; Measurement; Fusion; Navigation; Error; Measure; Extend; Kalman Filter; Sensor Fusion; Autonomous Vehicle	4.33	193	49.26%
		Sonar obstacle detection	Detect; Autonomously; Detection; Advantage; Link; Forward; Combine; Moor; Robust; Map; Forward Looking Sonar	4.21	75	37.50%
CL.08	Obstacle detection and avoidance in different conditions	Obstacle avoidance	Reach; Planning; Avoid; Goal; Unknown; Path; Motion; Controller; Behavior; Obstacle; Variety; Environment; Function; Obstacle Detection; Obstacle Detector; Obstacle Avoidance; Motion Planning; Unknown Environment	28.21	257	71.53%
		Multi-focal, Saccadic vision	Saccadic; Expectation; Action; Perception; Capability; Hierarchical; Hardware; Representation; Active; Multi; Mission; Architecture; Knowledge; Perform; Decision; Head; Control; Complex; Vision System	6.88	228	65.28%
		Night-time operativity	Night; Effectiveness; Light; Procedure; Feasibility; Segmentation; Locate; Front; Condition; Robustness; Fast; Estimate; Study; Distance; Process; Experimental; Automatic; Operate; Move; Stage; Digital; Analysis; Demonstrate; Scene; Result; Detect; Extract; Experimental Results; Navigation Systems; Image Segmentation; Vehicle Detection	6.05	296	88.19%
		Line detection	Edge; Mark; Marking; Curve; Street; Extraction; Detection; Fit; Width; Road; Interest; Lane; Region; Stage; Extract; Lane Detection; Detection Algorithm; Vehicle Detection; Edge Detection; Image Segmentation; Road and Street Marking	4.89	453	75.00%
CL.09	Traffic sign recognition	Smart cities	Future; Smart; Deployment; Public; City; Current; Mobile; Service; Infrastructure; Mobility; Provide; Smart City	25.81	130	47.32%
		Vehicular ad-hoc networks (VANETs)	Hoc; Attack; Intrusion; Ad; Vehicular; Security; External; Semi; Communication; File; Service; Cooperative; Network; Behavior; Simulator; Neural Network; Vehicular Ad Hoc Network; Network Security; Vehicle to Vehicle Communication; External Communication; Intelligent Intrusion Detection System; Security System	7.39	677	53.66%
		Traffic sign recognition	Color; Recognition; Region; Candidate; Image; Traffic; Recognize; Light; Shape; Segmentation; Classifier; Sign; Classification; Method; Feature; Detection; Gradient; Traffic Sign; Pattern Recognition	6.26	1444	78.54%
		Semantic context information	Semantic; Relationship; Aid; Language; Mobility; Infrastructure; Platform; Capture; Motor; Context; Key; Simple; Ontology; Domain; Dynamic; Map; Concept; Scene; Traffic Situation	4.63	248	63.90%
		Neural networks and deep learning	Deep; Convolutional; Learning; Neural; Training; Dataset; Network; Train; Classifier; Detector; Prove; Neural Network; Deep Learning; Machine Learning; Convolutional Neural Network; Vehicular Ad Hoc Networks; Intrusion Detection; Network Security; Deep Neural Network; Object Detection	4.41	531	47.32%
		Motion planning	Path; Planning; Avoid; Collision; Motion; Obstacle; Motion Planning; Path Planning; Collision Avoidance	4.07	131	20.98%
		Autonomous car drive	Assistance; Driver; Automobile; Advance; Advanced; Perceive; Intelligent; Automobile Driver; Intelligent System; Intelligent Vehicle; Intelligent Vehicle Highway System; Advanced Driver Assistance System; Driving Assistance; Intelligent Transportation System; Vehicle Control System; Traffic Control	4.01	334	55.61%
CL.10	Social impacts and integration of AVs	Intersection management	Intersection; Delay; Stop; Control; Signal; Management; Collision; Cross; Traffic; Protocol; Propose; Traffic Control; Intersection Management; Traffic Congestion; Control System; Traffic Management; Intersection Control; Street Traffic Control; Autonomous Intersection	14.31	3420	76.96%
		Shared autonomous vehicle fleet demand	Demand; Fleet; Service; Share; Operation; Mobility; Size; Ride; Trip; Urban; Transport; City; Travel; Fleet Operation; Urban Transportation; Transport Vehicle; Shared Autonomous Vehicle; Autonomous Mobility; Urban Mobility	4.22	2131	62.67%
		Acceptance	Perceive; Acceptance; Survey; Factor; Perception; People; Influence; Participant; Trust; Affect; Public; Public Transport; Online Survey; Risk Perception; Stated Preference; Technology Acceptance; Public Attitude; Public Road; Public Transportation; Public Acceptance; Willingness to Pay	3.88	881	43.38%
		Optimization issues	Programming; Linear; Problem; Program; Solve; Optimization; Optimal; Constraint; Schedule; Solution; Minimize; Integer Programming; Optimal Control; Integer Linear; Mixed Integer; Optimization Problem; Control Problem; Integer Linear Program; Linear Programming; Optimal Solution; Numerical Experiment; Predictive Control	3.26	1006	43.38%
		Human-computer interaction	Interaction; Human; Trust; Machine; Participant; Task; Design; Computer; Simulator; Human Computer Interaction; Human Driver; Human Engineering; Human Factor; Human Driver; Car Driving	3.05	899	56.41%

		Large scale deployment	Scale; Large; Large Scale; Scale Deployment; Control Mechanism	2.89	92	14.81%
		Travel demand	Estimate; Travel; Choice; Trip; Travel Time; Travel Behavior; Travel Demand; Mode Choice; Shared Autonomous Vehicle; Stated Preference; Discrete Choice	2.82	580	37.75%
CL.11	Human-Computer Interaction and ethical dilemmas	Ethical and moral dilemma	Ethical; Ethics; Philosophical; Moral; Aspect; Dilemma; Argue; Make; Decision; Principle; Legal; Situation; Philosophical Aspect; Ethical Decision; Make Decision; Moral Dilemma; Ethical Dilemma; Robot Ethics	17.25	817	54.01%
		Neural networks and deep learning	Deep; Neural; Network; Camera; Learning; End; Steering; Image; Visual; Learn; Vision; Performance; Input; Deep Learning; Neural Network; Automobile Steering Equipment; Convolutional Neural Network; Machine Learning; Learning System; Computer Vision; Deep Neural Network; Convolutional Neural Networks; Learning Algorithm	4.53	635	45.50%
		Public concern	Concern; World; Technology; Future; Public Concern	4.08	150	43.80%
		Motion planning	Avoidance; Obstacle; Collision; Path; Motion; Planning; Algorithm; Simulation; Navigation; Collision Avoidance; Motion Planning; Navigation System; Path Planning; Obstacle Avoidance; Simulation Result	3.39	430	40.88%
		Trust in human-computer interaction	Human; Man; Machine; Interaction; Trust; Robot; Computer; Engineering; Interact; Human Factor	3.30	1374	72.02%
CL.12	Testing and risk assessment	Verification and validation	Verification; Correctness; Verify; Decision; Property; Formal; Respect; Check; Make; Tool; Formal Verification; Decision Making	23.73	192	45.81%
		Neural networks and deep learning	Neural; Deep; Image; Input; Network; Adversarial; Technique; Learning; Robustness; Camera; Training; Recent; Include; Deep Neural Network; Deep Learning; Machine Learning; Learning System; Learning Algorithm; Adversarial Example	5.40	728	54.19%
		Testing	Testing; Test; Generation; Automatically; Reality; Virtual; Drive; Automatic; Demonstrate; Car; Software; Generate; Autonomous Driving; Software Testing; Driving Car; Software Engineering; Safety Testing; Test Cases; Computer Software; Test Scenario	4.33	702	77.83%
		Modeling and simulation of dynamic systems	Graph; Bond; Modeled; Dynamic; Wheel; Theory; Model; Fault; Deal; Validate; Intelligent; Intelligent System; Intelligent Autonomous Vehicle; Bond Graph; Graph Theory; Bond Graph Model; Autonomous Vehicle	3.98	453	70.94%
		Artificial intelligence attack	Artificial; Intelligence; Machine; Learning; Attack; Security; Physical; Network; Neural; Neural Networks; Artificial Intelligence Attack; Network Security	3.53	498	54.19%
		Computer vision	Computer; Time; Unit; Platform; Program; Real; Processing; Run; Vision; Computer Vision; Computer Graphic; Graphics Processing; Test Case	3.48	255	59.61%
		Risk assessment	Risk; Assessment; Safety; Hazard; Run; Support; International; Automotive; Situation; Safety Engineering; Safety Critical Systems; Automotive Systems; Risk Assessment; Vehicle Safety; Safety Critical Application	3.33	283	55.67%
		Cyber-physical systems	Cyber; Physical; Embed; Smart; Virtual; Embedded System; Virtual Reality; Cyber Physical System	3.25	192	33.00%
		Automobile steering equipment	Steering; Equipment; Track; Automobile; Wheel; Path; Automobile Steering Equipment; Path Tracking	3.24	102	27.09%
CL.13	Automated Storage and Retrieval System (AVS/RS)	Transport logistics	Pick; Production; Shuttle; Move; Order; State; Supply Pick	18.83	51	40.68%
		High-density storage areas	Density; High; Transfer; Area; Flexibility; Effect; Aisle; Detail; Capacity; Throughput; Cycle; Parameter; Address; Location; Vertical; Warehouse; Tier; Unit; High Density Storage Area; Dual Command Cycle; Cycle Time	6.87	196	89.83%
		Event simulation and automation software	Arena; Commercial; Software; Average; Complete; France; Rack; Number; Configuration; Variable; Study; Determine; Define; Warehouse; Arena Commercial Software	6.01	155	91.53%
		Vehicle movement	Horizontal; Vertical; Lift; Analyze; Movement; Travel; Insight; Network; Semi; Solve; Transaction; Decomposition; Tier; Improve; Queue; Queuing Network; Vertical Movement	4.78	245	79.66%
		Unit Load Automated Storage & Retrieval System	Unit; Load; Design; Automate; Technology; Transaction; Queuing Network; Unit Load Storage and Retrieval	4.19	174	83.05%
		Agent-based simulation	Environment; Agent; Order; Recent; Dynamic; Implement; Efficient; Tool; Flexibility; Agent Based Simulation; Multiagent Simulation	3.80	67	57.63%
		Rail-guided vehicles	Guide; Rail; Tool; Problem; Include; Propose; Address; Optimal; Rail Guided Vehicles	3.64	64	66.10%
		Transition cycle-times	Time; Cycle; Transaction; Aisle; Cycle Time; Storage and Retrieval	3.29	127	76.27%
		Queuing network	Handle; Material; Technology; Alternative; Automate; Automation; Key; Open Queuing Network; Queuing Network;	3.16	139	61.02%
		Evaluation of system performance	Research; Multi; Decomposition; Evaluate; Insight; Detail; Develop; Tier; Approach; System Performance	3.11	86	62.71%

Table B.1. Thematic clusters: main keywords (Granularity Level 1), central topics (Granularity Level 2), and core research themes (Granularity Level 3). EI: Eigenvalue; FR: Frequency; CO: Co-occurrence

Declaration of interests

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

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: