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Article

Methodology for AI-Based Search Strategy of Scientific Papers: Exemplary Search for Hybrid and Battery Electric Vehicles in the Semantic Scholar Database

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Abstract: The rapid development of artificial intelligence (AI) has significantly enhanced productivity, particularly in repetitive tasks. In the scientific domain, literature review stands out as a key area where AI-based tools can be effectively applied. This study presents a methodology for developing a search strategy for systematic reviews using AI tools. The Semantic Scholar database served as the foundation for the search process. The methodology was tested by searching for scientific papers related to batteries and hydrogen vehicles with the aim of enabling an evaluation for their potential applications. An extensive list of vehicles and their operational environments based on international standards and literature reviews was defined and used as the main input for the exemplary search. The AI-supported search yielded approximately 60,000 results, which were subjected to an initial relevance assessment. For the relevant papers, a neighbourhood analysis based on citation and reference networks was conducted. The final selection of papers, covering the period from 2013 to 2023, included 713 papers assessed after the initial review. An extensive discussion of the results is provided, including their categorisation based on search terms, publication years, and cluster analysis of powertrains, as well as operational environments of the vehicles involved. This case study illustrates the effectiveness of the proposed methodology and serves as a starting point for future research. The results demonstrate the potential of AI-based tools to enhance productivity when searching for scientific papers.

Keywords: search strategy; methodology; artificial intelligence; literature review; battery electric vehicles; hydrogen-powered vehicles

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1. Introduction

The rise of artificial intelligence (AI), which enhances productivity and a global push for net-zero depending on green solutions for efficient resource use [1], are considered major trends. The latter depends on the emission of greenhouse gases and is therefore linked to the fuel used and efficiency of vehicle powertrains [2]. Innovations across all vehicles, such as battery electric cars [3], hydrogen trains [4], and electric aircrafts [5], are being implemented.

AI implementation for scientific applications is driven by upcoming tools such as Chat GPT [6] and Semantic Scholar [7,8]. A recent interview with data workers revealed four advantages of AI. It can eliminate repetitive tasks, offers a potentially higher capability than humans, runs at low cost, and is valued faithfully and tirelessly. In contrast, seven disadvantages were listed: limited capability of creation; lack of context understanding; inconvenient communication with AI; difficulties in enhancing human relationships; the required overhead for AI application; the risk of unreliable, outdated, or domain-agnostic training data; and ethical concerns [9].

AI tools seem to be predestined for supporting researchers in conducting literature reviews. Especially in the case of systematic reviews with a specific research question and systematic search approach [10], a takeover of tasks by AI tools could be beneficial in terms of time, effort, and quality of the conducted review. However, the authors are not aware of any methodologies for conducting systematic reviews or meta-analyses using AI-based tools.

The goal of the systematic literature review was to synthesise information in a transparent and reproducible manner [10]. Using a predefined methodology can reduce bias and enhance the reliability of the outcomes [11]. Thus far, most methodologies for conducting systematic literature reviews have been developed in the field of medicine [12–19], followed by social sciences [20], marketing [21], and management [22]. In addition, in the field of engineering, systematic literature reviews and meta-analyses can significantly contribute to informing policies regarding state-of-the-art technologies and perspectives on their usage.

Research on the use of AI tools for conducting literature reviews has predominantly focused on the medical field [23–26]. This strong emphasis on medicine presents a significant hurdle for adapting AI methods to engineering-related reviews. Wagner [27], Bolanos [28], and Torre-López [29] provide a comprehensive overview of possible applications for AI tools in literature reviews, but they do not specifically address the establishment of a standardised methodology for conducting a literature search.

Although some authors have developed methodologies for systematic reviews applied to engineering fields [30,31], no methodology has focused on the use of powerful AI tools for the search and selection of relevant publications. The purpose of this study was to develop a methodology for an AI-based search strategy as a starting point for a literature review in an engineering-related field. Furthermore, the draft was evaluated by searching for vehicles powered by batteries and hydrogen powertrains.

2. Material and Methods

To develop and evaluate this methodology, an approach for AI-based research and the basic terms of vehicles and powertrains is elaborated to create a basis for this study.

2.1. Approach

2.1.1. Drafted Approach

According to the PRISMA statement, 27 elements are necessary for a systematic review [32]. To exploit the efficiency benefits of AI, an automated process for finding relevant papers on a specific topic can be drafted, which suggests adopting the steps of a search strategy, selection and data collection process, data items, risk study of assessment bias, effect measures, synthesis methods, reporting bias assessment, and certainty assessment.

The six-step approach is illustrated in Figure 1. AI tools can be used to automate Steps III and V. The other steps were performed manually to control and ensure the output quality.

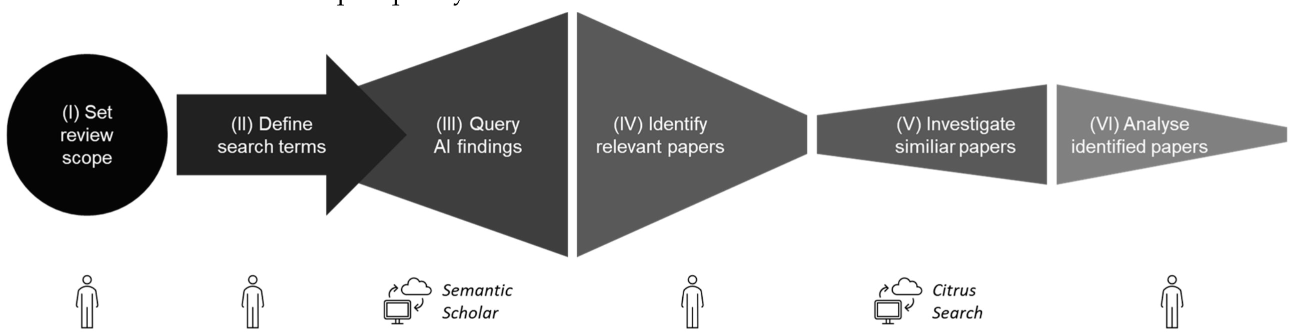

Figure 1. AI based research approach.

2.1.2. Step I: Set the Scope

The first step was to set the scope defined by the rationale for the review and clarified it by an explicit statement of the objectives or addressed questions [32]. The purpose of the developed approach is to validate the eligibility of AI for a systematic review based on the findings of vehicle powertrain technologies.

2.1.3. Step II: Define the Search Terms

Instead of defining targeted databases, registers, and websites [32], the search strategy must focus on search terms entered into the AI tool as a key step in the selection process. The decision "whether a study met the inclusion criteria of the review" [32] depends on the data collection process and needs to be broken up and split up into the initial choice of the tool, an upstream paper crawling, and downstream result screening.

For the automated part, it must be assumed that the approach by the AI can neither be comprehended nor controlled. Therefore, two issues need to be addressed. First, an uncertainty of term interpretation will occur. An example might be the differentiation by the search tool of wordings such as "review" and "study". Second, it must be ensured that the examined database section is selected within appropriate scope to ensure provision of correct findings. For example, while the search query can be limited to a specific field of study, as discussed in the next chapter, it cannot be excluded that beyond the initial filtering papers of other categories are searched as well.

To address the first issue, a broad range of studies should be conducted, and synonyms should be used. Even though the use of possible synonyms might lead to duplication of the identified publications, this method allows us to minimise the risk of missing relevant publications. The search terms were set up as ordered pairs of four-word groups represented by the following Cartesian products S_x:

$$S_x = P_i \times V_j \times A_k \times K_l$$

Vector P_i should define the powertrain, Vector V_j should define the vehicle, Vector A_k is supposed to be a specific extra search add for detailing, and vector K_l should define the specific type of study. Indexes $(\ )_x$, $(\ )_j$, $(\ )_k$, and $(\ )_l$ describe specific variations resulting in differentiated search terms.

To generate the search terms for the queries, the technical terms defining the powertrain and vehicles, as well as the search, add, and type of study, must be determined. To ensure a broad search, possible synonyms must be considered. This results in the following generic vectors:

$$P_i = (powertrain_{i1}, \ldots, powertrain_{in})$$

$$V_j = (vehicle_{j1}, \ldots, vehicle_{jn})$$

$$A_k = (searchadd_{k1}, \ldots, searchadd_{kn})$$

$$K_l = (kindofstudy_{l1}, \ldots, kindofstudy_{ln})$$

2.1.4. Step III: Query AI Findings

A study concluded that with the right search strategy, the results from Semantic Scholar searches are promising, and in a test case with software engineering scientific papers, 98.88% in this field where covered [33]. Based on this, Semantic Scholar was chosen for the selection process in this study. The downside of the search strategy relying solely on Semantic Scholar might be a limitation due to the unknown database and search algorithm. However, initially it should be ensured that all relevant publications within this first database are found. A measure to mitigate this risk is include in Section 2.1.5. If the results seem not promising, a second loop with another database might be used.

To queue the search terms, a Python script was programmed using the application programming interface of Semantic Scholar with its own authentication, to generate a CSV file with all findings for each search term. An example version of the code is presented in Supplementary Materials.

To set the right starting point for the search the main settings for this script included a definition of the field of study, a limitation of ten papers per search term, and the required fields per paper. These fields include the specific search term, Semantic Scholar ID, title, year of publication, author information, DOI, and number of citations as search filters.

2.1.5. Step IV: Identify Relevant Papers

The manual part of the selection process followed the automated part. The results of the search using the Semantic Scholar API were the starting point for identifying relevant papers. This section is composed of three steps.

1. Filtering out duplicates resulting from the definition of overlapping search terms;
2. Filtering out duplicates and errors resulting from the incorrect entries in the Semantic Scholar database;
3. Content assessment in terms of obtaining of targeted information.

Many search terms should be considered to ensure the completeness of the output publication list. However, one publication may have been identified by using multiple search terms. These duplicates were not considered for further investigation. However, it is necessary to check whether duplicates contain relevant information for detailed analysis (e.g., one finding must be applicable to more than one vehicle).

Furthermore, a critical consideration of the remaining results from the Semantic Scholar database is required. Python code only requests data from the Semantic Scholar API, but it does not perform a quality check of the gathered data. Therefore, every incorrect entry in the Semantic Scholar database would result in an incorrect entry into the project database. Therefore, manual data control must be implemented. To ensure high-quality output data, all entries with any of the following issues must be filtered. These issues might include duplicated publications based on the DOI (especially due to overlapping search terms), missing titles, or an obviously wrong title (for example, DOI instead of the publication title), missing DOI or an incorrect DOI format, missing authors or obviously wrong authors (for example, DOI instead of the author names), or a publishing date out of the defined scope.

Until this point, no content checks have been performed. However, the objective of this review was to extract concrete information from the gathered publications. For the initial content assessment, aspects such as language, field of study, title, number of citations, and abstract must be considered.

At this stage of the process, many publications are expected, with tens of thousands of orders of magnitude. Therefore, content assessments should be performed sequentially. This means that language should be the first criterion if language issues occur, and abstract assessment should be the last criterion only in unclear cases. In addition, cases of withdrawn papers may also occur.

2.1.6. Step V: Investigate Similar Papers

Owing to the new approach, a quality loop within the Semantic Scholar database is suggested to ensure that all relevant papers within that database are identified. Every keyword search has drawbacks which can lead to important contributions being overlooked in the literature review. The search terms may be too broad or ambiguous, resulting in poor accuracy. In addition, papers may have been missed because their specific taxonomy for a relevant concept was not included in the set of search terms. To mitigate the blind spots of keyword searches, we supplement it with a similarity-based approach: new candidate papers are discovered by examining research that is closely related to the papers already gathered.

Several tools have been developed for facilitating this process. Citation Gecko [34] provides a visual interface for browsing references and citations of a set of input papers. Connected Papers [35] uses metrics such as co-citations and bibliometric coupling to determine which papers are most related and do not rely solely on direct citations or references. Citrus Search [36] similarly analyses the network of citations and references between papers to compare them. To capture the unique position of a publication in the citation graph and compare it with other publications, it employs a graph-embedding algorithm. Graph-embedding algorithms such as Node2Vec [37] are machine-learning techniques which map nodes in a graph to a vector representation. Graph-embedding representations have been shown to effectively capture the nuances of the underlying graph and perform well in tasks such as link prediction, node classification, and clustering [38].

For the review, Citrus Search might be used to automatically gather paper recommendations by supplying the already identified relevant research as input to its similarity search. To make optimal use of the tool, we perform multiple iterations, where the output of the similarity search is deduplicated against already found publications, manually checked for relevance, and the relevant results are again supplied to the similarity search.

2.1.7. Step VI: Analyse Identified Papers

For the relevance check, the same criteria as those for the content assessment of papers found during the initial search using the defined search terms are used. Iterations are performed until convergence to a set of relevant publications can be observed, i.e., until similarity search does not produce any additional potential relevant results. Therefore, the number of relevant papers may be tracked as the main driver to ensure complete exploitation of the papers within the database.

After the last loop of investigation of similar papers and content assessment, a final list of relevant papers is developed. This is to be understood as the starting point for a detailed analysis to collect data that defines the outcomes [32] needed for the consecutive review paper. However, this final step was not within the scope of this study.

2.2. Brief Introduction of Vehicles

As the first step in preparing the search terms for the case study, an overview of the existing vehicles must be generated. In the dynamic landscape of transportation, vehicles encompass a wide array of modes spanning land, air, and sea. According to ADR, vehicles are self-propelled devices designed for the transportation of one or more people or goods [39]. The detailed breakdown of existing vehicles shown in chapter 8.1 is derived from the following sources:

Land:

- ISO 3833 [40] focusing on street motor vehicles;
- ADR categorisation for additions regarding wheelchairs, ride-on lawnmowers, and agricultural and construction machinery [39];
- A German standard for railway applications [41].

Maritime:

- A naval architecture scheme [42];
- SOLAS convention [43] for fishery additions;
- Two European directives [44,45] focusing on maritime vehicles.

Aerospace:

- A scheme from the International Civil Aviation Organization [46];
- Electronic Code of Federal Regulations [47].

Based on these inputs, the vehicle overview shown in Figure 2 is generated.

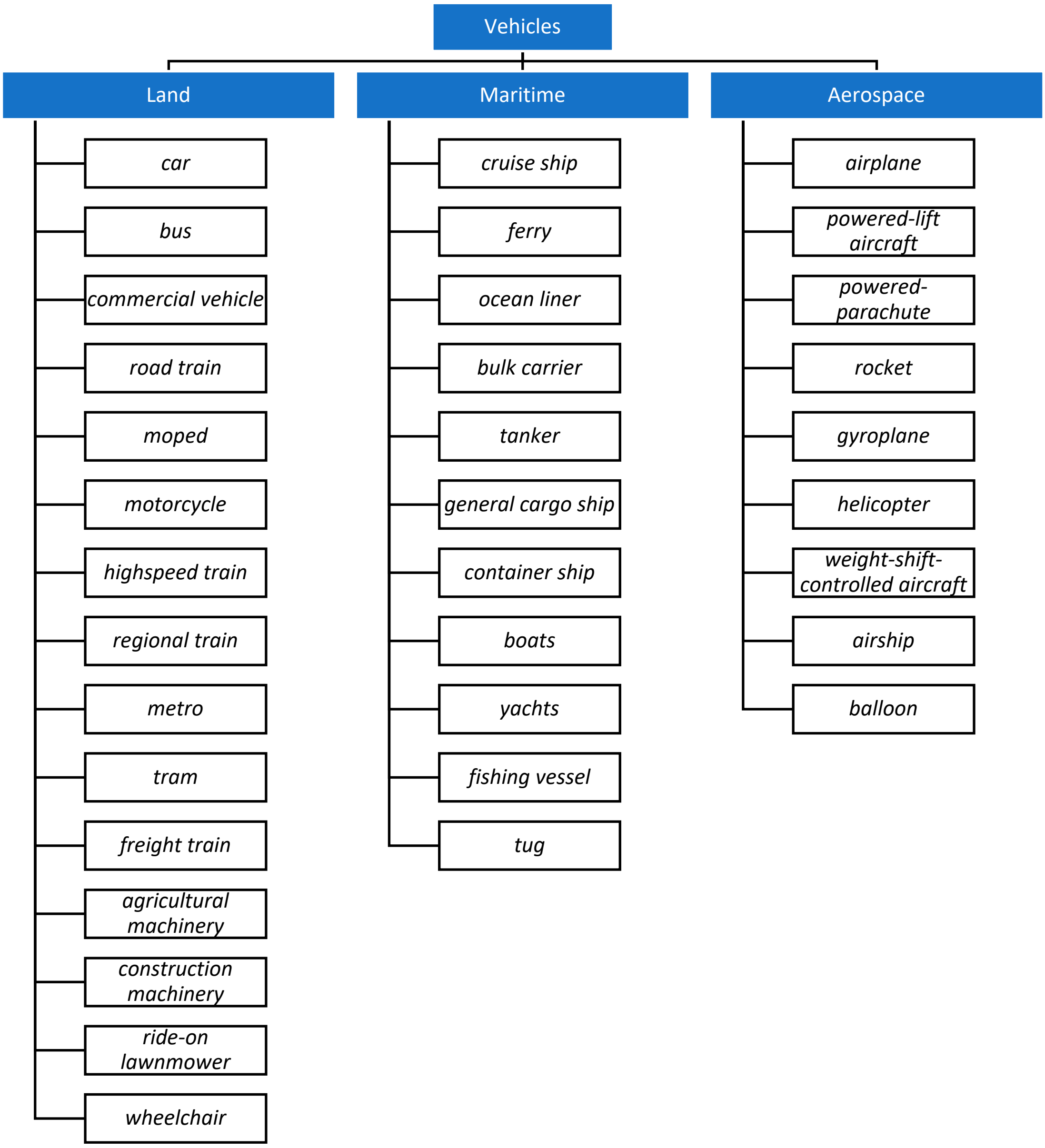

Figure 2. Comprehensive vehicle overview per operational environment.

2.3. Brief Introduction of Powertrains

Second, to prepare the search terms for the case study, an overview of the existing powertrains for previously defined vehicles must be generated. As the world gravitates towards sustainable mobility solutions, there exists a dichotomy between traditional propulsion methods of the "old world", including internal combustion engines powered by gasoline, diesel, turbines, and the like, and the innovative technologies of the "new world" such as hybrid drivetrains and fuel cells. It must be noted that hydrogen, in general, can be used in electrochemical or thermomechanical applications [48]; therefore, it can be applied in both the old and new world.

Vehicles can be classified by their powertrain into internal combustion engine vehicles, hybrid electric vehicles, and all-electric vehicles [49]. Electrochemical storage systems, classified as primary, secondary, and tertiary elements, are required for hybrid electric vehicles and all-electric vehicles [50]. Electrochemical energy storage devices with irreversible or reversible cell reactions, such as batteries, are the primary or secondary elements. The continuous reactions used in fuel cells are defined as tertiary elements [50]. For all-electric vehicles, a distinction can be made between battery electric vehicles and fuel-cell electric vehicles, resulting in the use of components or elements such as batteries, hydrogen, or fuel cells [49].

3. Case Study: Meta-Analysis of Battery Electric vs. Hydrogen Vehicles

3.1. Step I: Introduction of Scope and Case Study

The methodology described here was used to create a database for a meta-analysis of electric and hydrogen battery vehicles for various use cases. The main objective of this meta-analysis was to assess the technological and economic feasibility of using one or both hybrid powertrains in different scenarios. Therefore, a comprehensive approach using a wide range of investigated vehicles and operating conditions is required.

In addition to the technological feasibility, the design of powertrain systems should also be considered. Therefore, publications have provided detailed information on the design of powertrain systems, such as the dimensions of storage systems, packaging constraints, and components used.

Generally, a meta-analysis should answer the following questions:

1. Which powertrain is technologically feasible for the case considered?
2. Which powertrain is economically feasible in the considered case?
3. What are the technological details of the system considered in the case study?

3.2. Step II: Define the Search Term

To ensure a gapless query for the different powertrains, vehicles, and types of studies, the search terms were defined in a dense manner, that is, consciously accepting overlaps between the different search terms, resulting in duplicated publications. The search terms were defined by combining three groups, powertrains, vehicles, and types of studies, with search addition as an option. Each group is described briefly in the following sections.

3.2.1. Powertrains

To include the required powertrains of vehicles, search terms were defined by covering the technical principles of energy storage and conversion. The search term elements are listed as vectors P_1, P_2, and P_3, based on the introduction in Section 2.3.

$$P_1 = (\text{hydrogen, electric, hydrogen powered, battery powered, fuel cell, battery electric})$$

$$P_2 = (\text{hydrogen, battery})$$

$$P_3 = (\text{hydrogen, battery electric})$$

3.2.2. Vehicles

The investigated vehicles were defined based on a wide spectrum of standards, conventions, and regulations, as discussed in Section 2.2. This approach resulted in 35 different vehicles defined in this study.

V = (car, bus, commercial vehicle, road train, moped, motorcycle, highspeed train, regional train, metro, tram, freight train, cruise ship, ferry, ocean liner, bulk carrier, tanker, general cargo ship, container ship, boats, yachts, fishing vessel, tug, airplane, powered-lift aircraft, powered-parachute, rocket, gyroplane, helicopter, weight-shift-controlled aircraft, airship, balloon, agricultural machinery, construction machinery, ride-on lawnmower, wheelchair)

3.2.3. Search Adds

To specify the search terms, variants A_2 "deployment" and A_3 "powertrain" were added to basic variant A_1. Therefore, the three vectors are as follows:

$$A_1 = (1)$$

$$A_2 = (\text{deployment})$$

$$A_3 = (\text{powertrain})$$

3.2.4. Kind of Studies

To cover a wide range of case studies in the literature, multiple equivalent search terms were defined. These cover not only the case study synonyms, but also reports, evaluations, prototypes, and equivalent descriptions.

K_1 = (review, report, summary, findings, investigation, analysis, research, comparative study, evaluation, benchmark, assessment, rating, examination, feasibility study, case study, in-depth study, exemplar study, single case, research, examples, models, prototype)

$$K_2 = (1)$$

4. Results

4.1. Step III: Queried Search Terms in the Process

Table 1 shows the derivation of the search terms based on the groups discussed in Section 3.2. For a better overview, the S1, S2, and S3 searches are further subdivided in the following section. Search S_1 consisted of search term groups 1.1–1.6, search S_2 used search term groups 2.1 and 2.2, and search S_3 included search term groups 3.1 and 3.2. Each search term group consisted of multiple terms. Every search term group uses one of the entries from the vector P_1. For example, the search term group 1.1 contains all the search terms with the search term element "hydrogen", as it is the first entry of the vector P_1. Search term 2.2 uses the search term element "battery" as the second entry of vector P_2 in combination with other search term elements, as shown in Table 1. An example for S_1 is the search term "hydrogen car review".

Table 1. Search term logic and derived combinations.

Searches	Derived Combinations
$S_1 = P_1 \otimes ((V \otimes A_1) \otimes K_1)$	5145
$S_2 = P_2 \otimes ((V \otimes A_2) \otimes K_2)$	70
$S_3 = P_3 \otimes ((V \otimes A_3) \otimes K_1)$	1470
$\sum$	6685

4.2. Step IV: Identified Relevant Papers

All of the steps for identification of the relevant paper discussed in Section 2.1 were applied in this study. In total, 55,206 publications were identified in Step III (see Figure 1). After filtering out duplicates resulting from overlapping search terms, 48,827 papers (88.4%) were removed from the list. Furthermore, 2024 (3.7%) entries were incorrect because of errors in the Semantic Scholar database or query process. Furthermore, 936 papers were published before 2013 and were removed from the list because the study focuses on papers published in the last decade. It must be noted that only papers published and indexed in the Semantic Scholar database by the autumn of 2023 were considered.

In the next step, a content assessment of the remaining 3419 papers from Step III was performed. For successful content assessment, the information required for the study was defined. The objective of this study is to review the recommendations for powertrains based on vehicle and boundary conditions such as range or location. Furthermore, data related to the dimensioning of the relevant energy-storage components should be gathered. Based on this, the information desired for the study is defined in Table 2. This table can be complemented during the study. However, it should already be comprehensive during the relevance assessment of the publications. After significant changes, a new relevance assessment of publications is required.

Table 2. Summary of searched information as a basis for the relevance assessment.

Relevant Information			Vehicle
Operational scenario	Vehicle requirements	Range (km)	
		Pay load (t)	
		Lifetime (a)	
		Operation time (h/d)	
		Efficiency (kWh/km)	
		Operating temperature range (°C)	
		...	
	Economical aspects	Market entry (date)	
		Fix costs (€)	
		Variable costs (€)	
		...	
Powertrain	System	Components powertrain	
		Packaging constraints (l)	
		...	
	Design	Pressure H2 storage (bar)	
		Sizing H2 storage (l)	
		Capacity battery (kWh)	
		Voltage battery (V)	
		Peak pulse battery discharge (A)	
		Efficiency (%)	
		...	

Of 3419 papers, 413 were listed as relevant. For these publications, an investigation of similar papers was carried out using Citrus Search (Step V). In the first loop, 2830 additional papers were identified, 286 of which were listed as relevant. In the second loop, the relevant papers from the first loop were analysed using Citrus Search, which yielded 292 further publications. A manual check led to a rejection rate of 278, leaving 14 considered to be relevant. In the last loop, 21 papers were identified, none of which were listed as relevant. In total, 713 relevant papers were identified in this case study.

A summary of all of the steps in the identification of relevant papers is shown in the Sankey diagram in Figure 3. The search term groups related to hydrogen powertrains are marked in blue, and those focusing on batteries are green.

4.3. Investigated Similar Papers

As mentioned in Section 4.2, a total of 3143 considered publications were derived from three loops of investigations of similar papers using Citrus Search. The publications assessed as relevant in Step IV were used as inputs for the first loop of a similar investigation. For each relevant paper, a maximum of ten neighbouring papers was found, as described in Section 2.1.5. Subsequently, a relevance assessment of this sample was performed, resulting in the rejection of 2544 papers. A total of 286 papers (10.1%) were assessed as relevant, which is a slightly lower ratio than that of the initial query in Step III. For the second loop, only 286 relevant papers were used as inputs. Again, a maximum of ten papers were searched for each entry. However, the second loop resulted in only 292 similar papers, of which 14 were relevant. Here, the ratio was significantly lower at 5.1% of the relevant papers. In the last loop, 21 papers were identified, none of which were considered relevant. Thus, convergence is observed in Step V, as shown in Figure 4. Due to this fact and the known sufficient coverage of publications in the Semantic Scholar database [33], no additional query in another database was performed.

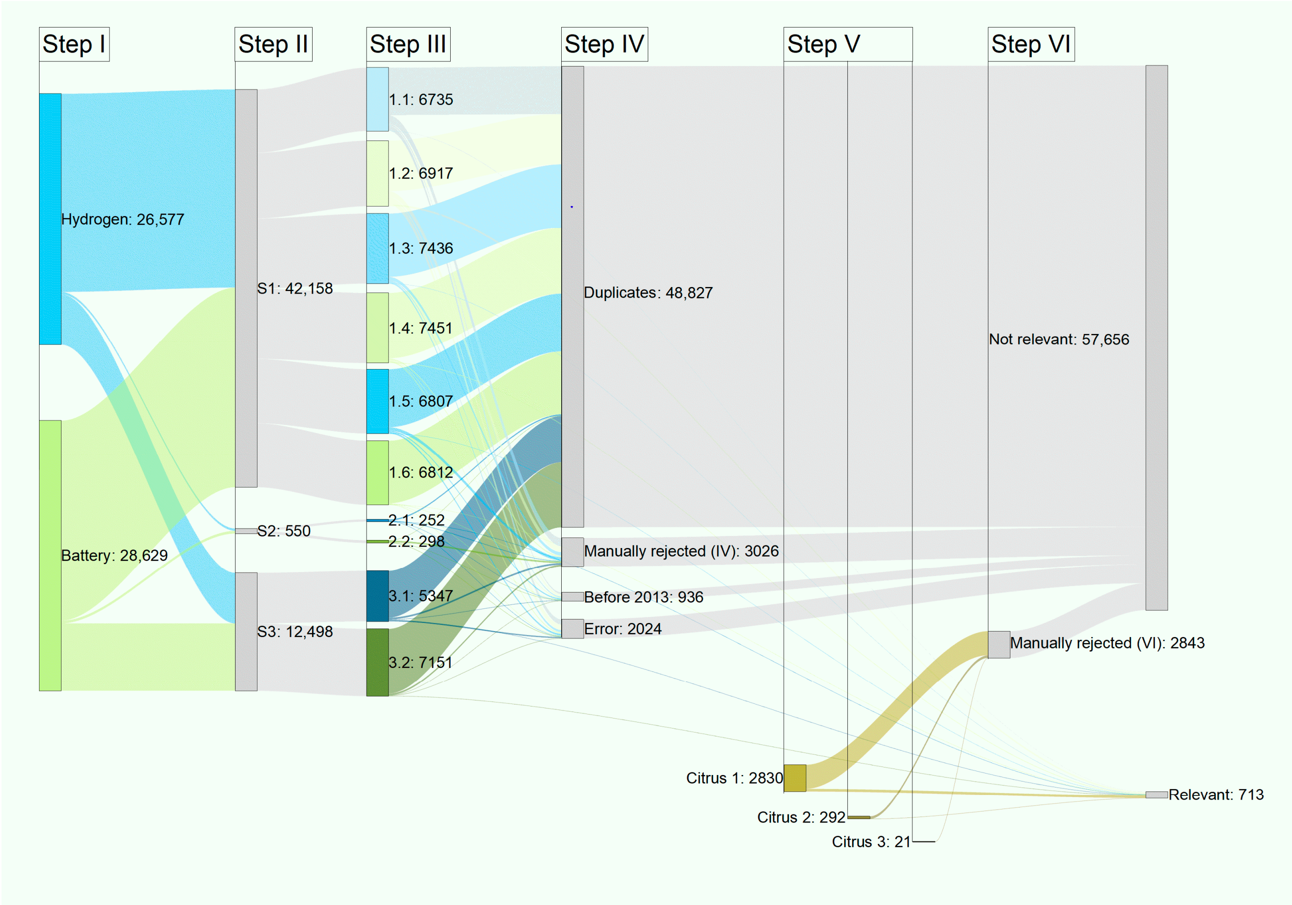

Figure 3. Sankey diagram of the publication search and relevance assessment.

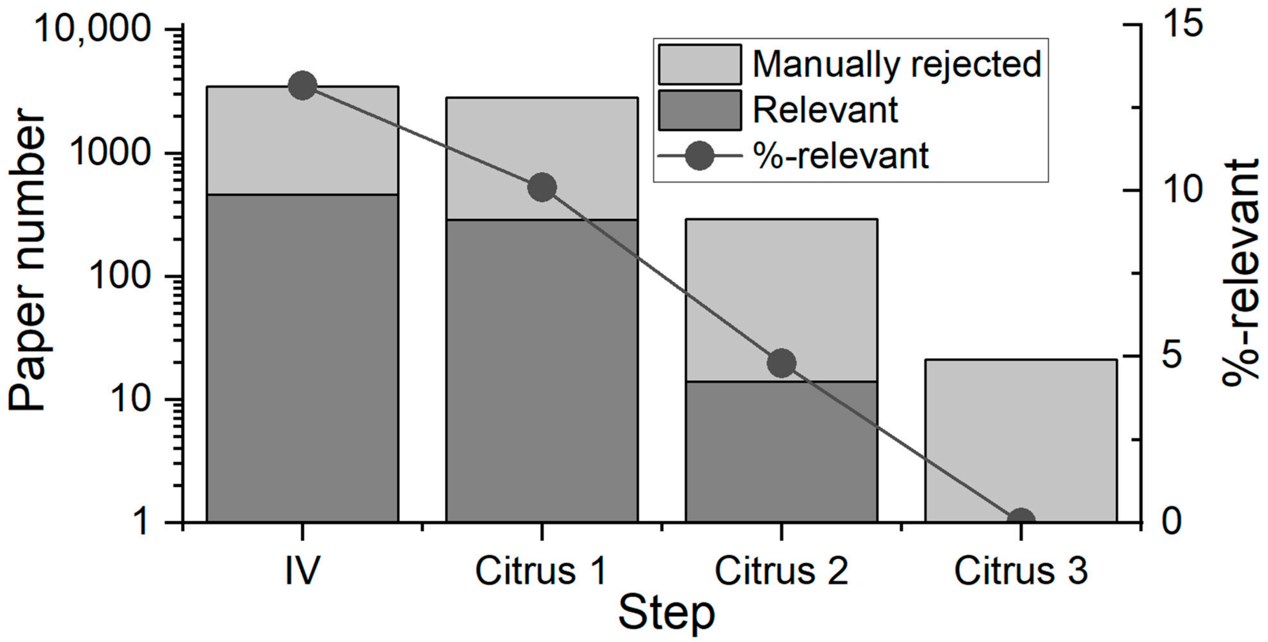

Figure 4. Convergence of the similar paper investigation with Citrus Search.

4.4. Analysed Identified Papers

Figure 5 shows the distribution for every year of publishing of relevant papers found with particular search term groups in Step III, as well as those found in two loops using Citrus Search in Step V. Here, similar to Figure 3, the blue colour indicates papers found using hydrogen-related search terms, and the green colour is used for battery-related search terms.

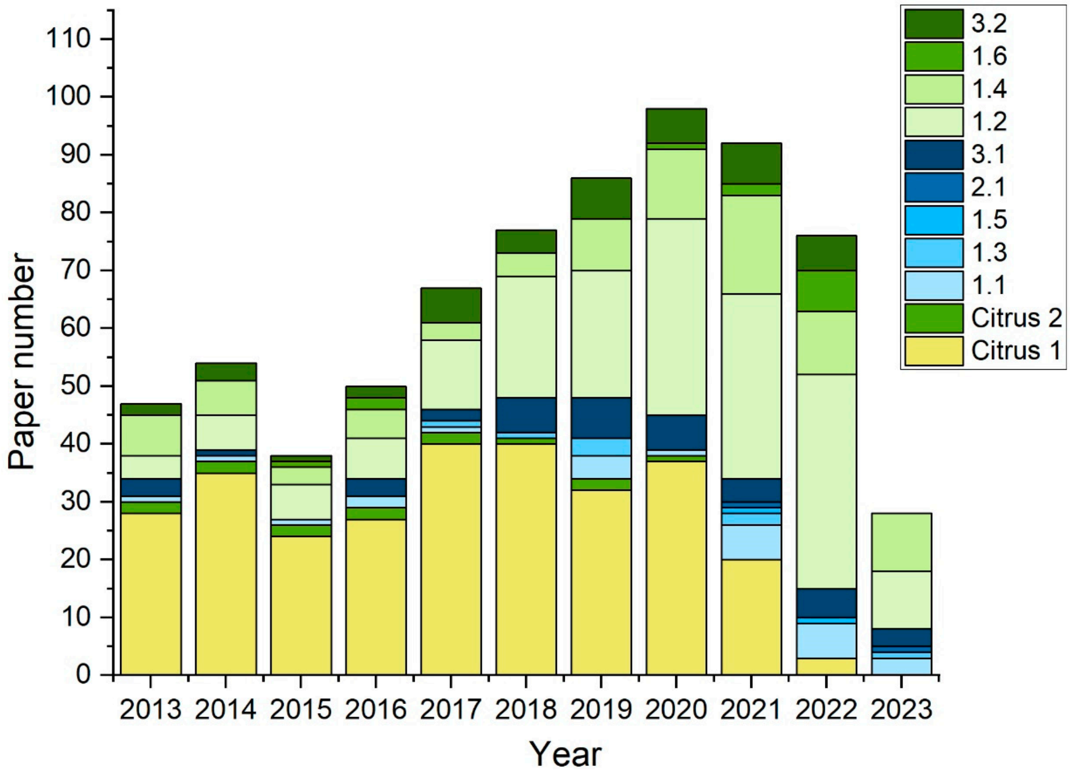

Figure 5. Distribution of the relevant papers throughout the years.

In general, it can be observed that the number of relevant papers grew from 2013 to 2021, with the exception of 2015. A change in this trend can be noted in 2022. This can be traced to the significantly lower number of similar papers published in 2022, found in Step V. However, the search for similar papers is based among others on the citations network. Therefore, for newer papers with undeveloped citation networks, it might be challenging to find similar relevant papers with Citrus Search or similar tools. A further reduction in the number of relevant papers can be observed in the year 2023. Since the search was carried out in the second half of 2023, this number can be related to papers not yet published or those not yet listed in the Semantic Scholar database.

The search terms related to battery electric powertrains led to a significantly higher number of relevant papers than those related to hydrogen powertrains. On the one hand, this could indicate a higher number of relevant research conducted on battery electric powertrains. The hypothesis that more papers related to hydrogen powertrains count as grey literature and were filtered out because of the lack of DOI owing to their novelty could not be proven. However, the search terms that led to a finding did not necessarily provide information about the paper content. In particular, review papers on electric vehicles, comparative studies, and feasibility studies including multiple powertrains can be easily found using more general search terms. These were included in search terms 1.2, 1.4, and 1.6, which were counted as battery-related search terms. In particular, the search term 1.2 yielded a high number of relevant papers (197), which is over 25% of all papers assessed as relevant in the study. On the other hand, no relevant paper resulted from the search 2.2. A detailed analysis of the paper content is required to precisely assess the research interests of the relevant papers.

As mentioned in Section 2.1.5, Citrus Search uses a graph-embedding algorithm to represent the position of papers in the citation network as an embedding vector. It interprets the proximity of the papers in the resulting vector space as a measure of how similar the positions of these papers in the citation network are; papers with a low distance between their embedding vectors are assumed to be closely related. For this study, we made use of this property of the embedding vectors to perform a visual analysis of our search results and to attempt to identify clusters in the research landscape. To allow for visualisation in three-dimensional space, the embedding vectors for all papers were subjected to a dimensionality reduction using a principal component analysis. The resulting three-dimensional vectors were used to create the following figures. As shown in Figure 6, the results can be visualised as a cloud, as shown on the left. Segments are represented by markers in green for "Battery", red for "Hydrogen", and blue for "Identified Neighbours". The cloud spans the space defined by coordinates x from −2 to 2, y from −2 to 3, and z from −4 to 4. Notably, the regions for Battery and Hydrogen are distinguishable from each other.

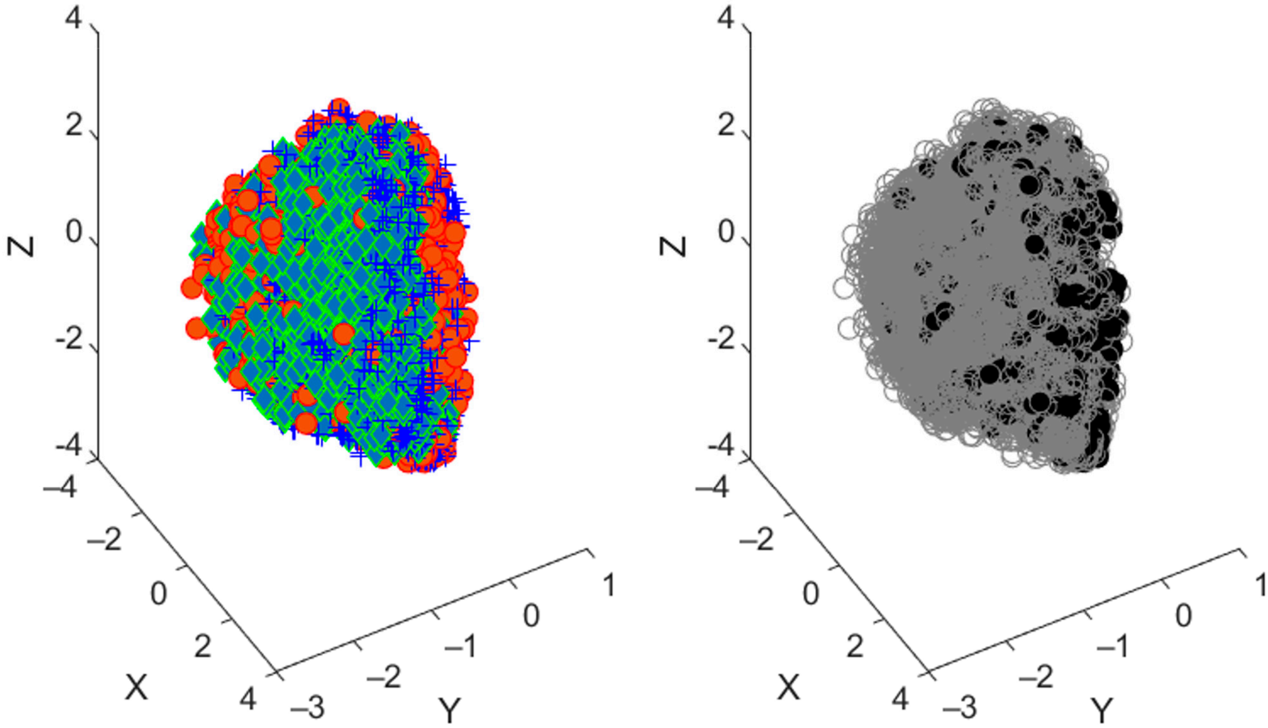

Figure 6. Overview research results and distribution relevant vs. irrelevant paper.

The distribution of papers assessed as relevant or irrelevant is depicted on the right. It is important to note the apparent clustering, which indicates that there are more battery papers than hydrogen papers, as shown in Figure 3. The papers can also be clustered according to the authors' initial assessment of the operational environments. For example, cars, trains, and wheelchairs are grouped under "Land". Papers that could not be categorised without a complete reading or that pertained to multiple operational environments were placed in the Overarching category. Even when viewed within each operational environment as presented in Figure 7, Battery and Hydrogen can be distinguished from one another. The share of the relevant papers is ~40% for Land, 28% for Aerospace, 18% for Overarching, and 15% for Maritime.

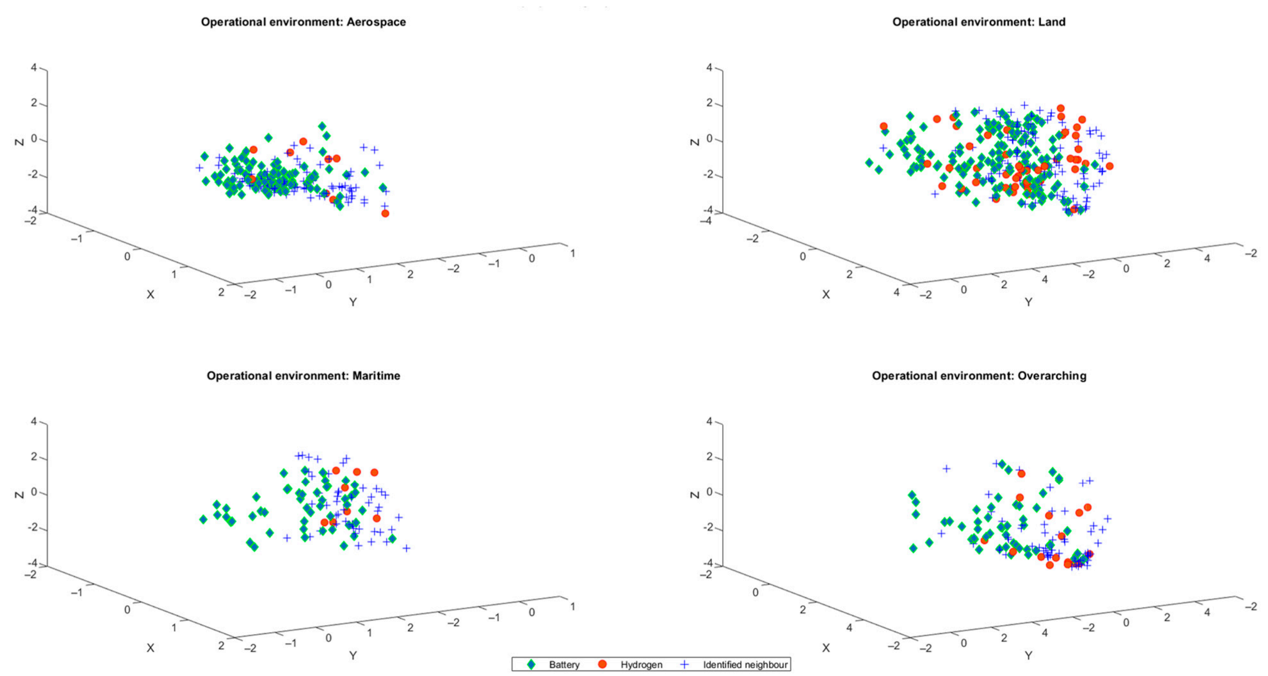

Figure 7. Overview relevant research results per operational environment.

A cluster analysis was performed to investigate the spatial distribution of relevant data points across the different operational environments and to identify patterns within these. Using "Gaussian Mixture Modeling" in Matlab, the data were partitioned into several clusters to visually highlight and analyse distinct groups of points. The clusters are shown in Figure 8.

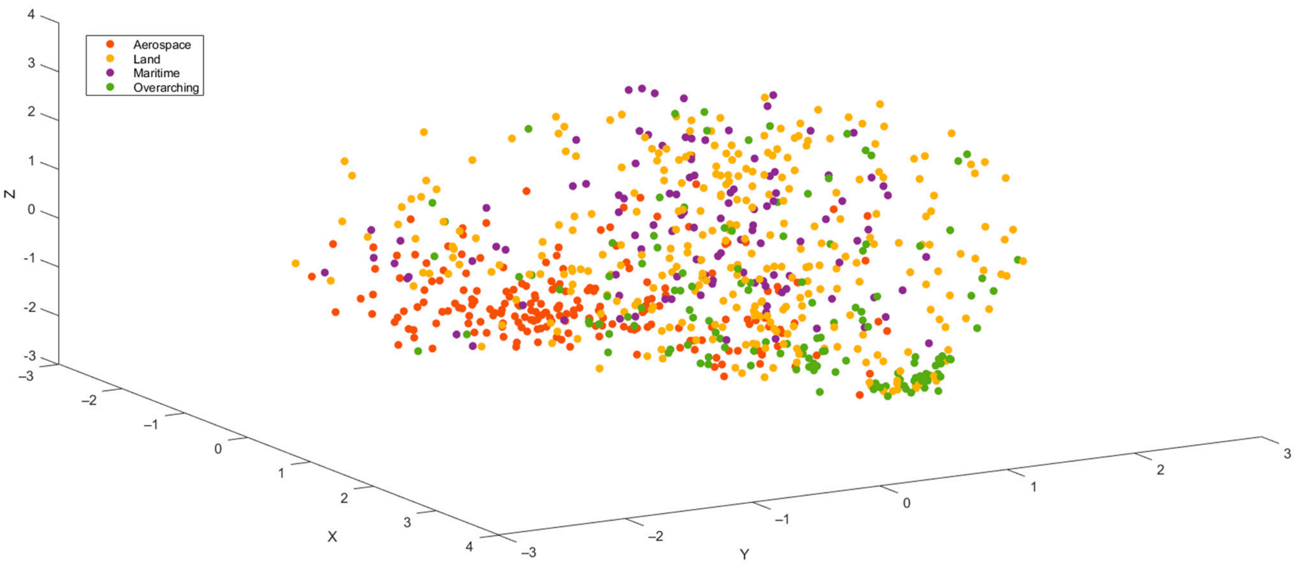

Figure 8. Clustering of the different operational environment.

The figure shows that the papers for the operational environment Land are widely dispersed. For the operational environment Maritime, no focal point is discernible. Papers categorised as Overarching are mainly situated near the operational environment Land, which aligns with the expectation that the term "battery electric vehicle" is typically used for cars. The operational environment Aero has its own focal point.

5. Discussion

Regarding the general approach, it was found that the repetitive task of research, the utilisation of various search terms, was efficiently realised at low cost.

The exemplary search indicates that the AI process is independent from the perseverance of the researcher, synonyms, and taxonomy, and, therefore, a thorough analysis can be performed. As shown in Figure 3, the specific and overlapping search terms resulted in duplicates, which also indicates that AI can generalise the search. It can be concluded that general and fewer search terms might be used when accepting missing papers on specific vehicle types.

It was also proven by the convergence analysis that the number of identified papers declined over each loop, which might indicate that the border of the specific neighbourhood was reached and that the Semantic Scholar database was fully exploited. The study might be concluded by extending the presented approach to another database besides Semantic Scholar. This would also address the aspect of the domain agnostic data from Sematic Scholar, as the authors have no insights into the scope of the provided database. Hence, important papers might not have been discoverable.

Besides the risk of missing papers in the database, it must also be stated that the still-needed process of manual rejection might include misleading papers in the list of identified papers or exclude relevant papers due to biases. Thus, the next recommended step is to examine and challenge the 713 identified papers as well their references. In this consecutive study, the PRISMA approach should be continued, focusing on the steps' bias assessments and certainty assessments. It is to be noted that this step is necessary for the method validation in agreement with good research praxis.

The performed cluster analysis of the found papers, which is based on the citations and reference network, delivers a clear differentiation between the papers related to battery vehicles and those on vehicles with hydrogen propulsion. On the other hand, the relevant data points of vehicles in the considered operational environments are widely spread. This behaviour indicates that the linkage of the considered papers might be rather powertrain-related and not vehicle-related. Only for the papers from the operational environment Aerospace could a focal point be observed.

6. Conclusions

In this study, an efficient six-step approach for AI-based research and a list of 713 potentially relevant papers on powertrains of vehicles with battery electric and or hydrogen propulsion is presented. For this elaboration, an automated crawling of circa 60,000 papers from Semantic Scholar based on 6700 search terms for more than 30 vehicle descriptions was conducted. Based on the exemplary search, a trend for battery and hydrogen papers since 2018 can be deducted. The drill-down was complemented by a structured neighbourhood analysis with Citrus Search, and the effectiveness of the approach was proven by the analysed convergence. The result is that potentially 57,656 irrelevant and 713 relevant papers were identified. A key contributor of relevant papers was the similarity search with Citrus Search.

Among all of the relevant papers, a low share referred to hydrogen propulsion. The authors could not map the propulsion technologies and vehicles or their respective operational environments and therefore recommend a reference analysis after a full in-detail evaluation of the relevant papers as a next step. Within the consecutive analysis, the content of the relevant papers should be extracted according to the drafted Table 2.

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References

1. Naughtin, C.; Hajkowicz, S.; Schleiger, E.; Bratanova, A.; Cameron, A.; Zamin, T.; Dutta, A. Our Future World: Global Megatrends Impacting the Way we Live Over Coming Decades. 2022. Available online: https://doi.org/10.25919/0yax-yx96 (accessed on 14 April 2024).
2. Conway, G.; Joshi, A.; Leach, F.; García, A.; Senecal, P.K. A review of current and future powertrain technologies and trends in 2020. *Transp. Eng.* **2021**, *5*, 100080. [CrossRef]
3. Poullikkas, A. Sustainable options for electric vehicle technologies. *Renew. Sustain. Energy Rev.* **2015**, *41*, 1277–1287. [CrossRef]
4. Nqodi, A.; Mosetlhe, T.C.; Yusuff, A.A. Advances in Hydrogen-Powered Trains: A Brief Report. *Energies* **2023**, *16*, 6715. [CrossRef]
5. Nagy, A. Electric aircraft—Present and future. *Prod. Eng. Arch.* **2019**, *23*, 36–40. [CrossRef]
6. Lund, B.D.; Wang, T. Chatting about ChatGPT: How may AI and GPT impact academia and libraries? *Libr. Hi Tech News* **2023**, *40*, 26–29. [CrossRef]
7. Ammar, W.; Groeneveld, D.; Bhagavatula, C.; Beltagy, I.; Crawford, M.; Downey, D.; Dunkelberger, J.; Elgohary, A.; Feldman, S.; Ha, V.; et al. Construction of the Literature Graph in Semantic Scholar. *arXiv* **2018**, arXiv:1805.02262.
8. Matthews, D. Drowning in the literature? These smart software tools can help. *Nature* **2021**, *597*, 141–142. [CrossRef]
9. Li, H.; Wang, Y.; Liao, Q.V.; Qu, H. Why is AI not a Panacea for Data Workers? An Interview Study on Human-AI Collaboration in Data Storytelling. *arXiv* **2023**, arXiv:2304.08366.
10. Snyder, H. Literature review as a research methodology: An overview and guidelines. *J. Bus. Res.* **2019**, *104*, 333–339. [CrossRef]
11. Moher, D.; Liberati, A.; Tetzlaff, J.; Altman, D.G.; PRISMA Group. Preferred Reporting Items for Systematic Reviews and Meta-Analyses: The PRISMA Statement. *Ann. Intern. Med.* **2009**, *151*, 264–269. [CrossRef]
12. Khan, K.S.; Kunz, R.; Kleijnen, J.; Antes, G. Five Steps to Conducting a Systematic Review. *J. R. Soc. Med.* **2003**, *96*, 118–121. [CrossRef] [PubMed]
13. Harris, J.D.; Quatman, C.E.; Manring, M.M.; Siston, R.A.; Flanigan, D.C. How to Write a Systematic Review. *Am. J. Sports Med.* **2014**, *42*, 2761–2768. [CrossRef] [PubMed]
14. Pati, D.; Lorusso, L.N. How to Write a Systematic Review of the Literature. *HERD Health Environ. Res. Des. J.* **2018**, *11*, 15–30. [CrossRef] [PubMed]
15. Linares-Espinós, E.; Hernández, V.; Domínguez-Escrig, J.L.; Fernández-Pello, S.; Hevia, V.; Mayor, J.; Padilla-Fernández, B.; Ribal, M.J. Methodology of a systematic review. *Actas Urol. Esp.* **2018**, *42*, 499–506. [CrossRef]
16. Barry, E.S.; Merkebu, J.; Varpio, L. State-of-the-art literature review methodology: A six-step approach for knowledge synthesis. *Perspect. Med. Educ.* **2022**, *11*, 281–288. [CrossRef] [PubMed]
17. Crowther, M.; Lim, W.; Crowther, M.A. Systematic review and meta-analysis methodology. *Blood* **2010**, *116*, 3140–3146. [CrossRef]
18. Whittemore, R.; Knafl, K. The integrative review: Updated methodology. *J. Adv. Nurs.* **2005**, *52*, 546–553. [CrossRef] [PubMed]
19. Aromataris, E.; Pearson, A. The Systematic Review: An Overview. *AJN Am. J. Nurs.* **2014**, *114*, 53–58. [CrossRef]
20. Davis, J.; Mengersen, K.; Bennett, S.; Mazerolle, L. Viewing systematic reviews and meta-analysis in social research through different lenses. *SpringerPlus* **2014**, *3*, 511. [CrossRef]
21. Palmatier, R.W.; Houston, M.B.; Hulland, J. Review articles: Purpose, process, and structure. *J. Acad. Mark. Sci.* **2018**, *46*, 1–5. [CrossRef]
22. Tranfield, D.; Denyer, D.; Smart, P. Towards a Methodology for Developing Evidence-Informed Management Knowledge by Means of Systematic Review. *Br. J. Manag.* **2003**, *14*, 207–222. [CrossRef]
23. Jin, Q.; Leaman, R.; Lu, Z. PubMed and beyond: Biomedical literature search in the age of artificial intelligence. *eBioMedicine* **2024**, *100*, 104988. [CrossRef] [PubMed]
24. Ma, J.; Wu, X.; Huang, L. The Use of Artificial Intelligence in Literature Search and Selection of the PubMed Database. *Sci. Program.* **2022**, *2022*, 8855307. [CrossRef]
25. Schoeb, D.; Suarez-Ibarrola, R.; Hein, S.; Dressler, F.F.; Adams, F.; Schlager, D.; Miernik, A. Use of Artificial Intelligence for Medical Literature Search: Randomized Controlled Trial Using the Hackathon Format. *Interact. J. Med. Res.* **2020**, *9*, e16606. [CrossRef]

26. Orgeolet, L.; Foulquier, N.; Misery, L.; Redou, P.; Pers, J.-O.; Devauchelle-Pensec, V.; Saraux, A. Can artificial intelligence replace manual search for systematic literature? Review on cutaneous manifestations in primary Sjögren's syndrome. *Rheumatology* **2020**, *59*, 811–819. [CrossRef]
27. Wagner, G.; Lukyanenko, R.; Paré, G. Artificial intelligence and the conduct of literature reviews. *J. Inf. Technol.* **2022**, *37*, 209–226. [CrossRef]
28. Bolaños, F.; Salatino, A.; Osborne, F.; Motta, E. Artificial intelligence for literature reviews: Opportunities and challenges. *Artif. Intell. Rev.* **2024**, *57*, 259. [CrossRef]
29. De La Torre-López, J.; Ramírez, A.; Romero, J.R. Artificial intelligence to automate the systematic review of scientific literature. *Computing* **2023**, *105*, 2171–2194. [CrossRef]
30. Torres-Carrion, P.V.; Gonzalez-Gonzalez, C.S.; Aciar, S.; Rodriguez-Morales, G. Methodology for systematic literature review applied to engineering and education. In Proceedings of the 2018 IEEE Global Engineering Education Conference (EDUCON), Santa Cruz de Tenerife, Spain, 17–18 April 2018; IEEE: Tenerife, Spain, 2018; pp. 1364–1373. [CrossRef]
31. Kitchenham, B.; Brereton, P. A systematic review of systematic review process research in software engineering. *Inf. Softw. Technol.* **2013**, *55*, 2049–2075. [CrossRef]
32. Page, M.J.; McKenzie, J.E.; Bossuyt, P.M.; Boutron, I.; Hoffmann, T.C.; Mulrow, C.D.; Shamseer, L.; Tetzlaff, J.M.; Akl, E.A.; Brennan, S.E.; et al. The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *Syst. Rev.* **2021**, *10*, 89. [CrossRef]
33. Hannousse, A. Searching relevant papers for software engineering secondary studies: Semantic Scholar coverage and identification role. *IET Softw.* **2021**, *15*, 126–146. [CrossRef]
34. Walker, B.J. CitationGecko 2024. Available online: https://doi.org/10.5281/zenodo.7068284 (accessed on 14 April 2024).
35. Tarnavsky Eitan, A.; Smolyansky, E.; Knaan Harpaz, I.; Perets, S. Connected Papers 2024. Available online: https://www.connectedpapers.com/ (accessed on 14 April 2024).
36. Mayer, J.; Palmer, M. Citrus Search 2024. Available online: https://citrus-search.com (accessed on 14 April 2024).
37. Grover, A.; Leskovec, J. node2vec: Scalable Feature Learning for Networks. *KDD Proc. Int. Conf. Knowl. Discov. Data Min.* **2016**, *2016*, 855–864.
38. Goyal, P.; Ferrara, E. Graph Embedding Techniques, Applications, and Performance: A Survey. *Knowl.-Based Syst.* **2017**, *151*, 78–94. [CrossRef]
39. Agreement concerning the International Carriage of Dangerous Goods by Road 2023. Available online: https://unece.org/transport/standards/transport/dangerous-goods/adr-2023-agreement-concerning-international-carriage (accessed on 14 April 2024).
40. *ISO 3833:1977*; Road Vehicles. ISO: Geneva, Switzerland, 1977; p. 12.
41. *DIN EN 15663:2019-03*; Bahnanwendungen—Fahrzeugreferenzmassen. DIN: Berlin, Germany, 2019; p. 37.
42. *Introduction to Naval Architecture*; Elsevier: Amsterdam, The Netherlands, 2013; Available online: https://doi.org/10.1016/C2011-0-07775-X (accessed on 10 November 2024).
43. International Convention for the Safety of Life at Sea (SOLAS); IMO. 1974. Available online: https://www.imo.org/en/About/Conventions/Pages/International-Convention-for-the-Safety-of-Life-at-Sea-(SOLAS),-1974.aspx (accessed on 14 April 2024).
44. *Directive 2013/53/EU of the European Parliament and of the Council of 20 November 2013 on Recreational Craft and Personal Watercraft and Repealing Directive 94/25/EC Text with EEA Relevance*; The European Parliament and the Council of the European Union: Strasbourg, France, 2013.
45. Directive 2009/45/EC of the European Parliament and of the Council on Safety Rules and Standards for Passenger Ships. 2009, p. 139. Available online: http://data.europa.eu/eli/dir/2009/45/oj (accessed on 14 April 2024).
46. ICAO. *Doc 8168 Aircraft Operations Procedures for Air Navigation Services Volume I—Flight Procedures*; International Civil Aviation Organization: Montreal, QC, Canada, 2018.
47. CFR 1.1 Title 14: Aeronautics and Space; National Archives And Records Administration, 04/24. Available online: https://www.ecfr.gov/current/title-14 (accessed on 14 April 2024).
48. Müller, K. Wasserstoff: Perspektiven der Nutzung in Energie, Verkehr und Chemie. *Chem. Unserer Zeit* **2024**, *58*, 46–51. [CrossRef]
49. Tie, S.F.; Tan, C.W. A review of energy sources and energy management system in electric vehicles. *Renew. Sustain. Energy Rev.* **2013**, *20*, 82–102. [CrossRef]
50. Doppelbauer, M. *Grundlagen der Elektromobilität: Technik, Praxis, Energie und Umwelt*; Springer Fachmedien: Wiesbaden, Germany, 2020. [CrossRef]