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Research article

Mapping the evolution of hybrid choice model research: A Scientometric review of intellectual structure, machine-learning trends, and global collaboration

Mashail M. AL Sobhi*

Department of Mathematics, Umm-Al-Qura University, Makkah 24227, Saudi Arabia

* **Correspondence:** Email: mmsobhi@uqu.edu.sa.

Abstract: Hybrid choice models combine discrete-choice theory with latent psychological constructs and are now analyzed alongside machine-learning and computational approaches. However, the evolution of this research field over time, the structure of its skills, the interdependencies among its ideas, and its computational evolution have not yet been fully documented. This study is a reproducible scientometric review of hybrid choice model studies published in the Dimensions database until 2026. *N* unique publications remained after screening out duplicates and ineligible records. We analyzed publication trends, journal influence, author and institutional collaborations, international research networks, keyword co-occurrence, co-citation relationships, and bibliographic-coupling structures. We quantified machine-learning trends using a prespecified keyword taxonomy, annual prevalence measures, method-specific frequencies, and temporal co-occurrence analysis. The results showed a continued rise in HCM research and its focus in transportation research, a shift in focus toward health and environmental decision-making, and a growing focus on specific machine-learning methods. The findings are not a direct measure of the scientific quality of the articles or predictive of their superiority and should be viewed in terms of publication, citation, thematic and collaboration patterns between articles. The study offered a repeatable snapshot of HCM research and opportunities to integrate interpretable, externally validated machine learning behavioral choice theory in a computationally scalable way.

Keywords: hybrid choice model; bibliographic coupling; scientometric analysis; co-citation analysis; machine learning
Mathematics Subject Classification: 62P20, 68T01

1. Introduction

A hybrid choice model is a modeling technique that aims to reconcile discrete choice models with behavioral theories. It specifically incorporates unseen factors into the decision-making process, including the impact of attitudes, decision protocols, and perceptions. The origin of hybrid choice models may be attributed to various researchers [1]. Ben-Akiva et al. subsequently formalized the general hybrid-choice framework [2], while integrated choice and latent-variable models connected structural equations, measurement indicators, and discrete-choice outcomes within a unified probabilistic system [3]. Subsequent research addressed the estimation requirements and computational challenges associated with these models [4]. There are four principal advantages of the hybrid choice models. The first advantage is explicitly modeling unobserved heterogeneity [5], capturing factors such as the influence of latent variables, such as attitudes toward taste parameters [6]. The second benefit is improved parameter estimation efficiency, facilitated by additional information from indicators of latent variables. Third, hybrid choice models enhance behavioral realism by transparently representing the individual's decision-making approach, unlike discrete choice models [7]. The latter typically relies on utility functions that depend on observable variables but do not explicitly account for factors such as risk aversion in an individual's preferences [8]. Finally, hybrid choice models offer policy relevance, as latent-variable models can yield more sensible predictions, especially as latent-variable values evolve [9]. Additionally, these models facilitate market segmentation based on latent variables, enabling more targeted policy measures [10].

1.1 Research significance and data collection

This study aims to collect information on choice modeling from the large volume of data generated over the past few years. A scientometric study investigates quantitative and statistical aspects of scientific research, including publication trends, citation rates, collaboration dynamics, and related characteristics. Scientometric analysis examines and quantifies scientific endeavors to better understand how they are organized. It examines changes within research domains, the effects of published works, the impact of authors and organizations, and the evolution of knowledge across time.

It also focuses on field mapping, visualization, and evaluating indicators for policy-making and corporate strategy. The current study is a tool for assessing research results and analyzing large datasets that are often too large to store on a single machine or manage using traditional data structures, tools, or standard visual programming. The scientometric analysis examines several aspects, including annual publication output, the nations that produce the most publications, and collaboration among research groups. It also analyzes the frequency of specific keywords and the evolution of research focus from subject to theme.

Methodological innovations in hybrid choice model are multifaceted and suitable for many uses [11]. Direct successors to traditional models include discrete choice models extended with latent variable models to reflect subject heterogeneity [12]. New developments have introduced machine learning techniques, including neural networks and ensemble models, to improve prediction precision and interpretability [13]. However, these approaches are problematic due to high computational complexity, parameter instability, and limited contextual robustness [14,15]. Why these are crucial to address: These shortcomings in methodological development limit the potential to make HCM frameworks more realistic and practical.

This study has three important contributions to the literature on hybrid choice modeling [16]. First, it provides an integrated scientometric mapping of the intellectual, thematic, and collaborative structure of HCM research, using a combination of publication-trend analysis, keyword co-occurrence analysis, author and journal co-citation analysis, bibliographic coupling analysis, and country-level collaboration networks in a single analytical framework [17]. This mix enables researchers to pinpoint not only the most impactful publications and contributors but also the connections through which knowledge has evolved across the field. Second, the study defines the substantive shift in the HCM field from its traditional focus on transportation applications to health economics, environmental policy, marketing, behavioral decision-making and machine-learning-based analysis. Third, it brings into the picture the patterns observed in these studies and compares them with the methodological development of HCM, from classical random-utility models to integrated choice and latent variable models and, more recently, to neural, data-driven, and computationally enhanced choice models. The present investigation examines the overall framing, development, transdisciplinary innovation, and emerging computational focus of the research domain, rather than studies focused on a single HCM application or estimator.

In view of this, the following research questions are addressed: What has been the trend of the volume and disciplinary breakdown of HCM research over time? Who were the key authors, journals, institutions, countries and publications? What are the major themes and approaches in the literature today? Finally, what is the effect of machine learning and related computational innovations on the new trend of hybrid choice modeling?

The rest of the manuscript is organized as follows. Section 2 examines conventional choice models based on utilities, latent variable integration, and the recent linkage between HCM and computational learning approaches. Section 3 describes the database search, eligibility screening, scientometric indicators, and network-construction procedures. Section 4 presents results on publications, citations, co-authorship, keywords, and bibliographic coupling. Section 5 presents methodological and interdisciplinary implications of the findings, while Section 6 summarizes the main conclusions, limitations and avenues for future research.

2. Review of dominant approaches

2.1. Traditional utility-based models

These models identify utility from choices made and relate it to explanatory variables [18]. One important benefit is that these models are relatively simple and easy to interpret. Nonetheless, this approach cannot measure unobservable psychological parameters, which limits its predictive accuracy in complex decision-making scenarios. Hybrid choice modeling builds on the random utility model (RUM). The utility ω_{in} for individual i choosing alternative n can be expressed as:

$$\omega_{in} = \Lambda_{in} + \varepsilon_{in}, \tag{1}$$

where Λ_{in} is the deterministic component, a linear function of observed variables X, defined as:

$$\Lambda_{in} = \varsigma' X_{in}, \tag{2}$$

where ε_{in} is the random component that captures unobserved preferences and is typically assumed to follow an extreme type-I distribution. The probability of individual *i* choosing alternative *n* under a multinomial logit model is:

$$P_{in} = \frac{\exp(\Lambda_{ij})}{\sum_{j \in C_i} \exp(\Lambda_{ij})}, \tag{3}$$

where C_i is defined as the choices available to individual i, the deterministic utility of alternative *n* is represented by Λ, and j is the summation index over all the available alternatives. This standard multinomial-logit specification provides a clear, easily interpretable choice probability but does not explicitly capture psychological factors such as attitudes, perceptions, or decision-making approaches. This framework struggles to explain variables such as attitudes and perceptions as mental entities. This model assumes preference data homogeneity and does not comprehensively integrate latent facets. However, this model offers transparency, interpretability, and theoretical clarity.

2.2. Latent variable integration

Random-utility models are conventional models that explain choice behavior by observed alternative attributes and individual attributes [19]. However, psychological constructs such as environmental concern, perceived convenience, risk perception, technological trust, or service satisfaction cannot be observed and may also influence behavioral decisions [20]. These constructs are modeled as latent constructs and linked to both observable personal constructs and discrete choices in hybrid choice models. The model detects unobserved individual attributes by including other elements, known as latent variables, in the modeling process, such as attitudes and perceptions [21,22]. As a result, the model's applicability increases, its explanatory power improves, and it accounts for behavioral subtleties [23,24]. However, it imposes an additional computational burden and assumes accurately measured item psychometric properties in the estimation [25,26]. To address unobservable factors, latent variables ℓ_i are incorporated into the utility function:

$$\omega_{in} = \varsigma' X_{in} + \lambda' \ell_i + \varepsilon_{in}. \tag{4}$$

The coefficient vector in Eq (4) is β, the vector of latent constructs for individual i is λi, the alternative-specific effects of the latent constructs are λ and the random utility component is ε in alpha. The latent constructs can be related to observable individual characteristics through the structural equation Here ω_{in} denotes a vector of the observed individual characteristics, κ is a matrix of structural parameters, and ε is the structural disturbance. This specification puts the latent variables and the utility coefficients into two different sets, and gives a more consistent representation of the unobserved behavioral heterogeneity ℓ_i is a latent variable, often modeled using a structural equation:

$$\ell_{in} = \kappa' W_{in} + \eta_{in}. \tag{5}$$

Here W_{in} is the parameter for the latent variable, κ' factor loading matrix, and η_{in} is the error term. It enhances understanding of decision-making compared to providing only the mean, but its limitations include increased computational time and the difficulty of measuring latent variables.

2.3. Relationship between hybrid choice models and machine learning

This paper suggests two potentially complementary methodological traditions: hybrid choice modeling and machine learning. Conventional HCM is a behaviorally structured probabilistic model based on random-utility theory [27]. It includes a latent construct (such as attitudes, perceptions, intentions, or preferences) that is modeled with structural and measurement equations and a discrete-choice component [28]. It has major goals: behavioral interpretation, parameter identification, uncertainty representation, and uncertainty-relevant inference [29]. In contrast, machine-learning methods typically focus on flexible function approximation, predictive performance, representation learning, automated feature extraction, or scalable optimization [30]. Neural networks, tree ensembles, kernel methods, attention models, and other learning algorithms can capture nonlinear relationships without the same utility-theory structure as a traditional HCM [31]. The two might be related in several ways. First, machine learning can approximate the nonlinear utility components while preserving a probabilistic choice kernel [32]. Second, neural encoders can produce latent representations of high-dimensional behavioral, textual, sensor or sequential data. Third, machine-learning techniques can aid variable selection, missing-data imputation, heterogeneity identification, and model diagnostics [33]. Fourth, novel optimization and variational-inference methods can further enhance the scalability of HCM estimation [34,35]. Lastly, explainable-AI methods can aid additional diagnosis for flexible hybrid models, but these explanations should not substitute for behavioral ones [36,37]. For this study, the term 'machine-learning-related HCM research' describes publications that involve or relate to machine-learning approaches in the context of choice modeling, latent behavioral structures, preference prediction, or estimation [38,39]. It does not mean that all publications on neural networks or on artificial intelligence are HCM [40–42]. Neither the use of machine-learning jargon nor the mere mention of an "empirical comparison" is sufficient to indicate that the model is more effective at predicting outcomes [43,44].

3. Methodology

3.1. Proposed model for data search strategy

The HCM in Machine Learning for analyzing scientific databases is a systematic approach that combines discrete-choice methodologies (traditional utility-based models) with latent-variable methods to assess and select data from large samples [45,46]. In this context, let the set of keywords associated with each category of algorithms, such as hybrid choice model with temporal (HCMT), hybrid choice model with heterogeneous effects (HCMHE), and hybrid choice model with extended preferences (HCMEP), be represented as

$$k(c_i) = \sum_{i=1}^{n} c_i \forall\ i = 1,2,3\,, \tag{6}$$

where $k(c_i)$ denotes different categories defined by keywords; each category contains a set of words used to outline the range of data to be extracted from Dimension AI. The process starts with the identification phase, where records corresponding to each category are retrieved by combining these keywords with "or" operators, forming a search string:

$$S = \bigcup_{i=1}^{n} k(c_i), n = 3, \tag{7}$$

where S is the search string and $k(c_i)$ the set of keywords belonging to the category i. In the screening and eligibility phases, the model also introduces new latent variables for including and excluding the identified records [47]. The model's hidden layers continuously evaluate the latent variables of relevance, author credibility, and publication quality [48,49]. These implicit entities will be represented by the symbol: $L = L_1, L_2, ..., L_m$, a situation whereby m is the number of latent factors that influence the decisions made. These latent variables interact with the discrete choices (inclusion/exclusion decisions) at each level of the review and can therefore be modeled as a probabilistic model of the decisions. The inclusion probability P included for a given paper can be modeled as:

$$P_{include} = \frac{\exp(W + \theta L)}{1 + \exp(W + \theta L)}, \tag{8}$$

where W is the observed weights (discrete choices stemming from the keyword matching), and θL is the impact of latent variables L on the inclusion determination. The weight defines the contribution of latent factors toward the final decision. During the exclusion phase, we remove common records found across multiple categories using an AND NOT exclusion to reduce cross-category interference. This phase ensures that the retrieved records only belong to their respective categories by enforcing the condition:

$$k(c_1) \not\subset \{k(c_2), k(c_3), k(c_4)\}.$$

This makes it easy to ensure that records other than HCMT are not mixed with HCMHE records, and that records other than HCMHE are not mixed with HCMT records. Finally, the systematic analysis phase uses network-based approaches, including keyword clustering and author co-citation. Such analyses usually rely on comparisons of selected records, and their influence may be defined using both manifest variables (i.e., the appearance of certain terms) and latent variables (i.e., the quality and influence of authors). The last model therefore combines filter decisions in the filtration stage with probabilistic variables in the analysis stage, while the overall model provides the best predictions for the most informative records to include in the final review dataset.

3.2. Experimental frameworks in HCM studies

To ensure the scientometric analysis aligns with experimental frameworks, the results are organized into three main groups based on the frameworks used in HCM research. The first group, stated preference and revealed preference methods, emphasizes their use in transport and urban contexts, where information on hypothetical and real decisions is obtained. The second group, behavioral and psychometric approaches, uses latent variables, including attitudes and perceptions, to deepen understanding of human behavior in decision-making. Finally, technological enhancements examines the use of new applications, such as neuroimaging, virtual reality, and eye-tracking, which have shifted HCM research methodology toward discovering higher-level cognitive and behavioral data. Each category provides a detailed list and description of studies, key methodologies, and samples that demonstrate each category's unique significance to the literature. This approach suggests that the theoretical framework is diverse and interdisciplinary, and that HCM can evolve and be applied across disciplines using a variety of research methods. Figure 1 shows the literature analysis framework.

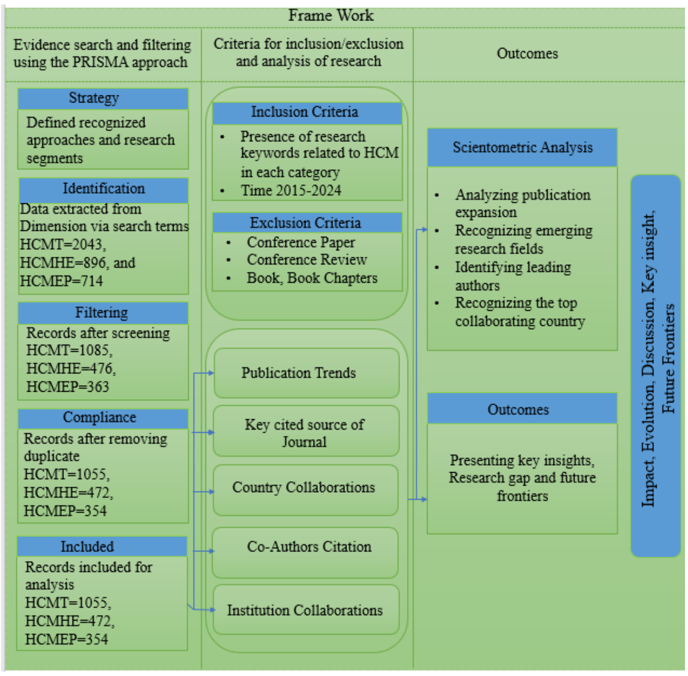

Figure 1. Literature analysis framework.

The scientometric analysis consisted of performance analysis and science mapping. Performance analysis summarized publications, citations, publication distribution, geographic participation, and temporal changes. Science mapping focused on relationships among authors, institutions, countries, journals, publications, references, and keywords, using co-authorship, co-citation, bibliographic coupling, and co-occurrence networks. We measured publication productivity as the number of eligible publications associated with an entity. Citation impact was measured by both raw and year-normalized citation counts. Bibliographic coupling compared similarity between two entities by the number of references they shared, while co-citation compared the number of times subsequent publications cited both entities. These indicators capture different aspects of the literature and do not substitute for one another when measuring scientific quality. For co-authorship networks, we applied fractional counting to publications authored by multiple people to ensure each publication's weight is distributed in total rather than fractionally among its authors, institutions, or countries. To map the existence and strength of conceptual relationships in keyword co-occurrence, document co-citation, and bibliographic-coupling analyses, we used full counting. Each figure caption states the counting method. We standardized author names by incorporating ORCID information, normalizing initials, incorporating institutional affiliation data, and manually reviewing high-frequency records. We grouped abbreviated, translated, and departmentalized institution names together, as well as names from parent organizations. We used a single country vocabulary for country names. We combined keyword variants, including singular and plural forms, abbreviations, spelling variants, and close synonyms, using a thesaurus file. The supplementary file S3 contains the thesaurus file.

Records were eligible if hybrid choice modeling (an integrated choice and latent variable model) or an equivalent latent variable choice model was a substantive theoretical, methodological or applied component of the study. A record was kept if any of the following was true:

- The study developed, extended, estimated, compared or validated an HCM or an integrated choice and latent variable model.
- The study used an HCM in an empirical decision problem.
- The study was a methodological review, and HCMs were one of the main issues addressed.
- The study included machine learning or computational techniques specifically incorporated within the framework of a behavioral choice model or latent variable choice structure.
- Records were not included if:
- The terms hybrid, choice, and model were used independently of HCM methodology.
- The word HCM appeared only as a by-product in the abstract or reference list.
- The record did not meet the criteria for a publication covered by the protocol.
- Bibliographic metadata essential for proper citation and use of the information is missing.
- The record duplicated another publication.
- The publication was a correction, editorial notice, news item, presentation or other excluded document type.
- Complete bibliographic data were not available to determine relevance.

The first method used to find duplicate records was by DOI number. If no DOI information was found, duplicates were identified using a combination of the normalized title, publication year, and the first author's surname. We lowercased the titles, removed punctuation and extra spaces, and manually reviewed minor typographical variants. If more than one version of the same work was found in conferences or journals, we kept only one if it was viewed as two separate publications; otherwise, we kept the more complete version.

3.3. Annual publications and content focus of articles

To identify the most prominent research subjects and leading journals, we used the Dimensions AI analyzer to analyze the Dimensions database. Based on the statistical findings, the primary journals featuring publications on hybrid choice modeling (HCM) included "Transportation Research Part A: Policy and Practice" (17%), "Sustainability" (11%), "Transportation" (11%), "SSRN Electronic Journal" (9%), "Transportation Research Record Journal of the Transportation Research Board" (7%), and "Journal of Choice Modelling" (7%) (refer to Figure 2 for a more detailed breakdown). Together, these categories accounted for about 76% of the estimated Dimension articles.

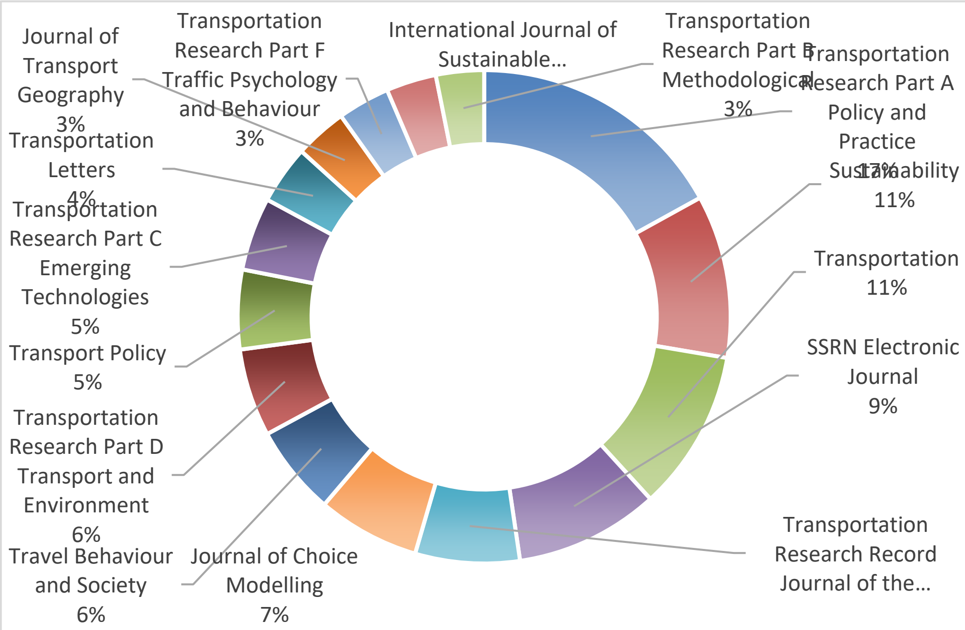

Figure 2. Leading journal on HCM with their percentages.

3.4. Sub-domain

This study reports the frequency of journal publications and literature reviews, with 82% being original research articles and 18% being assessments of prior literature. . The “hybrid choice model” field shows considerable scholarly activity, with 1,871 papers, 14 datasets, 5 grants, and 1 patent. Table 1 details these steps, including the focus area. Two policy documents outline practical uses and some policy implications; however, no clinical trials have been conducted. These findings show a vibrant and influential academic environment in hybrid choice modeling. The analysis of research publications from 2013 to 2026 revealed increasing trends (Figure 3), with streams categorized into Commerce, Management, Tourism, and Services; Transportation, Logistics, and Supply Chain; and Built Environment and Design, which scored 1271, 1055, and 691, respectively. Table 1 categorizes these areas for HCM’s contribution, which makes up about 75% of the total number of articles and citations. To our knowledge, interest in HCM has increased since 2015, with a sharp rise in publications in 2026 (Figure 4). While growth is evident in recent volumes, it is slightly below our expected rate. Other changes also reflect a shift toward new ideas within HCM research. For this study, the basic search of the Dimension AI collection used the title “hybrid choice model” and searched by title/abstract/keywords/author/affiliation, with the time frame set to 1998-2026. The search on January 25, 2026, gave 1,869 hits. For scientometric analysis, I generated a “.CSV” file with citation data and bibliographic details

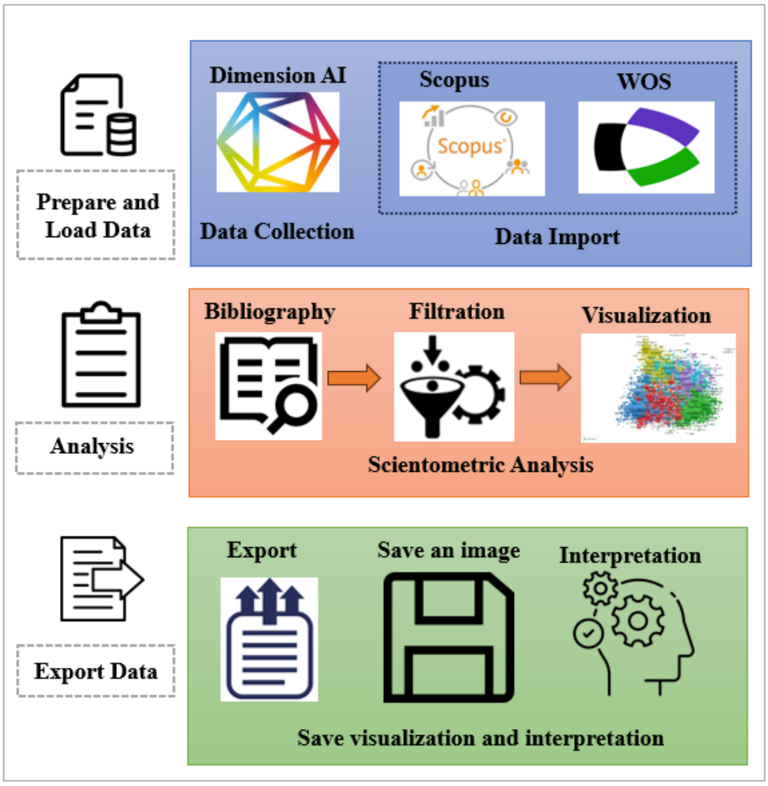

Figure 3. Fundamental analysis actions supported by VOSviewer.

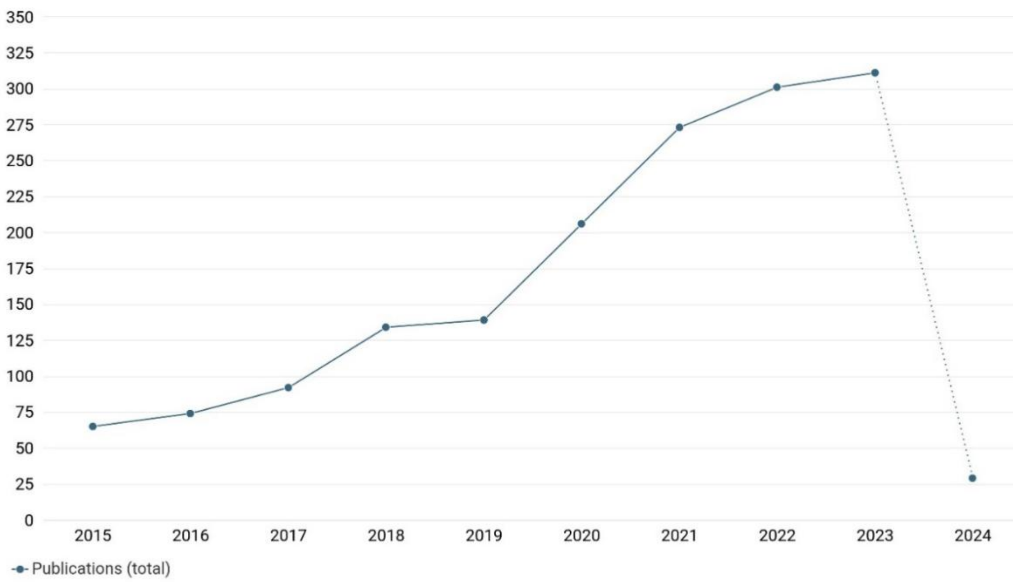

Figure 4. Visual illustration of total number of publications on HCM.

Table 1. Focused research areas on HCM and their publications.

Research field	Publication	Citation	AC	Percentages
HCM+ Transportation	1055	22272	21.11	56.08
HCM +Health Economics	472	1098	14.00	25.09
HCM+ Environmental Policy	354	547	9.50	18.83

3.5. Scientometric analysis on the basis of experimental framework

Science mapping is the technique of showing, analyzing, and modeling a scientific field. It helps researchers navigate patterns and trends in large bibliometric datasets and conduct further investigations in the specified scientific area. Another way to understand the future perspectives of any given field is bibliometric analysis, which is also a simple way to identify current research interests. However, it has some visualization drawbacks; first, the method is very helpful for establishing relations among authors, countries, and organizations. Consequently, the scientometric research on hybrid energy systems used publication records retrieved from Dimension.

3.5.1. Journal citations

The citation analysis of the journals on the list provides additional information on the field's thematic organization. Journals that are often cited together may share common research interests. However, spectral clustering categorizes related journals fairly well, though it does not account for the fact that co-citations do not necessarily imply high thematic similarity. Restrictions include eliminating journals with fewer than 15 articles and 150 citations, and reducing coverage of potentially significant-scope, well-focused journals. Moreover, network densification with citation ties might distort clustering, as journals with different research methods may still relate to the same themes, as presented in Figure 5. Node size, which reflects publication output, may distort the picture of journal impact, and the temporal distribution of citations (see Figure 6) is only partially considered. The breakdown of the results into distinct research areas, however, makes it easy to map out the current status of dominant areas that have attracted significant research; however, it does not account for emergent or even sub-discipline research, and indeed the interpretation of revealed preferences does come with those methodological considerations on its head, and the top 15 journals that published articles on the Hybrid choice model are presented in Figure 7.

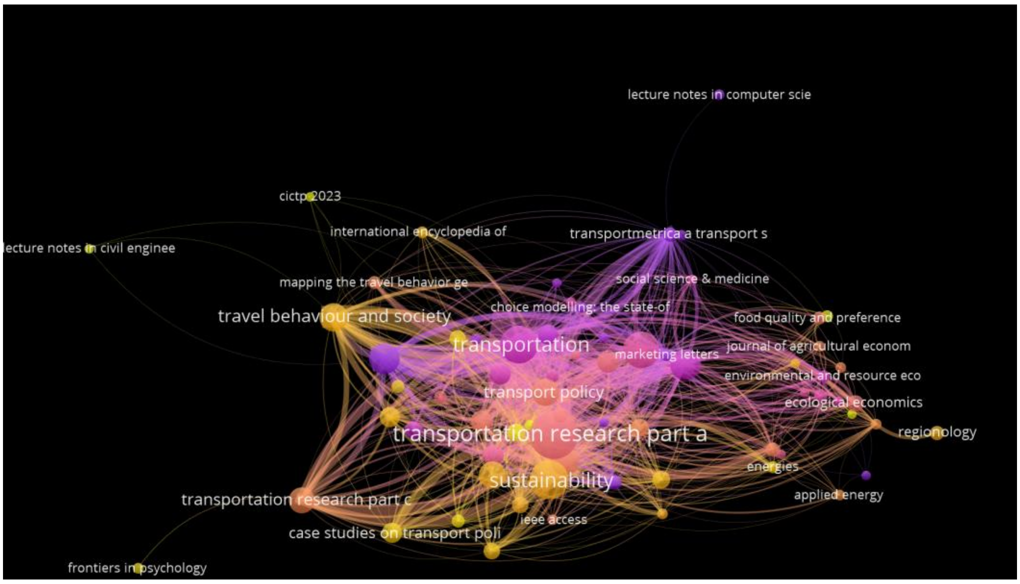

Figure 5. Overlay visualization of journal citations.

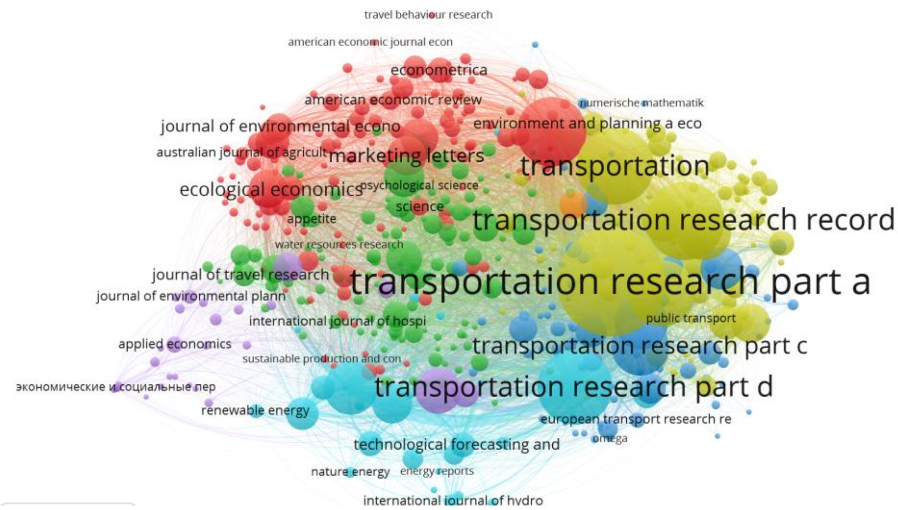

Figure 6. Visual illustration of interconnected citation relationships, showing both co-citation connections and key cited journal sources.

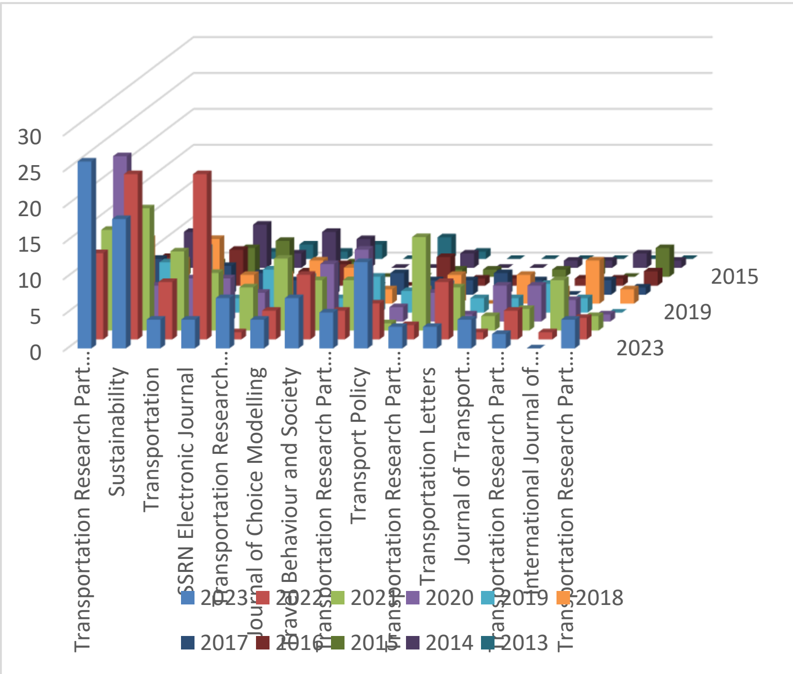

Figure7. Top 15 Journals published on HCM.

3.5.2. Co-occurrence analysis

Co-author scientrometric analysis on HCM by authors:

The authors' co-author network of HCM research also stands highly centralized based on the selected 151 authors who have published at least five articles and citations. This filter includes only the most productive authors, highlighting top contributors who have dominated the field [50,51].

However, this criterion introduces bias, as it excludes emerging scholars or those who could have contributed significantly but did not meet the required number of publications or citations [52,53]. Hess, Cherchi, and Timmerms are the dominant authors, as expected given the stated preference for highly productive researchers with high impact factors; however, this focus may narrow the field's vision, risking the exclusion of heterodox opinions from authors who are not yet well known. Also, the identification of 17 clusters of 107 authors indicates that co-authorship networks mainly reflect the key priorities set by senior scholars in the field, supporting the consolidation of expert intellectual leadership (see Figure 8 and Table 2 for more detail).

Table 2. Ten most productive authors in the finalized HCM dataset.

Rank	Authors	Documents	Citations	Total Link Strength
1st	Hess, Stephane	49	1686	42
2nd	Cherchi, Elisabetta	33	1095	39
3rd	Timmermans,Harry	26	1035	33
4th	De Dious Ortuzar,Juan	25	2042	21
5th	Rasouli, Soora	20	1011	26
6th	Abou-Zeid, Maya	19	557	21
7th	Ben-Akiva, Moshe	18	1475	21
8th	Farooq, Bilal	16	88	15
9th	Sottile, Eleonora	15	126	27
10th	Polydoropoulou	14	635	15

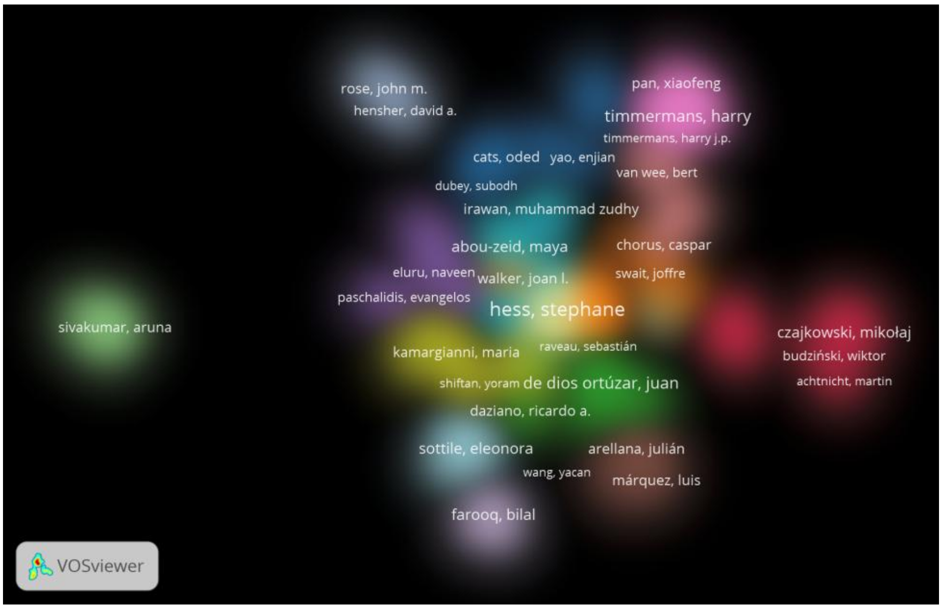

Figure 8. Visual illustration of a co-authored scientometric analysis of the author's research on hybrid choice models.

Co-author scientrometric analysis on HCM by institution:

The co-authorship analysis by institution shows a strong dependence of the overall results on leading educational institutions, with the University of Leeds having the highest number of publications and citations. This aligns with the stated interest in the contributing institutions in the HCM field. Although this institutional focus also reveals a bias toward high-profile universities, it may limit the growth of small-scale universities or those in certain regions. Identifying 153 organizations (see Table 3) with dense collaborative connections strengthens the view that leading universities, such as Delft University of Technology and the University of Technology, embrace the HCM research area. This focus on identifying key institutions reflects a broader tendency in academic literature to correlate collaboration and recognition with institutional status [54,55]. In this regard, although the study is all about establishing who the best contributors are in the HCM field (see Figure 9), we find that this could be a shortcoming in the sense that the study might not unravel diverse thought leaders or methodologies from the HCM smaller and relatively unknown institutions that might otherwise present richer and more ground-breaking HCM ideas or approaches.

Table 3. Top organizations contributing to hybrid choice models (HCM).

Rank	Organization	Country	Documents	Citations	Total link strength
1st	University of Leeds	England	70	2585	59
2nd	Eindhoven University of Technology	Netherlands	50	1595	48
3rd	Pontificia Universidad Católica de Chile	Chile	47	1126	41
4th	Delft University of Technology	Netherlands	46	2217	42
5th	Technical University of Denmark	Denmark	31	1189	45
6th	Beijing Jiaotong University	China	29	365	19
7th	University of Warsaw	Poland	27	787	29
8th	Southeast University	China	25	290	20
9th	Technical University of Berlin	Germany	23	608	34
10th	Newcastle University	UK	22	336	34

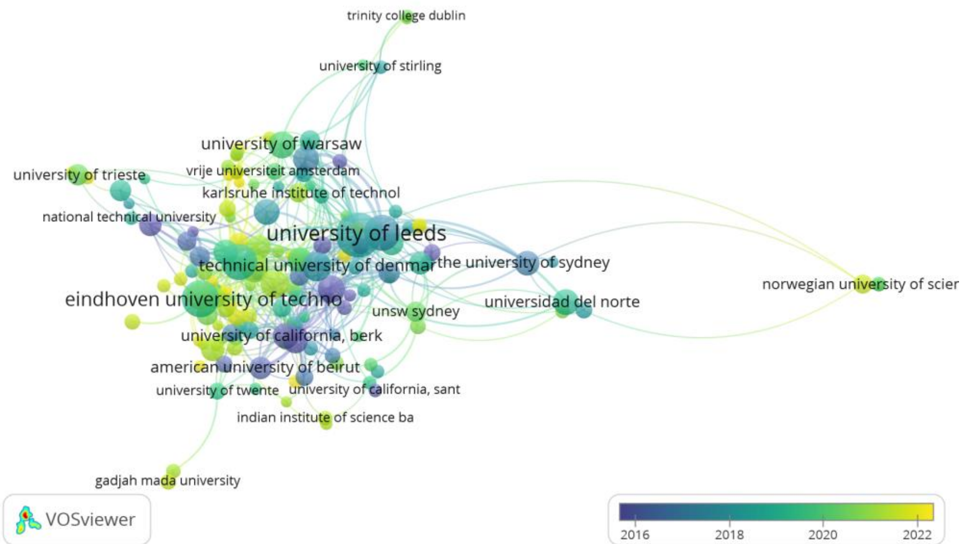

Figure 9. Visual illustration of a co-authored scientometric analysis on the institute to HCM.

Co-authorship scientometric analysis by country:

The evaluation of co-authorship by country further corroborates the international scope of HCM [56] research across the 72 countries that met the minimum requirement of 2 articles. The top sources are the United States, China, and the United Kingdom, suggesting readers chose nations known for high research productivity and higher citation rates, as presented in Tables 4 and 5. This finding aligns with the stated interest in using publications and citations to evaluate impact, yet it also shows that some countries dominate research because of greater resource endowments and more developed research facilities. Although this dominance demonstrates that completed HCM-oriented research [57] has a global focus, it may replace the work of countries with less research funding but that are highly specialized in it. For example, although Chile and Spain produce fewer publications (see Figure 10), they remain relevant in global research output. The revealed preference for more productive countries may thus restrict the field's heterogeneity [58], as it prioritizes the prospect of abundance over the appreciation of novel ideas that countries with lower output but diverse research methods may offer for HCM.

Table 4. Ten institutions with the largest HCM publication outputs.

Rank	Country	Documents	Citations	Total link strength
1st	United States	313	8868	228
2nd	China	285	3736	139
3rd	United Kingdom	215	6818	214
4th	Netherlands	148	4353	138
5th	Italy	122	2240	70
6th	Germany	115	3112	93
7th	Australia	103	2248	100
8th	Canada	96	2818	77
9th	Chile	69	2103	65
10th	Spain	62	1657	57

Table 5. Top 10 authors contributing to hybrid choice models (HCM).

Clusters	Countries (Documents, Number of links, Total link strength)
Cluster #1	Belgium (30,219, 20), Canada (43, 1911,96), China (43, 2040,285), Greece (40,571,47), Hungary (20,8,10), Indonesia (32, 184, 20), Luxembourg (24,84,6), Malaysia (23,8,14), Pakistan (22, 52,9), South Korea (35,381,39), Taiwan (25,73,16), Vietnam (20,30,5)
Cluster #2	Czechia (24, 140,8), Germany (44,1798,115), Ireland (25,93,8), turkey (3,4,9), United Kingdom (33,210,215), Norway (14,40,44), Spain (15,55,62), Poland (16,44,41), Sweden (22,51,38)
Cluster #3	New Zealand (12,28,14), Portugal (7,11,13), Australia (24,96,103), Saudi Arabia (8,16,12)
Cluster #4	United States (31,228,313), Russia (1,1,13), Japan (14,43,50), Lebanon (9,19,20), Bangladesh (4,9,10), France (13,27,22)
Cluster #5	South Africa (14,32,78), Colombia (7,15,35), Brazil (3,4,8), India (13,22,57), Chile (18,64,69), Austria (18,30,13), Israel (10,18,15), Singapore (9,13,10), Denmark (19,72,44)

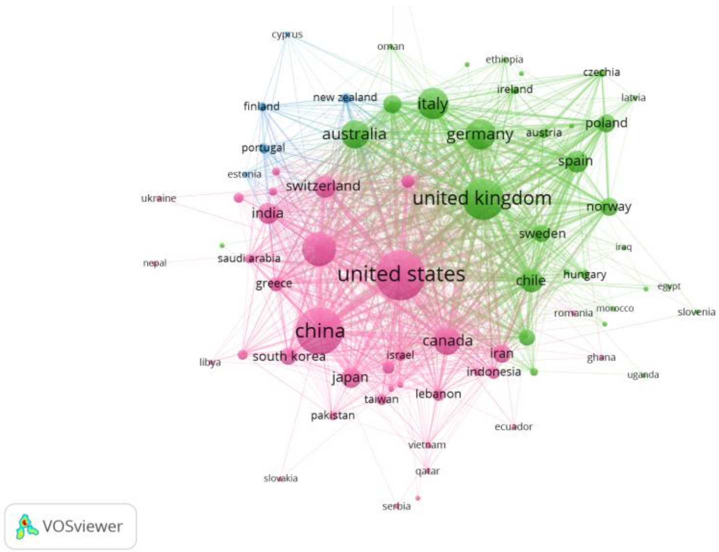

Figure 10. Network of collaborations between countries.

3.5.3. Bibliographic coupling

Bibliographic coupling and citations by articles:

The bibliometric study of the most frequently cited papers in the choice modeling field, shown in Figures 11 and 12, reveals which papers have had the greatest impact. The filter criteria selected only documents with a citation count of at least 462, thereby excluding papers with low impact. To the external observer, this approach seems to place great emphasis on the citations themselves and their tally as an index of scholarly importance. Nevertheless, this choice prioritizes voluminous materials, which can obscure new or specialized research that is less well cited. First, equating popular attention with citation counts unintentionally constrains the analysis, potentially reducing the impact of promising works that are less frequently cited than those by more established authors or those published more recently.

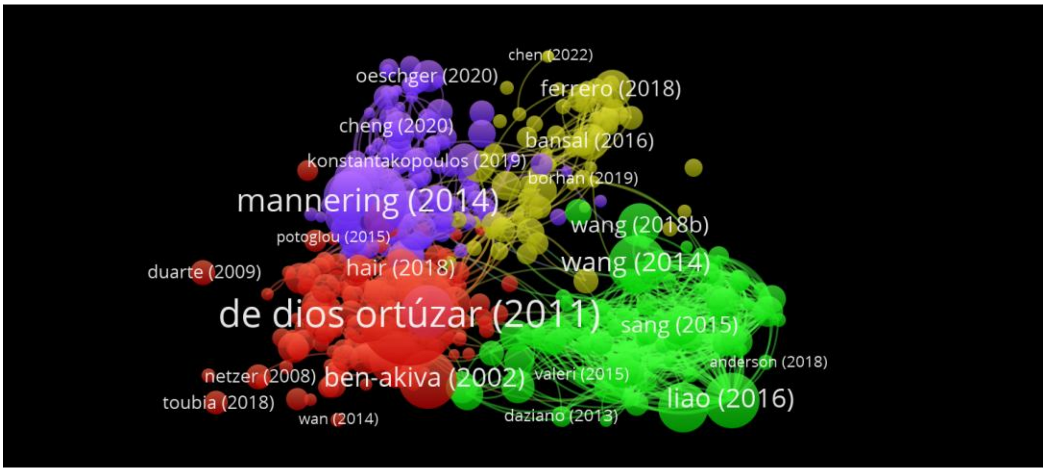

Figure 11. Visual illustration of bibliographic coupling by articles.

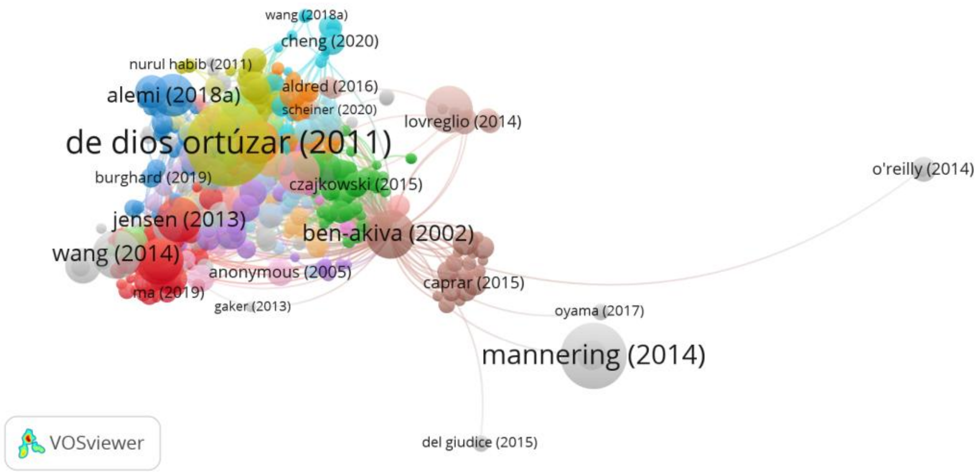

Figure 12. Visual illustration of citation by articles.

Moreover, visualizing only articles most closely related to others means that weak coupling does not drive the visualization. In addition, visualizing only 'set-in' articles can be seen as focusing on staking out well-established patterns in the literature while possibly overlooking the 'outliers'–the papers that present fresh, new, or unusual points of view on the topics or methods under discussion. The analysis, presented as a visualization, highlights seven large clusters that show the thematic similarity of the works most frequently cited in hybrid choice modeling. This citation-based clustering reveals the field's major trends. Nonetheless, because certain labels had to be partially obscured for visualization, the generated map may not fully capture the existing literature.

The chosen criteria of simplicity and clear legend legibility could lead to omitting significant but less-associated works that do not belong to any of the large groups. For example, the work titled "Future Transportation: the network with the highest density (sustainability, complexity, and individualization of choices), the article with the most connections (1442) might not emphasize its support for sustainability or its theory of individual choice modeling" is represented in Table 6. This focus on citation strength, while helpful for extracting core topics, may miss lines of research that appear less connected in citation space but can offer valuable insights. The revealed preferences in the citation network analysis highlight the prominence of specific papers and journals, such as "consumer preferences for electric vehicles" and "hybrid choice models".

Table 6. Top 10 most-cited publications by total citation count.

Rank	Authors	Year	Titles	Journal	Citations count	Total link strength
1st	De dios Ortuzar	2011	Future transportation: Sustainability, complexity, and individualization of choices	Communications in Transportation Research	1442	649
2nd	Mannering	2014	Analytic methods in accident research: Methodological frontier and future directions	Analytic Methods in Accident Research	855	82
3rd	Ben-Akiva	2002	Hybrid Choice Models: Progress and Challenges	Marketing Letters	473	173
4th	Liao	2016	Consumer preferences for electric vehicles: a literature review	Transport Reviews	429	1209
5th	Jensen	2013	On the stability of preferences and attitudes before and after experiencing an electric vehicle	Transportation Research Part D Transport and Environment	394	368
6th	Hess	2019	Apollo: A flexible, powerful, and customizable freeware package for choice model estimation and application	Journal of Choice Modelling	371	259
7th	Walker	2002	Generalized random utility model	Mathematical Social Sciences	360	393
8th	Hackbarth	2013	Consumer preferences for alternative fuel vehicles: A discrete choice analysis	Transportation Research Part D Transport and Environment	353	337
9th	Alemi	2018	What influences travelers to use Uber? Exploring the factors affecting the adoption of on-demand ride services in California	Travel Behaviour and Society	350	204
10th	Wang	2018	Exploring the Influence of Built Environment on Car Ownership and Use with a Spatial Multilevel Model: A Case Study of Changchun, China	International Journal of Environmental Research and Public Health	254	263

Cognitive aspects of model usage and future directions were designed to look to both the past and the future, because growth occurs by learning from the past to improve the present and by envisioning the future to direct efforts to the right areas. However, these assumptions rely on citation frequency and link strength, with an emphasis on the success of the most-cited papers. This also reduces the workload for communications in transportation research and transport reviews. This could perpetuate the hegemony of specific establishments and journals and restrict the dissemination of research published in relatively lesser-known or multidisciplinary journals. This dominance of transportation theories among the articles under review reveals a virtual preference for one subfield of choice modeling. Although this aligns with traditional approaches to hybrid choice modeling, the approach we pursue in the study may lead to over-specification and over-embellishment, limiting its applicability to related areas such as health systems, marketing analytics, and even environmental studies. This thematic concentration tends to favor the joint concentration of field influence in certain areas over diverse research.

Bibliographic coupling and citations by researchers:

According to Dimension AI data, over 678 researchers have at least 10 articles on choice modelling, indicating consistent contributors to the topic. The average number of publications was 18.6, with a maximum of 149. This study explores the similarity of research activities through bibliographic coupling, measuring common references among publications and co-citation relations, which gauge how often third-party articles cite them jointly. Co-citation networks provide an alternative to bibliographic pairing networks for assessing researchers' influence on the related literature. The bibliographic coupling map (Figure 13) shows researchers with a similar knowledge base. In contrast, the citation map in Figure 14 identifies groups of researchers whose first-authored publications have similar impact because they are frequently cited together. In the bibliographic coupling map, node sizes are proportional to each researcher's number of articles, with a minimum of 15 articles and a maximum of 150 total citations. In the co-citation map, node sizes are proportional to the number of local citations to each researcher's first-authored articles within the field, with a minimum of 10 citations. In general, we consider only the first author of each publication when analyzing researchers' co-citation relations (Zhao & Strotmann, 2008). The visualization algorithm inevitably renders some nodes' labels in gray text or masks them entirely. We made every effort to maximize label visibility while maintaining map readability, but masking some nodes was unavoidable.

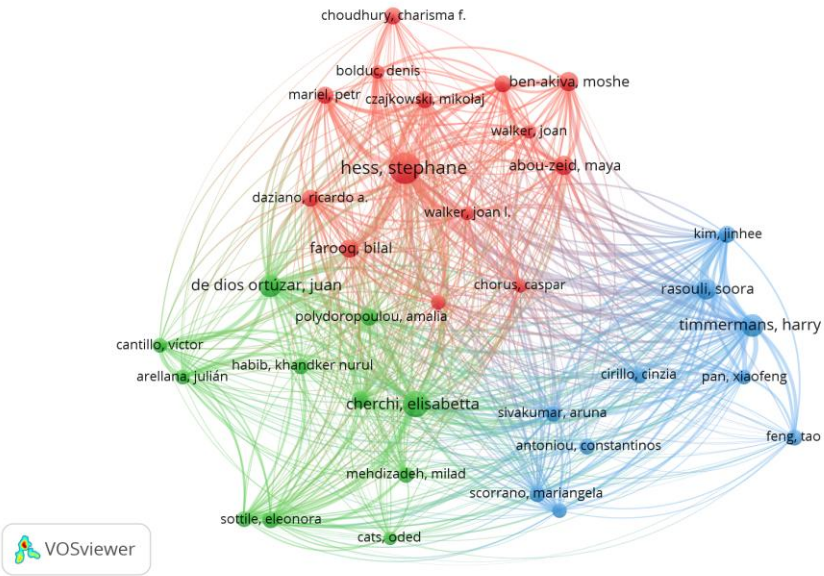

Figure 13. Visual illustration of bibliographic boupling by authors.

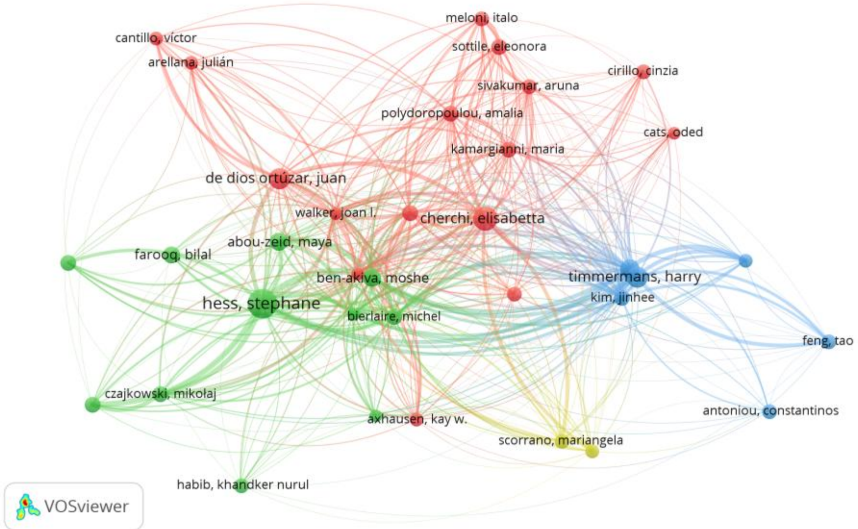

Figure 14. Visual illustration of citations by authors.

We also identify collaboration and co-authorship networks within the choice modeling literature at both the author and organization levels. Figure 15 illustrates the author collaboration network, where node sizes correspond to the number of documents and link thickness indicates the number of co-authored publications. While 16 clusters are identified, only the major ones are displayed to maintain map legibility. The network uses minimum cut-offs of 10 articles and 76 citations for visualization, so the number of links does not necessarily reflect each researcher's total co-authors or the extent of collaboration with other researchers (see Table 7).

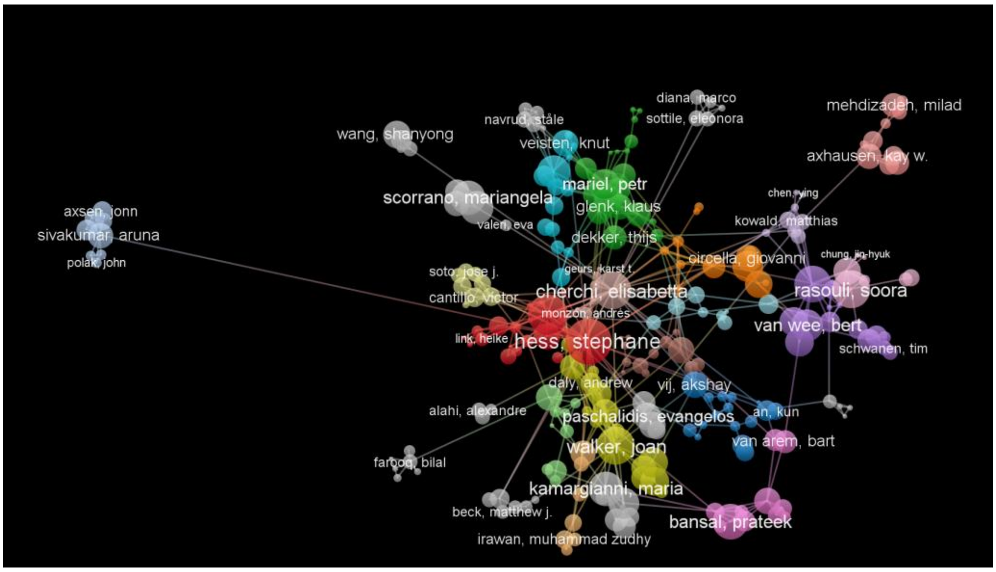

Figure 15. Network of collaboration between authors.

Table 7. Clusters depicting co-authorship connections among prominent authors in the choice modeling field with author names within each cluster in alphabetical order.

Cluster No. (Items) /Author(s)	Authors (number of links, total link strength, Documents)
1 (5)/ n= 10	Arellana, Julian (4,15,11); Bahamondi Birke, Francesco (1,1,18); Cantillo, Victor (3,15,11); De Dios Ortuzar, Juan (6,12,25); Marquez, Luis (2,9,9)
2 (5)/ n=10	Choudhury, Charisma f. (3,9,14); Hess, Stephane (9,17,47); Mariel, Petr (2,7,14); Meyerhoff, Jurgen (2,6,8); Yao, Enjian (2,2,8)
3 (5)/ n=10	Abou-zeid, Maya (3,8,18); Ben-Akiva, Moshe (8,14,16); Bierlaire, Michel (2,2,13); Walker, Joan (5,6,8); Zhao, Jinhua (1,2,8)
4 (4)/ n=8	Cherchi, Elisabetta (9,24,31); Thorhauge, Mikkel (3,8,8); Vij, Akshay (4,6,9); Walker, Jaon l. (4,6,10)
5 (3)/ n=6	Bolduc, Denis (5,7,9); Daziano, Ricardo a. (2,3,14); Farooq, Bilal (1,1,16)
6 (3)/ n=6	Antoniou, Constantinos (1,2,13); Kamargianni, Maria (3,8,14); Polydoropoulou, Amalia (3,7,14)
7 (3)/ n=6	Meloni, Italo (3,26,13); Piras, Franscesco (2,18,9); Sottile, Eleonora (3,2,15)
8 (2)/ n=4	Hensher, David a. (3,6,8); Rose, John m. (1,4,9)
9 (2)/ n=4	Chorus, Caspar (2,4,8); Kroesen, Maarten (1,3,8)
10 (2)/ n=4	Manca, Francesco (1,8,8); Sivakumar, Aruna (2,9,13)

4. Discussions

HCM research can be viewed in broad terms as having three stages, with the final two stages to be confirmed by the completion of annual and keyword data. Random-utility models and psychometric and latent-variable structures dominated the foundational phase. The expansion phase broadened to include vehicle choice, travel behavior, environmental preferences, and technology adoption. The computational phase has begun to focus on machine learning, neural representations, scalable estimation, explainability, and high-dimensional behavioral data. These phases are not fixed moments, but successive shifts in the relative salience of methodological and application themes. Co-citation networks identify networks of publications commonly cited together, while bibliographic-coupling networks identify publications or authors that share similar knowledge bases. A large center of transportation-related research reflects HCM's history of developing travel-behavior applications. Other areas, such as health, environmental policy, technology uptake, and computational modeling, show shorter or younger groups, indicating disciplinary growth. However, the small cluster size does not necessarily indicate limited scientific importance; it may reflect delayed entry into the literature, a small disciplinary community, or citation differences. The machine-learning analysis needs to separate absolute from relative prevalence. Part of the rise in publications on HCMs of ML may reflect overall growth in the literature.

However, the annual share of statistical machine learning better indicates machine learning's relative contribution to HCM research. Method-specific frequencies and temporal co-occurrence networks also indicate if growth is focused on neural networks, ensemble methods, representation learning, explainable AI or other areas. The introduction of the term machine learning does not constitute methodological integration either. Some publications might coincide machine learning with as a comparator or future direction. The results should therefore differentiate studies that only mention ML, studies that compare to ML and studies that explicitly incorporate ML into a choice model. Author, institutional, and country networks provide information on the distribution and exchange of HCM knowledge. A network's total link strength reflects the extent to which links exist between nodes in the network, but not necessarily the quality of the science. Countries or institutions with high output can benefit from larger research systems, a transport-research program, better funding structures, and longer involvement in the field. On the other hand, low-output areas may be underestimated due to database coverage, the term used (or its absence), limited resources, or limited international cooperation. Based on the scientometric and thematic analysis, several gaps are identified. First, HCM applications are mostly limited to transportation, with relatively little use in healthcare, environmental behavior, digital services, education, and public-policy decision-making. Second, research has focused on the predictive flexibility of machine learning without a corresponding assessment of its identification, uncertainty, calibration, interpretability, or fairness. Third, cross-country validation remains limited, and the transferability of constructs at the latent and learned-representation levels across populations is still questionable. Fourth, relatively few open HCM datasets and standardized evaluation protocols exist to facilitate reproducible benchmarking. Fifth, integration of longitudinal, multimodal, sensor, and textual data remains underdeveloped. Finally, behavioral modelers, statisticians, computer scientists, domain experts, and policy researchers need to engage in more dialogue and integration to create models that are predictive, interpretable, computationally scalable, and behaviorally defensible.

5. Conclusions

This study conducted a scientometric review of research on hybrid choice models based on a finalized set of bibliographic records taken from the Dimensions database. The study analyzed the field's development and intellectual structure using publication-performance analysis, keyword co-occurrence, co-authorship, co-citation, bibliographic coupling, and international-collaboration networks. The results suggest that HCM research has moved beyond its historical support for transportation choice research and now encompasses other areas such as health economics, environmental decision-making, technology adoption, marketing, and other applications that rely on understanding behavior. The network results identify journals, publications, authors, institutions, and countries influential in the indexed literature, and reveal the role of collaborative and shared citation structures in shaping the research domain. The terms also indicate growing interest in new technologies, such as machine learning, neural networks, computational estimation, behavioral heterogeneity, and interpretable decision analysis.

The results indicate publication, citation, thematic, and collaboration patterns, not evidence of the author's scientific influence or methodological excellence. Publication counts reflect productivity; citation measures indicate a scholar's visibility and are subject to age and field effects; bibliographic coupling is based on shared reference foundations; and co-citation measures are based on recognition of the scholar in later publications. None of these measures is independent in terms of scientific quality or a model's predictive performance. The study has some limitations. It is based on the coverage and indexing of the Dimensions database and may miss publications covered by indexing in other databases. The outcome depends on the query format, the final search date, document restrictions, the name-standardization process, and the network thresholds. Citation counts may favor older publications over newer ones unless they are normalized; a threshold-based visualization may also reduce the number of recent authors and topics. Furthermore, the use of machine-learning language does not prove that the research was accurate in prediction or effective in practice. Future studies could analyze the differences in bibliographic coverage between Dimensions, Scopus and Web of Science, repeat the analysis on the data longitudinally, apply topic modeling or dynamic-network analysis, conduct a systematic review to investigate the content and methodological quality of HCM studies, and use the benchmark choice datasets to assess the empirical performance, the interpretability, the fairness and the computational efficiency of machine-learning-assisted HCMs. Such work would complement the descriptive and relational evidence provided by the present scientometric study. However, recent advances in machine learning, big data analytics, and advanced estimation methods have broadened the applicability of HCM. These improvements significantly enhanced dynamic behavior capturing, spatial and temporal considerations, and the delivery of more accurate HCM estimates for complex real-life decision-making. HCM literature predicts that as computational capabilities mature, HCM will advance and provide finer-grained decision-making across a broad array of industries. The record selection procedure was not statistically trained using a screening classifier, but was based on deterministic database querying and prespecified eligibility criteria. Therefore, the present analysis does not calculate latent relevance, author credibility, or publication-quality scores, nor does it quantify the predictive power of probabilistic screening compared with the manually adjudicated inclusion decision. Although this approach is more procedurally transparent, it also depends heavily on database quality, query quality, variation in terms used, and index quality. A possible future extension would be to build a labeled dataset of screenshots and compare conventional keyword retrieval with supervised, weakly supervised, and latent variable screening models.

Several promising areas for future HCM development exist. First, a real-time data stream, including feeds from social media, GPS trackers, and wearables, can dramatically change how choice models are created and deployed. It would also help us better understand the situational and contextual factors that constrain or promote decision-making. Furthermore, with advances in AI and deep learning, HCM can process larger volumes of data and more complex data, improving model reliability and effectiveness. Another future direction is applying HCM to other areas, including healthcare, environmental management and decision-making, and behavioral change, where human decisions are the main determinant of outcomes. In addition, future technical research directions include further developing the methodological aspects of HCMs, such as clarifying model interpretation and simplifying calculations to keep the models accessible and feasible for practical applications.

Use of Generative-AI tools declaration

The author declares he has not used Artificial Intelligence (AI) tools in the creation of this article.

Conflict of interest

The author declares no conflict of interest.

References

[1] K. Ashok, W. R. Dillon, S. Yuan, Extending discrete choice models to incorporate attitudinal and other latent variables, *J. Mark. Res.*, **39** (2002), 31–46. https://doi.org/10.1509/jmkr.39.1.31.18937

[2] M. Ben-Akiva, D. McFadden, K. Train, J. Walker, C. Bhat, M. Bierlaire, et al., Hybrid choice models: Progress and challenges, *Mark. Lett.*, **13** (2002), 163–175. https://doi.org/10.1023/A:1020254301302

[3] M. Ben-Akiva, J. Walker, A. T. Bernardino, D. A. Gopinath, T. Morikawa, A. Polydoropoulou, Integration of choice and latent variable models, In: *Perpetual motion: Travel behaviour research opportunities and application challenges*, Amsterdam: Elsevier, 2002, 431–470. https://doi.org/10.1016/B978-008044044-6/50022-X

[4] D. Bolduc, R. Alvarez-Daziano, On estimation of hybrid choice models, In: *Choice modelling: The state-of-the-art and the state-of-practice*, Bingley: Emerald Group Publishing, 2010, 259–287. https://doi.org/10.1108/9781849507738-011

[5] A. Borriello, J. M. Rose, Global versus localised attitudinal responses in discrete choice, *Transportation*, **48** (2021), 131–165. https://doi.org/10.1007/s11116-019-10045-3

[6] A. Borriello, P. F. Burke, J. M. Rose, If one goes up, another must come down: A latent class hybrid choice modelling approach for understanding electricity mix preferences among renewables and non-renewables, *Energy Policy*, **159** (2021), 112611. https://doi.org/10.1016/j.enpol.2021.112611

[7] A. Borriello, S. Scagnolari, J. M. Rose, Reducing the randomness of latent variables using the evaluative space grid: Implementation in a hybrid choice model, *Transp. Res. Part F Traffic Psychol. Behav.*, **62** (2019), 192–211. https://doi.org/10.1016/j.trf.2018.12.018

[8] J. Buckell, D. A. Hensher, S. Hess, Kicking the habit is hard: A hybrid choice model investigation into the role of addiction in smoking behavior, *Health Econ.*, **30** (2021), 3–19. https://doi.org/10.1002/hec.4173

[9] E. Cherchi, A stated choice experiment to measure the effect of informational and normative conformity in the preference for electric vehicles, *Transp. Res. Part A Policy Pract.*, **100** (2017), 88–104. https://doi.org/10.1016/j.tra.2017.04.009

[10] S. Choo, P. L. Mokhtarian, What type of vehicle do people drive? The role of attitude and lifestyle in influencing vehicle type choice, *Transp. Res. Part A Policy Pract.*, **38** (2004), 201–222. https://doi.org/10.1016/j.tra.2003.10.005

[11] C. G. Chorus, M. Kroesen, On the (im-)possibility of deriving transport policy implications from hybrid choice models, *Transp. Policy*, **36** (2014), 217–222. https://doi.org/10.1016/j.tranpol.2014.09.001

[12] R. A. Daziano, Taking account of the role of safety on vehicle choice using a new generation of discrete choice models, *Saf. Sci.*, **50** (2012), 103–112. https://doi.org/10.1016/j.ssci.2011.07.007

[13] R. A. Daziano, D. Bolduc, Incorporating pro-environmental preferences towards green automobile technologies through a Bayesian hybrid choice model, *Transp. A Transp. Sci.*, **9** (2013), 74–106. https://doi.org/10.1080/18128602.2010.524173

[14] M. Haghani, M. C. J. Bliemer, D. A. Hensher, The landscape of econometric discrete choice modelling research, *J. Choice Model.*, **40** (2021), 100303. https://doi.org/10.1016/j.jocm.2021.100303

[15] S. Haustein, M. Thorhauge, E. Cherchi, Commuters' attitudes and norms related to travel time and punctuality: A psychographic segmentation to reduce congestion, *Travel Behav. Soc.*, **12** (2018), 41–50. https://doi.org/10.1016/j.tbs.2018.04.001

[16] S. Hess, Rethinking heterogeneity: The role of attitudes, decision rules and information processing strategies, *Transp. Lett.*, **4** (2012), 105–113. https://doi.org/10.3328/TL.2012.04.02.105-113

[17] S. Hess, D. A. Hensher, Making use of respondent reported processing information to understand attribute importance: A latent variable scaling approach, *Transportation*, **40** (2013), 397–412. https://doi.org/10.1007/s11116-012-9420-y

[18] S. Hess, J. W. Polak, Mixed logit modelling of airport choice in multi-airport regions, *J. Air Transp. Manag.*, **11** (2005), 59–68. https://doi.org/10.1016/j.jairtraman.2004.09.001

[19] M. V. Johansson, T. Heldt, P. Johansson, The effects of attitudes and personality traits on mode choice, *Transp. Res. Part A Policy Pract.*, **40** (2006), 507–525. https://doi.org/10.1016/j.tra.2005.09.001

[20] E. Kitrinou, A. Polydoropoulou, D. Bolduc, Development of integrated choice and latent variable models for the residential relocation decision in island areas, In: *Choice modelling: The state-of-the-art and the state-of-practice*, Bingley: Emerald Group Publishing, 2010, 593–618. https://doi.org/10.1108/9781849507738-027

[21] V. Kolarova, E. Cherchi, Impact of trust and travel experiences on the value of travel time savings for autonomous driving, *Transp. Res. Part C Emerg. Technol.*, **131** (2021), 103354. https://doi.org/10.1016/j.trc.2021.103354

[22] M. Kroesen, C. Chorus, The role of general and specific attitudes in predicting travel behavior—A fatal dilemma, *Travel Behav. Soc.*, **10** (2018), 33–41. https://doi.org/10.1016/j.tbs.2017.09.004

[23] M. Kroesen, C. Chorus, A new perspective on the role of attitudes in explaining travel behavior: A psychological network model, *Transp. Res. Part A Policy Pract.*, **133** (2020), 82–94. https://doi.org/10.1016/j.tra.2020.01.014

[24] L. La Paix, E. Cherchi, K. Geurs, Role of perception of bicycle infrastructure on the choice of the bicycle as a train feeder mode, *Int. J. Sustain. Transp.*, **15** (2021), 486–499. https://doi.org/10.1080/15568318.2020.1765223

[25] U. Liebe, J. Meyerhoff, Mapping potentials and challenges of choice modelling for social science research, *J. Choice Model.*, **38** (2021), 100270. https://doi.org/10.1016/j.jocm.2021.100270

[26] R. Maldonado-Hinarejos, A. Sivakumar, J. W. Polak, Exploring the role of individual attitudes and perceptions in predicting the demand for cycling: A hybrid choice modelling approach, *Transportation*, **41** (2014), 1287–1304. https://doi.org/10.1007/s11116-014-9551-4

[27] F. Manca, A. Sivakumar, J. W. Polak, The effect of social influence and social interactions on the adoption of a new technology: The use of bike sharing in a student population, *Transp. Res. Part C Emerg. Technol.*, **105** (2019), 611–625. https://doi.org/10.1016/j.trc.2019.02.010

[28] F. Manca, A. Sivakumar, J. W. Polak, Capturing the effect of multiple social influence sources on the adoption of new transport technologies and services, *J. Choice Model.*, **42** (2022), 100344. https://doi.org/10.1016/j.jocm.2022.100344

[29] P. Mariel, J. Meyerhoff, Hybrid discrete choice models: Gained insights versus increasing effort, *Sci. Total Environ.*, **568** (2016), 433–443. https://doi.org/10.1016/j.scitotenv.2016.06.019

[30] D. McFadden, The choice theory approach to market research, *Mark. Sci.*, **5** (1986), 275–297. https://doi.org/10.1287/mksc.5.4.275

[31] T. Morikawa, M. Ben-Akiva, D. McFadden, Discrete choice models incorporating revealed preferences and psychometric data, In: *Advances in econometrics*, Bingley: Emerald Group Publishing, 2002, 29–55. https://doi.org/10.1016/S0731-9053(02)16003-8

[32] J. de D. Ortúzar, Future transportation: Sustainability, complexity and individualization of choices, *Commun. Transp. Res.*, **1** (2021), 100010. https://doi.org/10.1016/j.commtr.2021.100010

[33] S. Rasouli, H. J. P. Timmermans, Influence of social networks on latent choice of electric cars: A mixed logit specification using experimental design data, *Netw. Spat. Econ.*, **16** (2016), 99–130. https://doi.org/10.1007/s11067-013-9194-6

[34] J. J. Soto, V. Cantillo, J. Arellana, Market segmentation for incentivising sustainable transport policies, *Transp. Res. Part D Transp. Environ.*, **99** (2021), 103013. https://doi.org/10.1016/j.trd.2021.103013

[35] E. Sottile, E. Cherchi, I. Meloni, Measuring soft measures within a stated preference survey: The effect of pollution and traffic stress on mode choice, *Transp. Res. Procedia*, **11** (2015), 434–451. https://doi.org/10.1016/j.trpro.2015.12.036

[36] E. Sottile, I. Meloni, E. Cherchi, A hybrid discrete choice model to assess the effect of awareness and attitude towards environmentally friendly travel modes, *Transp. Res. Procedia*, **5** (2015), 44–55. https://doi.org/10.1016/j.trpro.2015.01.017

[37] E. Sottile, I. Meloni, E. Cherchi, Hybrid choice model to disentangle the effect of awareness from attitudes: Application test of soft measures in a medium-size city, *Case Stud. Transp. Policy*, **5** (2017), 400–407. https://doi.org/10.1016/j.cstp.2016.09.001

[38] E. Sottile, F. Piras, I. Meloni, Could a new mode alternative modify psycho-attitudinal factors and travel behavior, *Transp. Res. Rec.*, **2673** (2019), 94–106. https://doi.org/10.1177/0361198119843478

[39] E. Sottile, F. Piras, D. Calli, I. Meloni, Why don't Italians cycle to work? An experimental analysis, *Case Stud. Transp. Policy*, **9** (2021), 362–373. https://doi.org/10.1016/j.cstp.2021.01.007

[40] M. Thorhauge, E. Cherchi, J. L. Walker, J. Rich, The role of intention as mediator between latent effects and behavior: Application of a hybrid choice model to study departure time choices, *Transportation*, **46** (2019), 1421–1445. https://doi.org/10.1007/s11116-017-9839-2

[41] M. Thorhauge, S. Haustein, E. Cherchi, Accounting for the theory of planned behaviour in departure time choice, *Transp. Res. Part F Traffic Psychol. Behav.*, **38** (2016), 94–105. https://doi.org/10.1016/j.trf.2016.01.009

[42] M. Thorhauge, J. Swait, E. Cherchi, The habit-driven life: Accounting for inertia in departure time choices for commuting trips, *Transp. Res. Part A Policy Pract.*, **133** (2020), 272–289. https://doi.org/10.1016/j.tra.2020.01.023

[43] M. Thorhauge, A. Vij, E. Cherchi, Heterogeneity in departure time preferences, flexibility and schedule constraints, *Transportation*, **48** (2021), 1865–1893. https://doi.org/10.1007/s11116-020-10114-y

[44] E. Valeri, E. Cherchi, Does habitual behavior affect the choice of alternative fuel vehicles?, *Int. J. Sustain. Transp.*, **10** (2016), 825–835. https://doi.org/10.1080/15568318.2016.1163445

[45] N. J. van Eck, L. Waltman, Software survey: VOSviewer, a computer program for bibliometric mapping, *Scientometrics*, **84** (2010), 523–538. https://doi.org/10.1007/s11192-009-0146-3

[46] B. van Wee, M. Kroesen, Attitude changes, modelling travel behaviour, and ex ante project evaluations, *Transp. Res. Interdiscip. Perspect.*, **16** (2022), 100724. https://doi.org/10.1016/j.trip.2022.100724

[47] A. Vij, Understanding consumer demand for new transport technologies and services, and implications for the future of mobility, In: *Data-driven multivalence in the built environment*, Cham: Springer, 2020, 91–107. https://doi.org/10.1007/978-3-030-12180-8_5

[48] A. Vij, J. L. Walker, Hybrid choice models: The identification problem, In: *Handbook of choice modelling*, Cheltenham: Edward Elgar Publishing, 2014, 519–564. https://doi.org/10.4337/9781781003152.00031

[49] A. Vij, J. L. Walker, How, when and why integrated choice and latent variable models are latently useful, *Transp. Res. Part B Methodol.*, **90** (2016), 192–217. https://doi.org/10.1016/j.trb.2016.04.021

[50] J. L. Walker, J. Li, Latent lifestyle preferences and household location decisions, *J. Geogr. Syst.*, **9** (2007), 77–101. https://doi.org/10.1007/s10109-006-0030-0

[51] J. L. Walker, Opening up the black box: Enriching behavioral models of spatial and travel choices, *J. Transp. Geogr.*, **14** (2006), 396–398. https://doi.org/10.1016/j.jtrangeo.2006.06.008

[52] J. L. Walker, M. Ben-Akiva, Advances in discrete choice: mixture models, In: *A handbook of transport economics*, Cheltenham: Edward Elgar Publishing, 2011, 160–187. https://doi.org/10.4337/9780857930873.00015

[53] J. L. Walker, M. Ben-Akiva, Generalized random utility model, *Math. Soc. Sci.*, **43** (2002), 303–343. https://doi.org/10.1016/S0165-4896(02)00023-9

[54] Y. Wang, Y. Wang, L. Xie, H. Zhou, Impact of perceived uncertainty on public acceptability of congestion charging: An empirical study in China, *Sustainability*, **11** (2019), 129. https://doi.org/10.3390/su11010129

[55] M. Wong, B. Farooq, ResLogit: A residual neural network logit model for data-driven choice modelling, *Transp. Res. Part C Emerg. Technol.*, **126** (2021), 103050. https://doi.org/10.1016/j.trc.2021.103050

[56] C. Wu, S. Le Vine, A. Sivakumar, J. W. Polak, Traveller preferences for free-floating carsharing vehicle allocation mechanisms, *Transp. Res. Part C Emerg. Technol.*, **102** (2019), 1–19. https://doi.org/10.1016/j.trc.2019.02.019

[57] C. Wu, S. Le Vine, A. Sivakumar, J. W. Polak, Dynamic pricing of free-floating carsharing networks with sensitivity to travellers' attitudes towards risk, *Transportation*, **49** (2022), 679–702. https://doi.org/10.1007/s11116-021-10190-8

[58] D. Zhao, A. Strotmann, Comparing all-author and first-author co-citation analyses of information science, *J. Informetr.*, **2** (2008), 229–239. https://doi.org/10.1016/j.joi.2008.05.004