Review

Machine Learning Approaches to Bike-Sharing Systems: A Systematic Literature Review

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Abstract: Cities are moving towards new mobility strategies to tackle smart cities' challenges such as carbon emission reduction, urban transport multimodality and mitigation of pandemic hazards, emphasising on the implementation of shared modes, such as bike-sharing systems. This paper poses a research question and introduces a corresponding systematic literature review, focusing on machine learning techniques' contributions applied to bike-sharing systems to improve cities' mobility. The preferred reporting items for systematic reviews and meta-analyses (PRISMA) method was adopted to identify specific factors that influence bike-sharing systems, resulting in an analysis of 35 papers published between 2015 and 2019, creating an outline for future research. By means of systematic literature review and bibliometric analysis, machine learning algorithms were identified in two groups: classification and prediction.

Keywords: bike-sharing systems; machine learning; classification; prediction; PRISMA method

1. Introduction

Changes are taking place in the future development of the transport sector. To this aim, concrete plans are already in place, such as the Sustainable Development Goals (SDGs) [1], the New Urban Agenda [2] and the Organisation for Economic Co-operation and Development (OECD) Greening Transport [3], and adopted by United Nations member states since 2016.

To cope with these challenges, the New Urban Agenda and OECD Greening Transport set up the guidelines for a sustainable future that connects to the SDG11 Cities and Communities [4].

Bike-sharing systems (BSS) improve urban accessibility, multimodality in transportation and mobility sustainability, and more cities in the world are implementing such sharing modes to tackle increased expansion of urban mobility, air pollution and changes in urban mobility patterns and behaviour, trends exacerbated by the recent pandemic crisis.

Since 2016, more than 1000 bike-sharing systems are running in 60 countries [5], and many improvements have been made in bike-sharing systems. The latest systems allow real-time data collection using sensors and wireless communications, generating large quantities of data [6]. The collected data improve intelligent processes of data analytics through machine learning techniques.

The aim of this paper is to contribute, with literature evidence, to the sustainable implementation of bike-sharing systems. Particularly, this systematic literature review targets the identification of the most relevant machine learning techniques applied in bike-sharing analytics, with an impact on and contributions to cities' mobility. Therefore, the broad analysis of this paper is useful to understand state-of-the-art solutions, as well as gaps in the current research.

Challenges in mobility nowadays aim to find the latest scientific contributions for the development of machine-learning-based techniques to provide solutions to tackle cities'

mobility phenomenon, particularly when dealing with bike-sharing systems. Based on the general overview described above, our study provides a systematic literature review (SLR) on this topic. The SLR research question was formulated as follows:

RQ1: What are the most promising machine learning techniques adopted by the community to better understand and improve bike-sharing systems in urban mobility?

To answer this question, an SLR methodology and qualitative analysis were used, as well as methods to assist in analysing the data.

The paper is structured as follows: Section 2 presents the SLR method that maps keyword identification search, repositories, bibliometric analysis and a bibliometric research tool for network analysis. In Section 3, we introduce our results, identifying the research themes and analysing keyword, author, title and abstract text occurrences, as well as the most cited publications and application, dimensions and methods. In Section 4, we discuss the results and identify research gaps and limitations. Finally, in Section 5, we raise our conclusions and draw lines for future work.

2. Method

The systematic literature review was performed by adopting the preferred reporting items for systematic reviews and meta-analyses (PRISMA) methodology [7], based on the PRISMA statement that consists of a checklist and a flow diagram.

The PRISMA checklist follows a structure with a title, abstract, introduction, methods, results, discussion and funding. For each section, there are specific items to be identified and described. The title and abstract follow an applicable structure. In the introduction, the rationale for the review and the questions to be addressed should be described. In methods, study characteristics, information sources, the search strategy including limits, the statement process for studies selected, eligibility criteria, data collection and data items are specified. Results provide screened results selection and characteristics of data extracted and the synthesis of results. The discussion involves a summary of findings, a discussion of the limitations and a general conclusion of results, with future work. The flow diagram is a four-phase flow diagram with the following phases: identification, screening, eligibility, and included.

We especially investigated the recommendations of two references. The first one, [8], helped to explore the stages of literature assessment, identifying the process (15 steps of the SLR), which we followed in our approach: step 1 is regarding the topic definition; step 2, formulation of the research question; step 3, identification of keywords; step 4, identification and search of electronic paper repositories; step 5, read and assess publications; step 6, data acquisition and data cleaning; steps 7–9, test and revise publications, resulting in step 10, production and revision of summary tables; step 11, draft methods; steps 12 and 13, evaluation and draft of key results and conclusions; step 14, draft introduction, abstract and references; and step 15, revise the paper till ready for submission.

The second study, [9], provided general guidelines that helped us develop the research question and scope of the SLR, on how to assess and address possible biases and synthesise the SLR results. According to such procedures, a time restriction on the publications was defined to scope the study: only papers published in the past five years, from 2015 to 2019, where included, and the search was performed in May 2020.

The process workflow consists of understanding all the stages of the study, as shown in Figure 1.

2.1. Keyword Identification and Search

An iterative search process was performed to identify publications that have in their titles, abstract or keywords the following expressions: bike-sharing (or bikesharing or bike-share or bike-sharing system) and machine learning, leading to the search query in Figure 2.
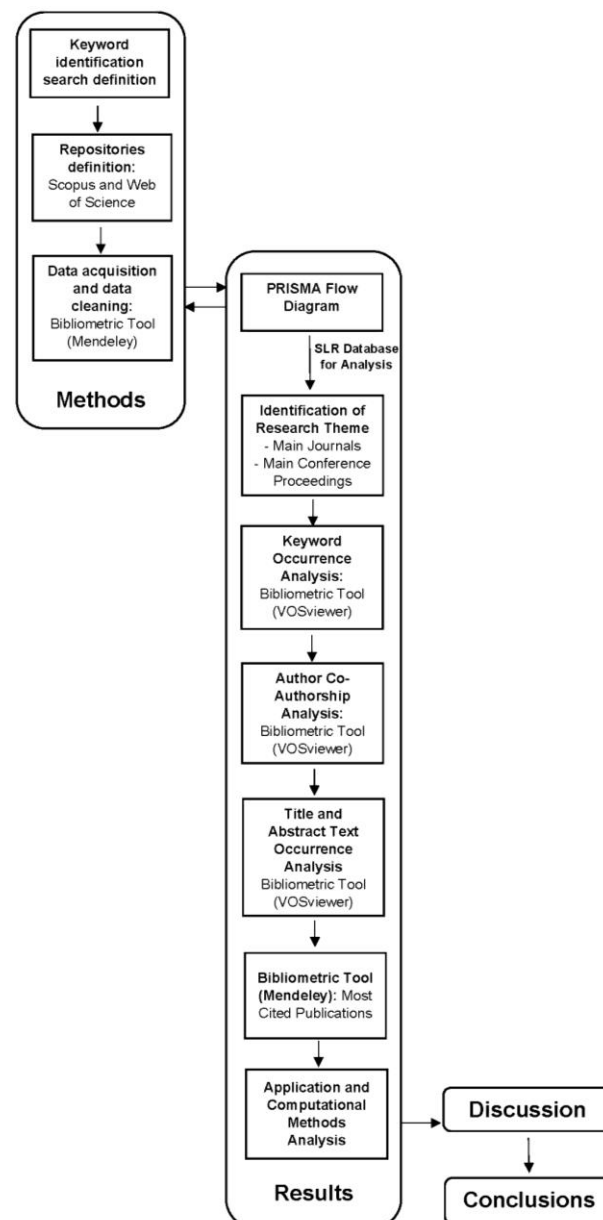
Figure 1. Process workflow.

Figure 2. Search Query.

2.2. Repositories

The papers considered were searched in two electronic repositories, Scopus and Web of Science. The covered topics were multidisciplinary, including, transportation, computer science, engineering, mathematics, environmental science, telecommunications, geography and multidisciplinary sciences. Although both repositories were used, the analysis showed that most of the included publications from Web of Science were in Scopus as well.

2.3. Bibliometric Analysis

Our SLR data set for quantitative and qualitative analysis resulted from the adapted PRISMA methodology. The SLR data set was structured using the Mendeley [10] open source tool, which allowed us to extract metadata and eliminate duplicates. Having duplicates in a bibliometric analysis would make it more complex, and the relative importance of a particular keyword, author or publication would decrease. Regarding metadata, the following were extracted: authors, publication metadata, references and citations.

2.4. Bibliometric Research Tool for Network Analysis

Aiming at performing network analysis on our SLR data set, illustrating the relations and interactions between the network's elements (nodes), we adopted the open source tool VOSviewer (https://www.vosviewer.com/). This tool was used to map, in a series of semantic networks, the keywords' co-occurrence and co-authors' co-occurrence in publications and allowed us to identify network properties, such as clusters and node centrality. Moreover, the tool calculates node links and weight, showing each node's importance in the network. This allowed us to identify the main keywords, authors, co-authors and their respective relations, within the SLR data set, for quantitative analysis.

Several graphs were then created in VOSviewer [11] depicting network clustering and centrality. The size of nodes represents the degree of centrality: the larger the node, the more times it is mentioned in the SLR data set. In addition, the thickness of edges represents the number of times two connected nodes are mentioned together, indicating their relevance in relation to each other. By default, the networks are distributed from the largest to the smallest in the graph (see Figure 4 as an example).

This tool was used to analyse the data set on keywords' co-occurrence and co-authors' co-occurrence. In the case of keywords, combinations were filtered, occurring only once in the network. In the diagrams generated by the tool, the bigger the size of a node, the more frequently the keyword is used. The thickness of the links between the nodes represents the number of times pairs of keywords occur (the thicker the line is, the more often the pair of words is used). With respect to co-authors, the same concept was applied: the larger the node is, the more publications the author has (within this SLR database for quantitative analysis), and the thicker the line is between two authors, the more often they collaborate within the timespan of the SLR (thickness of the line represents the number of publications they have together).

3. Results

3.1. PRISMA Flow Diagram

A PRISMA flow diagram illustrates our process of SLR data set creation for further quantitative and qualitative analyses (Figure 3). The initial step in this approach identified publications through a database search, resulting in a total of 162 publications (Scopus: 140; Web of Science: 22). The main inclusion criteria for such publications were original research papers written in English and published in peer-reviewed journals and relevant conference proceedings in said time period. Review papers, position papers and reports were excluded. Subsequently, we removed duplicates ($e = 20$). Then we performed abstract screening. Step 1 excluded articles without abstracts and out of the scope of the research ($e = 128$). Step 2 excluded articles not related to transport ($e = 9$), and step 3 eliminated from our survey papers not related to urban mobility ($e = 5$). Finally, the full texts of the remaining 35 papers were read, assessed and fitted on the scope of the research. As such, in the full-text-screening phase, all papers were considered and were eligible for systematic review. Therefore, this eligibility phase excluded none of such remaining papers. From these, 24 were published in scientific journals, whereas 11 were published in conference proceedings.
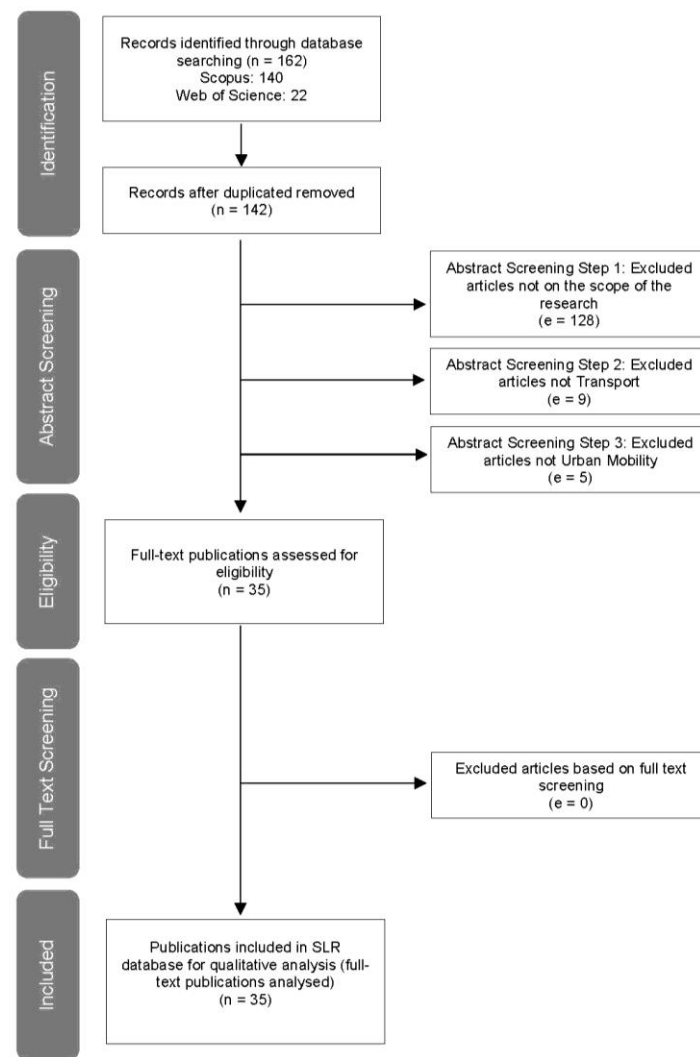
Figure 3. PRISMA flow diagram (*n* = retained; *e* = excluded).

3.2. Identification of Research Themes

The retained papers from journals and conference proceedings cover a wide spectrum of research fields, such as computer science, engineering, transportation, mathematics and environmental science, as shown in Tables 1 and 2.

Table 1. Main journals.

Journals	No.	Quartile Rank	Publisher Country	Field	Publisher
Transportation Research Part C: Emerging Technologies	5	Q1	United Kingdom	Transportation Computer science Engineering	Elsevier Ltd.
IEEE Access	2	Q1	United States of America	Computer science Engineering	Institute of Electrical and Electronic Engineers Inc
Journal of Transport Geography	1	Q1	United Kingdom	Transportation Environmental science	Elsevier Ltd.

Table 1. *Cont.*

Journals	No.	Quartile Rank	Publisher Country	Field	Publisher
Transportation	1	Q1	The Netherlands	Transportation Engineering	Kluwer Academic Publishers
Journal of Artificial Intelligence Research	1	Q1	United States America	Computer science	Morgan Kaufmann Publishers, Inc.
Neural Computing and Applications	1	Q2	Germany	Computer science	Springer Verlag
Computing	1	Q2	Germany	Computer science Mathematics	Springer Verlag
Journal of Logical and Algebraic Methods in Programming	1	Q1	The Netherlands	Computer science Mathematics	Elsevier BV
Journal of Urbanism	1	Q1	United Kingdom	Environmental science	Taylor and Francis Inc.
PLoS ONE	1	Q1	United States America	Computer science	Public Library of Science
Frontiers of Computer Science	1	Q2	Germany	Computer science Mathematics	Springer Verlag
Case Studies on Transport Policy	1	Q2	The Netherlands	Transportation	Elsevier BV
Complexity	1	Q1	Egypt	Multidisciplinary	Hindawi Limited
Smart Innovation, Systems and Technologies	1	Q2	Germany	Computer science Multidisciplinary	Springer Verlag
Journal of Cleaner Production	1	Q1	The Netherlands	Engineering	Elsevier BV
Applied Intelligence	1	Q2	The Netherlands	Computer science	Kluwer Academic Publishers

Table 2. Main conference proceedings.

Conference Proceedings	No.	Publisher Country	Field
Procedia Computer Science	2	The Netherlands	Computer science
Transportation Research Procedia	1	The Netherlands	Transportation
ACM International Conference Proceeding Series (ICPS)	1	United States of America	Computer science
ACM International Joint Conference on Pervasive and Ubiquitous Computing (Proceedings of the 2016)	1	United States of America	Engineering
5th IEEE International Conference on Models and Technologies for Intelligent Transportation Systems (MT-ITS)	1	United States of America	Engineering
IEEE Vehicular Technology Conference (2017)	1	United States of America	Computer science Engineering
IEEE Conference on Intelligent Transportation Systems, Proceedings (ITSC 2018)	1	United States of America	Computer science Engineering
IEEE International Conference on Big Data, Big Data (2018 Proceedings)	1	United States of America	Computer science Mathematics
IEEE International Conference on Mobile Data Management (2019 Proceedings)	1	United States of America	Computer science
2017 IEEE/ACIS 16th International Conference on Computer and Information Science (ICIS)	1	United States of America	Computer science Engineering
IEEE International Conference on Data Mining	1	United States of America	Engineering

Table 2. *Cont.*

Conference Proceedings	No.	Publisher Country	Field
Annual International Conference on Mobile Systems, Applications, and Services (14th Proceedings)	1	United States of America	Computer science Engineering
SIAM International Conference on Data Mining (SDM 2018)	1	United States of America	Computer science

3.2.1. Main Journals

In this study of a total of 35 papers, we analysed 22 journal papers, including *Transportation Research Part C: Emergent Technologies* (5), *IEEE Access* (2), *Journal of Transport Geography* (1), *Transportation* (1) and *Journal of Artificial Intelligence Research* (1). As shown in Table 1, most journals are Q1-quartile-ranked (13), representing 68%, and the remaining (9) are Q2 articles.

The five main fields identified in the analysis were computer science, engineering, transportation, environmental science and mathematics.

The 22 selected articles' publishers originate from five countries, with the largest set from the United Kingdom (7) and the Netherlands (5), followed by Germany (4), the United States of America (3) and Egypt (1). Top publishers identified are Elsevier Ltd. (6), Elsevier BV (3), Institute of Electrical and Electronic Engineers Inc. (2), Kluwer Academic Publishers (2) and Morgan Kaufmann Publishers, Inc. (1).

3.2.2. Main Conference Proceedings

The main conference proceedings identified in this study were Procedia Computer Science (2), Transportation Research Procedia (1), ACM (2), more specifically, the ACM International Conference Proceeding Series and the ACM International Joint Conference on Pervasive and Ubiquitous Computing (Proceedings of the 2016), and IEEE (7), specifically, the IEEE International Conference on Models and Technologies for Intelligent Transportation Systems, the IEEE Conference on Intelligent Transportation Systems, the IEEE International Conference on Big Data, Big Data and the IEEE/ACIS International Conference on Computer and Information Science.

Table 2 shows that the main research fields of the conference proceedings are computer science, engineering, mathematics and transportation, mostly published in the United States, with two published in the Netherlands.

3.3. Keyword Occurrence Analysis

Keyword occurrence analysis was performed using the mentioned bibliometric research tool for network analysis, VOSviewer. The analysis was performed using a full counting method, encompassing 44 screened keywords, with a minimum threshold of 1 occurrence. Of the total 44, only 35 keywords were selected for the purpose of the analysis (Table 3). Most of the analysed keywords were related to machine learning techniques applied to bike-sharing systems. The top five identified terms were big data (2 occurrences, 10 total link strength), bike-sharing (2 occurrences, 10 total link strength), deep learning (2 occurrences, 9 total link strength), long short-term memory networks (1 occurrence, 6 total link strength) and sharing mobility (1 occurrence, 6 total link strength), all aligned with the keyword search.

Table 3. Keyword occurrences ranked by link strength.

Keyword	Occurrences	Link Strength
big data	2	10
bike-sharing	2	10
deep learning	2	9
long short-term memory networks	1	6
sharing mobility	1	6
station-free bike-sharing	1	6
travel demand forecasting	1	6
bike-sharing systems	2	5
cycling	1	5
data mining	1	5
demand analysis	1	5
smart-card data	1	5
trip chaining	1	5
bike counts prediction	1	4
bike-sharing systems	1	4
bike-sharing	1	4
flow prediction	1	4
machine learning	1	4
mobility modelling	1	4
random forest	1	4
rebalancing	1	4
sharing economy	1	4
taxi	1	4
travel mode choice	1	4
urban computing	1	4
clustering algorithm	1	3
convolutional long short-term memory network	1	3
dock less bike-sharing system	1	3
long short-term memory	1	3
recurrent neural networks	1	3
shared bike demand prediction	1	3
short-term spatiotemporal distribution forecasting	1	3
spatial distribution	1	3
station-free bike-sharing system	1	3
time-series forecasting	1	3

In keyword co-occurrence analysis, 8 clusters (Figures 4 and 5) were identified with 35 items and 77 links. The biggest nodes of each cluster in the network were identified as bike-sharing systems (red), long short-term memory (cyan), machine learning (brown), clustering algorithm (yellow), big data (green), deep learning (orange), sharing mobility (purple) and bike-sharing (blue).

The connections among the research themes identified by keyword co-occurrence are shown in Figures 4 and 5. There is a large, interconnected network of keywords, as well as groups of keywords that occur together in individual articles, mostly in 2019. The keyword analysis showed fields of the research reinforcing the topics of machine learning and bike-sharing systems and identified machine learning techniques applied to bike-sharing systems, such as clustering algorithm and deep learning.

Looking closer at the interconnected network of Figure 6 (18 items, 4 clusters and 47 links), prediction algorithms, such as deep learning, convolutional long short-term and long short-term memory network, were identified regarding rebalancing, bike count prediction and flow prediction.
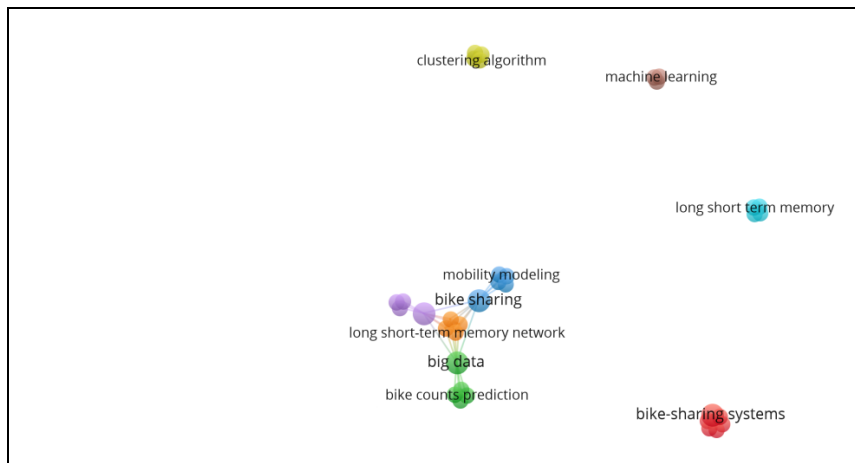
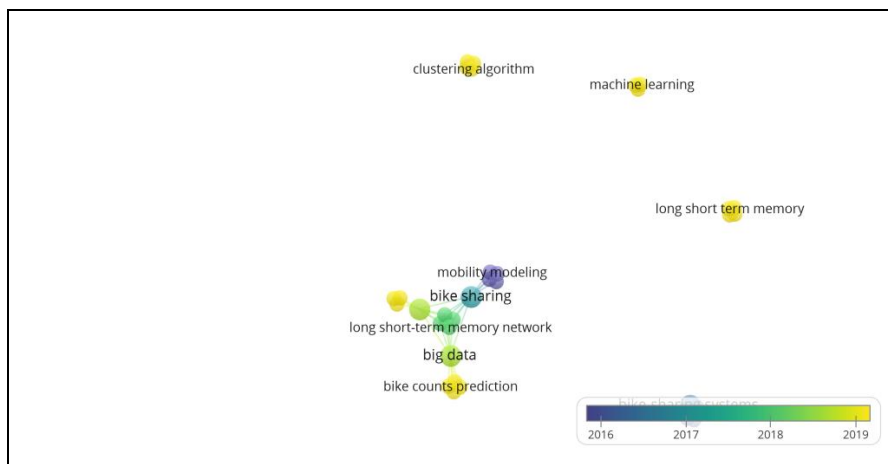**Figure 4.** Keyword occurrence network visualisation.

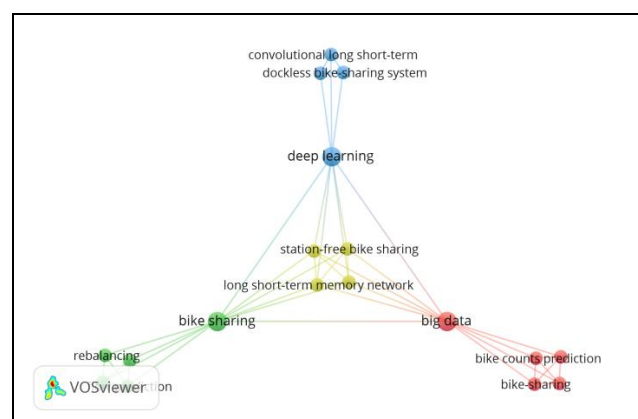**Figure 5.** Keyword occurrence by year overlay visualisation.

Figure 6. Keyword occurrence network visualisation (4 interconnected clusters).

Finally, machine learning techniques applied to bike-sharing systems were clearly defined in the SLR analysis, showing two main trends: clustering (classification) and prediction.

3.4. Author Co-Authorship Analysis

Author occurrence analysis was performed with the previously mentioned bibliometric research tool for network analysis, VOSviewer.

The analysis on authorship was performed using a full counting method, choosing the minimum threshold of 1, resulting in a total of 140 authors meeting the threshold, of which 35 authors were analysed (Figure 7).

Figure 7. Author co-authorship analysis network visualisation.

The top 10 identified authors were Chen, L. [12], Jakubowicz, J. [12], Li, S. [12], Ma, X. [12], Nguyen, T. M. T. [12], Pang, G. [12], Wang, L. [12], Wu, Z. [12], Yang, D. [12] and Zhang, D. [12], all with a link strength of 9.

In author co-authorship analysis, 7 clusters were identified with 35 items and 106 links. Cluster 1 (red) corresponds to the top 10 author co-authorship ranked by link strength (Table 4), Cluster 2 (green) has 8 items identified (Chen, W. [13], Fu, Y. [13], Li, Q. [13], Liu, J. [13], Qu, M. [13], Xiong, H. [13], Yang, J. [13] and Zhong, H. [13]), Cluster 3 (blue) has seven items identified (Ai, Y. [14], Chen, W. [14], Gan, M. [14], Ju, Y. [14], Li, Z. [14], Yu, D. [14] and Zhang, Y. [14]), Cluster 4 (yellow) has four items identified (Elhenawy, M. [15], Ghanem, A. [15], House, L. [15] and Rakha, H. A. [15]), Cluster 5 (purple) has four items identified (Hu, J. [16], Moscibroda, T. [16], Shu, Y. [16] and Yang, Z. [16]), Cluster 6 (cyan) has one item (Ma, X. [17,18]) and Cluster 7 (orange) has one item, Wu, J [19,20].
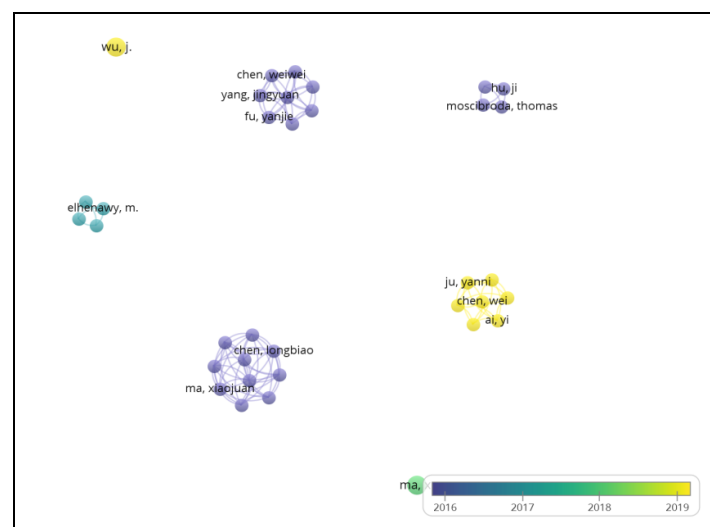
Cluster 3 and Cluster 7 correspond to authors who published articles in 2019. Cluster 4 corresponds to authors with publications in 2017 and 2018; as for the remaining authors, articles were published in 2016.

Figure 8 shows that the top 10 author co-authorship were published in 2016, showing that the academic community had strong ties in 2016.

The highest number of relevant articles were published from 2017 to 2019, showing that the academic community got broader with more researchers involved and more interested in machine learning techniques applied to bike-sharing systems, as shown in Section 3.5.

Table 4. Author co-authorship ranked by link strength.

Author	Documents	Link Strength
Chen, Longbiao	1	9
Jakubowicz, Jérémie	1	9
Li, Shijian	1	9
Ma, Xiaojuan	1	9
Nguyen, Thi Mai Trang	1	9
Pang, Gang	1	9
Wang, Leye	1	9
Wu, Zhaohui	1	9
Yang, Dingqi	1	9
Zhang, Daqing	1	9
Chen, Weiwei	1	7
Fu, Yanjie	1	7
Li, Qiao	1	7
Liu, Junming	1	7
Qu, Meng	1	7
Xiong, Hui	1	7
Yang, Jingyuan	1	7
Zhong, Hao	1	7
Ai, Yi	1	6
Chen, Wei	1	6
Gan, Mi	1	6
Ju, Yanni	1	6
Li, Zongping	1	6
Yu, Daben	1	6
Zhang, Yunpeng	1	6
Elhenawy, M.	1	3
Ghanem, A.	1	3
House, L.	1	3
Hu, Ji	1	3
Moscibroda, Thomas	1	3
Rakha, H. A.	1	3
Shu, Yuanchao	1	3
Yang, Zidong	1	3
Ma, X.	2	0
Wu, J.	2	0

Figure 8. Author co-authorship analysis by year overlay visualisation.

3.5. Title and Abstract Text Occurrence Analysis

This analysis (with VOSviewer) was performed on text data using a full counting method and included 749 screened items with a minimum threshold of 2 occurrences, resulting in 160 items. The relevance score was calculated for 40% of the sample as a standard reference for the calculation. The process result is shown in Table 5 for the 13 most relevant terms.

Table 5. Title and abstract text occurrences ranked by relevance.

Term	Occurrences	Relevance
gcnn model	2	2.08
gcnnrec ddgf	2	2.08
gcnnreg ddgf	2	2.08
gcnnreg ddgf model	2	2.08
lstm nns	4	1.77
sharing bike	4	1.71
deep learning approach	4	1.17
recurrent neural network	3	1.11
gru	2	1.07
clustering algorithm	4	0.86
conv lstm	2	0.83
prediction model	6	0.60
random forest	8	0.49

The analysis computed a network with 64 items, 8 clusters, 310 links and a total link strength of 987 (Figure 9). The network highlighted an eight-cluster network, being the biggest nodes of each identified as gcnn ddgf model (orange), neural network (brown), lstm nns (cyan), random forest (yellow), approach(green), algorithm(red), prediction model (purple) and prediction(blue). The identified machine learning techniques were also coherent with the ones identified in the keyword analysis, namely deep learning, clustering algorithm and long short-term memory, also suggesting other techniques, such as graph convolutional neural networks with data-driven graph filter (GCNN-DDGF) and neural networks (RNN and CNN).
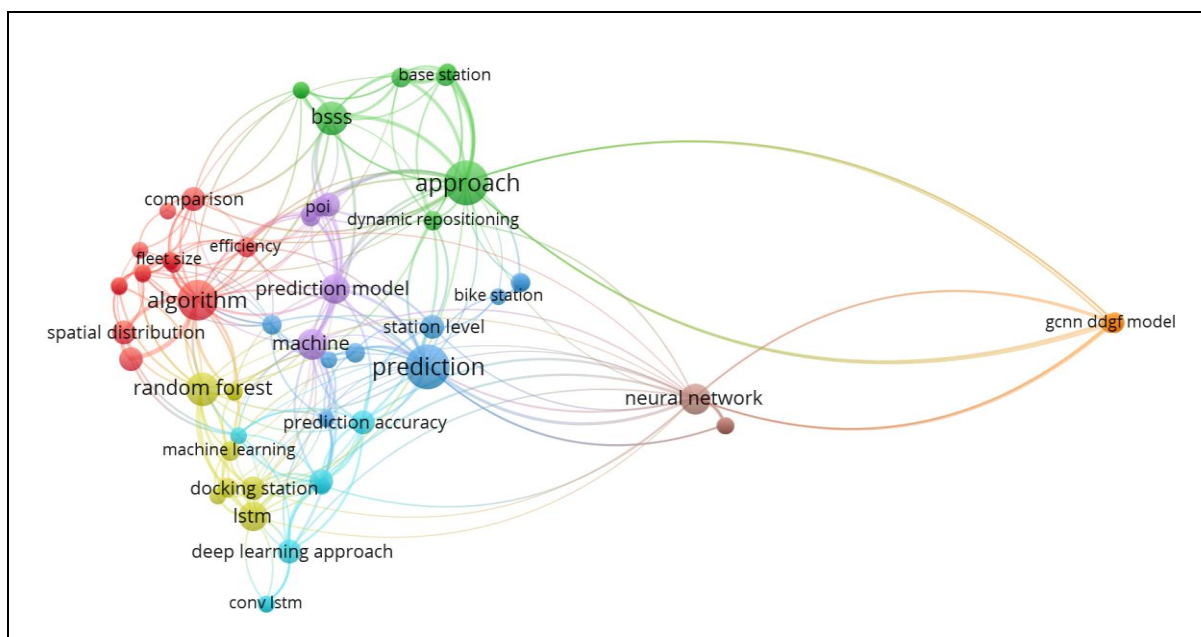

Figure 9. Title and abstract text occurrence network visualisation.

Figure 10 shows that neural network, a machine learning technique, is applied to bike-sharing systems studies in most of the articles published since 2016. A clear evolution is observed in the application of this machine learning technique [13,21–25] studied by authors till 2019.
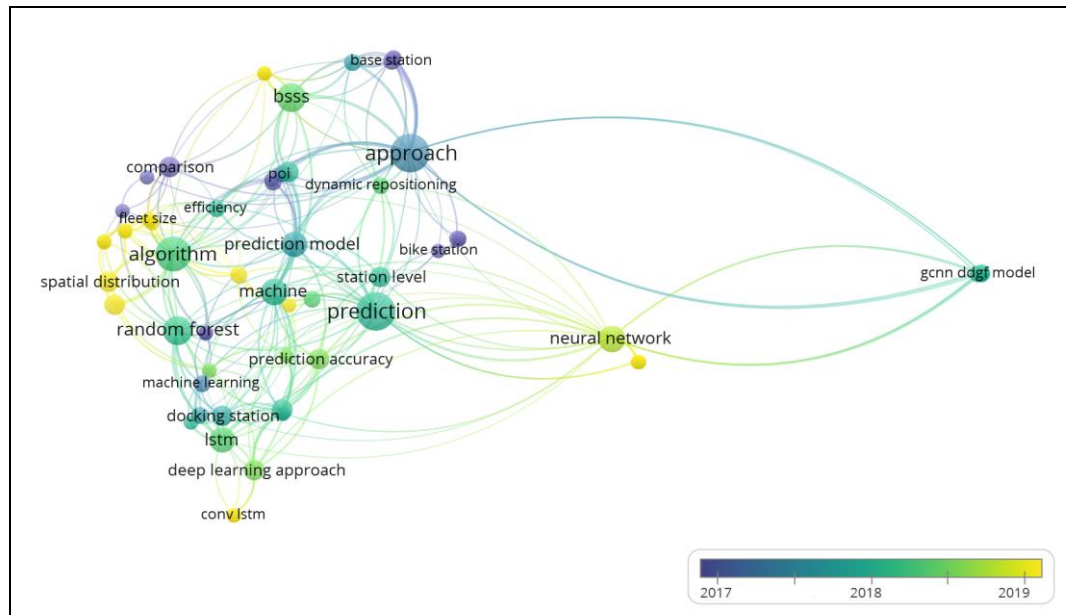

Figure 10. Title and abstract text occurrence by year overlay visualisation.

3.6. Most Cited Publications

Analysis of the most cited publications helped us identify the relevant research topics in the literature. To this aim, a search for the most cited, selected publications was conducted using Scopus and Web of Science data sets. This search showed publications that have been cited between 60 times and 1 time. The results of this process are shown in Table 6.

Table 6. Publications ranked by number of citations.

No.	Author(s)	Year	Article Title	Publication (Journal/Conference Proceeding)	No. of Citations
1	Yang, Z., Hu, J., Shu, Y., (...), Chen, J., Moscibroda, T.	2016	Mobility Modeling and Prediction in Bike-Sharing Systems	*Annual International Conference on Mobile Systems, Applications, and Services (14th Proceedings)*	60
2	Chen, L., Zhang, D., Wang, L., (...), Nguyen, T.-M.-T., Jakubowicz, J.	2016	Dynamic Cluster-Based Over-Demand Prediction in Bike Sharing Systems	*ACM International Joint Conference on Pervasive and Ubiquitous Computing (2016 Proceedings)*	57
3	Zhou, X.	2015	Understanding Spatiotemporal Patterns of Biking Behavior by Analyzing Massive Bike Sharing Data in Chicago	*PloS ONE*	54
4	Caggiani, L., Camporeale, R., Ottomanelli, M., Szeto, W.Y.	2018	A Modeling Framework for the Dynamic Management of Free-Floating Bike-Sharing Systems	*Transportation Research Part C: Emerging Technologies*	53

Table 6. *Cont.*

No.	Author(s)	Year	Article Title	Publication (Journal/Conference Proceeding)	No. of Citations
5	Ghosh, S., Varakantham, P., Adulyasak, Y., Jaillet, P.	2017	Dynamic Repositioning to Reduce Lost Demand in Bike Sharing Systems	*Journal of Artificial Intelligence Research*	43
6	Lin, L., He, Z., Peeta, S.	2018	Predicting Station-Level Hourly Demand in a large-scale Bike-Sharing Network: A Graph Convolutional Neural Network Approach	*Transportation Research Part C: Emerging Technologies*	36
7	Liu, J., Li, Q., Qu, M., (...), Zhong, H., Fu, Y.	2016	Station Site Optimization in Bike Sharing Systems	*IEEE International Conference on Data Mining (2015 Proceedings)*	35
8	Xu, C., Ji, J., Liu, P.	2018	The Station-Free Sharing Bike Demand Forecasting with a Deep Learning Approach and Large-Scale Datasets	*Transportation Research Part C: Emerging Technologies*	23
9	Bordagaray M., dell'Olio L., Fonzone A., Ibeas Á.	2016	Capturing the Conditions That Introduce Systematic Variation in Bike-Sharing Travel Behavior Using Data Mining Techniques	*Transportation Research Part C: Emerging Technologies*	23
10	Sarkar, A., Lathia, N., Mascolo, C.	2015	Comparing Cities' Cycling Patterns Using Online Shared Bicycle Maps	*Transportation*	22
11	Ai, Y., Li, Z., Gan, M., (...), Chen, W., Ju, Y.	2019	A Deep Learning Approach on Short-Term Spatiotemporal Distribution Forecasting of Dockless Bike-Sharing System	*Neural Computing and Applications*	15
12	Cagliero, L., Cerquitelli, T., Chiusano, S., Garza, P., Xiao, X.	2017	Predicting Critical Conditions in Bicycle Sharing Systems	*Computing*	13
13	Du, Y., Deng, F., Liao, F.	2019	A Model Framework for Discovering the Spatio-Temporal Usage Patterns of Public Free-Floating Bike-Sharing System	*Transportation Research Part C: Emerging Technologies*	12
14	Ashqar, H.I., Elhenawy, M., Almannaa, M.H., (...), Rakha, H.A., House, L.	2017	Modeling Bike Availability in a Bike-Sharing System Using Machine Learning	*IEEE International Conference on Models and Technologies for Intelligent Transportation Systems (5th Proceedings)*	12
15	Feng, Y., Wang, S.	2017	A Forecast for Bicycle Rental Demand Based on Random Forests and Multiple Linear Regression	*IEEE/ACIS International Conference on Computer and Information Science (16th Proceedings)*	10

Table 6. *Cont.*

No.	Author(s)	Year	Article Title	Publication (Journal/Conference Proceeding)	No. of Citations
16	Bacciu, D., Carta, A., Gnesi, S., Semini, L.	2017	An Experience in Using Machine Learning for Short-Term Predictions in Smart Transportation Systems	*Journal of Logical and Algebraic Methods in Programming*	6
17	Wang, B., Kim, I.	2018	Short- Term Prediction for Bike-Sharing Service Using Machine Learning	*Transportation Research Procedia*	5
18	Chen, P.-C., Hsieh, H.-Y., Sigalingging, X.K., Chen, Y.-R., Leu, J.-S.	2017	Prediction of Station Level Demand in a Bike Sharing System Using Recurrent Neural Networks	*IEEE Vehicular Technology Conference, 2016*	5
19	Chen, L., Ma, X., Nguyen, T.-M.-T., Pan, G., Jakubowicz, J.	2017	Understanding Bike Trip Patterns Leveraging Bike Sharing System Open Data	*Frontiers of Computer Science*	5
20	Ashqar, H.I., Elhenawy, M., Rakha, H.A.	2019	Modeling Bike Counts in a Bike-Sharing System Considering the Effect of Weather Conditions	*Case Studies on Transport Policy*	4
21	Zhou, Y., Huang, Y.	2019	Context Aware Flow Prediction of Bike Sharing Systems	*IEEE International Conference on Big Data, Big Data (2018 Proceedings)*	3
22	Jiang, J., Lin, F., Fan, J., Lv, H., Wu, J.	2019	A Destination Prediction Network Based on Spatiotemporal Data for Bike-Sharing	*Complexity*	3
23	Pan, Y., Zheng, R.C., Zhang, J., Yao, X.	2019	Predicting Bike Sharing Demand Using Recurrent Neural Networks	*Procedia Computer Science*	3
24	Wu, X., Lyu, C., Wang, Z., Liu, Z.	2019	Station-Level Hourly Bike Demand Prediction for Dynamic Repositioning in Bike Sharing Systems	*Smart Innovation, Systems and Technologies*	2
25	Duan, Y., Wu, J.	2019	Optimizing Rebalance Scheme for Dock-less Bike Sharing Systems with Adaptive User Incentive	*IEEE International Conference on Mobile Data Management (2019 Proceedings)*	2
26	Zhang, C., Zhang, L., Liu, Y., Yang, X.	2018	Short-Term Prediction of Bike-Sharing Usage Considering Public Transport: A LSTM Approach	*IEEE Conference on Intelligent Transportation Systems, Proceedings (ITSC 2018)*	2
27	Liu, L., Sun, L., Chen, Y., Ma, X.	2019	Optimizing Fleet Size and Scheduling of Feeder Transit Services Considering the Influence of Bike-Sharing Systems	*Journal of Cleaner Production*	1
28	Zhou, X., Wang, M., Li, D.	2019	Bike-Sharing or Taxi? Modeling the Choices of Travel Mode in Chicago Using Machine Learning	*Journal of Transport Geography*	1

Table 6. *Cont.*

No.	Author(s)	Year	Article Title	Publication (Journal/Conference Proceeding)	No. of Citations
29	Xu, H., Duan, F., Pu, P.	2019	Dynamic Bicycle Scheduling Problem Based on Short-Term Demand Prediction	*Applied Intelligence*	1
30	Zhao, Y., Dai, L., Peng, L., Song, Y., Zhou, Z.	2019	Analysis of Spatial Distribution of China's Station-Free Bike-Sharing by Clustering Algorithms	*ACM International Conference Proceeding Series*	1
31	Li, D., Zhao, Y., Li, Y.	2019	Time-Series Representation and Clustering Approaches for Sharing Bike Usage Mining	*IEEE Access*	1
32	Liu, X., Gherbi, A., Li, W., Cheriet, M.	2019	Multi Features and Multi-Time Steps LSTM Based Methodology for Bike Sharing Availability Prediction	*Procedia Computer Science*	1
33	Guo, Y., Shen, X., Ge, Q., Wang, L.	2018	Station Function Discovery: Exploring Trip Records in Urban Public Bike-Sharing System	*IEEE Access*	1
34	Liu, K., Wang, P., Zhang, J., Fu, Y., Das, S.K.	2018	Modelling the Interaction Coupling of Multi-View Spatiotemporal Contexts for Destination Prediction	*SIAM International Conference on Data Mining (SDM 2018)*	1
35	Zhou, M., Ding, J., Fang, H.	2018	Performance Modelling and Analysis of a Station-Free Bike Sharing System	*International Conference on Intelligent Autonomous Systems (ICoIAS 2018)*	1

From the five highlighted publications, we found that Yang, Z., Hu, J., Shu, Y., (...), Chen, J. and Moscibroda, T. [16], was the most cited with 60 citations, followed by Chen, L., Zhang, D., Wang, L., (...), Nguyen, T.-M.-T. and Jakubowicz, J. [12], with 57 citations; Zhou, X. [26], with 54 citations; Caggiani, L., Camporeale, R., Ottomanelli, M. and Szeto, W.Y. [27], with 53 citations; and, finally, Ghosh, S., Varakantham, P., Adulyasak, Y. and Jaillet, P. [28], with 43 citations.

The articles in Table 6 include these described above and suggest coherence with the results from previous analyses. These articles are major bodies of literature, and some of them represent key concepts in the field.

Interestingly, five of the most cited articles identified in Table 6 were published in Q1-ranked journals. We found that the articles were published in a diverse range of journals, and there is no outstanding leading journal in the field.

Moreover, and coherent to the analysis, the most cited article is also highlighted in the author co-authorship analysis (Section 3.4). In fact, Cluster 5 (purple) in Figure 7 groups the most cited author co-authorship [16], and Cluster 1 (red) groups most of the author co-authorship of the second-most cited article [12]. In both keyword occurrence analysis (Section 3.3) and abstract and title text occurrence analysis (Section 3.5), the term random forest was outstanding and is a technique adopted by the most cited publication [16].

3.7. Application and Method Analysis

To evaluate the applications and computing methods of each paper, a theoretical and conceptual framework was built, as shown below in Table 7.

Table 7. Application and method analysis.

No.	Author(s)	Application	Methods
1	Yang, Z., Hu, J., Shu, Y., (...), Chen, J., Moscibroda, T.	Build a spatiotemporal dynamic network to evaluate and predict station and city bike demand.	Random forest
2	Chen, L., Zhang, D., Wang, L., (...), Nguyen, T.-M.-T., Jakubowicz, J.	Weight a correlation network to model the relationship among bike stations and dynamically group neighbouring stations with similar bike usage patterns into clusters. Use Monte Carlo simulation to predict the over-demand probability of each cluster.	Weighted correlation network and Monte Carlo simulation (WCN-MC), auto-regressive integrated moving average (ARIMA), Bayesian Monte Carlo (B-MC), artificial neural network (ANN), Static clustering Monte Carlo (SC-MC), common contextual factor-based clustering Monte Carlo (CCF-MC)
3	Zhou, X.	Detect and visualise spatiotemporal bike flow clusters. Analyse station over-demand patterns across the city using hierarchical clustering to understand spatial distribution of stations with different temporal use signatures, biking behaviour and mobility patterns.	Community detection clustering, hierarchical clustering
4	Caggiani, L., Camporeale, R., Ottomanelli, M., Szeto, W.Y.	Spatiotemporal clustering, first grouping the data simultaneously by creating a cluster tree and second minimising the average squared distance between points in the same cluster. Forecast the trend of available bikes in each spatiotemporal cluster to understand how many bikes have to be repositioned to improve user satisfaction and system attraction.	Hierarchical clustering, K-means, nonlinear autoregressive neural network prediction
5	Ghosh, S., Varakantham, P., Adulyasak, Y., Jaillet, P.	Dynamic repositioning of bikes in conjunction with the routing solution and a scalable solution for the real-world large-scale bike-sharing systems.	Lagrange dual decomposition (LDD)
6	Lin, L., He, Z., Peeta, S.	Six types of GCNN models and seven benchmark models built and compared on a Citi Bike dataset from New York City to make spatiotemporal correlations patterns between stations and to predict station-level hourly demand in a large-scale bike-sharing network.	Graph convolutional neural network with data-driven graph filter (GCNN-DDGF)
7	Liu, J., Li, Q., Qu, M., (...), Zhong, H., Fu, Y.	Bike-sharing network optimisation approach of station site allocation in terms of the bike usage as well as the required rebalancing efforts by considering multiple influential factors: environment and complex public transportation networks.	Artificial neural network (ANN)
8	Xu, C., Ji, J., Liu, P.	Predict the bike-sharing trip gap, production and attraction: mobility pattern of the station-free bike-sharing at a citywide scale and development of dynamic demand forecasting models to predict the travel demand of station-free bike-sharing using the deep learning approach.	Long short-term memory neural networks (LSTM NNs)

Table 7. *Cont.*

No.	Author(s)	Application	Methods
9	Bordagaray M., dell'Olio L., Fonzone A., Ibeas Á.	Algorithm to classify trips of bike-sharing system (BSS) users in well-defined usage types by mining smart-card transactions, and spatiotemporal distribution and travel behaviour within public systems.	Rule-based classification, logistic regression (binary regression)
10	Sarkar, A., Lathia, N., Mascolo, C.	Model granular behavioural patterns on spatiotemporal variations and bike station redistribution.	Hierarchical clustering
11	Ai, Y., Li, Z., Gan, M., (...), Chen, W., Ju, Y.	A deep learning approach to address the spatiotemporal dependences, including the number of bicycles in the area, distribution uniformity, usage distribution and time of day.	Convolutional long short-term memory network (conv-LSTM)
12	Cagliero, L., Cerquitelli, T., Chiusano, S., Garza, P., Xiao, X.	Station performance occupancy-level prediction.	Bayesian classifier, L3 classifiers
13	Du, Y., Deng, F., Liao, F.	Model framework to explore the spatiotemporal usage patterns of free-floating shared bikes using the usage data to explore the impact of factors on the frequency in different districts.	Random forest, hierarchical clustering
14	Ashqar, H.I., Elhenawy, M., Almannaa, M.H., (...), Rakha, H.A., House, L.	Univariate and multivariate models for availability prediction of shared bikes at the station.	Random forest, least-squares boosting and partial least-squares regression (PLSR)
15	Feng, Y., Wang, S.	Multiple regression analysis has a great improvement when a random forest model is used to predict the demand for bicycle rental.	Multiple linear regression, random forest
16	Bacciu, D., Carta, A., Gnesi, S., Semini, L.	Compare machine learning techniques to predict and infer whether there is in use a bike that could be, with high probability, returned at the station where the user is waiting.	Gausian support vector machine (SVM) classifier, time series, random forest
17	Wang, B., Kim, I.	Short-term forecast for docking station usage with two RNN techniques and random forest (RF) to compare performance.	Recurrent neural networks (RNNs) (long short-term memory network (LSTM) and gated recurrent unit (GRU)), random forest
18	Chen, P.-C., Hsieh, H.-Y., Sigalingging, X.K., Chen, Y.-R., Leu, J.-S.	Predict both rental and return demand for every station at once, which is efficient for online balancing strategies.	Recurrent neural network (RNN)
19	Chen, L., Ma, X., Nguyen, T.-M.-T., Pan, G., Jakubowicz, J.	Approach to infer the spatiotemporal bike trip patterns from the public station feeds.	Sparse regularisation, weighted regularisation
20	Ashqar, H.I., Elhenawy, M., Rakha, H.A.	Quantify the effect of several variables (month of the year, day of the week, time of the day and various weather conditions) on the mean of bike counts for the Bay Area BSS network. Prediction model for the bike counts at each station over time as it is one of the key tasks in making the rebalancing operation more efficient.	Poisson regression model (PRM), negative binomial regression model (NBRM), random forest, Bayesian information criterion (BIC)

Table 7. *Cont.*

No.	Author(s)	Application	Methods
21	Zhou, Y., Huang, Y.	Context-aware framework to predict bike flows for both existing stations and new stations that incorporates spatiotemporal, network and environmental contexts in a synergistic manner.	Fuzzy logic (FL)-based adaptive neuro-fuzzy inference system for enhancing traveling comfort (FLC), auto-regression moving average (ARMA), artificial neural network (ANN), bipartite clustering
22	Jiang, J., Lin, F., Fan, J., Lv, H., Wu, J.	Prediction network based on spatiotemporal data.	Long short-term memory network (LSTM), convolutional neural network (CNN), candidate generation model (CGM), naïve Bayesian
23	Pan, Y., Zheng, R.C., Zhang, J., Yao, X.	Prediction of bike-renting in different areas of a city during a future period based on historical, weather and time data.	Community detection clustering, recurrent neural network (RNN), long short-term memory network (LSTM)
24	Wu, X., Lyu, C., Wang, Z., Liu, Z.	Prediction accuracy of the hourly bike number change at the station level.	Random forest (RF), gradient boosting regression tree (GBRT) and neural network (NN)
25	Duan, Y., Wu, J.	Rebalancing the dock-less bike-sharing systems.	Markov decision process (MDP), deep reinforcement learning (DRL)
26	Zhang, C., Zhang, L., Liu, Y., Yang, X.	Prediction approach to historical usage and real-time passengers of public transport and neural networks to establish the connection among them.	Long short-term memory (LSTM)
27	Liu, L., Sun, L., Chen, Y., Ma, X.	Optimisation of fleet size and schedules of feeder buses that connect metro and residential areas in the context of bike-sharing systems.	Non- dominated sorting genetic algorithm -II (NSGA-II), customised multi-objective optimisation algorithm based on particle swarm optimisation (MPSO)
28	Zhou, X., Wang, M., Li, D.	Spatiotemporal model for travel choices between two transport alternatives.	Logistic regression, regularised linear models with stochastic gradient descent (SGD) learning, nonlinear algorithms, K-nearest neighbours (K-NN), support vector machine (SVM), Gaussian naïve Bayes, decision tree (DT), neural network, random forest (RF)
29	Xu, H., Duan, F., Pu, P.	Dynamic bicycle scheduling (DBS) model based on short-term demand prediction.	K-means, random forest (RF), enhanced genetic algorithm (E-GA)
30	Zhao, Y., Dai, L., Peng, L., Song, Y., Zhou, Z.	Model characteristics of the spatial distribution of shared traffic resources through the relationship between the density of bicycle distribution and the geographical location.	K-means (KM), ant colony (ACO), fuzzy C-means (FCM), mean shift (MS)
31	Li, D., Zhao, Y., Li, Y.	Dimension reduction in count series data to enhance performance with clustering, classification and prediction.	Time series, hierarchical clustering, K-Means (KM), K-medoids, K-shape
32	Liu, X., Gherbi, A., Li, W., Cheriet, M.	Rebalance bikes efficiently among different bike-sharing dockers.	Long short-term memory (LSTM), recurrent neural network (RNN), deep neural network (DNN)
33	Guo, Y., Shen, X., Ge, Q., Wang, L.	Station function method validated by the analysis of spatiotemporal characteristics on traffic patterns for station clusters and evaluated by the comparison of clustering results with the data of point of interests and station names.	K-means (KM), latent dirichlet allocation (LDA)

Table 7. *Cont.*

No.	Author(s)	Application	Methods
34	Liu, K., Wang, P., Zhang, J., Fu, Y., Das, S.K.	Multi-view model that can learn the relationship of the spatial and temporal views and substantially enhance the predictive performances.	Multiple additive regression trees (MART), RankBoost (RB), LambdaMART (LM), ListNet (LN), RankNet (RN)
35	Zhou, M., Ding, J., Fang, H.	Performance analysis for station-free bike-sharing systems to evaluate the travel time, capacity planning and utilisation.	Monte Carlo (MC), continuous time Markov chain (CTMC), performance evaluation process algebra (PEPA)

This framework aims to understand most used machine learning techniques according to application and method. It provides the direction of research goals and outcomes and creates the scope for studies on our research-related criteria evaluation.

Several methods and dimensions were applied to BSS applications on SLR articles. Three out of the ten SLR most cited articles [26,27,29] refer to spatiotemporal variation analysis, addressing station spatial distribution with different temporal use, bike behaviour and mobility patterns.

Clustering algorithms, such as hierarchical clustering, community detection clustering and K-means, were tested in studies [26,27,29] to model granular behaviour patterns on bike station spatiotemporal redistribution. The dimension of the application changes according to studies, some using the techniques separately for each dimension (station, cluster and city levels) and others combining or overlapping on the three levels [26].

Of the 10 most cited SLR articles, studies suggest prediction models to address different applications. A random forest (RF) is applied in the study [30] of the most cited article to build a spatiotemporal dynamic network to evaluate and predict station and city bike demand.

On the other hand, the second-most cited article proposes a weight correlation network (WCN) to model the relationship among bike stations and dynamically group neighbouring stations with similar bike usage patterns into clusters, followed by artificial neural network (ANN) and Monte Carlo (MC) simulation to predict the over-demand probability of each cluster, looking at station- and cluster-level dimensions.

An artificial neural network (ANN) is used in a study [13] on the bike-sharing network optimisation approach of station site allocation, in terms of the bike usage and the required rebalancing efforts, by considering multiple influential factors, such as the environment and complex public transportation networks.

Graph convolutional neural network with data-driven graph filter (GCNN-DDGF) models [31] are used to implement spatiotemporal correlations patterns between stations and to predict the station-level hourly demand in a large-scale bike-sharing network.

A prediction model has been used in the latest studies [14,20,21,24,32,33], the long short-term memory neural network (LSTM NN). Xu [32] applied LSTM NNs in their study to predict the bike-sharing trip gap and mobility patterns of the station-free BBS at a citywide scale and to develop dynamic demand forecasting models of dynamic demand with the aim to predict the travel demand of station-free bike-sharing using the deep learning approach.

4. Discussion

Our SLR aimed to outline and identify the main machine learning techniques' contributions to BSSs in urban mobility, as well as to create a systematic, organised view of this research topic.

In this section, we discuss how the SLR answers our posed research question, which we recapitulate: What are the most promising machine learning techniques adopted by the community to better understand and improve bike-sharing systems in urban mobility?

4.1. Research Question Discussion

Our SLR analysis shows that the two main problems addressed by the proposed machine learning techniques are clustering (classification) and prediction applied to bike-sharing systems.

Clustering algorithms were analysed in Section 3.7 (Application and Method Analysis) and are mostly applied to imbalanced bike usage patterns regarding demand.

Reviewed papers apply clustering algorithms to a bike-sharing system's data by combining temporal and spatial attribute variables. More specifically, three clustering algorithms, namely hierarchical clustering [26,29,34], community detection clustering [26,27] and K-means clustering [27,35–37], were the most commonly used.

According to Caggiani [27], who analysed the performance of the three clustering algorithms, K-means clustering has been proven to be the best clustering algorithm to rebalance bike-sharing usage patterns.

Prediction methods are evolving, and there is now a wide variety of machine learning techniques and applications.

A random forest (RF) has been commonly used to explore the impact of factors on the bike-sharing usage frequency to understand the time-varying flow patterns and the spatial distribution of bike-sharing systems. Studies [15,21,30,34,38–40] have been conducted to improve the understanding of bike-sharing usage patterns and obtain insights into dynamic deployment of the bike-sharing system in urban areas.

A gradient boosting tree (GBT) and random forest (RF) were found [41] to provide the best results for the system-level demand using similar features.

A conventional artificial neural network (ANN) is one of the most used artificial intelligence algorithms for modelling time-series data in transportation. However, an ANN is unable to fully capture the characteristics of time-series data [12,13,23], as an ANN does not take into account the temporal dependencies in the model structure. To overcome the limitation associated with ANNs, feed-forward deep neural networks have been proposed, such as the recurrent neural network (RNN). Recurrently connecting hidden layers at different timestamps, an RNN [24,41] accounts for the temporal dependencies and produces good predictive performance on time-series data. Lately, the RNN has evolved [21] with optimal model structures (sequence length, time interval) for better prediction.

Moreover, traditional RNNs have a difficulty in finding the optimal window size in modelling time-series data, as they rely on predetermined time lags to learn temporal sequence processing [42,43].

Recurrent neural networks, namely long short-term memory units (LSTMs), are a type of artificial neural network designed to recognise patterns in sequences of data, such as numerical time-series data from sensors. RNNs and LSTMs differ from other neural networks as they have a temporal dimension. An LSTM NN is used to develop a dynamic demand forecast model in studies [32] for station-free bike-sharing systems. To overcome the limitations associated with RNNs in modelling time-series data with long-term dependencies, an LSTM NN [14,21,24,32,33] has been used to fit the time-series data of station-free bike-sharing.

Related work shows particularly good performance results with RNNs, using LSTM, and gated recurrent unit (GRU) blocks on station demand. A study [21] shows that there is a prevalence of three short-term prediction methods: LSTM, GRU and RF; and of three performance evaluation methods: mean square error (MSE), mean absolute error (MAE) and mean absolute percentage error (MAPE).

4.2. Research Gap Discussion

Our SLR analysis concluded that the main research gap is related to the selection of machine learning techniques that are best fitted and have better performance to solve BSSs at a multilevel scope, aiming at accelerating an evolving process still on-going. Therefore, we realised that more research is required with more case studies and different features to validate and improve future modelling strategies.

Additionally, our analysis has a second research gap: we realised that only a few studies [44] have analysed the implementation of the bike-sharing system in cities, such as Lisbon (the GIRA bike-sharing system), and none, to the best of our knowledge, has yet applied machine learning techniques in classification and prediction problems in the context of this use case. The Civil Engineering Research for Sustainability (CERIS), a research group in Lisbon University—Técnico (https://ceris.pt/), published studies on quantifying carbon emission reduction, time and money saved and health impact regarding the Lisbon bike-sharing system GIRA (that went into operation in 2017) compared to other transport modes. Findings [44] showed that 29% of car trips, 21% of metro trips and 12% walking shifted to the GIRA system in 2018. However, this study does not present any references, neither to the GIRA network expansion nor to multimodal integration. The novelty of GIRA and its expansion process has raised relevant questions, which requires more in-depth analysis. How bike-sharing improves the accessibility of urban mobility in Lisbon and how the expansion of the bicycle-sharing system impacts urban mobility in this city are among those questions.

The two gaps pointed out offer an opportunity for further research to be addressed in future work.

4.3. Study Limitation Discussion

Our SLR method has limitations of not being able to identify the literature outside the parameters given by the researcher. The selected articles do not cover an exhaustive list of publications in the field of machine learning techniques for BSSs. In fact, the analysed literature is an initial map of the research fields, from 2015 to 2019, with general trends and outlines of the main gaps in research, related to the last technological features of a dock-less BSS.

Research from previous years from 2008 onwards can also be of interest, particularly with regards to the scope of the technological evolution of machine learning techniques applied to fourth-generation BSSs, which are characterised by having docking stations.

Future research in this domain may also benefit from gathering data from more repositories than the two—Scopus and Web of Science—selected for the purpose of this work.

Our keyword selection for the publication search took a broader scope of machine learning techniques applied to BSSs. Future research might benefit by looking at specific machine learning techniques, especially prediction models applied to BSSs.

5. Conclusions

The PRISMA methodology outlined the SLR and created an organised view of machine learning techniques applied to BSSs for future information retrieval.

Recent technological developments in station-free BSSs fuelled new research in the last couple of years, with contributions to service improvement in urban mobility.

Our survey showed that in the latest BSS studies, classification and prediction problems are the two issues mostly addressed by machine learning techniques.

Clustering analysis is mainly used to explore BSS spatiotemporal patterns at different city scales. Hierarchical clustering is showed to be the most efficient algorithm to group sites with similar characteristics [33], unlike K-means clustering, which is best suited to rebalance BSS usage patterns [26]. The RF is a robust algorithm to discard outliers and noise and has an advantage of dealing with complex, nonlinear and high-dimensional data. Additionally, it estimates the importance of the input variables of different factors. The literature [37] showed that it has a more sophisticated accuracy rate compared to the multinomial logistic regression method. In a latest study [33], an RF is mainly used to analyse general features of travel distance and time of BSS trips.

Our SLR results suggest that LSTM NNs, a deep learning technique, are the recommended model to be used to identify mobility patterns of the station-free BSS, as well as for dynamic demand forecasting models, able to predict the travel demand of station-free bike-sharing.

Given the identified knowledge gaps, we can raise some recommendations for future work within the overarching theme of machine learning techniques applied to BSSs. Promising areas for further research lie in modelling the spatiotemporal dimension of BSSs in urban mobility, in analysing synergies with other transport modes in multimodal networks [45] and in addressing gaps on urban mobility bridging, with machine learning techniques applied to public transport multimodality and to network expansion strategies.

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