Bibliometric analysis of quality of service in public transportation: current and future trends

Retsepile Kalaoane, Walter Musakwa, Alain Kibangou, Trynos Gumbo, Innocent Musonda, Abraham Matamanda

▶ **To cite this version:**

Retsepile Kalaoane, Walter Musakwa, Alain Kibangou, Trynos Gumbo, Innocent Musonda, et al.. Bibliometric analysis of quality of service in public transportation: current and future trends. Scientific African, 2024, 23 (March), pp.e02059. 10.1016/j.sciaf.2024.e02059 . hal-04396702

HAL Id: hal-04396702
https://hal.science/hal-04396702

Submitted on 16 Jan 2024

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

Distributed under a Creative Commons Attribution - NonCommercial - NoDerivatives 4.0 International License

BIBLIOMETRIC ANALYSIS OF QUALITY OF SERVICE IN PUBLIC TRANSPORTATION: CURRENT AND FUTURE TRENDS

Retsepile C Kalaoane[1], Walter Musakwa[2], Alain Kibangou[3], Trynos Gumbo[1], Innocent Musonda[4], Abraham R Matamanda[5]

[1]Department of Urban and Regional Planning, University of Johannesburg, Johannesburg, South Africa

[2]Department of Geography, Environmental Studies and Energy Studies, Faculty of Science, Auckland Park Campus, University of Johannesburg, Johannesburg, South Africa

[3]Univ. Grenoble Alpes, CNRS, Inria, Grenoble INP, Gipsa-Lab 38000, Grenoble, France

[4]Department of Construction Management and Quantity Surveying, Faculty of Engineering and the Built Environment, University of Johannesburg, Johannesburg, South Africa

[5]Department of Geography, University of the Free State, Bloemfontein, South Africa

Abstract

Public transport is a fundamental aspect of urban life and its quality of service can significantly impact the daily life of passengers. Research on quality of service in public transport is vital to creating efficient and inclusive public transport systems. This study which is both timely and imperative, provides a systematic literature review and bibliometric analysis of quality of service in public transport with special focus on gender and machine learning. The study employed a systematic search in Web of Science using relevant keywords. Based on 270 published articles on the Web of Science, we evaluate the state of knowledge through keyword analysis, co-occurrences, and co-citations. It appears that key themes in quality of service in public transportation have shifted from efficiency to user satisfaction and perceptions. However, there is limited literature on public transport service quality in the global south, particularly in Africa, compared to the global north. In particular, the study revealed that the total publications focusing on gender in Africa is two. Moreover, much of the literature on the African continent emanates from authors and countries outside the continent. It often does not reflect the lived realities of the state of public transport

in Africa. Similarly, emerging issues pertaining to machine learning and gender in public transport also require consideration. This paper paves the way for policy, practice, and further research. The review will be useful reference for evolutions of quality of service in public transport research.

Keywords: *PRISMA, Vosviewer, Quality of service, Public transport, Gender, Machine learning*

1. Introduction

The quality of public transport services is always a major challenge in African cities (Luke and Heyns, 2020). Indeed, the deteriorating quality of service in public transport is evident through poor access to economic opportunities and the unreliability of public transportation. To the other end, high costs and longer commuting hours for local and national travel have further limited access to human life's important needs (Guevara *et al*. 2020). The poor quality of service makes it difficult to break the current habit of using motor vehicles and switching to alternative sustainable means of transport, such as public transport (Mugion *et al*. 2018). Over the years, public transport has been regarded as an effective tool to address multiple societal challenges of sustainability and liveability (Friman *et al*. 2019; Oort and Yap, 2021). An effective public transport system cause the least harm to the environment while offering a mobility service to everyone choosing to use it (Park and Chowdhury, 2018).

Striving for improved quality of service in public transport to increase customer satisfaction has sparked the interest of researchers (Paulley *et al*. 2006; De Oña *et al*. 2013; Cantillo *et al*. 2022). However, public transport studies are confronted with challenges of the lack of literature in the African continent on the quality of service, gender, and machine learning. A search on Web of Science (WoS) identified 270 published articles with only 2 articles focusing on public transport and gender issues in Africa. In Ghana, Adom-Asamoah et al. (2021) conducts a study on the quality of service in public transport by looking closely at Ghana’s intra-city public transport. Their study shows that passengers choose to minimise the frequency use of public transport due to poor customer care. Though the paper is categorized under gender considerations, its content does not address the gender aspect in public transport. Additionally, Moghayedi et al. (2023) utilized socio demographics information to analyse modal choice among women in South Africa when using public transport,

employing a Structure Equation Model (SEM). Their research demonstrate that service quality and socio demographic background influence modal choice. The study further underscores the need for incorporations of new technologies in public transportation studies in Africa.

Globally, the focus on the quality of service, gender and machine learning in public transport has been identified in transport research (Dell'Olio et al. 2011; Wei et al. 2022). Previous research has provided valuable insights on service quality, user satisfaction, performance, efficiency and quality of service in public transport (De Oña *et al*. 2015; Tirachini *et al*. 2017; Chen *et al*; 2022). In one study, Haghighi *et al*. (2018) develops an evaluation framework using unsupervised machine learning applied to twitter data, where people expressed their opinions about the satisfaction with services provided by Salt Lake City local transit system. Indeed, machine learning has been developed to explore different concepts in different disciplines (Okoroafor et al. 2022; Sholevar et al. 2022) including public transport.

In the field of gender studies, Dash *et al*. (2022) conducts an analysis on service quality and and passenger satisfaction among bus riders in Baku. Their findings indicate that inadequate bus services significantly reduce passenger satisfaction with socio-demographic information playing no role in this regard. Furthermore, Freista et al. (2023) examined gender differences in perception of bus transport service quality in Brazil. Using an Importance Performance Analysis and Tarrant and Smith methodology for the analysis. The results indicate that factors such as waiting time, scheduling and maintenance were important to both men and women. However, gender differences emerged with women placing greater importance to safety and treatment while men prioritized cost and rules than the actual bus service quality. Nonetheless, these studies have not addressed the gender dimensions extensively in public transport, lived experience on perception and expectations.

Inlight of evolving technology, dynamic changes in customer preferences, the increasing need for sustainable and inclusive transportation options, remains unexplored territory in understanding the dynamics of quality of service in public transport particularly concerning gender related issues and potential of machine learning techniques to enhance service quality. Consequently, the increase in knowledge in public transport research has made it hard to comprehend all the

research done, making it important to undertake a bibliometric analysis and review of literature to identify emerging research focus and key areas. Thus, this paper aims to use Bibliometric analysis and Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) to document the the state of the art of knowledge of quality of service in public transport, identify new trends and emerging themes in the literature.

Following this introduction, we discuss the methodological issues relating to the bibliometric analysis and PRISMA method focusing on how the data was gathered and analysed for this paper. The following section presents findings obtained from the bibliometric analysis. Next, these findings are discussed and a conclusion is provided to wrap the study.

2. Materials and Methods

The review of the literature was executed using PRISMA protocols (Moher *et al*. 2016) and bibliometric analysis.

2.1 Information Sources and Search

Web of Science (WoS) and Scopus are the main used database for research in bibliometric analysis. WoS was selected as the only database used in this paper. Although both databases use interdisciplinary approaches, WoS contains comprehensive coverage in literature (Mongeon and Hus, 2016). Introduced by the Institute of Scientific Information (ISI) in 1964, WoS has since evolved in scientific research coverage with the most impact and is a widely used database for systematic literature research (Birkle *et al*. 2020). WoS compared with Scopus was the best fit for this paper as Zhu and Liu (2020) stated that WoS is widely used and effective in practice.

All studies relating to the research were eligible for review with no specification on publication years. The database search in WoS was conducted and classified using the following keywords. The database search and the subsequent analysis were both carried out on a global scale.

- “Quality of service” AND “Public transport”
- “Quality of service” AND “Public transport” AND “Gender”
- “Quality of service” AND “Machine learning” AND “Public transport”

2.1.1 Keywords Defined

Quality of service: Is a multifaceted concept. Generally, QoS is defined as the level of service and customer satisfaction that public transport users experience when using a public transport systems (Machado *et al*. 2018; De Oña *et al*. 2021). It includes various factors that contribute to the overall experience of the passenger. This ranges from reliability, accessibility, travel time etc.

Machine Learning: Machine learning is a subset of Artificial Intelligence (AI), allowing a system to adapt and learn from the available data (Bi *et al*. 2019). It uses algorithms that progressively learn from data to enhance their ability to understand data patterns and make predictions (Peng *et al*. 2021).

The inclusion criteria were all articles published in the field of quality of service in public transport (Table 1).

Table 1: Inclusion and exclusion criteria for the data collection extracted from the database

Inclusion criteria	**Exclusion criteria**
All articles with topics in the quality of service in public transport	Studies outside public transport scope
All articles with topics relating to gender dimensions in quality of service in public transport	Unpublished thesis and dissertations
All articles with topics relating to machine learning techniques used in public transport	Newspapers, conference papers
Language: English	Non-English language
Countries: Looked from globally then Africa	

The search in the literature was directed by screening titles and abstracts for each article to confirm eligibility. The in-depth information on the selection process is presented in Figure 1 as guided by the PRISMA protocols. PRISMA is a method used successfully to extensively scan all literature to find answers to a specified research question for a study (Selcuk, 2019). The method is employed because it eliminate the bias resulting from the traditional methods of conducting a literature review. In Addition, PRISMA guidelines increase validity of the findings of the study (Page *et al.* 2021) and present the results in a coherent manner.

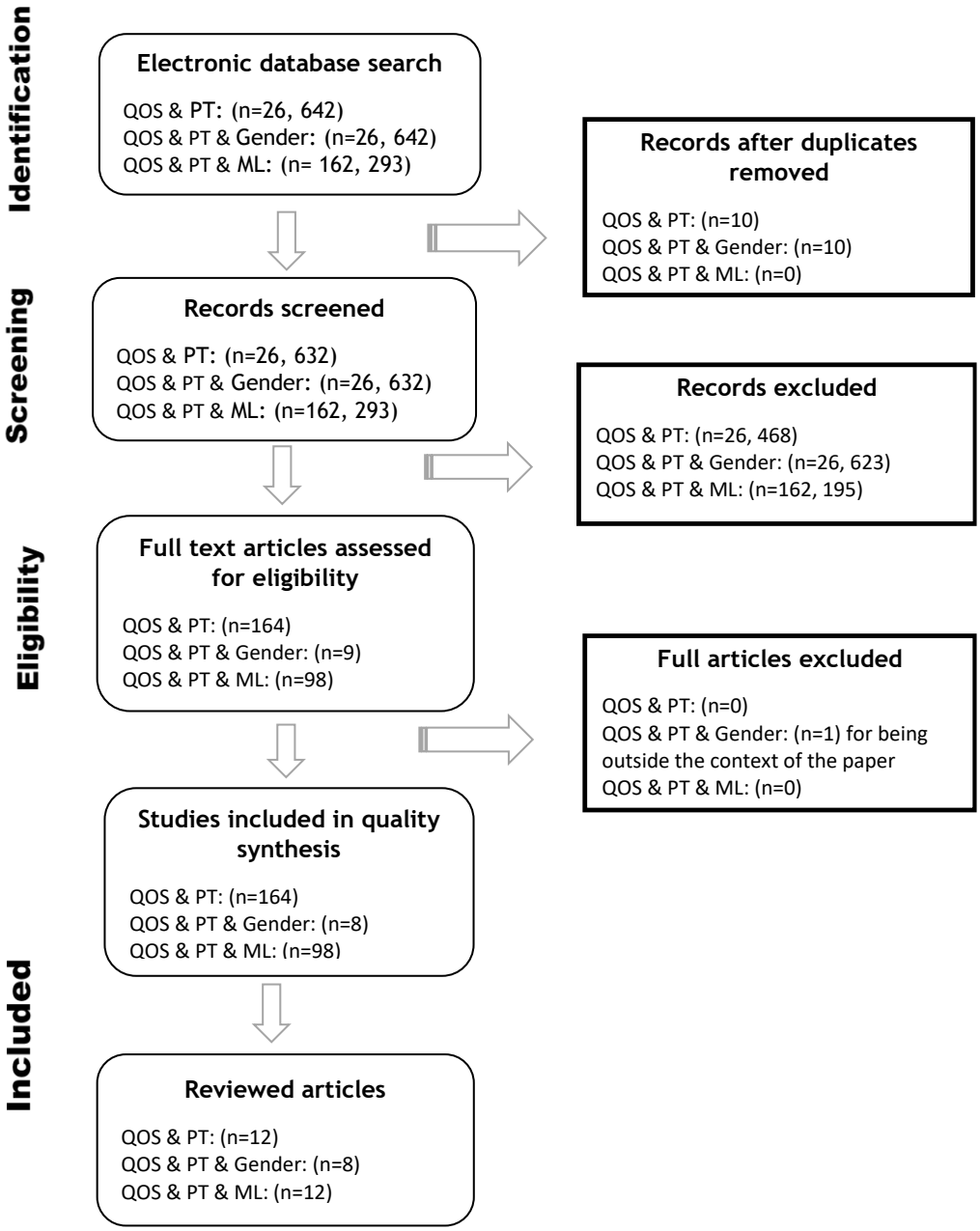

Figure 1: PRISMA flow diagram

Adapted from Moher *et al*. (2016)

The review identified 26,642 studies in WoS, of which 10 were duplicates and consequently removed. 26,632 were used for this study. After examining the title and abstract of each article and refining the scope of quality of service in public transport, 26,468 studies were excluded because they did not meet the eligibility for the present review. Following the guidelines of PRISMA, a total of 164 articles were eligible for the present review in this paper.

We also searched the terms “Quality of service” AND “Public transport” AND “Gender” resulting in 26,642 studies in WOS, of which 10 were duplicates and therefore removed, resulting in 26,632 being used for the initial analysis. After examining the title and abstract for each article and refining the scope of quality of service in public transport, with special reference to gender, 26,623 studies were excluded. Exclusion was because they did not meet the eligibility for the present review. After the screening stage, 9 articles were taken further into the eligibility stage. Of the 9 articles, 1 was excluded for it was outside the scope and only referred to non-motorised transport. The final 8 articles were eligible for the present review in this paper.

Lastly, for “Machine learning” AND “Public transport”, we identified 162,293 studies in WOS. After examining the title and abstract of each article and refining the scope of machine learning in public transport, 162,195 studies were excluded because they did not meet the eligibility for the present review. Following the guidelines of PRISMA, 98 articles were eligible for the present review in this paper. The reviewed articles during the inclusionary phase (Figure 1) were selected based on the highest cited articles in each group.

3. Bibliometric analysis

Bibliometric analysis is used in academic literature to provide a quantitative evaluation of published literature (Van Nunen *et al*. 2017). It is the best technique used to comprehend a vast amount of academic literature on a given topic or concept. Based on statistical sampling, bibliometric analysis assesses the impact of a published article relating to a study and the extent of its impact on the rest of the literature (Soosaraei *et al*. 2018). Figure 2 shows the procedure used in conducting the bibliometric analysis.

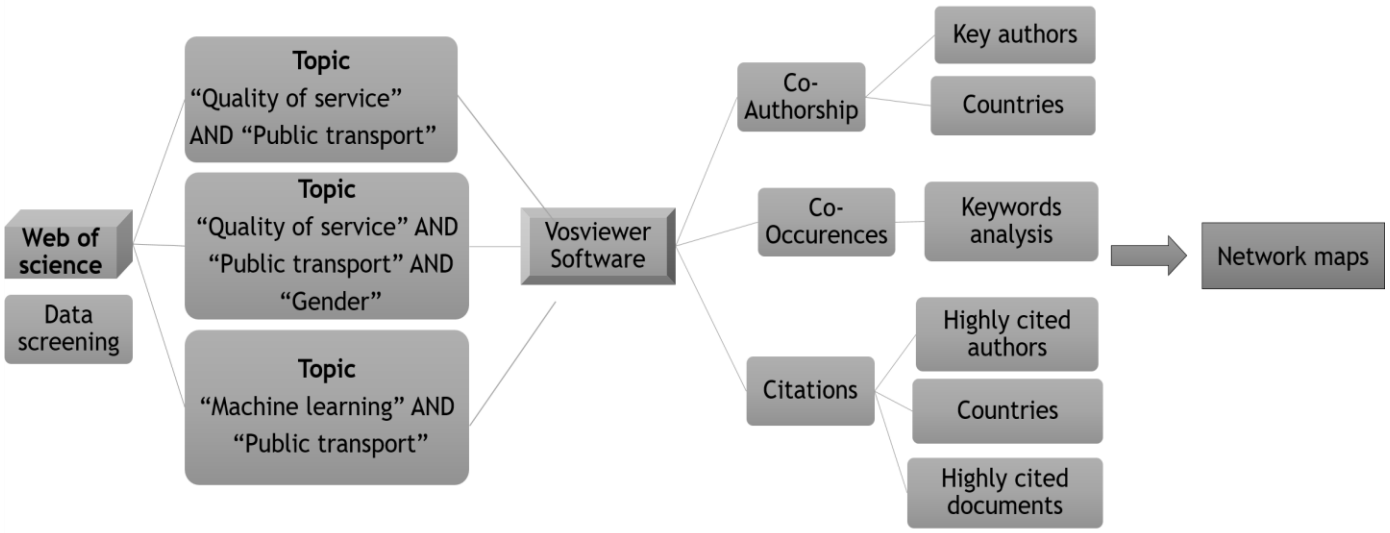

Figure 2: A guide on the bibliometric analysis for this paper

The analysis enabled this study to identify knowledge in concepts, identify major authors, their influence and overall research impact on the quality of service, public transport and machine learning. Upon completion of the search phase, data retrieved from WoS was used for the analysis using VOSviewer software version 1.6.17 (Al Husaeni and Nandiyanto, 2022). The data was then analysed to assess the co-occurrences, citations, and co-authorships using VOSviewer as depicted in Figure 2. The interpretations of bibliometric maps and tables produced through VOSviewer are explained in Table 2.

Table 2: overall interpretation of bibliometric analysis maps

Concept	Description
Clusters	Groups of items, differentiated by a different colour.
Items	Items are the objects of interest. For example, researchers, publications
Total link strength	The total strength of the connection between researchers, keywords, in cases of authorship analysis, the higher the value, the higher the co authorship
Links	It is the relationship between items, these may be co authorship connections with researchers, keywords, publications
Network	A group of items and their connections (links)

In addition to the information provided in Table 2. The illustrated circles in the Figures represent the occurrence of the concept. The bigger the size of a circle, the higher the keyword occurrence in published articles relating to the quality of services in public transport using machine learning techniques. Thus, the larger the label and circle of the keywords, the more important it is. The distance between the keywords shows the relationship between the keywords. The shorter the distance between the keywords, the stronger their relation (Yu *et al*. 2020). The colours are used to distinguish different clusters.

VOSviewer is a software that provides a visual analysis of the literature review such as trends, research focus and hotspots (Zhang *et al*. 2021; Soegoto *et al.* 2022). Although Citespace has been used in several articles (Kumar Sood *et al*. 2021; Nyathi *et al*. 2022), VOSviewer remains the primarily used software in the research fields because it can comprehend vast information while giving credible results. Transportation research have tapped into bibliometric analysis using VOSviewer software. In one study, Ceccato *et al*. (2021) used VOSviewer to analyse the safety of passengers during the trip duration and along transportation nodes. The study uncovered 245 articles related to safety concerns in railway modes from 1990 to 2020, which advocated for further research into passengers' safety concerns. Seemingly, Allam and Sharif (2022) studied the concept of smart mobility in western cities. The study mapped dynamics and identified thematic focus in smart mobility using VOSviewer.

4. Results and Discussions on bibliometric analysis

4.1 Publication trends of Quality of service

The initial publication on service quality in public transport globally emerged in the early 1990s. Most of the articles focused on supplying the quality of service in public transport through scheduling to increase efficiency in bus transit for the benefit of transit companies' production growth. Over time, there was a slump, probably due to the low influence of studies. It was not until 2010 that research grew in this phenomenon due to more people researching, which simultaneously increased citations (see Figure 3).

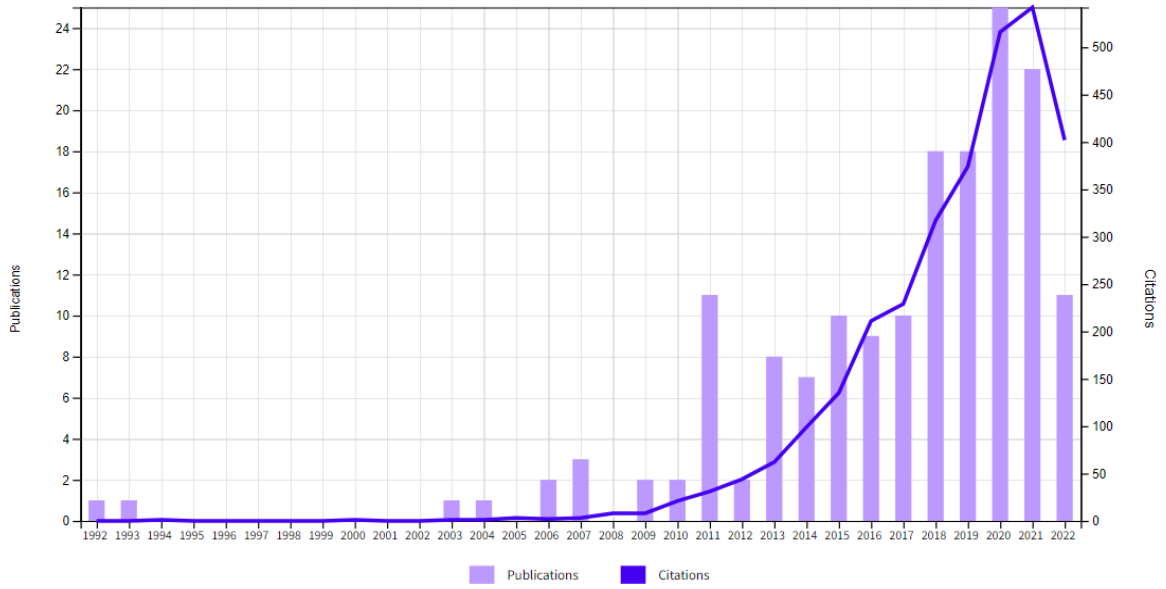

Figure 3: Times Cited and Publications over Time in quality of service and public transport

Although there was a slight decline in 2019 in publications and citations on the topic, research on the quality of services in public transport has been growing which shows a spark of interest and investment in that field. The research has grown significantly, especially since 2015, with 10 publications. The increase in publications was during debates around sustainability that include sustainable modes of transport.

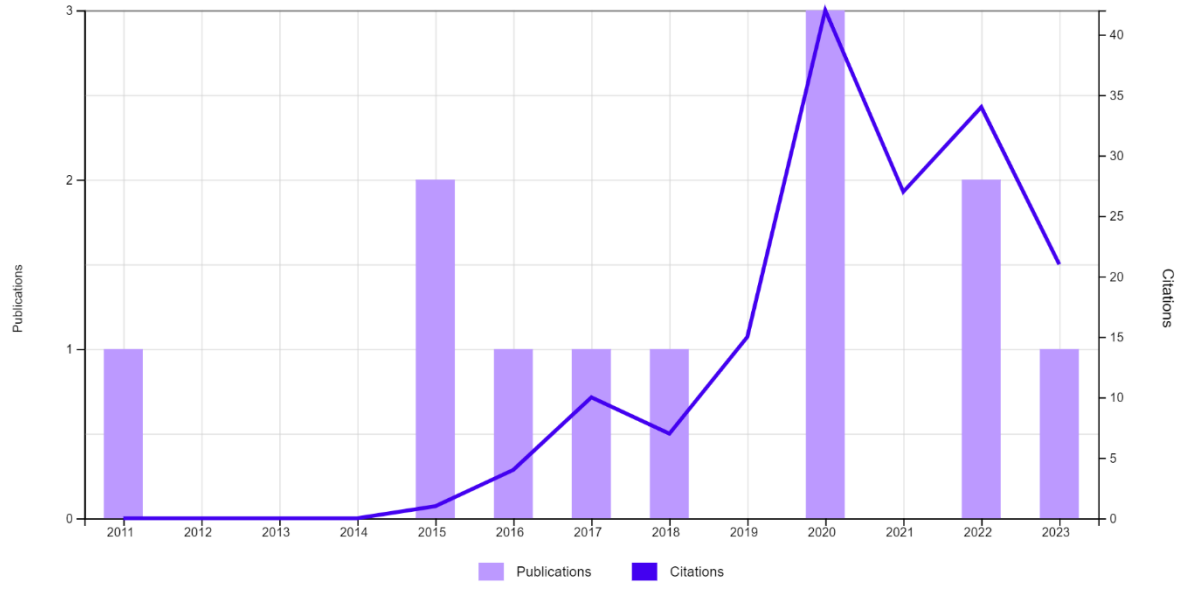

Figure 4: Times Cited and Publications over Time in quality of service in public transport and gender

It can be noted that the quality of service in public transport, with special reference to gender issues, is an under-examined area of research (Figure 4) globally. The

research can only be traced back to 2011. In 2020, there were only 2 reviewed publications cited 12 times and this was the most influential body of work.

Moore (2011), whose focus was on health issues around women, studied females' problems with drugs and alcohol. As a result, one of the indicators was the lack of public transport and the study indicated a lack of research on women's geographical barriers in accessing public transport. In addition, Chaudhary (2020) studied service quality in Bus-Rapid Transit in India through the perceptions of user's perspective, the results showed that the perception of public transport users depended heavily on gender, educational level, employment status, and reasons for travel. The popularity of sustainable development goals (SDGs), especially SDG 11.2 (advocates for efficient, equal, and sustainable access to women and other vulnerable groups) led to increasing research in public transport and gender dimension.

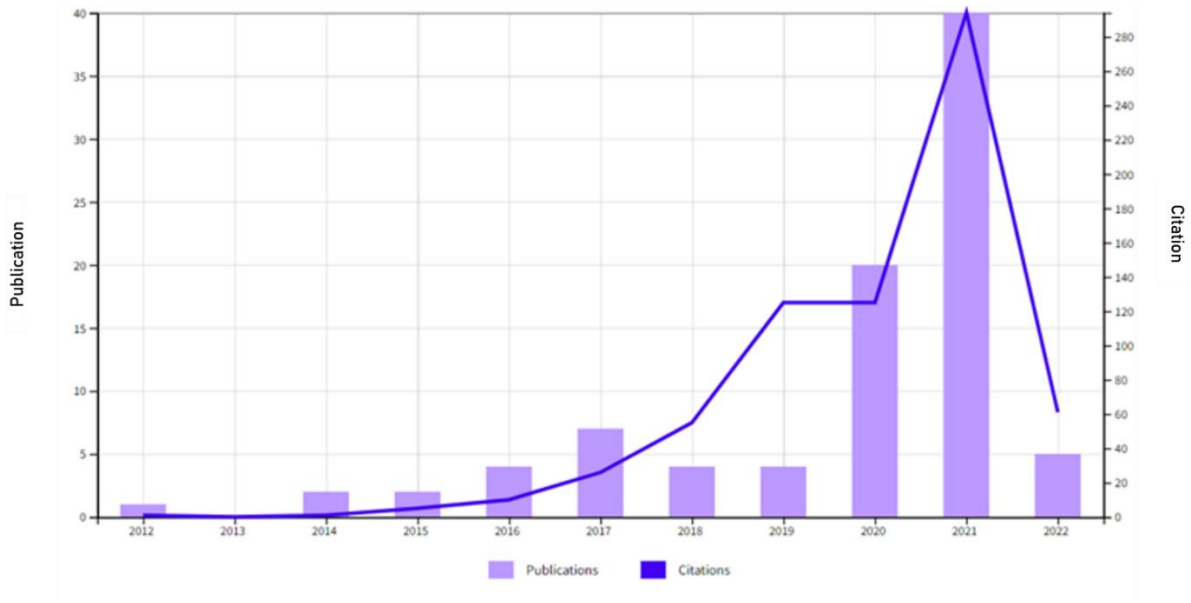

Figure 5: Times Cited and Publications over Time in quality of service in public transport and Machine

In addition to the gender dimension in research, machine learning has greatly impacted public transport research (Figure 5). Research in machine learning in public transport can be dated back to 2012. In 2012 researchers like Mendes-Moreira *et al*. (2012) focused more on using regression methods to predict travel time. The most cited body of work in this field is a study by Hagenauer and Helbich (2017), with 103 citations. The study compared the predictive performance of seven carefully chosen machine learning classifiers to analyze choice in different modes of transport using

Dutch travel data. The availability of big data has increased research in machine learning as a way to solve current mobility challenges.

Publications on quality of service in public transport research are highly cited by countries in the global north. Spain and the USA are the leading countries by citation and most of its research focuses on unpacking service quality by investigating different methodologies in evaluating customer satisfaction (Dell'Olio *et al*. 2011; De Oña *et al*. 2015). Spain also possesses an advantageous location that connects it with countries in Europe and America. Authors from China highly cite publications in machine learning and public transport. Of the 98 articles retrieved from Web of Science, 23 are published in China, for example, China's research areas are on assessing health issues in public transport (Zhou *et al*. 2021), predicting car crashes using trained algorithms (Ijaz *et al*. 2021) and developing warning models for bus transport users (Liu *et al*. 2020). Overall, the highest citations by countries come from countries that fall under the group of 7 organisations that rank among the wealthiest countries globally. Moreover, most of these highly cited papers are written by authors from countries in the global north. These publications may not reflect African realities making it difficult to fully comprehend the dynamics that exist in public transportation services.

4.2 Quality of service in public transport

4.2.1 Keywords analysis

A co-occurrence network analysis was performed and the results yielded six clusters represented by *red, green, navy blue, light blue, purple* and *yellow* colour coding (Figure 6). The keyword analysis was based on the 270 publications identified in WoS. In the *red cluster*, the dominant keywords are machine learning, transport, impact, COVID 19 and big data. Interconnected with this cluster is the *green cluster*. The Green cluster whose dominant keywords are modelling, framework, algorithms, networks and reliability. In the current technological era, big data has been leveraged to solve current transportation challenges cities face. As a result, machine learning has been used across various studies to predict, understand and solve emerging issues in the transportation sector (Wei *et al*. 2022). Indeed, models developed using machine learning techniques have been used to predict and mimic the realities in transportation and their impacts on solving the recent COVID-19 pandemic

(Gkiotsalitis and Liu, 2022). A novel spatio-temporal model developed by Ciancia *et al*. (2018) detected vehicle movements and problems. The model was later used to detect faults in motor vehicle around the world.

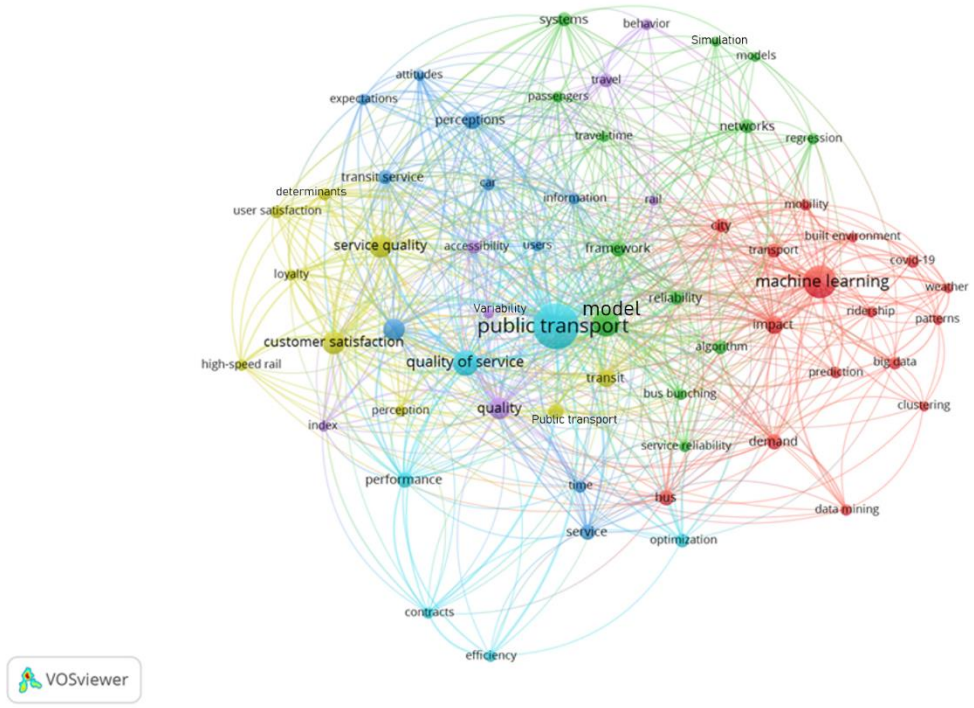

Figure 6: A Co-occurrence network analysis of keywords on quality of service in public transport research

The third cluster assigned to the *navy blue* colour code is centred on user satisfaction, perceptions, expectations and attitudes in public transport. The cluster is closely related to the *yellow cluster* on themes such as customer satisfaction, user satisfaction, service quality, determinants and high-speed rail in public transport. The two clusters show that the experience of public transport users is important, as they help understand a public transport industry's ability to meet user expectation to improve service quality (Joewono and Kubota, 2007). Passenger satisfaction highly depends on service quality and perceived value (De Vos *et al*. 2022). Customer satisfaction is mostly explored in conventional modes of transport like buses and rail. In a bid to attract people to use high-speed rails which are the mobility options providing the least harm to the environment (Lawrence *et al*. 2019). There are many cases where high-speed railways and Bus Rapid Transit (BRT) has positively impacted countries that have been devoted to increasing user satisfaction. For example, In China, high-speed rail has significantly boosted economic growth by

connecting people to different economic activities at lower transportation costs (Dong, 2018).

The next grouping is the *light blue* cluster which speaks to improving the quality of service in public transport. The focus is on issues of quality of service, optimization and efficiency. Lastly, the *purple* cluster ties closely to the light blue cluster. Since the dominant keywords in the cluster are accessibility, travel behaviour and quality. Most of the research on travel behaviour and accessibility is closely related to gender. Zheng *et al*. (2022) identified the gender bias on satisfaction levels in public transport among bus users in Brazil. Morton *et al.* (2016) look at expectations by examining the quality of services using a developed indicator by the Scottish government that entails assessing different attributes by scaling them across bus passengers from different socio-economic backgrounds to look at the impacts. The study reveals that females have higher expectations regarding service delivery and tend to have a negative opinion of different attributes.

Moreover, Morton (2018) investigates the perceived quality of service in bicycle sharing as means of public transport. Bicycle-sharing schemes are making their way in the public transport industry, and the conclusion is that availability, maintenance and accessibility are the determining factors. Abenoza (2017) divided the respondents into groups based on their socio-demographics, accessibility and travellers patterns to determine important attributes in service quality and how they evolve with time. The results revealed that customer boundaries, trip duration, network and operations were the highly attributed to people's choice of public transport usage.

The analysis shows a clear direction of the key areas on which research on the quality of service in public transport has been focusing. Machine learning and public transport are the most researched keywords, with an occurrence of 88 and total link strength of 272. This opens floodgates for research to harness on the availability of machine learning, especially in African cities where less research has been done. Seemingly, gender does not form part of the keywords because most studies look at gender as after effect and do not primarily look at gender as the main research focus.

4.2.2 Full-text analysis

335 Table 3 provides insights into various research conducted in the field of quality of
336 service in public transport. The analysis is based on the most influential body of work
337 determined by the highest citation.

338 Table 3: Analysis of research on the quality of service in public transport

CLUSTER	KEYWORDS	KEY STUDIES		
		AUTHORS	TITLE	YEAR
Red Cluster	Machine learning Impact transport covid 19 Big data Built environment data mining City Bus Predictions clustering	El Mahrsi, MK; Come, E; Oukhellou, L; Verleysen, M	Clustering Smart Card Data for Urban Mobility Analysis	2017
		Hagenauer, J; Helbich, M	A comparative study of machine learning classifiers for modelling travel mode choice	2017
		Islam, MF; Fonzone, A; MacIver, A; Dickinson, K	Use of ubiquitous real-time bus passenger information	2020
		Gkiotsalitis , K; Liu, T	Periodic Optimization of Bus Dispatching Times and Vehicle Schedules Considering the COVID-19 Capacity Limits: A Dutch Case Study Perspective	2022
		Wei H, Bao H, Ruan X.	Predicting and optimizing thermal transport properties with machine learning methods	2022
Green cluster	Model framework reliability algorithms networks	Salva, JR; Sierra, M; Alanis, AKJ; Kaplan, S; Prato, CG	Role of Social Climate in Habitual Transit Use by Young Adults to Work and Leisure Activities Evidence from Colombia and Mexico	2015
		Singh, N; Kumar, K	A review of bus arrival time prediction using artificial intelligence	2022
Navy Blue Cluster	Perceptions expectations attitudes Users satisfaction	De Oña , J; De Oña , R; Eboli, L; Mazzulla, G	Perceived service quality in bus transit service: A structural equation approach	2013
		Arabikhan, F; Postorino, MN; Dupont-Kieffer, A; Gegov, A	Gender-Based Analysis of Zones of Tolerance for Transit Service Quality Considering Intelligent Transportation Systems	2016
		Efthymiou, D; Antoniou, C; Tyrinopoulos, Y; Skaltsogianni, E	Factors affecting bus users' satisfaction in times of economic crisis	2018
Yellow cluster	Customer satisfaction user satisfaction service quality determinants high speed rail	Paulley, N; Balcombe, R; Mackett, R; Titheridge, H; Preston, J; Wardman, M; Shires, J; White, P	The demand for public transport: The effects of fares, quality of service, income and car ownership	2006
		Chen, JP; Yan, N; Lin, SL; Chen, SJ	Comparative Analysis of the Influence of Transport Modes on Tourism: High-Speed Rail or Air?	2022

Purple cluster	Accessibility travel behaviour quality	Holmgren, J De Oña, R; De Oña, J Cantillo, A; Raveau, S; Munoz, JC	Meta-analysis of public transport demand Analysis of transit quality of service through segmentation and classification tree techniques Fare evasion on public transport: Who, when, where and how?	2007 2015 2022
Light blue cluster	Public transport quality of service optimization efficiency	dell'Olio, L; Ibeas, A; Cecin, P He, PL; Jiang, GY; Lam, SK; Sun, YD	The quality of service desired by public transport users ML-MMAS: Self-learning ant colony optimization for multi-criteria journey planning	2011 2022

The research in public transport is highly focused on harnessing the use of machine learning in public transport (Table 3). Firstly, De Oña *et al*. (2015) sought to understand the complex nature of service quality in public transport, by exploring evolutions in methodological approaches to service quality and attributes affecting service quality. Data mining and cluster analysis were the best techniques to evaluate service quality (De Oña *et al*. 2015). Indeed, the use of new techniques to evaluate service quality has increased over time. Yuan (2020) used embedding network, which has important impact compared to traditional machine learning models. El Mahrsi *et al.* (2017) assess mobility patterns in public transport by using smart card data.

Through passengers clustering, they could identify passengers travelling patterns that shed light on why traffic is experienced during morning hours, and inform the operators of the number of buses needed to accommodate the customers. Likewise, Hagenauer and Helbich (2017) used machine learning classifiers to build algorithms to evaluate service quality. Islam (2020) used ubiquitous real-time passenger information (URTPI) to enhance the perceived quality of public transport service and enables travellers to make better pre-trip and en-route travel choices. URTPI is an under-researched area because it has only 2 studies.

Moreover, Hu (2016); Singh and Kumar (2022) developed a framework using algorithms to predict the arrival time of buses. The use of machine learning, as stipulated in the previous sections, is used to identify, predict and understand issues in public transportation. On the other hand, during the COVID-19 pandemic, among others, public transportation health concerns rose. Thus, Gkiotsalitis and Liu (2022) introduced an optimization model that was used to prevent the spread of COVID-19

by estimating expected passenger arrival time. He *et al*. (2022) research is on optimization to better service quality in public transport.

Different attributes determine quality of service in public transport. Paulley *et al*. (2006) evaluate the factors that influence public transport demand in Britain. Findings revealed that fares in buses tend to increase over time, negatively affecting service quality in bus transport. Dell'oli (2011) postulates that waiting time, cleanliness, and comfort are the most influential attributes affecting modal choice for public transport users. Moreover, Dell'olli states that the most valued attributes for potential users are trip duration, waiting time and occupancy. However, the desired quality of services in public transport is dependent on a variety of issues. De Oña *et al*. (2013) uses a weighted mean to analyse important factors in public transport service quality. The results are that service, comfort and driver's behaviour had the highest weight and the methodology was proven through the findings to be the best in determining important attributes in public transport. Holmgren (2007) states car ownership, petrol prices and any variable that affects the supply determine service quality.

In addition, Gender differences in public transport have been identified globally as well. Salva *et al*. (2015) stipulate that gender difference exists in public transport because both males and females encounter different experiences while in transit. De Oña (2015) analysed the quality of service and travel behaviour among different groups based on their shared socio-economic profile. The findings indicate that punctuality and information availability while using public transport are held in high regard among all demographics. Nevertheless, accessibility received a lower rating from females compared to men. In a study conducted in Reggio, Calabria by Arabikhan (2016) focus on investigating expectations and perceptions of service quality based on gender. Notably, women exhibits a high tolerance of poor quality of service in the realm of public transport. Often, this is associated to the societal norms as confirmed by Uteng and Turner (2019), women play more supporting roles in transportation while men are involved in decision making and policy making.

To evaluate quality of service in public transport, Efthymiou (2018) states that the improvement in service quality has attracted new users due to access to information, and service delivery. However, the attribute's importance differs over time. Fare evasion, a concept used when one uses public transport without paying, is a problem

experienced by many countries. It sparked research interest as it puts constraints on bus transport, eventually affecting service quality. Cantillo *et al*. (2022) use Chile as a case study to identify the people involved and the location where fare evasions take place. Although most of the people involved in fare evasion are men, women ultimately end up suffering due to protective measures to prevent bus fare evasion. In Athens, Greece, women fare evasion heavily depends on the evaders' socio-economic profile, especially gender (Milioti *et al*. 2020). The results indicate the gender dimensions that exist in the quality of service in public transport.

The increase in public transport usage is determined by the quality of service in public transport. Hence, Chen *et al*. (2022) argue that improving the quality of services in high-speed rail results in a positive impact on the economy. Efthymiou (2017) makes a comparison analysis of Athens's public transport demand between 2008 and 2013. Results reveal an increase in public transport usage due to high maintenance costs of motor vehicles, increased vision for sustainability and improved services.

4.2.2 Emerging trends and further research

Figure 7 represents the results of all existing, current and emerging trends in quality of service in public transport, gender and machine learning research from 2017 to 2020. The timelines are divided into four clusters indicated by the colour codes (navy blue, turquois blue, green and yellow).

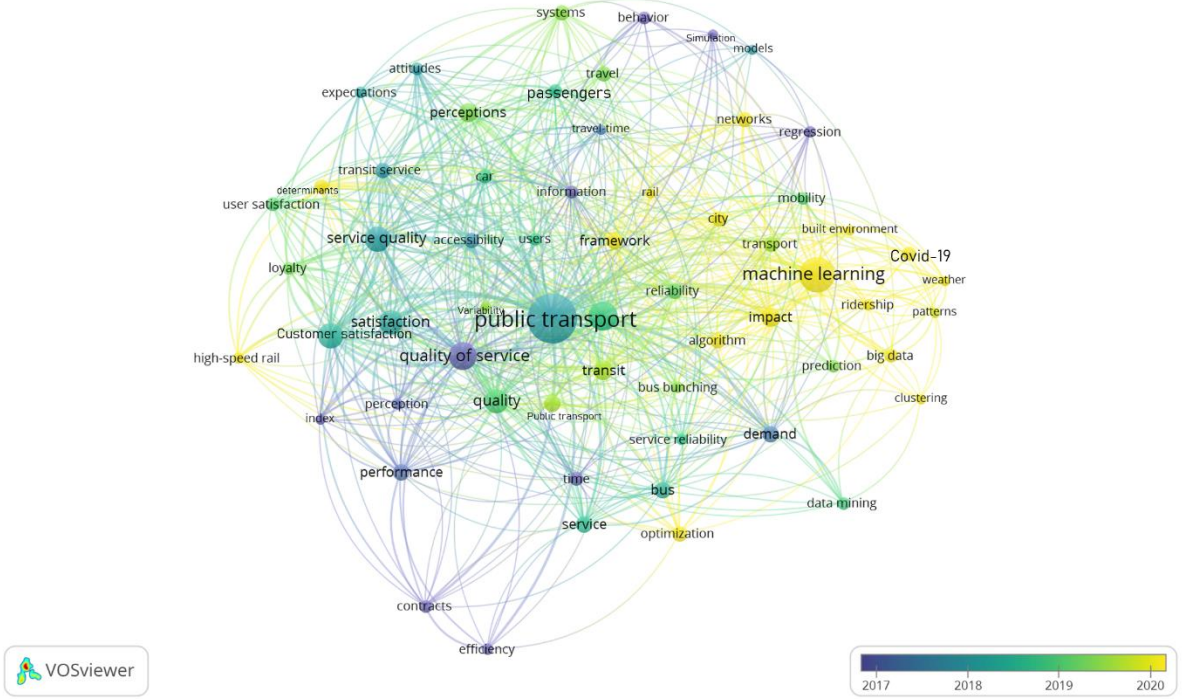

Figure 7: Emerging trends in research on the quality of service in public transport

The *navy blue cluster* indicate the trend topics in research on quality of service in public transport from 2017 to 2018. *A turquois blue cluster* presents trend topics from 2018 to 2019. In addition, 2019 to 2020 are presented by a *green cluster* while 2020 to 2022 presented by a *yellow cluster*. Research from 2017-2018 focused on quality of service, contracts, performance, perceptions, behaviour, and simulation. Between 2018 and 2019, most research was based on public transport, customer satisfaction, service, models, and expectations. In 2019 to 2020, research focused on user satisfaction, perceptions, systems, travel and transport.

Previous studies have focused more on efficiency in public transport for profitability (Pullen, 1993). However, the concern on service quality gained momentum around early 2000s. The emerging themes in research during that time shifted towards service delivery and attitudes among different passenger groups (Morton *et al*. 2016). The results from the study revealed that socio-economic cohorts influences travel behaviour and satisfaction. Thus, from 2017, the research focused more on building an improved public transport system for customer satisfaction. To achieve these, different methodologies such as modelling, simulations and regression were explored to find solutions to maximise user satisfaction (Tirachini *et al*. 2017; Ingvardson and Nielsen, 2019).

The emerging trends and future trends from 2020 focus on machine learning, in particular, frameworks, big data, impact, optimization, city, networks, and patterns. The emerging trends are due to the availability of big data (Mitroshin *et al*. 2022), concern about the lived experiences of public transport users (Yuxue *et al*. 2022), and the urge to shift from car ownership to public transport to solve issues that come with increased car ownership in cities (Goodarzian *et al.* 2023).

One study in particular by Liu (2020) leveraged a support vector machine to predict passenger flow. Results show that accurate predictions and early warning of passenger flow in a bus enabled the bus dispatchers to maintain efficient bus services. Aparicio *et al*. (2021); Bustamante *et al*. (2022) use machine learning to analyse travel patterns in public transport during the pandemic. The research focus does not incorporate issues on gender role in public transport. Socio- economic dynamics of a society shows a clear picture of the underlining issues. Thus, in the future more research on the gender dynamics in transportataion can be explored (Bustamante *et al*. 2022). Although research focusing on machine learning, service quality in public transport is increasing as discussed in this paper, there is limited research based on African cities.

Most of the emerging topics do not look at non-conventional modes of public transport like minibus taxis, yet, they form important part of mobility in African cities (Moyo *et al*. 2022). Additionally, availability of big data has also opened a door for researchers to use data from social media as a reliable data source to create new application in transport, analyse and predict human behavior (Tran, 2022). Furthermore, as stated by Wang *et al*. (2019) most of the research in this area should move towards integrating the use of machine learning through deep learning. Athough machine learning has done a lot of improvement in public transport system, research direction should move to harnessing the emerging AI and deep learning techniques in public transport research to find solutions and shortcomings of the public transport system (Farazi et al. 2022). Also, there is a need to train deep reinforcement learning agent in real life scenarios within public transport system (Farazi *et al*. 2021)

Conclusions

The paper provided a comprehensive transport literature and intensively examined literature pertaining to quality of service, gender and machine learning in public

transport. This review will be useful reference for transport and evolutions of quality of service in public transport research. Research in quality of service can be dated back to 1992 (Figure 1) in public transport. Around early 2011 and 2012, issues on gender and machine learning were introduced in public transport. The machine learning techniques act as a blueprint to potentially bridge the gap between realities vs. practice. De Oña *et al*. (2021) uses machine learning techniques in European cities to assess the relationship between service quality, satisfaction and loyalty in Public transport. The study marked a milestone for European policies in putting more enthuses on service quality in public transport.

In addition, introductions of algorithms paved the way for futuristic strategies, planning policies in public transport. Machine learning has proven to be a successful tool for mimicking and predicting realities in public transport (Guevara *et al*. 2020). Horcher and Tirachini (2021) state that although machine learning and modelling have been used over time, the concepts need to be further explored in the Public transport sector.

The gender dimensions in quality of service and public transport suggest that it has not been fully incorporated, because women and men experience public transport differently. Most of the research focus on gender to investigate customer satisfaction and expectation. These demonstrate a shift in research from public transport-orientated thinking to more concerns on user satisfaction (Díez-Mesa *et al*. 2018). These include understanding the socio-demographic background of both private and public transport users in understanding quality service satisfaction (Rasca and Saeed, 2022). It is expected that research on gender dimensions and machine learning in public transport will be expected to increase tremendously, especially amid SDGs and New Urban Agenda that strive for cities to join in the fight to achieve sustainability.

The Majority of the most influential publications are derived from countries in the global south, with only 2 articles published in Africa. The lack of research in Africa also opens a wide door for further research in the field of quality of service in public transport. The reseach will inform policy on the important attributes that users value to attract more people to use public transport.

Reference

Abenoza, R.F., Cats, O. and Susilo, Y.O. 2017. Travel satisfaction with public transport: Determinants, user classes, regional disparities and their evolution. *Transportation Research Part A*, 95, 64–84, http://dx.doi.org/10.1016/j.tra.2016.11.011.

Adom-Asamoah, G., Asibey, M.O. and Nyarko, S. 2021. Rethinking or Affirming the "Affordability" Debate on the Efficiency of Urban Public Transport Usage: Case of Kumasi, Ghana. *Transportation in Developing Economies*, 7(2), 1-14, https://doi.org/10.1007/s40890-021-00131-6.

Al Husaeni, D.F. and Nandiyanto, A.B.D. 2022. Bibliometric using Vosviewer with Publish or Perish (using google scholar data): From step-by-step processing for users to the practical examples in the analysis of digital learning articles in pre and post Covid-19 pandemic. *ASEAN Journal of Science and Engineering*, 2(1), 19-46.

Alicea, M., McDonald, A.P., Tang, C. and Yang, J. 2020. Exploring the Application of Machine Learning Algorithms to the City Public Bus Transport. In *2020 IEEE 14th International Conference on Big Data Science and Engineering (BigDataSE)*, 22-27.

Allam, Z and Sharif, A. 2022. Research Structure and Trends of Smart Urban Mobility. *Smart cities*, 5, 539-561, https://doi.org/10.3390/smartcities5020029.

Aparicio, J .T., Arsenio, E. and Henriques, R. 2021. Understanding the impacts of the COVID-19 pandemic on public transportation travel patterns in the City of Lisbon. *Sustainability,* 13(15), 1-18, https://doi.org/10.3390/su13158342

Arabikhan, F., Postorino, M.N., Dupont-Kieffer, A. and Gegov, A. 2016. Gender-based analysis of zones of tolerance for transit service quality considering intelligent transportation systems. *Transportation Research Record*, 2541(1), 73-80, https://0-doi-org.ujlink.uj.ac.za/10.3141%2F2541-09.

Bi, Q., Goodman, K.E., Kaminsky, J. and Lessler, J. 2019. What is machine learning? A primer for the epidemiologist. *American journal of epidemiology*, 188(12), 2222-2239, https://doi.org/10.1093/aje/kwz189.

527 Birkle, C., Pendlebury, D.A., Schnell, J. and Adams, J. 2020. Web of Science as a
528 data source for research on scientific and scholarly activity. *Quantitative*
529 *Science Studies*, 1(1), 363-376, https://doi.org/10.1162/qss_a_00018.

530 Bustamante, X., Federo, R. and Fernández-i-Marin, X. 2022. Riding the wave:
531 Predicting the use of the bike-sharing system in Barcelona before and during
532 COVID-19. *Sustainable Cities and Society*, 83, 1-16,
533 https://doi.org/10.1016/j.scs.2022.103929.

534 Bustamante, X., Federo, R. and Fernández-i-Marin, X. 2022. Riding the wave:
535 Predicting the use of the bike-sharing system in Barcelona before and during
536 COVID-19. *Sustainable Cities and Society*, 83, 1-15,
537 https://doi.org/10.1016/j.scs.2022.103929

538 Cantillo, A., Raveau, S. and Muñoz, J.C. 2022. Fare evasion on public transport: Who,
539 when, where and how? *Transportation Research Part A: Policy and Practice*,
540 156, 285-295, https://0-doi-org.ujlink.uj.ac.za/10.1016/j.tra.2021.11.027.

541 Ceccato, V., Gaudelet, N. and Graf, G. 2021. Crime and safety in transit environments:
542 a systematic review of the English and the French literature, 1970–2020. *Public*
543 *transport*, 1, 1-49, https://doi.org/10.1007/s12469-021-00265-1.

544 Chaudhary, M.L. 2020. Commuters' perceptions on service quality of bus rapid transit
545 systems: Evidence from the cities of Ahmedabad, Surat and Rajkot in
546 India. *Eur. Transp./Trasp. Eur*, *79*, 1-16.

547 Chen, J.P., Yan, N., Lin, S.L. and Chen, S.J. 2022. Comparative Analysis of the
548 Influence of Transport Modes on Tourism: High-Speed Rail or Air? City-Level
549 Evidence from China. *Transportation Research Record*, 1–13,
550 https://doi.org/10.1177/03611981221106476.

551 Chun-xiao, Z., Yao, L., Yang, W., Ya-fei, Y., Xiao, H. and Ya-juan, Z. 2020. Research
552 status of transportation field based on keyword co-occurrence analysis. *IOP*
553 *Conf. Series: Earth and Environmental Science*, 587, 1-12,
554 https://doi:10.1088/1755-1315/587/1/012093.

555 Ciancia, V., Gilmore, S., Grilletti, G., Latella, D., Loreti, M. and Massink, M. 2018.
556 Spatio-temporal model checking of vehicular movement in public transport

557 systems. *International Journal on Software Tools for Technology Transfer*, 20,
558 289–311, https://doi.org/10.1007/s10009-018-0483-8.

559 Dashdamirov, F., Javadli, U. and Verdiyev, T. 2022. Comparative analysis of the
560 weight and quality of urban bus transport services: a case study of Baku.
561 Zeszyty Naukowe. *Scientific Journal of Silesian University of Technology*, 116,
562 99-111, https://doi.org/10.20858/sjsutst.2022.116.6.

563 Daziano, R.A. and Rizzi, L.I. 2015. Analyzing the impact of a fatality index on a
564 discrete, interurban mode choice model with latent safety, security, and
565 comfort. *Safety science*, 78, 11-19.

566 De Oña, J. 2021. Understanding the mediator role of satisfaction in public transport: A
567 cross-country analysis. *Transport policy*, 100, 129-149,
568 https://doi.org/10.1016/j.tranpol.2020.09.011.

569 De Oña, J. and De Oña, R. 2015. Quality of service in public transport based on
570 customer satisfaction surveys: A review and assessment of methodological
571 approaches. *Transportation Science*, 49(3), 605-622,
572 https://doi.org/10.1287/trsc.2014.0544

573 De Oña, J., De Oña, R., Eboli, L. and Mazzulla, G. 2013. Perceived service quality in
574 bus transit service: A structural equation approach. *Transport policy*, 29, 219-
575 226, http://dx.doi.org/10.1016/j.tranpol.2013.07.001.

576 De Oña, J., Est´evez, E. and De Oña, R. 2021. Public transport users versus private
577 vehicle users: Differences about quality of service, satisfaction and attitudes
578 toward public transport in Madrid (Spain). *Travel Behaviour and Society*, 23,
579 76-85, https://doi.org/10.1016/j.tbs.2020.11.003.

580 De Oña, J., Estévez, E. and De Oña, R. 2021. How does private vehicle users perceive
581 the public transport service quality in large metropolitan areas? A European
582 comparison. *Transport Policy*, 112, 173-188,
583 https://doi.org/10.1016/j.tranpol.2021.08.005.

584 De Oña, J., Estévez, E. and De Oña, R. 2021. Public transport users versus private
585 vehicle users: Differences about quality of service, satisfaction and attitudes

toward public transport in Madrid (Spain). *Travel Behaviour and Society*, 23, 76-85, https://doi.org/10.1016/j.tbs.2020.11.003.

De Vos, J., Le, H.T. and Kroesen, M. 2022. Does commute duration attenuate the effect of travel mode choice on commute satisfaction? *Travel behavior and society*, 28, 13-21, https://doi.org/10.1016/j.tbs.2022.02.004.

Dell'Olio, L., Ibeas, A. and Cecin, P. 2011. The quality of service desired by public transport users. *Transport Policy*, 18(1), 217-227, https://doi:10.1016/j.tranpol.2010.08.005.

Díez-Mesa, F., De Oña, R. and De Oña, J. 2018. Bayesian networks and structural equation modelling to develop service quality models: Metro of Seville case study. *Transportation Research Part A: Policy and Practice,* 118, 1-13. https://doi.org/10.1016/j.tra.2018.08.012.

Dong, X. 2018. High-speed railway and urban sectoral employment in China. *Transportation Research Part A: Policy and Practice*, 116, 603-621, https://doi.org/10.1016/j.tra.2018.07.010.

Efthymiou, D. and Antoniou, C. 2017. Understanding the effects of economic crisis on public transport users' satisfaction and demand. *Transport Policy*, 53, 89-97, http://dx.doi.org/10.1016/j.tranpol.2016.09.007.

Efthymiou, D., Antoniou, C., Tyrinopoulos, Y. and Skaltsogianni, E. 2018. Factors affecting bus users' satisfaction in times of economic crisis. *Transportation Research Part A: Policy and Practice*, 114, 3-12, https://0-doi-org.ujlink.uj.ac.za/10.1016/j.tra.2017.10.002.

El Mahrsi, M.K., Come, E., Oukhellou, L. and Verleysen, M. 2017. Clustering Smart Card Data for Urban Mobility Analysis*. IEEE Transactions on Intelligent Transportation Systems,* 18(3), 712-728.

Farazi, N.P., Murshed, M.N. and Hadiuzzaman, M. 2022. Application of machine learning to investigate heterogeneity in users' perception of intercity train service quality in developing countries. *Case Studies on Transport Policy*, 10(1), 227-238, https://doi.org/10.1016/j.cstp.2021.12.004.

615 Farazi, N.P., Zou, B., Ahamed, T. and Barua, L. 2021. Deep reinforcement learning in
616 transportation research: A review. *Transportation research interdisciplinary*
617 *perspectives*, 11, 1-21, https://doi.org/10.1016/j.trip.2021.100425.

618 Freitas, A.L.P., Silva Filho, M.T.S. and de Assis, D.A., 2023. An analysis of gender
619 differences and perception of influential criteria for the quality of urban bus
620 transportation: Evidence from Brazil. *Journal of Public Transportation*, 25, 1-12,
621 https://doi.org/10.1016/j.jpubtr.2023.100050.

622 Friman, M., Gärling, T. and Ettema, D. 2019. Improvement of public transport services
623 for non-cycling travelers. *Travel Behaviour and Society*, 16, 235-240,
624 https://doi.org/10.1016/j.tbs.2018.03.004.

625 Gkiotsalitis, K. and Liu, T. 2022. Periodic Optimization of Bus Dispatching Times and
626 Vehicle Schedules Considering the COVID-19 Capacity Limits: A Dutch Case
627 Study. *Transportation Research Record*, 1–13,
628 https://doi.10.1177/03611981221114119

629 Goodarzian, F., Ghasemi, P., Muñuzuri, J. and Abraham, A. 2023. Challenges to the
630 sustainable development of vehicle transport. *Advancement in Oxygenated*
631 *Fuels for Sustainable Developme*nt, 183-197, https://doi.org/10.1016/B978-0-
632 323-90875-7.00011-3.

633 Guevara, C.A., Tirachini, A., Hurtubia, R. and Dekker, T. 2020. Correcting for
634 endogeneity due to omitted crowding in public transport choice using the
635 Multiple Indicator Solution (MIS) method. *Transportation Research Part A:*
636 *Policy and Practice*, 137, 472-484, https://doi.org/10.1016/j.tra.2018.10.030.

637 Hagenauer, J. and Helbich, M. 2017. A comparative study of machine learning
638 classifiers for modeling travel mode choice. *Expert Systems with*
639 *Applications*, *78*, 273-282, https://0-doi-
640 org.ujlink.uj.ac.za/10.1016/j.eswa.2017.01.057.

641 Haghighi, N.N., Liu, X.C., Wei, R., Li, W. and Shao, H. 2018. Using Twitter data for
642 transit performance assessment: a framework for evaluating transit riders'
643 opinions about quality of service. *Public Transport*, 10, 363-377,
644 https://doi.org/10.1007/s12469-018-0184-4.

He, P., Jiang, G. Lam, S. and Sun, Y. 2022. ML-MMAS: Self-learning ant colony optimization for multi-criteria journey planning. *Information Sciences*, 609, 1052-1074, https://doi.org/10.1016/j.ins.2022.07.150.

Holmgren, J. 2007. Meta-analysis of public transport demand. Transportation Research Part A, 1021–1035, https://doi:10.1016/j.tra.2007.06.003.

Hörcher, D. and Tirachini, A. 2021. A review of public transport economics. *Economics of Transportation*, 25, 1-34, https://doi.org/10.1016/j.ecotra.2021.100196.

Hu, N., Legara, E.F., Lee, K.K., Hung, G.G. and Monterola, C. 2016. Impacts of land use and amenities on public transport use, urban planning and design. *Land use policy*, *57*, 356-367, http://dx.doi.org/10.1016/j.landusepol.2016.06.004.

Ijaz, M., Zahid, M. and Jamal, A. 2021. A comparative study of machine learning classifiers for injury severity prediction of crashes involving three-wheeled motorized rickshaw. *Accident Analysis & Prevention*, 154, 1-13, https://doi.org/10.1016/j.aap.2021.106094.

Ingvardson, J.B. and Nielsen, O.A. 2019. The relationship between norm, satisfaction and public transport use: A comparison across six European cities using structural equation modelling. *Transportation research part A: Policy and practise*, 126, 37-57.

Irtema, H.I.M., Ismail, A., Borhan, M.N., Das, A.M. and Alshetwi, A.B.Z. 2018. Case study of the behavioural intentions of public transportation passengers in Kuala Lumpur. *Case Studies on Transport Policy*, 6, 462-474, https://doi.org/10.1016/j.cstp.2018.05.007.

Islam, M.F., Fonzone, A., MacIver, A. and Dickinson, K. 2020. Use of ubiquitous real-time bus passenger information. *IET Intelligent Transport Systems*, *14*(3), 139-147.

Joewono, T.B. and Kubota, H. 2007. User satisfaction with paratransit in competition with motorization in Indonesia: anticipation of future implications. *Transportation,* 34, 337–354, https://doi.10.1007/s11116-007-9119-7

Kumar Sood, S., Kumar, N. and Saini, M. 2021. Scientometric analysis of literature on distributed vehicular networks: Vosviewer visualization techniques. Artificial

675 Intelligence Review, 54, 6309–6341, https://doi.org/10.1007/s10462-021-
676 09980-4.

677 Lawrence, M., Bullock, R. and Liu, Z. 2019. *China's high-speed rail development*.
678 Washington: World Bank Publications.

679 Liu, W., Tan, Q. and Wu, W. 2020. Forecast and early warning of regional bus
680 passenger flow based on machine learning. *Mathematical Problems in*
681 *Engineering*, 1-12, https://doi.org/10.1155/2020/6625435.

682 Luke, R. and Heyns, G.J. 2020. An analysis of the quality of public transport in
683 Johannesburg, South Africa using an adapted SERVQUAL model.
684 *Transportation Research Procedia*, 48, 3562-3576,
685 https://doi.org/10.1016/j.trpro.2020.08.095.

686 Machado, J.L., de Oña, R., Diez-Mesa, F. and de Oña, J. 2018. Finding service quality
687 improvement opportunities across different typologies of public transit
688 customers. *Transportmetrica A: Transport Science*, 14(9), 761-783,
689 https://doi.org/10.1080/23249935.2018.1434257.

690 Mendes-Moreira, J., Jorge, A.M., de Sousa, J.F. and Soares, C. 2012. Comparing
691 state-of-the-art regression methods for long term travel time
692 prediction. *Intelligent Data Analysis*, *16*(3), 427-449.

693 Milioti, C., Panoutsopoulos, A., Kepaptsoglou, K. and Tyrinopoulos, Y. 2020. Key
694 drivers of fare evasion in a metro system: Evidence from Athens, Greece. *Case*
695 *Studies on Transport Policy*, 8(3), 778-783, https://0-doi-
696 org.ujlink.uj.ac.za/10.1016/j.cstp.2020.06.005.

697 Mitroshin, P., Shitova, Y., Shitov, Y., Vlasov, D. and Mitroshin, A. 2022. Big data and
698 data mining technologies application at road transport logistics. *Transportation*
699 *Research Procedia*, *61*, pp.462-466, https://10.1016/j.trpro.2022.01.075.

700 Moghayedi, A., Mehmood, A., Matsika, E., Vanderschuren, M., Le Jeune, K., Ekpo,
701 C.O. and Chukwueke, I., 2023. Appraising the nexus between influencers on
702 the public transport choice by women commuters in South Africa. *Scientific*
703 *African*, 21, 1-16, https://doi.org/10.1016/j.sciaf.2023.e01820

704 Moher, D., Stewart, L. and Shekelle, P. 2016. Implementing PRISMA-P:
705 recommendations for prospective authors. *Systematic reviews*, *5*(15), 1-2,
706 https://doi.10.1186/s13643-016-0191-y.

707 Mongeon, P. and Paul-Hus, A., 2016. The journal coverage of Web of Science and
708 Scopus: a comparative analysis. *Scientometrics,* 106(1), 213-228,
709 https://doi.10.1007/s11192-015-1765-5

710 Moore, S. 2011. Providing drug and alcohol services to female offenders: exploring
711 gender and geographical barriers. *Drugs and Alcohol Today*, Emerald Group
712 Publishing Limited.

713 Moreira-Matias, L., Cats, O., Gama, J., Mendes-Moreira, J. and De Sousa, J.F. 2016.
714 An online learning approach to eliminate Bus Bunching in real-time. *Applied*
715 *Soft Computing*, *47*, 460-482.

716 Morton, G. 2018. Appraising the market for bicycle sharing schemes: Perceived
717 service quality, satisfaction, and behavioural intention in London. *Case Studies*
718 *on Transport Policy*, 6, 102-111, https://doi.org/10.1016/j.cstp.2017.11.003.

719 Morton, G., Caulfield, D. and Anable, J. 2016. Customer perceptions of quality of
720 service in public transport: Evidence for bus transit in Scotland. Case Studies
721 on Transport Policy, 4, 199-207, http://dx.doi.org/10.1016/j.cstp.2016.03.002

722 Moyo, T., Mbatha, S., Aderibigbe, O.O., Gumbo, T. and Musonda, I. 2022. Assessing
723 spatial variations of traffic congestion using traffic index data in a developing
724 city: lessons from Johannesburg, South Africa. *Sustainability*, 14(14), 1-16,
725 https://doi.org/10.3390/su14148809.

726 Mugion, R.G., Toni, M., Raharjo, H., Di Pietro, L. and Sebathu, S.P. 2018. Does the
727 service quality of urban public transport enhance sustainable mobility? *Journal*
728 *of Cleaner Production,* 174, 1566-1587,
729 https://doi.org/10.1016/j.jclepro.2017.11.052.

730 Nyathi, N.A., Musakwa, W., Delzeit, R. and Kuhn, N.J. 2022. Ecosystem Services in
731 Southern Africa: Current and Emerging Trends: A Bibliometric Review.
732 *Diversity*, 14(5), 1-22, https://doi.org/10.3390/d14050359.

733 Okoroafor, E.R., Smith, C.M., Ochie, K.I., Nwosu, C.J., Gudmundsdottir, H. and
734 Aljubran, M.J. 2022. Machine learning in subsurface geothermal energy: Two
735 decades in review. *Geothermics*, *102*, 2-16.

736 Oort, N. and Yap, M. 2021. Innovations in the appraisal of public transport projects.
737 *Advances in Transport policy and planning*, 7, 127-164,
738 https://doi.org/10.1016/bs.qtpp.2020.07.008.

739 Page, M.J., McKenzie, J.E., Bossuyt, P.M., Boutron, I., Hoffmann, T.C., Mulrow, C.D.,
740 Shamseer, L., Tetzlaff, J.M., Akl, E.A., Brennan, S.E. and Chou, R., 2021. The
741 PRISMA 2020 statement: an updated guideline for reporting systematic
742 reviews. *International journal of surgery*, 88, 1-9,
743 https://doi.org/10.1016/j.ijsu.2021.105906.

744 Park, J. and Chowdhury, S. 2018. Investigating the barriers in a typical journey by
745 public transport users with disabilities. *Journal of Transport & Health*, 10, 361-
746 368, https://doi.org/10.1016/j.jth.2018.05.008.

747 Paulley, N., Balcombe, R., Mackett, R., Titheridge, H., Preston, J., Wardman, M.,
748 Shires, J. and White, P. 2006. The demand for public transport: The effects of
749 fares, quality of service, income and car ownership. *Transport policy*, 13(4),
750 295-306.

751 Peng, G.C., Alber, M., Buganza Tepole, A., Cannon, W.R., De, S., Dura-Bernal, S.,
752 Garikipati, K., Karniadakis, G., Lytton, W.W., Perdikaris, P. and Petzold, L.,
753 2021. Multiscale modeling meets machine learning: What can we learn?.
754 Archives of Computational Methods in Engineering, 28, 1017-1037.

755 Pullen, W.T. 1993. Definition and measurement of quality of service for local public
756 transport management. *Transport reviews*, 13(3), 247-264.

757 Rasca, S. and Saeed, N. 2022. Exploring the factors influencing the use of public
758 transport by commuters living in networks of small cities and towns. *Travel*
759 *Behaviour and Society*, 28, 249-263, https://doi.org/10.1016/j.tbs.2022.03.007.

760 Salva, R.J., Sierra, M., Alanis, A.K.J., Kaplan, S. and Prato, C.G. 2015. Role of Social
761 Climate in Habitual Transit Use by Young Adults to Work and Leisure Activities:

762 Evidence from Colombia and Mexico. *Transportation Research Record*, 2512,
763 22-30, https://doi.10.3141/2512-03.

764 Selcuk, A.A. 2019. A guide for systematic reviews: PRISMA. *Turkish archives of*
765 *otorhinolaryngology*, 57(1), 57.

766 Sholevar, N., Golroo, A. and Esfahani, S.R. 2022. Machine learning techniques for
767 pavement condition evaluation. *Automation in Construction*, *136*, 1-17,
768 https://doi.org/10.1016/j.autcon.2022.104190.

769 Singh, N. and Kumar, K. 2022. A review of bus arrival time prediction using artificial
770 intelligence. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge*
771 *Discovery*, 1-29, https://doi.org/10.1002/widm.1457

772 Soegoto, H., Soegoto, E.S., Luckyardi, S. and Rafdhi, A.A. 2022. A bibliometric
773 analysis of management bioenergy research using Vosviewer application.
774 *Indonesian Journal of Science and Technology*, 7(1), 89-104,
775 http://ejournal.upi.edu/index.php/ijost/.

776 Soosaraei, M., Khasseh, A.A., Fakhar, M. and Hezarjaribi, H.Z., 2018. A decade
777 bibliometric analysis of global research on leishmaniasis in Web of Science
778 database. *Annals of medicine and Surgery*, 26, 30-37,
779 https://doi.org/10.1016/j.amsu.2017.12.014.

780 Tirachini, A., Godachevich, J., Cats, O., Muñoz, J.C. and Soza-Parra, J. 2021.
781 Headway variability in public transport: a review of metrics, determinants,
782 effects for quality of service and control strategies. *Transport Reviews*, 1-25,
783 https://www.tandfonline.com/action/showCitFormats?doi=10.1080/01441647.2
784 021.1977415.

785 Tirachini, A., Hurtubia, R., Dekker, T. and Daziano, R.A. 2017. Estimation of crowding
786 discomfort in public transport: Results from Santiago de Chile. *Transportation*
787 *Research Part A: Policy and Practice*, 103, 311-326,
788 https://doi.org/10.1016/j.tra.2017.06.008.

789 Tran, M., Draeger, C., Wang, X. and Nikbakht, A. 2022. Monitoring the well-being of
790 vulnerable transit riders using machine learning based sentiment analysis and
791 social media: Lessons from COVID-19. Environment and Planning B: Urban

792 Analytics and City Science. *EPB: Urban Analytics and City Science*, 0(0), 1-16,
793 https://0-doi-org.ujlink.uj.ac.za/10.1177%2F23998083221104489

794 Van Nunen, K., Li, J., Reniers, G. and Ponnet, K. 2018. Bibliometric analysis of safety
795 culture research. *Safety science*, 108, 248-258,
796 https://doi.org/10.1016/j.ssci.2017.08.011.

797 Wang, Y., Zhang, D., Liu, Y., Dai, B. and Lee, L.H. 2019. Enhancing transportation
798 systems via deep learning: A survey. *Transportation research part C: emerging*
799 *technologies*, 99, 144-163, https://doi.org/10.1016/j.trc.2018.12.004.

800 Wei, H., Bao, H. and Ruan, X. 2022. Perspective: predicting and optimizing thermal
801 transport properties with machine learning methods. *Energy and AI*, 1-36,
802 https://doi.org/10.1016/j.egyai.2022.100153.

803 Yu, Y., Li, Y., Zhang, Z., Gu, Z., Zhong, H., Zha, Q., Yang, L., Zhu, C. and Chen, E.
804 2020. A bibliometric analysis using VOSviewer of publications on COVID-
805 19. *Annals of translational medicine*, *8*(13).

806 Yuan, Y., Shao, C., Cao, Z., He, Z., Zhu, C., Wang, Y. and Jang, V. 2020. Bus dynamic
807 travel time prediction: Using a deep feature extraction framework based on rnn
808 and dnn. *Electronics*, *9*(11), 1-20, https://doi:10.3390/electronics9111876.

809 Yuxue, B., Bingchen, G., Jianjie, C., Wenzhe, C., Hang, Z. and Chen, C. 2022. Sitting
810 comfort analysis and prediction for high-speed rail passengers based on
811 statistical analysis and machine learning. *Building and Environment*, 225, 1-12,
812 https://doi.org/10.1016/j.buildenv.2022.109589.

813 Zhang, R., Lin, J., Chen, F. and Chen, M. 2021. Worldwide Trends of Research on
814 Periprosthetic Osteolysis: A Bibliometric Study Based on VOSviewer. *Indian*
815 *Journal of Orthopaedics*, *55*(5), 1326-1334, https://doi.org/10.1007/s43465-
816 021-00462-x.

817 Zheng, Y., Kong, H., Petzhold, G., Barcelos, M.M., Zegras, C.P. and Zhao, J., 2022.
818 Gender differences in the user satisfaction and service quality improvement
819 priority of public transit bus system in Porto Alegre and Fortaleza, Brazil. *Travel*
820 *Behaviour and Society*, 28, 22-37, https://doi.org/10.1016/j.tbs.2022.02.003.

821 Zhou, X., Guan, Z., Xi, J. and Wei, G. 2021. Public transportation operational health
822 assessment based on multi-source data. *Applied Sciences*, 11(22), 1-18,
823 https://doi.org/10.3390/app112210611.

824 Zhu, J. and Liu, W. 2020. A tale of two databases: The use of Web of Science and
825 Scopus in academic papers. *Scientometrics*, 123, 321-335.