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A bibliometric analysis and network visualisation of human mobility studies from 1990 to 2020: emerging trends and future research directions

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Abstract: Studies on human mobility have a long history with increasingly strong connections to multi-disciplines across social science, environmental science, information and technology, computer science, engineering, and health science. However, what is lacking in the current research is a summary of studies on human mobility to identify the evolutional pathway and future research directions. To address this gap, we conduct a systematic review of human mobility-related studies published from 1990 to 2020. Drawing on the selected publications retrieved from the Web of Science, we conduct a bibliometric analysis and network visualisation by CiteSpace and VOSviewer on publication years and numbers, authors and their countries and afflictions, citations, topics, abstracts, keyword, and journals. Our findings show that human mobility-related studies have become increasingly interdisciplinary and multi-dimensional, enhanced by the involvement of multi-source big data, the development of technologies, the innovation of modelling approaches, and the novel applications in various areas. We also summarise four future research directions proposed by top cited authors and mobility studies, in terms of data sources, modelling methods, applications, and technologies. We advocate in-depth research on human mobility to address real-world problems and contribute to social good as promising future orientations through integrating multi-source big data and advanced modelling methods facilitated by artificial intelligence, and machine and deep learning.

Keywords: Human mobility, literature review, bibliometric analysis, network visualisation, CiteSpace, VOSviewer

1. Introduction

Human mobility is one of the typical human behaviours in daily life. With the prevalence of diverse transport modes, human populations have become highly mobile in this modern world (Hasan et al., 2013). Understanding the pattern of human mobility serves as the foundation to reveal how people respond to and interact with urban and natural environment, to develop valuable applications in transportation, urban planning, epidemic disease controlling, and natural disaster evaluation (Gonzalez et al., 2008). As such, human mobility-related (HMR) studies have gained increasing attention from scholars in multiple disciplines and have become highly diverse in terms of its theoretical foundation, modelling techniques, empirical studies, and practical applications. However, a systematic literature review of HMR studies is lacking to have a holistic understanding of emerging trends, research hot spots and frontiers, and to guide and explore future research through the next research agenda.

HMR studies have been highly multi-disciplinary and are currently facing a period of intensive reorientation. Information and computer science, engineering, mathematical science, and physical science have more interests of modelling the pattern of human mobility (Barbosa et al., 2018); while social, environmental, biological, geographic, medical and health sciences more emphasise the relationship between human mobility and environmental factors, offering a wide range of applications in urban planning, infrastructure configuration, disaster prevention, and transport forecasting (Pappalardo et al., 2019). With the development of information and communication technologies in the past decade, human mobility patterns have significantly changed as the penetration of Internet and mobile devices make interpersonal communications much easier than before (Jurdak et al., 2015). The increase of transport networks and modes (e.g., low-cost air flights, high-speed trains, and sharing vehicles) makes travel more convenient (Song et al., 2016). Such technologies, in turn, largely enrich HMR studies by widely applied location-aware devices, the emerging sources of big data, and multi-scale modelling techniques. As such, there is a pressing need to examine the emerging trends of HMR studies to identify knowledge gaps where further studies are most needed and to propose future research initiatives and agenda.

This study aims to address the above need by 1) conducting a bibliometric analysis of HMR publications from 1990 to 2020; 2) visualising the network of HMR publications; 3) revealing research hot spots and frontiers; and 4) charting a future research agenda. Methodologically, we collect HMR literature in the Web of Science from 1990 to 2020 as the research object and uses the information visualisation software CiteSpace and VOSviewer to identify research hot spots, evolving trends, frontiers, and the connections of HMR studies to other disciplines. Our study not only provides a holistic picture of authors, institutes, countries, keywords, and categories of the current scholarship for researchers in the field of human mobility, but also depicts the connections of co-citation references, co-authorship and co-occurring keywords to guide those who have the interests to be engaged in this field. Based on the future work recommended by the top cited authors and current studies, we propose future directions towards which we can orientate our collective effort in human mobility research.

The rest of this paper is organised as below. The next section describes the data and methods used in this study. Then the analytical results are presented in terms of a summary description of HMR literature from 1990 to 2020, and the network visualisation of co-citations, co-authorships, and co-occurring keywords to reveal emerging trends, research hot spots and frontiers. Then future directions in terms of data sources, modelling approaches, applications and technologies are discussed together with a conclusive remark at the end.

2. Background

2.1 Human mobility-related studies

HMR studies have a long history dating back to the featured work about population mobility in the U.S. by Hugher, and the measures of intra-urban mobility by Corbally, both in 1930 (Hugher, 1930; Corbally, 1930). The information of human mobility can directly indicate the patterns of people's travel behaviour and moving trajectory, which could also indirectly reflect their travel preferences, living styles and habits, residential decisions, and psychological response to the surrounding environment (Bañgate et al., 2017). Due to the essential nature of human mobility, studies on human mobility have been multi-disciplinary and conducted in a wide range of research paradigms, including social science, environmental science, information and computer science, engineering, mathematical science, and physical science, biological science, and medical and health science (Web of Science, 2020). As human populations become highly mobile in the modern world with the prevalence of diverse transport modes, measuring human mobility serves as the essential method to study how human beings respond to and interact with urban and natural environment (Wang et al., 2011). Human mobility is normally quantified in both spatial and temporary dimensions based on the individual's trajectory of moves or the mobility flow between locations at the aggregated population level which can be further calculated as location-based mobility index (Zhao et al., 2016). HMR studies have different emphasis in different disciplines. HMR studies integrating into the field of information and computer science, engineering, mathematical science, and physical science have contributed a wide range of measuring and modelling approaches to capture human mobility patterns at both the individual and aggregated population level (Barbosa et al., 2018). Whereas, HMR studies in the field of social, environmental, biological, geographic, medical and health sciences have research focus on the relationship between human mobility and urban and natural environment, providing policy implications in urban planning, infrastructure configuration, disaster prevention, and transport forecasting (Pappalardo et al., 2019). Understanding the inter- and intra-disciplinary connections in HMR studies is important to explore the future research paradigm, which, however, has been rarely addressed in current scholarship – the knowledge gap that this study aims to fulfil.

With the development of information and communication technologies in the past decade, human mobility patterns have significantly changed as the penetration of Internet and mobile devices make interpersonal communications much easier than before (Jurdak et al., 2015) and the increase of transport networks and modes (e.g., low-cost air flights, high-speed trains, and sharing vehicles) makes travel more convenient (Song et al., 2016). Such technologies, in turn, largely enrich human mobility-related studies by widely-applied location-aware devices (e.g., smartphones and GPS receivers), the emerging sources of big data (e.g., from social media and transport smart-card), and multi-scale modelling techniques (e.g., from a population to individual level). As such, a systematic review of the HMR literature is needed to reveal the emerging trends of HMR studies and to propose future research initiatives and directions to extend the current research scope.

2.2 Bibliometric analyses and network visualisation for literature review

Methodologically, a bibliometric analysis is widely used for systematic literature review based on the number of citations to assess the importance and impact of publications and their connections with other disciplines (Ellegaard & Wallin, 2015). As one cornerstone of the development of science, scholarly citations are generally treated as an indication of the knowledge flow from the cited entity to the citing one in terms of how, why, and at what rate new ideas and technologies spread through a certain research domain knowledge (Jaffe & Trajtenberg, 1999). Specifically, the cited and citing entities are usually considered as the source and target of diffusion. As such, a variety of quantitative diffusion indicators has been used to describe the diffusion characteristics of knowledge production and to evaluate the impact of research, including citation counts, journal impact factors, field diffusion intensity, the countries and institutions of researchers (Börner et al., 2006).

Based on these indicators, a wide range of software tools have been developed to assist scientists to visualise the diffusion of knowledge and reveal the network pattern of citations, including CiteSpace developed by Chaomei Chen (2006), and VOSviewer developed by Nees Jan van Eck and Ludo Waltman (2010). Both are open-source software tools for analysing, detecting and visualizing trends and patterns in scientific literature. CiteSpace is available to analyse English and non-English literature based on multiple databases of scholarly publications; while VOSviewer is only available for English literature but with additional functions that CiteSpace does not have (e.g., density mapping). Therefore, our study uses both tools to conduct bibliometric analysis.

3. Materials and methods

3.1 Review materials

The data used in this study is collected from the Web of Science (WOS) Core Collection including science citation index expanded (SCI-Expanded) and social science citation index (SSCI). The timespan

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for search is set from 1990 to 2020 given that the number of publications per annual before 1990 is relatively small. The topic search consists of titles, abstracts, and keywords containing the term of *human mobility*, *mobility pattern*, *human trajectory*, *human migration*, *human immigration*, *population migration*, *population immigration*, *population mobility*, *rural mobility*, *urban mobility*, *migration flow*, *immigration flow*, *mobility network*, *migration network*, and *immigration network*. When inputting terms in the search box, these terms are enclosed in double quotation marks to ensure the search results must contain the same terms in titles, abstracts or keywords. This way of inputting search terms excludes search biases containing strings of a term in a different sequence, such as the topic '*human* reaction to high *mobility* group proteins…' which is beyond the scope of this literature review. Publication types are set to include all types (Table 1). Searching with the above criteria results in 5,728 publications with all types of documents, which are further exported with full records and cited references in a plain text format for further analysis.

Table 1. Research protocol

Research protocol	**Detail description**
Research database	WOS core collection: SCI-Expanded and SSCI
Publication type	All types: articles, review and editorial, conference proceeding papers, book chapters and review, meeting abstract, data papers, reprints, letters, correction and retracted publications.
Language	English
Year range	1990 to 2020 September
Search field	Topic including titles, abstracts, and keywords
Search term	Human mobility; mobility pattern; human trajectory; human migration; human immigration; population migration; population immigration; population mobility; rural mobility; urban mobility; migration flow; immigration flow; mobility network; migration network; immigration network
Data extraction	Export with full records and cited references in plain text format
Data analysis and visualisation	CiteSpace, VOSviewer
Sample size	5,728 publications

3.2 Methods

We commence with a descriptive summary of the bibliographic records in terms of the publication years, types, categories, institutes, and the most productive authors. Then two visualisation tools, CiteSpace (Chen, 2006) and VOSviewer (Van Eck & Waltman, 2010), are used to visualise the emerging trends of the HMR literature, research hot spots, and research frontiers. CiteSpace as a Java visualisation application relies on three central concepts: burst detection, betweenness degree (or centrality), and heterogeneity. The technical details and measures of these three concepts can be found in the user guideline by Chen (Chen, 2006). In general, burst detection is used to identify the nature of research hot spots and to detect sharp increases and changes of research interests in a speciality; betweenness degree can reflect the popularity or importance of nodes in a network; heterogeneity is used to identify the tipping points of research fields, and detect emerging trends and abrupt changes (Chen, 2006). The analytical procedure in CiteSpace consists of time slicing, burst and node defining, modelling, thresholding, and mapping. In our study, we define time-slicing as one-year interval, meaning all statistics are calculated every year. Burst terms are defined as keywords, abstracts, titles, institutes, countries, and categories of the bibliographic records, respectively. Nodes are defined to represent the betweenness degree (or centrality) of these burst terms. Then, the visualisation is conducted based on these settings with a threshold of presentation set to be minimum, only showing up the top 10% burst terms. Mapping layout is set as a network mode for authors, institutes, countries, abstracts, and a timeline mode for keywords to better illustrate its change over time. Furthermore, VOSviewer obsesses similar functions as CiteSpace but has one additional function of density mapping based on the

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frequency of a certain attribute such as keywords or authors (Van Eck and Waltman, 2010). We use both CiteSpace and VOSviewer to present the outcomes of bibliometric analyses, considering their complementary advantages.

The analytic workflow consists of four sets of bibliometric analyses in terms of the features of HMR publications, co-citation references, co-authorship, and co-occurring (Figure 1). First, a descriptive analysis of the selected 5,728 HMR publications is conducted based on year, type, author, category, and institute of publications. Second, co-citation references refer to two papers that appeared simultaneously in the third paper's citations. Accordingly, two articles are defined as having a co-citation relationship if they are cited by one or more articles at the same time. A co-citation reference analysis serves as an important indicator to detect the structure and characteristics of a specific domain. In this review, all publications are detected in several clusters (as the top 10% visibility setting) based on the research category with the most popular abstract and title terms shown in the map simultaneously. In addition, the top journals of co-citations and the top 10 most cited publications are analysed. Third, a co-authorship analysis is conducted based on the name of co-authors appearing in co-citation references, reflecting the most influential authors and the strength of research collaborations across countries and institutes. In this review, the nodes in the network are set to betweenness centrality to represent the importance of countries or institutes in the co-authorship network. Fourth, a co-occurring keyword analysis indicates the emerging trends, and research hotspots and frontiers based on all the selected publications or a particular category of the publications. Herein, we utilise a keyword density map and timeline map to examine the evolving trend of HMR studies. Finally, we propose future research directions in four aspects: involving multi-source mobility data, improving modelling approaches, integrating advanced techniques, and contributing to social good.

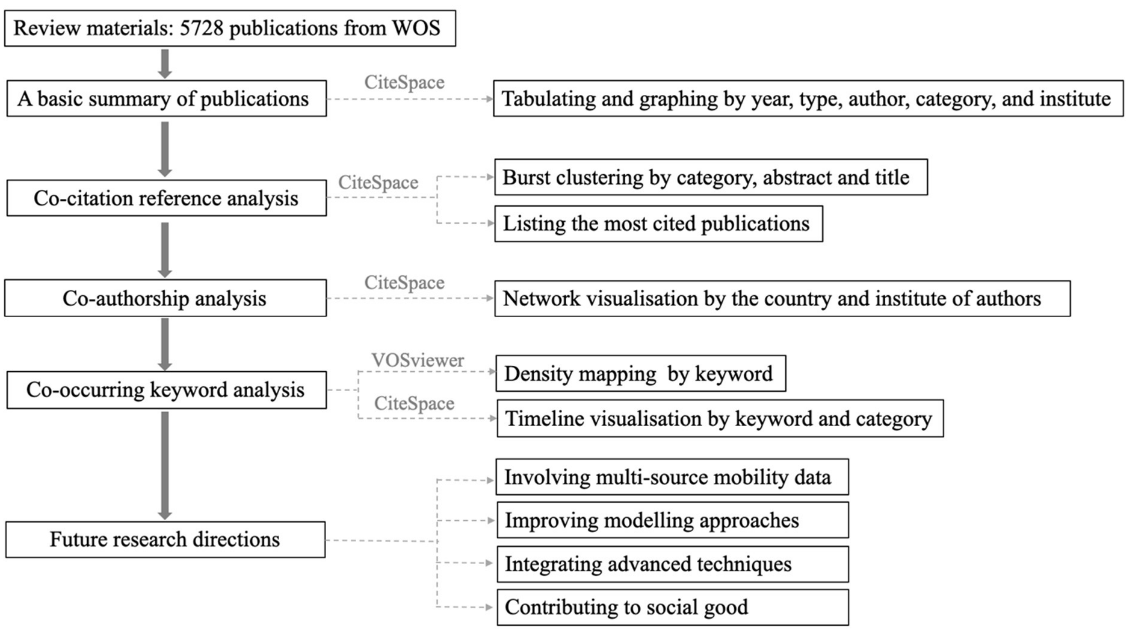

Figure 1. Analytical flowchart

4. Results

In this section, we first provide the basic summary of publications in terms of the number, type, author, category, institute of publications. We then present the analytical results by CiteSpace and VOSviewer based on co-citation references, co-authorship, and co-occurring keywords to depict the evolutional and emerging trend in the field of human mobility.

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4.1 The basic summary of publications

Figure 2 plots the annual trends of human mobility-related publications. Prior to 2006, HMR publications obtain a very slow increase with the annual publication number less than 100. The publication number decreases from 113 in 2006 to 84 in 2007 but increases again after 2007 to 381 in 2015. It is followed by a sharp increase after 2015, up to 707 in 2019. Table 2 shows the number and proportion of various publication types. The most frequent document type is articles, accounting for 87.67% of total publications, followed by 6.6% as review papers and editorial, and 2.89% as conference proceeding papers. Table 3 shows that the most productive author in HMR studies is Liu Y, whose research focuses on urban studies, travel patterns, and transportation. The other top nine authors have diverse research focuses mainly in the field of epidemic, disease transmission, urban mobility, and mobility modelling by using mobile phone and big data.

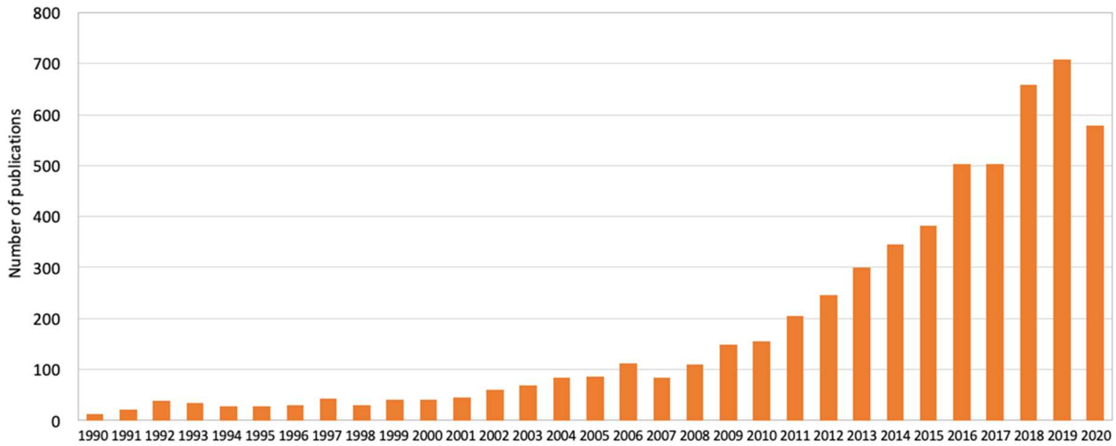

Figure 2. Number of human mobility-related publications from 1990 to 2020

Table 2. Types of human mobility-related publications

Type	Number	%
Articles	5,022	87.67
Review and editorial	378	6.60
Conference proceeding papers	166	2.89
Book chapter and review	80	1.40
Others*	82	1.43

Note: * include meeting abstract, data paper, reprint, letter, correction, and retracted publication.

Table 3. The top 10 most productive authors

Author	No. of publication	Main focuses
Liu Y	35	Urban studies, travel pattern, transportation
Ratti C	29	Mobile phone and big data, urban mobility
Tatem AJ	29	Malaria transmission, disease and health
Gonzalez MC	25	Modelling, individual trajectory, big data
Li Y	25	Mobile phone data, trajectory, modelling
Li X	23	Travel, big data, spatiotemporal modelling
Kwan MP	31	Geo-spatial studies, individual behaviours
Mari L	20	Epidemic, disease transmission
Rinaldo A	20	Epidemic cholera, disease transmission
Bertuzzo E	19	Epidemic, forecasting, transmission and outbreak

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HMR publications are classified to the total 99 default categories by WOS. According to academic discipline classifications (Australian Bureau of Statistics, 1998), we further aggregate 99 categories to 13 broad categories (Table 4). The largest proportion of HMR publications (25.08%) are in social sciences, including demography, sociology, urban studies, regional urban planning, ethnic studies, business, management, public administration, and international relationship. The second broad category (12.94%) is environmental sciences, followed by medical and health sciences (12.28%), information and computing sciences (10.75%), technology (9.90%), and multi-disciplinary (8.47%).

Table 4. HMR publications in broad categories and default categories

Broad categories	No. of default categories	No. of publications*
Social Sciences	23	2,557 (25.08%)
Environmental Sciences	6	1,319 (12.94%)
Medical and Health Sciences	21	1,252 (12.28%)
Information and Computing Sciences	7	1,096 (10.75%)
Technology	3	1,010 (9.90%)
Multidisciplinary	5	864 (8.47%)
Engineering	8	811 (7.95%)
Biological Sciences	11	637 (6.25%)
Mathematical Sciences	5	262 (2.57%)
Chemical Sciences	3	160 (1.57%)
Earth Sciences	4	154 (1.51%)
Physical Sciences	2	57 (0.56%)
Education	1	18 (0.18%)

Note: *: the sum-up of publications in each broad category is more than 5,728 because parts of publications fall into more than one broad category; the percentage in brackets indicates the proportion of publications in a certain category over the total.

Figure 3 shows the top 10 institutes with the most HMR publications. Chinese Academy of Sciences ranks the first (180), accounting for 3.14% of the publications in this field. The top 10 institutes include four American institutes, three British institutes, two Chinese institutes, and one French institute. A total of 1,172 publications are contributed by these institutes, accounting for 20.46% of the selected publications.

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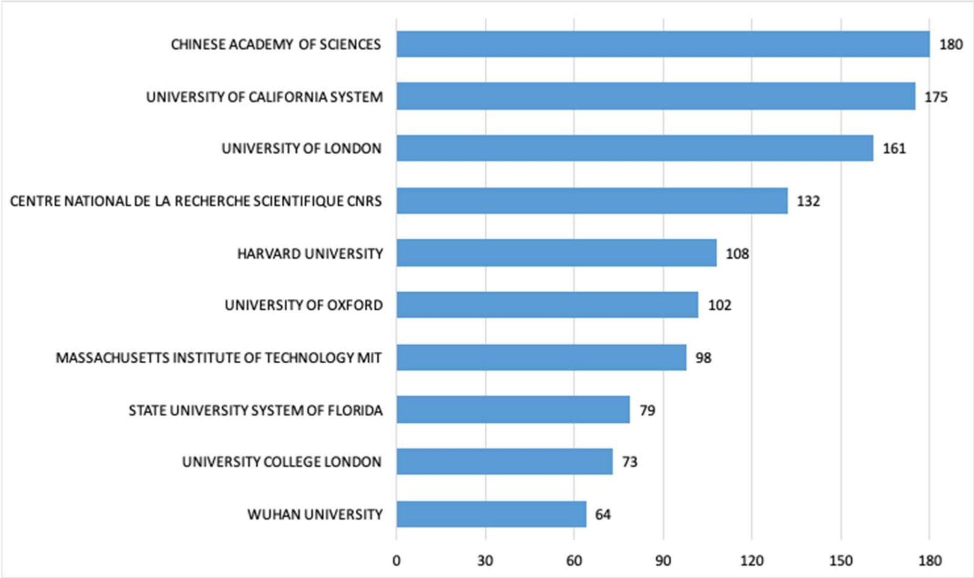

Figure 3. Top 10 institutes with the largest number of HMR publications

In summary, the amount of HMR publications increases rapidly since 2008, mainly published as academic articles in the field of social sciences, environmental sciences, and medical and health sciences. Research areas of the three most productive authors are mobility studies in urban, travel patterns, and transportation. The most productive institutes are mainly based in the U.S., UK and China.

4.2 Co-citation reference analysis

Figure 4 indicates the bursts of co-citation references in the top six categories by different colours and the node labels show the most popular abstract term (purple) and title term (blue) in that category. We set up the uniformed size of nodes for better visualisation and label the rank of the top six categories in front of their names. The largest burst of co-citation references (labelled as 1) falls in multi-disciplinary sciences with the most popular abstract term as *mobile phone* and the most popular title term as *mobile phone data*. The second-largest burst is about green and sustainable science and technology, followed by transportation, demography, applied mathematical sciences, and urban studies. In addition, multi-disciplinary sciences and urban studies are intertwined in the same burst (red colour) indicating the close connection between these two research categories, but the other four categories are relatively independent as being detected in different bursts (shown as different colours).

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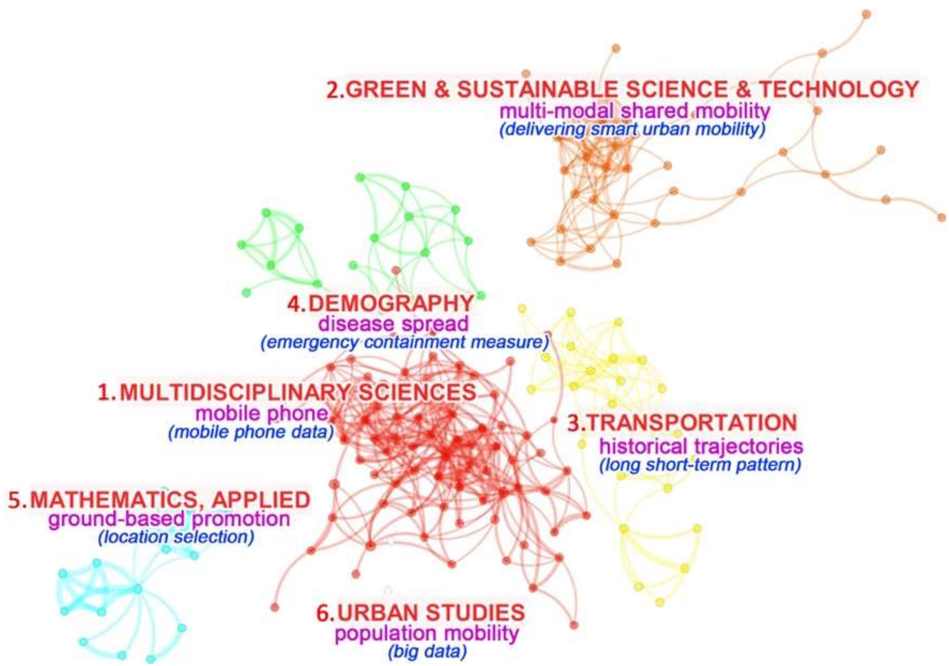

Figure 4. Bursts of co-citation references in the top six categories (red label) with abstract terms (purple label) and title terms (blue label)

Figure 5 shows the top journals of co-citation references. The top four journals with the largest number of co-citations is Nature (1827 as the number / 90 as the centrality), followed by Science (1711 / 75), the National Academy of Sciences of the U.S. (1614 / 88), and PLOS One (1364 / 39). Other highly cited journals include Scientific Reports (a Nature research journal), Lecture Notes in Computer Science, The Lancet, Journal of Transport Geography, and Physical Review E, Transport Research Record and Transportation Research Part C Emerging Technologies. Most of these highly cited journals are multi-disciplinary, and almost half of them are related to transport, physical, and computer sciences.

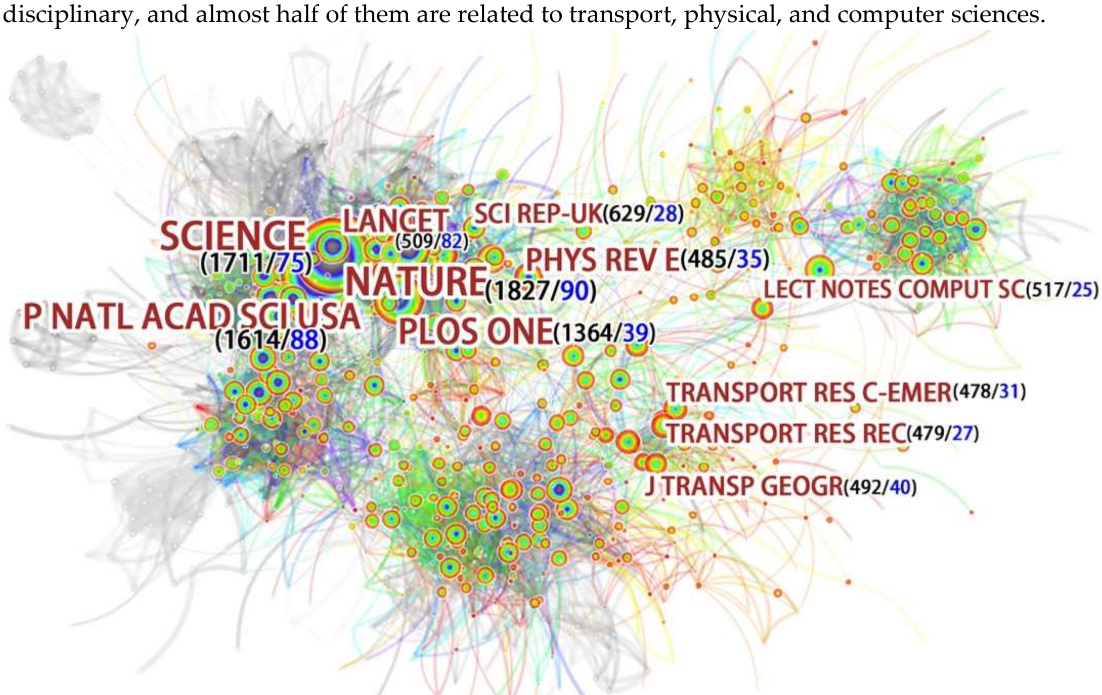

Figure 5. The most cited journals in co-citation references

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Table 5 shows the top 10 most cited HMR publications. The top two cited papers are in multi-disciplinary sciences in computer science and technology, published in Nature in 2008 by Gonzalez et al and in Science in 2010 by Song CM et al. (Gonzale et al, 2008; Song et al., 2010). Both papers model large-scale human mobility by using big data to reveal that humans follow simple and reproducible patterns despite the diversity of their travel history. The finding of inherent similarity in travel patterns has extended impacts on all phenomena driven by human mobility, from epidemic prevention to emergency response, urban planning, and agent-based modelling. Among these 10 publications, five publications are multi-disciplinary, across the category of computer science, physics, engineering, and telecommunications, providing methods to compute and model human mobility (Simini et al., 2012; Gonzalez et al., 2008; Song et al., 2010; Rhee et al., 2011; Schneider et al., 2013). Two publications are in medical and health science, quantifying the impact of human mobility on disease transmission (Wesolowski et al., 2012; Balcan et al., 2009). Two publications are in social science, related to urban studies and geography (Hawelka et al., 2014; Noulas et al., 2012). One publication is in transportation science and technology by using mobile phone big data (Alexander et al., 2015). In sum, the most cited publications are highly multi-disciplinary, computation-based, and method-oriented with diverse applications in social, medical, urban, and geographic studies.

Table 5. The top 10 most cited HMR publications

No. of being cited	Centrality	Author	Title	Journal	Category	Year
2832	35	Gonzalez MC	Understanding individual human mobility patterns	Nature	Multidisciplinary Sciences; Computer science and technology	2008
1469	39	Song CM	Limits of Predictability in Human Mobility	Science	Multi-disciplinary sciences; Computer science and technology	2010
678	38	Wesolowski A	Quantifying the Impact of Human Mobility on Malaria	Science	Medical and health science	2012
539	52	Balcan D	Multi-scale mobility networks and the spatial spreading of infectious diseases	Proceedings of the National Academy of Sciences of the United States of America	Multi-disciplinary sciences; Computer science; Medical and health science	2009
524	58	Simini F	A universal model for mobility and migration patterns	Nature	Multi-disciplinary sciences; Computer science and technology	2012
519	38	Song CM	Modelling the scaling properties of human mobility	Nature Physics	Multi-disciplinary sciences; Physics	2010

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454	11	Rhee I	On the Levy-Walk Nature of Human Mobility	IEEE ACM Transactions on Network	Computer science; Engineering; Telecommunications	2011
294	37	Noulas A	A Tale of Many Cities: Universal Patterns in Human Urban Mobility	PLOS One	Multi-disciplinary; Social science (Urban studies)	2012
274	33	Hawelka B	Geo-located Twitter as proxy for global mobility patterns	Cartography and Geographic Information Science	Social science (Geography)	2014
188	49	Schneider CM	Unravelling daily human mobility motifs	Journal of The Royal Society Interface	Multi-disciplinary sciences; Computer science and technology	2013
185	40	Alexander L	Origin–destination trips by purpose and time of day inferred from mobile phone data	Transportation Research Part C: Emerging Technologies	Transportation science & Technology	2015

4.3 Co-authorship analysis

The co-authorship analysis by country and institute reflects the countries or institutes where co-authors are highly concentrated and the degree of connections among countries or institutes in the field of human mobility. The different colours in Figure 6 indicate the diversification of research directions. Figure 6A shows that the U.S. has the largest research burst with 1017 publications and 65 as the degree of co-authorship connections to other countries, followed by England, Spain, Germany, France, Italy, and Canada. It indicates the diversity of international collaborations across geographic contexts. Figure 6B shows that the top institutes of co-authorship. The institute with the largest number of cited publications is the Chinese Academy of Sciences (centrality as 47), followed by University Oxford, University of Melbourne, Wuhan University, Harvard University, University of Washington, Nanjing University, Peking University, University College of London, Stanford University, and Massachusetts Institute of Technology. Among these institutes, six are from China, four from the U.S., two from the U.K., and one from Australia.

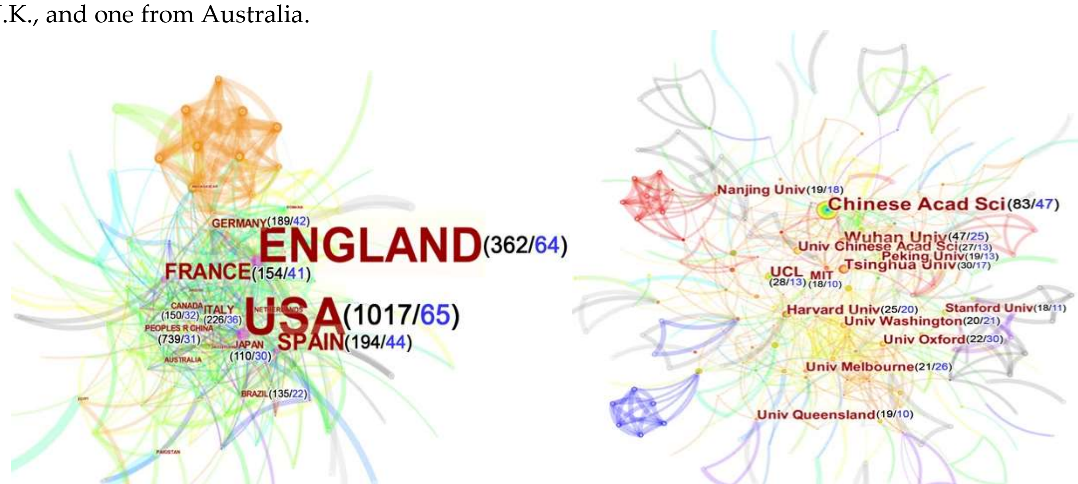

Figure 6. (A) Co-authorship analysis by country (B) Co-authorship analysis by institute

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Note: The number of publications is labelled in black and betweenness degree (centrality) is labelled in blue.

4.4 Co-occurring keywords analysis

The keyword density map (Figure 7) produced by VOSviewer uses colours and font sizes to represent the frequency of the keywords in HMR publications. The larger font size and lighter colour (yellow) indicate the higher frequency of keywords. It can be observed that there are two dense clusters in Figure 6. The cluster on the left has -frequently used keywords including *population*, *migration*, and *human migration*. They are closely surrounded by keywords including *disease*, *transmission*, *species*, *infection*, *sequence*, and *climate change*. As such, the left cluster is relevant to research in the domain of urban and social studies, epidemic and infectious diseases, public health, climate, and environmental sciences. In the cluster on the right side, the most frequently used keyword is *network*, followed by *service*, *urban mobility*, *algorithm*, *accuracy*, *infrastructure*, *experiment*, *efficiency*, and *vehicle*. Such keywords tend to be relevant to research in the domain of telecommunications, physics, technology, and transportation.

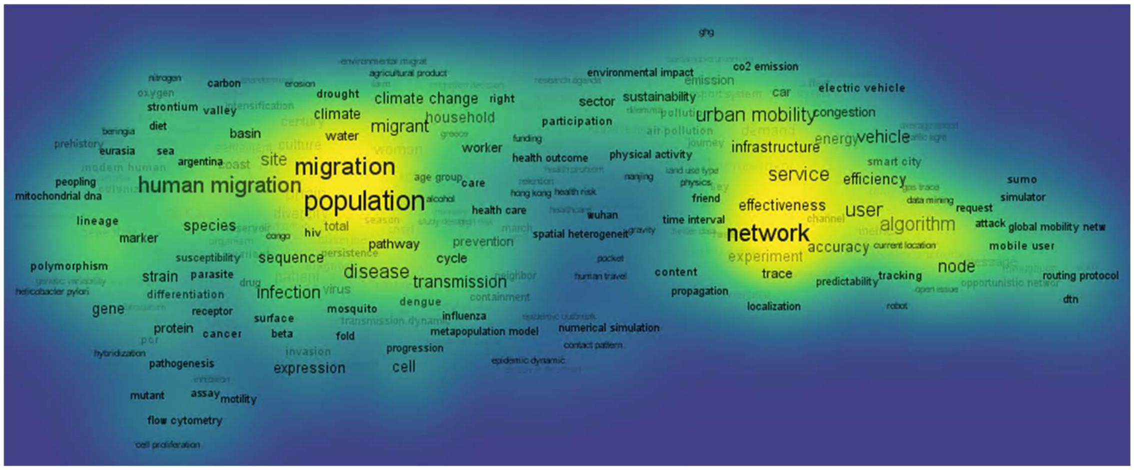

Figure 7. Keyword density visualisation

We further examine the emerging trends of HMR publications by category with the timeline view of co-occurring keywords (Figure 8). The most popular category is transportation, followed by genetics and heredity, infectious diseases, demography, telecommunications, physics and multi-disciplinary, archaeology, business and microbiology. Along with the horizon of each category, arch lines reflect the connection of two co-citations with the same co-occurring keywords. The colours of arch lines indicate the year of citations. The vertical grey lines separate the whole timeline into four intervals (1990-1999, 2000-2009, 2010-2019, and 2020). In the top category of transportation, the keywords are *cost*, *city* and *transport* in 1990-1999, then changed to *policy inequality*, *accessibility*, and *travel* in 2000-2009, further changed to *built environment*, *C02 emission*, and *public transport* in 2010-2019, and evolved to *automated vehicle* and *vehicle usage* in 2020. In the category of genetics and heredity, the keywords are evolved from *population sequence* and *distance* in 1990-1999 to *mixture-ethnic group* and *expansion* in 2010-2019. In infectious diseases, keywords have been evolving from *mortality* and *risk transmission* in the 1990s to *tuberculosis trend in developing countries*, *influenza*, *weather*, and *COVID-19* in 2020. The keywords in demography are relatively consistent with *climate change*, *weather*, *resettlement disasters*, *displacement*, *vulnerability*, and *adaptation* frequently appearing from 1990 to 2019, and with *artefact synchrony mitigation* as the research frontier in 2020. In telecommunications, keywords rarely appear before 2000 and become relatively more frequent in *global mobility network*, *mobility model*, *travel time*, and *internet* from 2001 to 2019, and change to *wireless communication* and *smart mobility* in 2020. In physics and multi-disciplinary fields, keywords are changed from *network pattern*, *urban mobility*, *travel pattern*, *global position system*, to more recently *smart card data* and *deep learning*. Keywords in archaeology evolve from *age*, *residential mobility* to *carbon*, *bone collagen*, and *stable isotope* more recently. Keywords in business

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change from *deforestation*, *exposure intervention*, *decision making*, and *living quality* before 2010, to more recently *air pollution* and *population exposure*. Finally, keywords in micro-biology change from *gene culture, protein, negative bacteria* before 2010 *to urbanisation, proliferation*, and *apoptosis* in 2010-2019 and become very few in 2020.

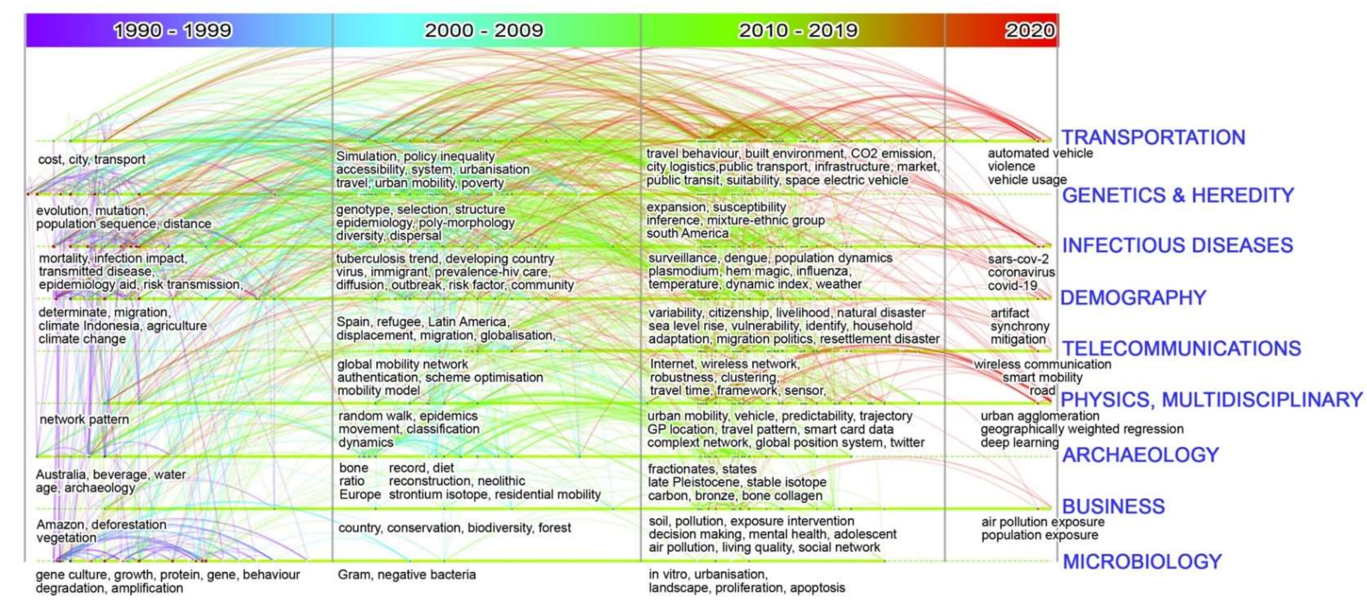

Figure 8. Timeline of co-occurring keywords in the top categories

In summary, HMR research has become increasingly popular across various disciplines with enhanced collaborations across countries and institutes. The top citied publications are commonly multi-disciplinary studies by providing frameworks, approaches, and applications to model human mobility, and integrating big data into the modelling process. The evolutional pathway of HMR studies shows the emerging source of big data provided by mobile devices, social media applications, and transport systems has been used to better track people's movement pattern. The development of computer science, information technology, and the Internet-of-things (IoTs) innovates modelling skills to better analyse and present the spatiotemporal pattern of human mobility and to improve simulation and prediction of human mobility. Cutting-edge technology such as deep learning, machine learning, and artificial intelligence has been used to build novel applications of human mobility in multi-disciplinary areas.

5. Future research directions

Based on the aforementioned findings from the bibliometric analysis and future work recommended by top cited authors and studies in each category, we summarise four directions for the next research agenda: involving multi-source mobility data, improving modelling approaches, integrating advanced techniques, and contributing to social good.

5.1 The involvement of multi-source mobility data

The nature of empirical data used in HMR studies is multi-dimensional and from multi-source, based on the spatial and temporal information of individuals' travel trajectory as well as the mobility flow at the aggregated level. First, transport systems are the common source providing mobility data, for example, the timetable of buses, trains, and flights (Okraszewska et al., 2018). However, they can only represent the scheduled mobility flows but not the actual mobility occurring across places. More recently, smart-card-based big data provided by smart transport systems become the emerging data source to model human mobility based on the location and time of boarding and alighting of travellers (Liu et al., 2019). Second, our findings indicate that another mainstream data source is individual-based tracking data provided by mobile phones or other telecommunication devices with the function of global positioning system (GPS) to record the spatial and temporal information of mobile phone users (Jiang et al., 2017). The rapid development of smartphones in the past decade has extended the GPS-derived data source to large IT companies (e.g., Google and Apple) with the capability to collect the location and time of mobile phone application users via the provision of mapping services. Individual-based tracking data has become a top-rated source in HMR studies because of its high accuracy, wide usage, and real-time collection. They can be further aggregated at different spatial and temporal scales, generating a variety of index-based mobility data. For example, the Google Community Mobility Reports (2020) measures the impact of the COVID-19 pandemic on human mobility by comparing human mobility during the pandemic to the pre-pandemic period by tracking people's visits to six types of places extracted from Google Map (e.g., workspace, parks, transit stations, and grocery stores). Similarly, other IT companies, including Baidu, Apple, Foursquare, and Safegraph, also published a variety of mobility indices, social distancing indices, and mobility reports, which have been widely used in COVID-19 related research. Third, a more recent data source is the data retrieved from the increasingly popular social media applications (e.g., Facebook and Twitter). Such social media data contain spatial and temporal information obtained from users when they choose to post contents with locations, generating diverse index-based mobility data at the aggregated levels, such as the mobility-based responsive index (Huang et al., 2020; Jurdak et al., 2015). Future studies need to put efforts to compare the quality of these multi-source mobility data and explore the possible replacement of data to improve data availability to public and researchers. There is also a pressing need to construct a universal standard to control data quality, unify data processing procedures, and facilitate data sharing.

The enrichment of these multi-source mobility data inevitably brings in limitations in terms of data quality, coverage, and processing, as well as concerns on privacy protection issues (De Montjoye et al., 2013). Individual-based mobility tracking data retrieved from mobile phone signals, GPS devices, or social media apps could be biased due to the limited group of phone users (e.g., young and middle-aged adults) or application users who post content with locational information (Jurdak et al., 2015). Such a bias in data representativeness will further introduce inaccuracy when individual-based mobility tracking data are aggregated to index-based or flow-based mobility data at a certain spatial or temporal scale. Additionally, the usage of individual-based mobility tracking data also raises privacy and security concerns. Governments have been making efforts to strengthen relevant regulations. Data providers have achieved a consensus that these data must be anonymous and unidentifiable to ensure fully transparent and accountable privacy-preserving solutions. Researchers need to beware of these limitations and choose the appropriate data sources.

5.2 The improvement of the modelling of individual and collective mobility patterns

The involvement of these multi-source mobility data will enrich the modelling work in future HMR studies, linking mobility to other research objects in multi-disciplines by understanding the spatiotemporal metrics of mobility, the association of mobility and other phenomena, and the simulation and prediction of mobility. There are three types of fundamental metrics commonly used to model human mobility in current scholarship (Barbosa et al. 2018) – trajectory-based, network-based, and social-based metrics – each type of metric has its specialties and characteristics that can be integrated into future studies. Trajectory-based metrics are based on the trajectory of individuals' mobility and usually quantified as jump lengths, mean square displacement, time duration, speed, interval, the radius of gyration, entropy index, or the most frequented locations (Barbosa et al. 2018; Wang et al. 2019). Network-based metrics use graphic visualisation to characterise human mobility. In the network visualisation, nodes can represent a group of locations visited by people, and edges can represent related pairs of locations in the historical trajectories. Network-based metrics are usually quantified as the degree of centrality, betweenness centrality, closeness centrality, or eigenvector

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centrality (Wang et al. 2019) as well as motifs and origin-destination matrices (Schneider et al., 2013). Social-based metrics are based on the co-occurrence between two people and usually quantified as the frequency of co-occurrences, the closeness of important locations, the probability of co-occurrences, and/or the similarity of historical trajectories (Wang et al. 2019). Future work can contribute to comparing different metrics to explore the potential replacement of measures to address data unavailability by comprehensively using multiple mobility metrics.

The great challenge of modelling mobility patterns also lies in how to improve the accuracy and adequacy of modelling approaches by involving multimodality (or multiple-scale models) at both the individual level and the aggregated population level. On the one hand, individual mobility is subject to a certain level of uncertainty associated with individuals' free will and arbitrariness in their actions, leading to a degree of stochasticity in mobility patterns. Consequently, individual-level models borrow concepts and methods from the classic Brownian-motion models (Bian et al., 2016) and continuous-time random-walk models (Brockmann et al., 2006), and have been developed to more recent Lévy flight, preferential return, recency, and social-based models (Barbosa et al. 2018). However, many studies assert that individuals' trajectories are not random; instead, possessing a high degree of regularity and predictability (Song et al., 2010). Future efforts need to better capture and exploit such regularity and predictability of mobility to forecast an individual's future whereabouts and to construct more realistic models of individuals' mobility.

On the other hand, population-level models (e.g., gravity models and radiation models) describe the aggregated mobility of many individuals and aim to reproduce origin-destination matrices by estimating the average number of travellers between any two places during a certain period (Simini et al., 2012; Sen & Smith, 2012). Most modelling approaches derive the mobility flows as a function of a range of relevant variables of the places considered, such as mutual distances, areal characteristics, and the demographic and socioeconomic level of population levels (Barbosa et al., 2018). However, as discussed previously, mobility occurs over multiple spatiotemporal scales (termed as multimodal), and thus, future studies need to have a more comprehensive picture of human mobility by accounting of the effects of multimodality and creating hybrid models as the interpolation between the individual-level and population-level (Yan et al. 2017). For example, a hybrid framework for carrying out human mobility analysis based on the multimodal structure of transport systems has been developed in recent years in the context of multilayer networks in British and French cities (Boccaletti et al., 2014; Kivelä et al., 2014; Gallotti & Barthelemy, 2014; Alessandretti et al., 2016). Within such networks, layers may correspond to different transportation modes (e.g., flights, buses, and trains) and connections between layers constitute the interchanges between these modes. Constructing multilayer networks is to associate locations to nodes and flows, and frequency of travel to links between different transportation modes. In this case, the optimal time for a person travelling between a given origin-destination pair can be calculated using optimal path algorithms across the multilayer structure (Barbosa et al., 2018). Similarly, future studies can formulate such hybrid modelling frameworks in other applications, such as controlling mobility to prevent the transmission of multi-diseases by developing multi-layers to track population's contact with one disease, respectively.

5.3 The integration of artificial intelligence techniques in human mobility studies

The rapid development and recent advances of artificial intelligence techniques, including high-performance computing, storage, and data modelling using machine learning and deep learning methods, bring new opportunities for human mobility studies in terms of data creation, modelling approaches, and applications (Pappalardo et al., 2019). The intersection of mobility data management and artificial intelligence is becoming a promising direction to build a new database (e.g., smart moving objects database developed by Xu et al., 2019) with the advantage of automatic approaches of recommending system settings for the provision of solutions. Such a smart moving objects database has the capability to establish a complex data structure and provide intelligent data extraction. In that

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case, mining and analysing trajectory data is not limited to spatiotemporal data but will incorporate sentiment and descriptive attributes to find the relationship between human mobility and subjective matters (e.g., personality and emotion) (Xu et al., 2019). In addition, the combination of unprecedented mobility data and machine learning approaches have brought on immense advancement in intelligent transportation systems. In particular, traffic forecasting as the core function has been developed to predict future traffic conditions based on historical data, including traffic flow and control, route planning, parking service, and vehicle dispatching (Song et al., 2016). Such intelligent transportation systems can be used to estimate not only regular mobility behaviours but also special events such as public gatherings.

Another future direction is the integration of deep learning into mobility modelling approaches. Deep learning can be defined as an artificial neural network based on which deep learning models with the support of intelligent systems can facilitate the understanding of the deep knowledge of human mobility (Kim & Song, 2018) and provide solutions and prediction for complex nonlinear relationships between mobility and other objects. Several well-known deep learning models include deep neural networks (DNN), convolutional neural networks (CNN), recurrent neural networks (RNN), and deep belief network (DBN) which have been used to explore the relationship between human mobility and personality and to understand human mobility and transportation patterns (e.g., Song et al., 2016, 2017; Kim & Song, 2018; Ouyang et al., 2016). Applications combining mobility and deep learning have been developed in the field of disaster prevision, transport planning, and scenario prediction. For example, DeepMob, as an intelligent transport system with deep learning architecture has been constructed for simulating and predicting human's future evacuation behaviours or evacuation routes under different conditions of natural disasters (Song et al., 2017). DeepTransport, another intelligent system, was used to understand human mobility and transportation patterns using GPS-based big data (Song et al., 2016). It can automatically simulate or predict the persons' future movements and their transportation mode in the large-scale transportation network. DeepSpace, an online learning system based on CNN, can deal with the continuous mobile data stream and provide multi-scale prediction models to analyse the mobile big data to predict human trajectories (Ouyang et al., 2016). Future studies can extend along this direction to create intelligent databases, platforms, models, and systems that can be used in the diverse field of disease control and prevention, smart city planning, environmental management, and ecological conservation where human mobility intertwines with the surrounding environment.

5.4 The contribution of human mobility studies to social good

Through involving multi-source mobility data and developing hybrid mobility models, future HMR studies can greatly contribute to several aspects of social good through promoting population health, designing sustainable smart cities, and providing humanitarian supports to conflicts, wars, and natural disasters.

The first aspect of social good is to improve population health. The development of human genomic technology strengthens our understanding of the relationship between human mobility and the development of genetic diseases. In the context of worldwide migration, moving to a new environment causes genetic adaptation, which could further affect disease susceptibility. For example, the genetic risk of type 2 diabetes decreased worldwide as people migrated from Africa to East Asia (Corona et al., 2013). Additionally, human mobility is an important factor in the geographic spread of contagious diseases. Understanding human mobility helps to control the distribution of contagious diseases, including malaria (Wesolowski et al. 2012), HIV (Isdory et al., 2015), and dengue fever (Wesolowski et al., 2015). The effectiveness of disease control can be estimated by measuring the association between disease distribution and human mobility histories before and after disease control. One of the application is the evaluation of policies and interventions that restrict population movement during the COVID-19 pandemic (Hadjidemetriou et al. 2020, Kraemer et al. 2020).

The second aspect of social good is to help build smart and safe cities. The construction of smart cities can integrate the simulation and prediction of human mobility to improve transport planning, service, and infrastructure planning, human settlement, public security, and citizens' quality of life (Nam and Pardo, 2011). In transport planning, mobility information can be used to monitor and predict traffic dynamics, including traffic flows, congestions, and accidents, by better understanding the supply and demand of the public transport system to improve its efficiency (Pan et al., 2013). In service and infrastructure planning, human mobility to visit particular locations (e.g., shopping centres) indicates the demand for its location and services. Measuring the mobility to certain infrastructures can guide urban planning and configuration through to improve the equal distribution of public facilities and services in cities (Pan et al., 2013). In human settlement, mobility flows between suburbs can be used to locate residential concentrations where the development of real estate is most needed. In public safety, tracking people's daily routine routes that are usually repetitive travel between the home and workplace on weekdays can be used to detect individuals' abnormal behaviours and atypical activities for the prevention of crimes (Li et al., 2012).

The third aspect of social good is to provide humanitarian supports to cope with natural disasters and social conflicts. Simulating the historical settlement pathway of people forcibly displaced by the effects of climate change, conflicts, wars, and other catastrophic events can help to predict human displacement in future, and accordingly to promote humanitarian responses to protect their resettlement (e.g., Bengtsson et al., 2011; Afifi et al., 2016; Bank et al., 2017). Such modelling work that needs to involve the measures of human mobility is particularly important for low-lying coastal regions where an extensive number of large cities are nested in face of natural disasters caused by sea-level rise, storm surges, tsunami, and flooding. The measures of human mobility can be controlled as parameters in predictive models, reflecting different scenarios of human adaptation and response to natural disasters and social conflicts (Liu et al., 2019). Such mobility-oriented applications are promising in future studies given to the complexity of real-world issues and the uncertainty of human-environment interactions.

6. Conclusions

We conduct a systematic literature review of HMR studies published from 1990 to 2020 by a bibliometric analysis and network visualisation. In doing this, we analyse 5,728 HMR related publications retrieved from WOS to identify the emerging trends, research hot spots and frontiers in the field of human mobility. Over the past three decades, HMR studies have become increasingly interdisciplinary, multi-dimensional, and edge leading by involving multi-source big data, innovative modelling approaches, cutting edge technologies, and novel applications in multi-disciplinary areas. Based on the evolutional pathway revealed in this study, we recommend future research directions in terms of data sources, modelling methods, applications, and technologies. Considering the importance of human mobility in people's daily life, we advocate future research to address real-world problems and contribute to social good through integrating multi-source big data and advanced modelling methods facilitated by artificial intelligence, and machine and deep learning. We call for multi-disciplinary contributions to enhance HMR studies and to explore human-environment relationship and interaction.

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Data Availability Statement

The data presented in this study are openly available in Web of Science at https://login.webofknowledge.com/error/Error?Src=IP&Alias=WOK5&Error=IPError&Params=&PathInfo=%2F&RouterURL=https%3A%2F%2Fwww.webofknowledge.com%2F&Domain=.webofknowledge.com

Conflicts of Interest

The authors declare no conflict of interest.

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