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Research Article

Mobile Technology and Studies on Transport Behavior: A Literature Analysis, Integrated Research Model, and Future Research Agenda

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The prevalence of mobile technology has been significant in transport research. Despite a growing application spectrum of smartphone uses and interests in mobility inference, little effort has been put into discussing theories, models, and research topics based on a systematic study of scholarly sources rooted in the interdisciplinary area of mobile technology and transport. Therefore, a timely and comprehensive synthesis of the current state of research is deemed to be required. A literature analysis, following PRISMA guidelines, aims to identify the successful development and implementation of the mobile technology that can be employed for behavior studies in transport. A review of the Web of Science Core Collections, JSTOR and SAGE databases, is performed. A rigorous screening process is used to collect key articles to construct the general image of existing knowledge. In addition, this study suggests an integrated research model to summarize how previous studies attain behavioral outcomes and a research agenda to identify unresolved research questions that future research can address. Two hundred fourty-eight papers meet the inclusion criteria. This study demonstrates that mobile technology is helpful for a better understanding of the various types of transport behaviors. They can be categorized according to their system designs and research topics: (1) Smartphone apps in sustainable transport and travel planning were studied in a remarkable collection of articles. (2) As individual's mobility was under question, cellular signaling data were prominent for the formulation of analytical models. (3) CDRs, WiFi, and GPS data have increasingly been used, but the share of the modeling techniques for all mobile information systems has remained low. It shows that system designers could supply more desirable and appealing features in most areas. However, applications for the movement of goods are limited, although freighting has moved toward digitalization.

1. Introduction

Mobile technology is one of many growing topics in mobility inference. This trend is driven by digitalized transport in the visualization and capitalization of Big Data [1]. While mobile technology has been referred to in various contexts, in this paper, we define it within the transport sector as the "employment of smartphones and expanding cellular networks to integrate and influence mobility." Focusing on the current state of research, the research scope of mobile technology in transport behavior studies could be mobile data techniques and the utilization of smartphone apps. Mobile phone data techniques revolve around the collection and analysis of information that is sent or received from a device in a cellular network. In this respect, call detail records (CDRs) [2], Global Positioning System (GPS)/global navigation satellite system (GNSS) data [3], and cellular signals [4] are the most researched types of mobile data. The utilization of smartphone apps addresses the interface design [5], user adoption [6], and behavioral outcome [7], such as a mode switch and user response to real-time information, within the transport system.

On the contrary, mobile phone data hold the promise of helping produce accurate transport measures and representative models of human behavior and a new era for activity-based modeling [8]. This is considered a complement to traditional surveying, which is considered expensive to conduct and unsuitable for capturing spatial mobility patterns that have a high level of informality [9]. To understand individual mobility patterns, there is a need to develop efficient algorithms for various travel behavior inferences such as transport mode detection, travel route map-matching and analysis in tandem with the spatial-temporal organization of activities. To support this development, it is essential to know what types of behavior studies within the transport sector can be performed and what types of mobile phone data are needed for these studies. On the contrary, mobile technology also benefits from an understanding of individual mobility patterns because the providers are increasingly utilizing their collected transport measures to customize their individualized service. To this purpose, it becomes vital that the transport measures can be transformed into useful behavioral preferences, which rely heavily on the algorithms designed for travel behavior inference.

Most roles of existing technologies can be fulfilled by smartphone apps designed and implemented in a user-centric manner. The ever-increasing proportion of users who have access to mobile devices creates an opportunity to establish previously unavailable data sets. There has been little established about what opportunities location data collected from mobile technology provide for transport behavior research, how riders' transport behaviors are affected by mobile phone use, what features and contents of mobile information systems they adopt, and which heuristics approach is available with mobile phone data.

The promising impact of mobile technologies in transport was showcased at the beginning of the 21st century [10]; however, it remains unknown what type of mobile technology can be used to analyze, influence, and collect mobility. Literature reviews have been conducted with an explicit focus on a causal relationship that will benefit the mobility of passengers and goods. However, previous literature reviews have been limited in at least one of the following aspects: (1) reviews usually synthesize contributions by analyzing a single perspective, such as transport surveying; a single focused issue, primarily sustainability, or a single transport mode; (2) most reviews have examined papers published before 2015; and (3) literature analysis of papers on smartphone apps has become scarce in recent years.

This paper proposes a literature study to reflect the progress over the past two decades in the interdisciplinary research area of mobile technology and transport behavior understanding. We first reviewed previous works and outlined their categories. In the next step, each of the paper was scrutinized to assess the most widely applied mobile technology in transport. An integrated research model was proposed to conceptualize the corresponding research process as a guideline for creating a practical and empirically grounded understanding of mobility in the digital age. The research agenda presented in this paper could serve as the guideline of crucial steps for a sustained research endeavor. The remainder of this study is arranged as follows: the methodology of the literature analysis on mobile technology in transport behavior studies and its coverage is summarized in Section 2. The results for analyzing the state-of-the-art is then detailed in Section 3, followed by its critical discussion with the common terms and challenges identified from the literature in Section 4. A discussion on the future research agenda and recommendations for continued researches concludes this paper.

2. Methods

This literature study focuses on the identification of mobile technology to provide critical insights and a meaningful inference of mobility. This is the lens through which the articles were identified, reviewed, and understood. Given the growing number of studies published over the past two decades, it is urgent to explore the application and methodological diversity in this field to provide a forward-looking of digitalized transport. The objective of this literature study is to provide a critical discussion of trends, an integrated research model and a future research agenda to answer the following research question:

(i) What are the successful development and implementation of mobile technologies in transport behavior studies?

The literature analysis was conducted based on the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) guidelines, as shown in Figure 1. The identification of suitable publications was performed by searching the Web of Science Core Collection, SAGE Journals, and JSTOR databases. All of these databases cover top-notch journal articles, laying the groundwork of sufficient literature analysis. The search identified papers published between 2000 and 2020 during the duration of the substantial growth of interdisciplinary research interests on mobile technology in transport.

2.1. Search Terms. The individual paper reviewer selected keywords to ensure a comprehensive and broad coverage of transport behavior research, as shown in Table 1. Provided indexing rules in databases, search queries on research scopes and context specificality were combined, with the terms "app," "digitali*," and "mobile application" focusing on the usage of mobile phones and relevant technologies and the terms of "mobilit*," "tourism," "supply SAME chain," and so forth addressing the core activities.

2.2. Article Inclusion Criteria. Based on an individual paper examination process, inclusion criteria with regard to content and research topic were applied to construct the sample. First, included papers must be peer-reviewed articles written in English. Second, the contribution must be

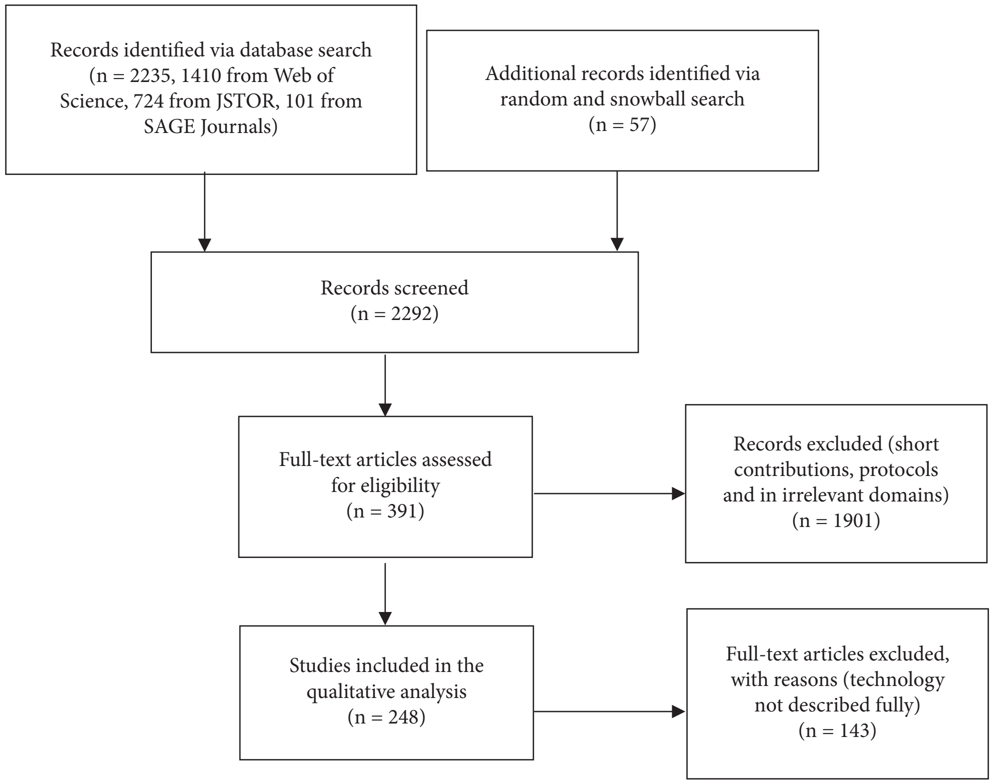

Figure 1: PRISMA flow diagram of the assessment procedure and results: number of records included and excluded and reasons.

Table 1: Queries employed for the databases.

Database	Queries for passenger transport studies	Queries for tourism studies	Queries for freighting transport studies
Web of Science core collection	TI = (“app” OR “digitali*” OR “mobile application*” OR “mobile*”) AND (TS = (“transport” OR “mobilit*” OR “modal” OR “commut*”)) AND (TS = “behavio*”)	TI = (“app” OR ”digitali*” OR “mobile application*” OR “mobile*”) AND (TS = (“travel” OR “touris*”)) AND (TS = “behavio*”)	TI = (“app” OR “digitali*” OR “mobile application*” OR “mobile*”) AND (TS = (“freight*” OR “supply SAME chain*” OR “delivery” OR “logistics*”)) AND (TS = “behavio*”)
JSTOR	ti:(“app” OR “digitali*”OR “mobile application” OR “mobile*”) AND (“behavio*” OR “passenger SAME transport” OR “flow” OR“accessibility”)	ti:(“app” OR “digitali*”OR “mobile application” OR “mobile*”) AND (“behavio*” OR “tourism” OR “tourist” OR “trip planning”)	ti:(“app” OR “digitali*”OR “mobile application” OR “mobile*”) AND (“behavio*” OR “logistics” OR “freight”)
SAGE journals	For [[title app] OR [title digitali*] OR [title mobile application] OR [title mobile*]] AND [[keywords passenger] OR [keywords human]] AND [[keywords mobility] OR [keywords accessibility]]	For [[title app] OR [title digitali*] OR [title mobile application] OR [title mobile*]] AND [[keywords touris*] OR [keywords visit*] OR [keywords recreation*]]	For [[title app] OR [title digitali*] OR [title mobile application] OR [title mobile*]] AND [[keywords freight*] OR [keywords logistics*] OR [keywords delivery] OR [keywords supply chain]]

concerned with the actual measurement of transport behavior changes or attitudinal modifications toward technology adoption. After fulfilling these preconditions, they were included in the qualitative analysis only if they met one of the following criteria:

(1) *Problem-Solving Paper*. The research employed a type of mobile phones, mobility collectors, or any smartphone apps. Articles on smartphone apps showcased their system and interface designs.

(2) *Review and Synthesis Paper*. The research records the main methodological points of the existing deployment of mobile phones in transport behavior studies, followed by a summary and evaluation of the changes resulting from the revolutionary mobile information and communication technologies.

2.3. Literature Mapping. To understand development flows, research trends were streamlined through networking visualizations in CiteSpace, which identifies networks, emerging tendencies, collections and collaborations among the scientific literature [11]. It is hard to determine the effects of the informative visualization that could be delivered by a given configuration because the clarity and complexity of diagrams depend on the network size in CiteSpace.

Therefore, we selected the composition that realizes the best balance between legibility and visualization details. Citation frequency determines the sizes of labels and nodes. The larger a node and label, the more cited the reference. Links and notes indicate the first time that two references were cocited and the year interval, respectively.

3. Results

The records for the qualitative analysis were identified using the PRISMA procedure. There were 248 total scientific articles, among which 142 revolved around the effectiveness of smartphone apps, 90 addressed mobile phone data, and 16 performed synthesis and review of existing literature, as listed in Table 2.

The screening process derived the aims of transport behavior studies integrating mobile technology. The following research purposes are identified: mobility pattern analysis, technology adoption, policy impact assessment, and advances in methodology and technology. The contributions targeting mobility pattern analysis emphasize the collection, visualization, and prediction of selected mobility indicators with a strong reliance on mobile Big Data. The category of technology adoption includes articles working on successful communication for user engagement influenced by design factors, for example, values, usefulness, and appearances. Policy studies handle the impact of the proposed technological development by measuring individual behavioral outcomes in the transport area. Advances in methodology promote the scientific development of modeling and analytics using mobile phone data.

3.1. Mobile Technology in Transport Behavior Studies: A Review. Smartphone apps have been the most extensively used end-to-end solution for mobile device and affect an individual's mobility relationship, as shown in Figure 2. In particular, such apps are a promising tool for route planning and trip organization. Even in early successful app implementations, mobile phones rendered real-time and localized transport information. Watkins et al. investigated the impact of real-time data on transit riders through the convenience of an information system [12], providing evidence that real-time mobile information reduces the perceived and actual wait time. Tsirimpa [13] presented a case study for the Athens Metropolitan Area, Greece, in 2009 to explore real-time travel information from mobile devices. Both individuals' attitudes and the effect of information acquisition on activity rescheduling were considered. To quantify the primary impacts, statistical methods could infer riders' characteristics, and studies could estimate choice models [14] and generalized estimating equations [15] based on a travel choice survey of smartphone users.

Using innovative smartphone apps, riders are informed of the positive consequences of taking a given trip with more sustainable options. Tailored messages and recommendations transformed the way mobility approaches environmental stewardship. Meireles and Riberiro's study showed that more than 60% of nonregular cyclists at the regional level considered smartphone apps to lead more people to use bicycles [164]. Cycling mobile apps should prioritize route calculation and location-based services associated with the built environment, according to the questionnaire. Asitha and Khoo found timing information to be the most critical factor in travel decisions [165]. A linear relationship for information provision with the usage of smartphone apps contributed to the overall intervention of transport mode choice. In addition, personalized campaigns promote sustainable transport, as showcased by di Teulada and Meloni's research on the steering role of a smartphone app in carrying out a voluntary travel behavior change program [166].

Smartphone apps collected detailed user data regardless of transport mode and built environment, unlike traditional surveys. It also facilitated the interaction of data from sensors and end users to establish real-time calibration advantages. Faghih Imani et al. identified trips based on app-based data collection and algorithms [16]. The travel mode for trip legs and purpose could be recorded with proper interface design and streamlined process quality assessment. Lynch et al. [109], via a smartphone-based household travel survey, showed methods for increasing the representation of hear-to-reach riders. Vich et al. analyzed the factors that influenced the extent of activity spaces of suburban commuters at the individual and environmental levels using data from smartphone apps, in which the effectiveness of the calculation method for measuring activity spaces was explored [17]. The results indicated that spatiotemporal and socioeconomic factors were strong determinants of the activity space geography.

Research on smartphone apps and transport also takes technology adoption as a central topic. Park and Ohm designed an integrated research model to analyze the behavioral intention to employ mobile map services [110]. In this study, users' employment of mobile map services was decided by the satisfaction with and perceived usefulness of those services. The moderating effect of mobile usage was evident on behavioral intention and facilitation conditions [111]. Mallat et al. proposed a technology adoption model and trust theories to explore users' intention to adopt mobile ticketing services in public transport [112]. Mobility, availability of other alternatives, and time pressure in the service usage situation corresponded to the adoption decision. Apps were also used in freighting. By surveying 217 adopters, Schoenherr showed that mobile devices and applications help decision-makers rapidly realize and respond to operational circumstances in supply chains [154].

Smartphone apps have been used directly to promote safe transport for pedestrians and individuals' health and well-being. Taking advantage of mobile devices' functionality for integrating personal behavior models, smartphones are increasingly valuable tools for activity-based transport. Bopp et al. found that active travel is influenced by time, distance from the destination, and health concerns [192]. Route planning and projected time for a commute are the most frequently requested app features. Rezae et al. evaluated the motivational effect of an assistive transport app to support autistic mobility [193], which requires crowd information and accessible scenarios for riding public

Table 2: Catalog of reviewed papers.

Focused research issue		Research scope	Mobile date category	Context	Transport mode	Geographical placement of activities	Temporal placement of activities
Route or mode selection	[2–4, 10, 12–27] [28–51] [52–72] [73–108]	App (45); data system (57)	Cellular signal (10); CDRs (21); GPS (21); WiFi (7); accelerator (4); GNSS (1); Internet traffic (1); usage data (2)	Passenger transport (84); tourism (16)	Automobile (34); public transport (36); train (12); air transport (1); walking (24); cycling (17)	Indoor (2); local (24); metropolitan (49); regional (12); national (13)	Single trip (13); Same-day (11); day-to-day (54)
Smartphone usage	[5, 7, 109–116] [117–133] [134–161] [162, 163]	App (49); data system (8)	GPS (3); Internet traffic (1); user data (6)	Passenger transport (28); tourism (16)	Automobile (34); public transport (36); train (12); air transport (1); walking (24); cycling (7)	Indoor (2); local (24); metropolitan (49); regional (12); national (13)	Single trip (13); Same-day (11); day-to-day (54)
Sustainable mobility	[164–191]	App (18); data system (10)	GPS (5); accelerator (2); usage data (3)	Passenger transport (26); tourism (1); freight transport (1)	Automobile (23); public transport (18); train (7); air transport (1); walking (15); cycling (19)	Local (8); metropolitan (14); regional (3); national (3)	Single trip (5); Same-day (1); day-to-day (15)
Health	[192–203]	App (4); data system (6)	GPS (3); accelerator (2); physiology (1)	Passenger transport (10)	Automobile (2); public transport (2); walking (2); cycling (3)	Local (4); metropolitan (3); regional (1); national (1)	Single trip (5); Same-day (1); day-to-day (15)
Safety	[204–213]	App (8); data system (2)		Passenger transport (26); tourism (1); freight transport (1)	Automobile (23); public transport (18); train (7); air transport (1); walking (15); cycling (19)	Local (8); metropolitan (14); regional (3); national (3)	Single trip (1); Same-day (2); day-to-day (4)
General transport behavior or experience	[9, 214–232]	App (10); data system (10)	Cellular signal (2); GPS (3); WiFi (1); accelerator (1)	Passenger transport (17); tourism (2)	Automobile (6); public transport (7); train (1); air transport (1); walking (7); cycling (6)	Indoor (1); local (4); metropolitan (10); regional (2); national (1)	Single trip (3); Same-day (4); day-to-day (9)
Misc.	[233–237]	Data system (2)	Cellular signal (1)	Tourism (1); freight transport (2)	Walking (1)	Metropolitan (2)	
Synthesis/ review	[108, 238–252]						

transport. To detect negative emotions during driving, smartphone apps have been developed to quantify raw physiological data as valid measures of stress [194]. Weber et al. elucidated the effects of riders engaging via smartphone apps and their activity registration to confirm the growing interest in bicycle ridership via digital encouragement [195].

3.2. Mobile Phone Data. Following the screening process, we identified the following types of mobile phone data: cellular signals, CDRs, global positioning system data/global navigation satellite system data, mosion sensor data, and usage data. In transport behavior studies, the cellular signal data set consists of anonymous mobile tracking record collected from mobile operators. A CDR is produced when a device connects to the cellular network for events, such as calling, texting, handover, and location update. Global positioning system data are the autonomous related geospatial and time information gathered from satellite positioning. Motion sensor data account for the physical behavior of mobile devices. User data reflect analytics, trends, and usage information generated and owned by riders.

3.2.1. Cellular Signals. Thanks to the indispensable usage of mobile phones in daily life activities, cellular signaling data enable transport behavior studies to expand spatial and temporal coverage. Cellular signal data could be useful in transport demand modeling, a discovery from Caceres et al.'s work [18]. The data constructed origination-

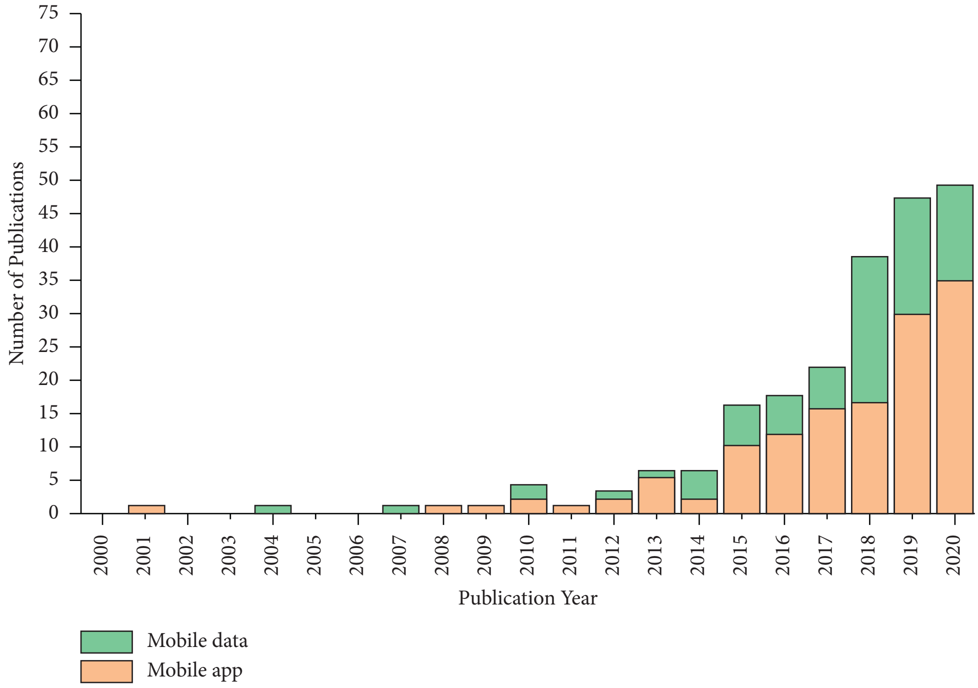

Figure 2: Research scope of the studies on mobile technology in transport behavior.

destination matrices covering most human movements to visualize regional mobility patterns with a low granularity of the zoning system. Asakura and Hato focused on a tracking survey method for individual travel behavior in an urban area using the cellular phone system [92]. This made tracking metropolitan mobility much easier. Fine-grained transport mode information could be extracted by applying supervised methods to cellular signaling data sets, according to Chin et al.'s study [4]. Passenger behavior during air transport could be realized by leveraging records from the major communication carriers [215]. The distribution of passenger flows, aggregated from mobile data, is consistent with those from traditional methods, which sheds light on future developments of complex transport systems.

3.2.2. CDRs. CDRs offer diaries of phone activity. They are primarily used for business billing purposes. Owing to the facilitated access to these data sources, CDRs could be a reliable source of illustrating points of interest and keeping track of phone system usage. As a complement to traditional transport surveys, Phithakkitnukoon et al. proposed a detection algorithm to process CRD in their mode choice study [19]. This study found that social ties determine ridership among public transit and automobiles. By identifying temporal regularity in human urban mobility, call activity volume gathered from mobile networks could estimate the aggregated distribution of the metropolitan population over time, as suggested by Sevtsuk and Ratti's research [20]. It was not just aggregation-based on CDRs; Calabrese et al. formulated a multivariate regression model to predict human mobility [21], indicating the value of such data sources as representative of individual mobility as well as for understanding intraurban variation. In addition to GIS data, CDRs can further be added with geographical references—Williams et al. designed six novel measures of mobility that integrate both mobile phone records and detailed GIS data to analyze the spatial nature of human mobility [22], clarified the influence of human mobility on microlevel human behavior and well-being and macrolevel social organization and change.

3.2.3. GPS/GNSS Data. GPS/GNSS data have been used to investigate spatial mobility with a high zoning resolution and low levels of wear-related concerns. It is thus a well-suited data collection method for the continuous recording of time series. In particular, it is possible to portray the structure of habits in mobility. Supported by such data, planners can identify additional, unplanned routes in parallel to the utilization of major road infrastructure, according to Joseph et al.'s study [9]. Bernardi et al. focused on the relationship between cyclists' route choices and various attributes of the transport network by using GPS traces [23]. This research detected some rare traits of cyclists to repeat preferred trips via the shortest route. Toader et al. used geospatial Big Data to investigate collaborative mobility [24]. With the help of GPS traces, the opportunities and behavioral changes for shared mobility solutions can be recognized automatically. A powerful analytical approach for urban transport could be developed into the incorporation of GPS and transactional data, as demonstrated by Lu et al. [25]. To summarize what has been stated thus far, the use of GPS data is not limited to mobility inference but serves navigation, localization, and ubiquitous computing systems.

3.2.4. Motion Sensor Data. In addition to GPS component, various sensors, such as accelerometers, gyroscopes, and magnetometers, are currently built into smartphones to detect changes and generate data by measuring device movements and aspects of the environment. Jimenez et al. used smartphone sensor data to estimate real-time energy consumption [167]. The results showed that the model's accuracy could be improved by including the classification of the driving style. Kinematic changes recorded by smartphone sensors can sufficiently represent passenger ride comfort as a key factor of service quality [196]. In addition, pervasive sensing is becoming accepted in the transport sector. This point is best illustrated by Zhou, Yu, and Sullivan's research on real-time control, which built a chained random forest model to transform smartphone data into information on various travel modes [72]. This delivered good performance in both indoor and outdoor environments with 93.8% overall accuracy.

3.2.5. Usage Data. Researchers have begun to collect various types of user behavior data to figure out design issues when technology adoption is mentioned. They are deployed to improve user authentication, create user interfaces, and address the needs of riders. Semanjski et al. developed a research model based on support vector machines to understand the role of the spatial context of human movements from mobile-sensed Big Data [26]. The results demonstrated a success rate of 94% achieved by the proposed model. Louveton et al. developed a car-following task within a driving simulator environment to study driver-mobile interactions [114]. Common tasks, that is, binary decision, list selection, and slide bar, were evaluated by the authors. Suh et al. investigated the last-mile delivery problem based on environmental impacts and discussed the use of mobile-enabled social networks [168]. Cottrill et al. presented the design, development, and implementation of a smartphone-based prompted-recall travel survey [115]. They found that a clear workflow and simple user interaction are essential to maintain participation rates.

3.3. Analysis of Trends. The collection and analysis of GPS/GNSS data have been the most prominent methods for understanding transport behaviors. Between 2000 and 2010, as shown in Figure 3, there were few studies using mobile phone data. In 2004, mobile technology in transport behavior studies started using cellular signals. Again, the emerging role of cellular signals is observed between 2015 and 2020. The presence of CDRs is evident in mobility studies during all time periods. The distribution of data types among across periods presents an increasing diversity of mobile techniques in recent years. In line with diversified methods over the past 5 years is the specific mobile phone data that was not stated with regard to information and characteristics. These new data from mobile technology are categorized as miscellaneous.

Mobility flow analysis and technology adoption were the predominant research questions addressed in all periods, as shown in Figure 4. Most studies addressed the critical process that guarantees riders the necessary acquisition of services, information, and transport products between 2010 and 2015. Following this, mobile phones are increasingly used for mobility analysis. This is a promising research theme allowing humanitarian interventions to better understand population movement in urban areas. Articles addressing methodological and technical aspects of mobile phone use and related approaches to scientific developments have constituted a large proportion of all research efforts in the recent years. However, polity assessment and evaluation remain largely underexplored in the literature compared with other research streams.

Passenger transport was the most common sector studied, as shown in Figure 5. The research interest spearheaded in 2010, after which the application of mobile phones in the tourism sector addressed technology adoption and travel experience. Despite a diversified landscape of research themes, in 2020, forty-six of 59 articles touched upon behaviors in passenger transport, and only thirteen articles were related to tourism and freight transport. Currently, the ability to collect mobility data from smartphones, improved system design, and utilization of pervasive strategies was the main driver of digital adoption among riders.

Compared with passenger transport and tourism, we identified few publications on freight transport, covered by a limited number of articles during the span of the studied period; however, emerging freight apps afford a mechanism of consolidation and transshipment on the mobile Internet [253]. There is an ever-growing scientific research effort in mobile ICT, on-time delivery performance, and greater visibility into the movement of goods [233]. However, their behavioral consequences of implementing sustainable processes have not been thoroughly studied. Thus, the intersection of mobile technology and freight transport is still quite innovative and underexplored.

The literature study categorized geographical placements of travels that include certain areas at the within-building, local, metropolitan, regional, and national levels, as Figure 6 shows the number of articles published during the study period. Research in this field has been conducted at the national level with nationally important mobility characteristics. 2019 saw the most systematic studies at the national level after a steady growth of publications over the years. Mobile-based techniques addressing regional mobility issues were rarely studied before 2016 but have increased in recent years. In addition, a number of studies have demonstrated that mobile phone use has a clear influence on transport behavior at the local scale.

Using mobile technology to study transport behavior in metropolitan areas touched upon the simultaneously growing demands of mobility and changes in riders' expectations in urban systems. This literature study observed that a continuously growing number of studies are performed at a macro level to introduce innovative mobility inference based on data collected from a large number of inhabitants as well as device holders. This contributed to the potential transformation of mobility in the investigated area through the integrated design, application, and analytics of smartphone apps.

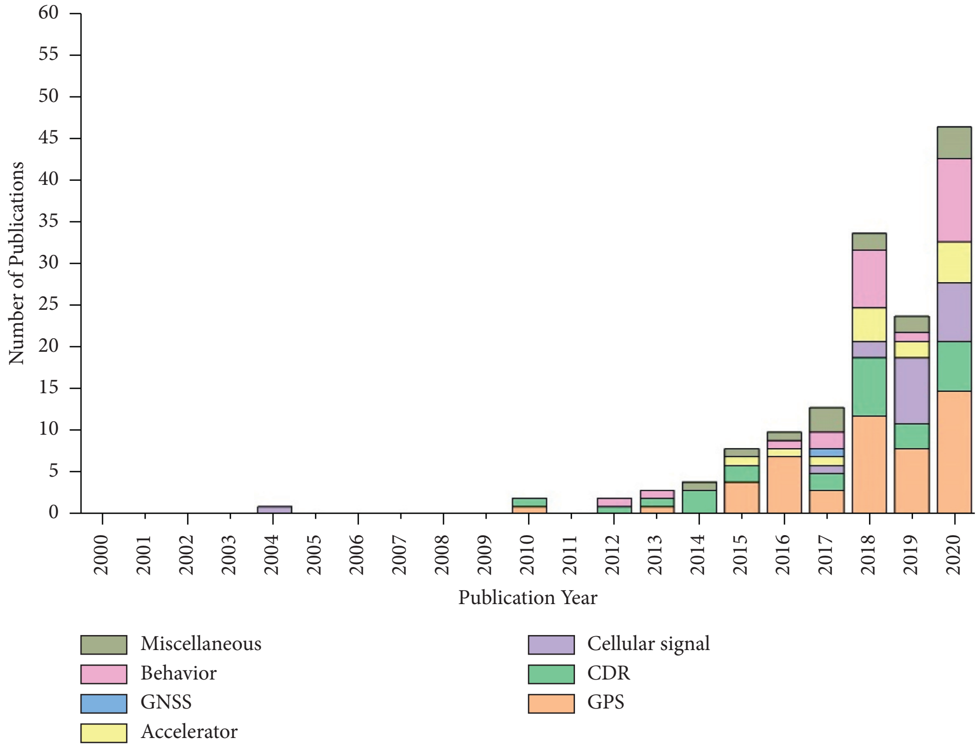

Figure 3: Categories of data for the study of mobile technology in transport behavior.

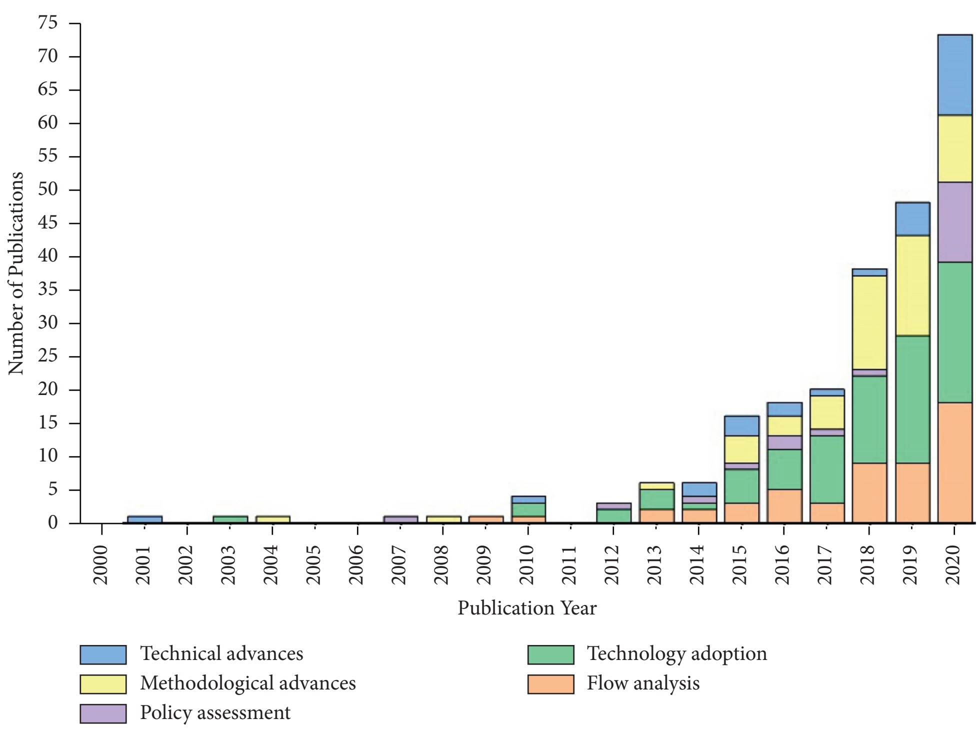

Figure 4: Aims of research for the study of mobile technology in transport behavior.

We also examined the transport mode recognition of the included articles. We deducted that public transport, walking, and cycling are currently focused on providing opportunities for increased accessibility before and after trips, with over two-thirds of the relevant studies published in 2019 and 2020, as shown in Figure 7. We attribute the high research interest to the proliferation of wearable sensors, location-based technology, and

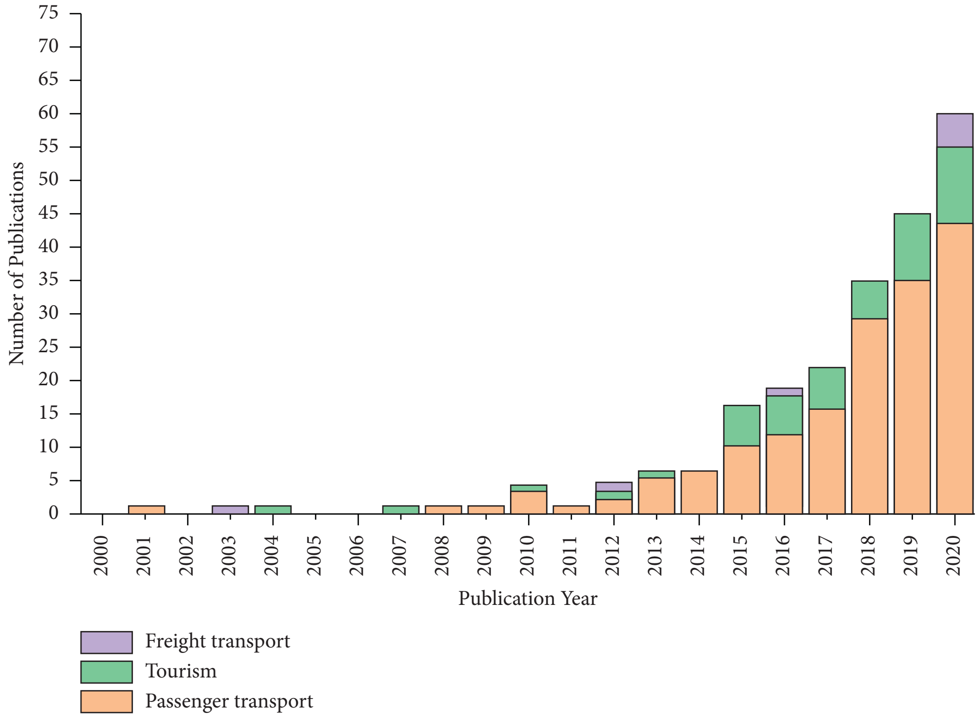

Figure 5: Investigated sectors for the study of mobile technology in transport behavior.

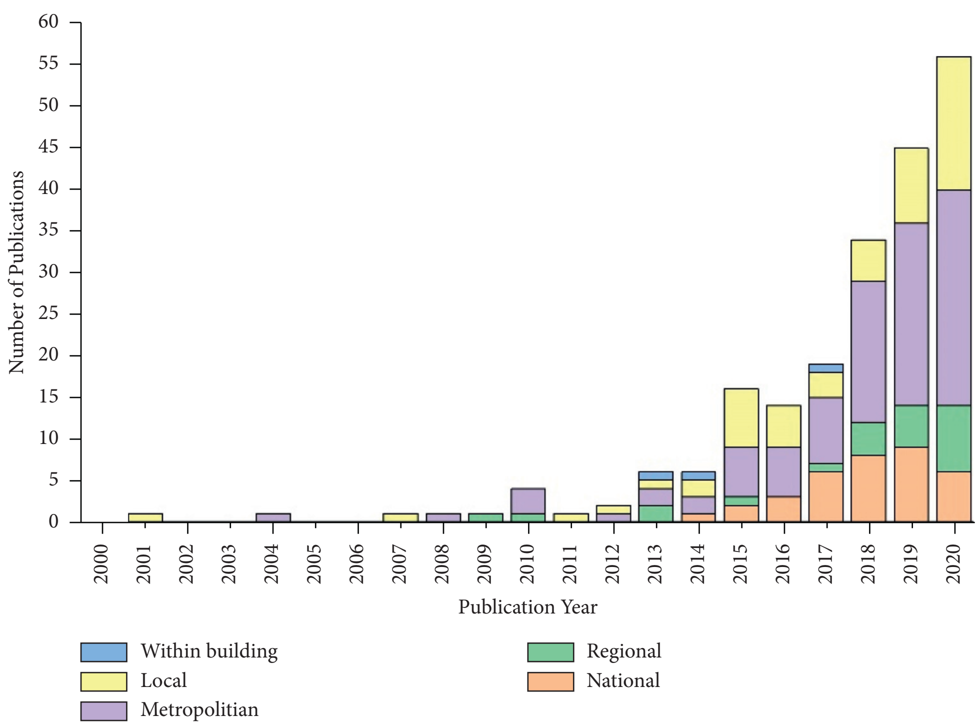

Figure 6: Spatial placements of activities for the study of mobile technology in transport behavior.

efficient algorithms. The trend and focus of research on walking and cycling modes revealed the scholarly attention given to accessibility issues in the public realm. With regard to the particular modes under which research on the topic was conducted, thirty-seven of the research papers (25%) revolved around automobiles. In addition, nine papers on trains and three papers on air transport were included.

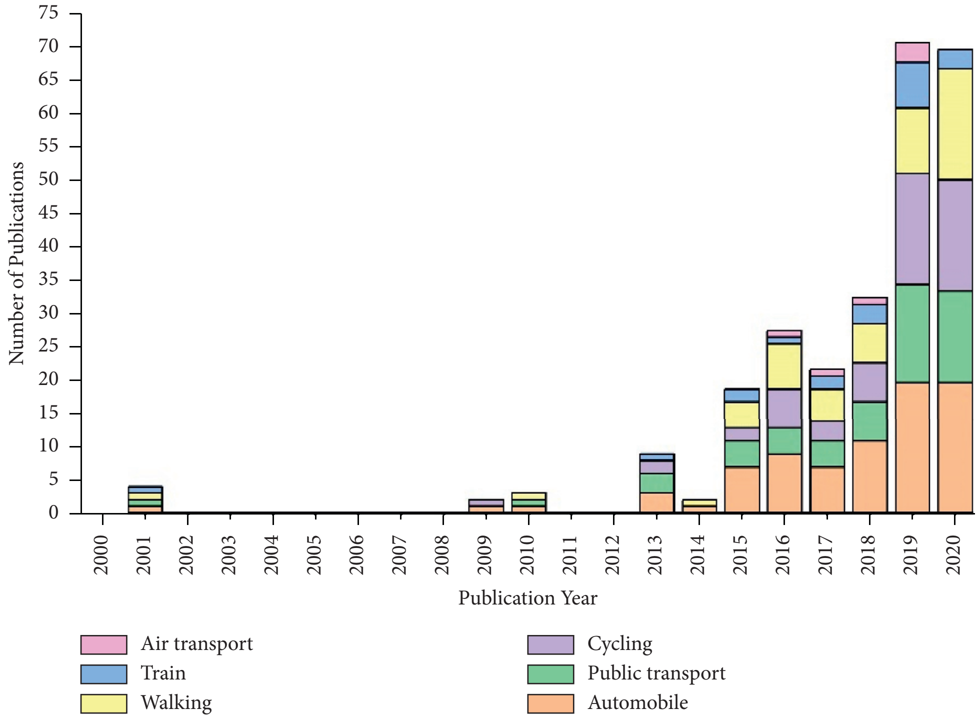

Figure 7: Investigated modes for the study of mobile technology in transport behavior.

We identified the core of pervasive mobile computing in transport behavior studies as the computational ability to facilitate effective communication via messages and thus making the acquisition of transport services and products more frequent on a mobile device. Table 3 presents a summary of the pervasive computing methods in the studies. Researchers have evaluated ways of interacting that enrich mobility. The literature analysis identified two major classifications in the forms of pervasive computing. The first collection of studies deployed real-time systems. These studies consistently show that the provision of timely and appropriate information on travel was key to the performance of transport systems in general and transport decision-making in particular.

The other stream of research on pervasive computing focused on behavioral outcomes of gamification mechanisms, including points, badges, and leaderboards. Points were found to be the most popular engagement method used to create a sensation of involvement and growth. Leaderboards allowed friendly competition between riders and meaningful conversations about a certain objective, usually being carbon footprint reduction, active travel miles, and energy savings. Badges let riders receive appreciation for their efforts and help them recognize the value of behavior changes. They have been increasingly used in smartphone app design and implementation.

3.4. Bibliometric Investigation. The bibliometric investigation included 236 articles. After visualizing these groups in Figure 8, we identified remarkable citation networks. Each of them is associated with an obvious research linkage. The links and their tone indicate that most networks in the interdisciplinary area of research are spearheading and significant. The central network published most of its articles in analytical models, which expanded to various subjects in the proximity of travel behavior and systems. There are also articles published on behavioral models and promotion, mainly with travel products. The other networks are smaller but more concentrated than the central network.

Figure 9 illustrates that many small networks of institutions have written most articles to explore the challenges of right technological use. The central networks comprised multiple renowned universities with a continuous effort on mobile phone data analytics. In the core of the network is, among others Massachusetts Institute of Technology who collaborated with research groups in North America, Europe, and Asia, conducting a wide variety of mobility studies. Recent networks exhibited strong collaborations in the broader areas of smartphone app developments.

Figure 10 presents the CiteSpace map of the most frequently occurring keywords and their respective co-occurrence links. The years on the x-axis correspond to the first time the keyword was mentioned as a declared keyword. The most frequent keywords are time, system, model, travel behavior, technology acceptance model, information, pattern, smartphone, usage, mode choice, and bicycle. Noticeably, apps and data types have not been selected. This means that studies focus on real-world problems encountered by the users and the transport system. As expected, bicycle and mode choice are the most recent keywords. They reflect that research interests have focused on improving the use of slow modes instead of the information system itself. Between 2010 and 2015, the relatively high frequency of the

Table 3: Summary of pervasive computing methods and references.

Pervasive computing method		Description	Representative case studies
Real-time systems		Provides information to transport providers or customers about the current status of the transport system	[12, 15, 39, 42, 48, 49, 65, 72, 74, 75, 79, 95, 100, 116, 126, 137, 144, 164, 189, 193, 225]
Gamification	Point-based system	Used to offer immediate incentives for completing a trip or riding environmental transport modes	[70, 166, 172, 178, 180, 182, 183, 190, 192]
	Badges	Symbolizes rewards to thank riders for their commitment and motivates riders to work on the next challenge	[70, 172, 182, 190, 202]
	Leaderboards	Visualizes the standing of a group of riders with regards to certain advocacy topics	[178, 182]

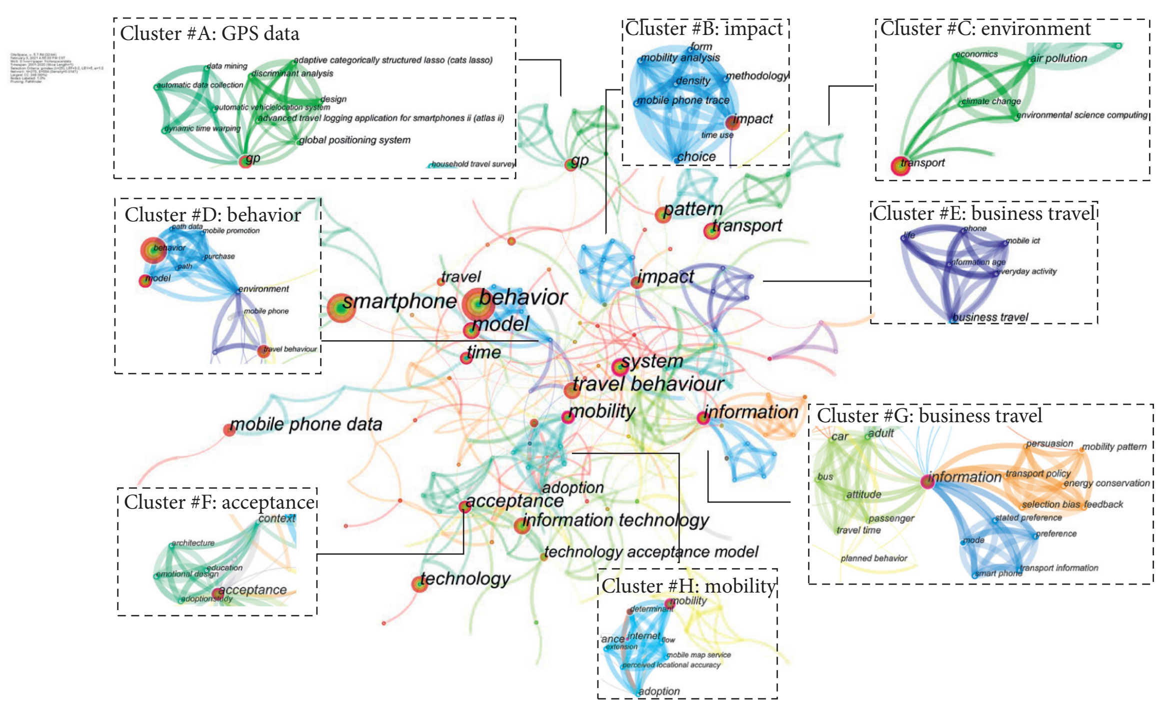

Figure 8: Cluster view of keyword concurrence of references during 2000–2020.

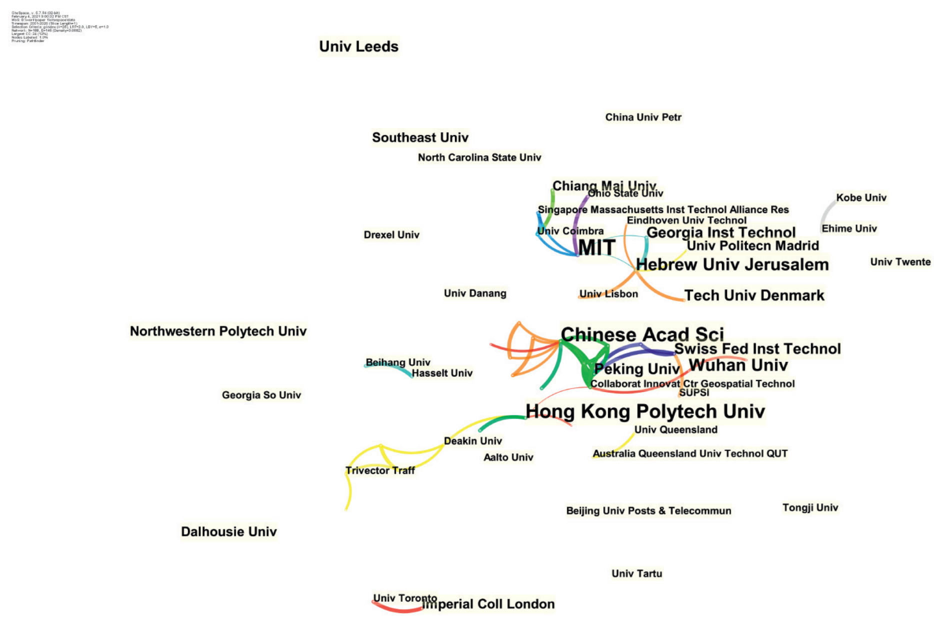

Figure 9: Cluster view of institutional collaboration network of references during 2000–2020.

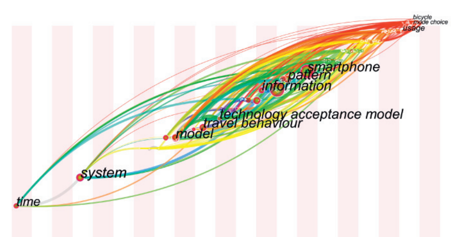

Figure 10: Temporal evolution of research keywords of references cited during 2000–2020.

words "technology acceptance model" and "information" indicates how information design and user adoption have been substantial. On one hand, the research on the time dimension is conducted from a systemic perspective, as "time" and "system" were keywords in 2000 and 2004, respectively.

3.5. Integrated Research Model. Even if previous studies have deployed mobile phones in transport behavior studies, the literature study revealed that no integrated research model had been drafted to summarize the intersection in these domains, including system design, data collection, transport analytics, and behavioral outcomes. By acknowledging the contributions already made in the existing literature, this study suggests an integrated research model, as shown in Figure 11, to reflect the research questions being asked, the underlying research logic, and the selection of research methods.

The literature analysis revealed that the two decades of progress consisted of research on topics in mobility (connection, accessibility, sustainability, safety, and health), interests in methodological advances (transport modeling, fine-grained mode detection, data collection methods, and analytics), and applications of well-established statistical techniques (structural equation models, logit models, and regression models). Our findings signify the growing utilization of a variety of mobile phone data before wide access to researchers, designers, and decision-makers.

Through the article-by-article examination of related work in this study, we found that transport app design has been supported with increasingly appealing features and contents. Studies have confirmed that mobile phone use leads to transport behavior changes through the mediation of riders' technology acceptance and adoption. Accordingly, the research model posits that design elements of smartphone apps influence riders' mobility, which in turn help make informed decisions in the geographical context. Drawing on the previous findings, the research model posits that riders' geographical and temporal placement of mobility still constructs all the orientation-destination relations; in the era of mobile phone use, it will stem from the interaction between (1) app-based design elements and (2) riders' technology acceptance and adoption and the transport behavioral outcomes.

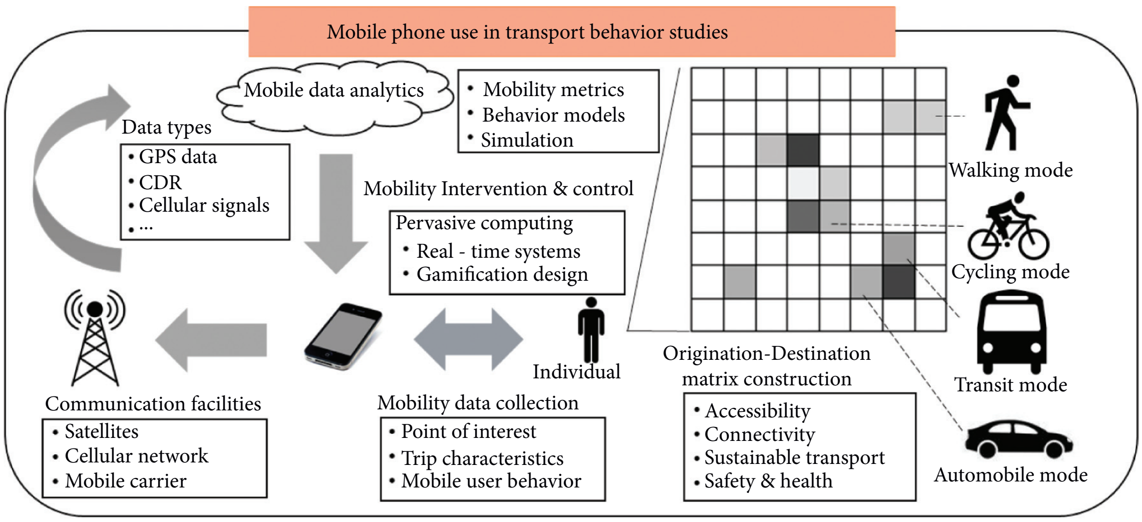

Figure 11: Integrated research model based on the synthesis of progress made in 2000–2020.

4. Critical Discussion

The literature review demonstrated that mobile technology in smartphone apps and data systems could be employed for transport behavior understanding, as summarized in Table 4. Smartphone apps are appropriate for real-time information, whereas the movement of individuals is efficiently collected by cellular signals, CDRs, GPS/GNSS, and usage data. GPS/GNSS data are essential source for understanding all aspects of mobility provided that the assessment is increasingly conducted based on tracks, open data, and GIS tools. Transport systems are characterized by connection, accessibility, and rider-centered services, substantially benefiting from emerging paradigms in the digital age. In this process, using GPS data is still the most important step to supply highly accurate spatial-temporal data, recognizing the overall visibility and traceability from transport behavior understanding to the assessment of network performance.

Cellular signals are beneficial for mobility pattern analysis because the signals facilitate data collection at the disaggregated level. The advantage of signal data is the accuracy in estimating crow flow and density, a difficult task to achieve with traditional surveying methods [247]. Individual choices of transport routes and destinations are described by the preferences of service attributes. By collecting and analyzing data at the cellular positioning level, it is possible to obtain valuable origination-destination matrices [254]. With the help of geographical information, we can estimate travels and identify transport modes [255]. This insight is at another level of behavior understanding than other types of mobile data can deliver.

With regard to algorithms, cellular signals and CDRs data are appropriate to apply supervised learning, clustering, and transport mode detection, whereas GPS data could be organized by advanced programs of automatic variogram fitting and hot spot discovery. Clustering algorithms are chosen for the usage data and app evaluation due to their efficient segmentation of groups.

Regression models have been constructed to analyze mobile phone network data. Multinominal logit analysis is prevalent for investigating the choice outcomes of services and products, even influenced by digitalization. The strength of logit analysis attributes to the scalability of the model, as transport survey can be complemented by smartphone data that reveal more behavioral dynamics. Structural equation models address the relationships between multiple exogenous and endogenous, often unobserved, variables and are employed in observational research of usage data and app evaluation. In addition, it is a data-processing method for the GPS travel survey.

This section presents how the studies on mobile phone use in transport behavior studies can constitute a discussion on the mobility value of mobile phone data, pervasive user-centric design, forward-looking at freight transport, digital adoption, and the major impacts of mobile technology on transport systems.

4.1. Further Interpretation of Mobile Data Value from a Scientific Perspective. While employing mobile phone data is increasing, its contested value remains largely unexplored. Most of the existing literature emphasizes the process of combining data from multiple sources. However, previous studies have started capturing value from new data from an activity location inference perspective but in an extreme case of an epicenter [256]. Of particular importance is the ability to leverage these mobile data, but little understanding is acquired with regard to their mobility value from different perspectives. This point can be best studied by investigating the relationship of mobility, data, and construction of value, as Spinney and Lin discovered [257]. Stakeholders can now not only assess the causal effect but also interpret the hybridity of movements converted into data that have not been previously available. Based on the literature study, we argue that sourcing, management, and analysis of mobile phone data cannot merely be treated as one specific and delimited type to well-defined data science. Instead, the ways that

Table 4: Mobile technology for transport behavior understanding.

	Smartphone apps	Cellular signals	CDRs	GPS/GNSS data	Usage data
Technology preparation	A software that matches riders with transport service providers	Mobile phone network data collected by telecommunication operators for maintenance purposes	Geolocation data for each rider's route	Details about user's arrival, visiting and time spending with technological features	
Available algorithms	Naïve bayes, clustering, trace processing, route planning	Tower signal triangulation, moving-or-staying identification, supervised learning, clustering, data transfer, fuzzy logic	Supervised learning, clustering, mode detection, behavior based	Automatic variogram fitting, prey-predator, clustering, hot spot discovery, learning, fuzzy logic, map-matching, recursive search, trip-breaking, route planning, critical point, gravity estimation	Parameter estimation, clustering, recursive search, search heuristic
Statistical models	Structural equation models, model of the theory of planned behavior, discrete choice models, logistic regression, multilevel regression	Multiple liner regression, bimodal	Proc mixed, logistic regression, general liner model	Regression tree, bayesian multilevel regression, linear regression, structural equation models, discrete choice models	Discrete choice models
Application area	All	Route or mode selection, general transport behavior or experience	Route or mode selection	Route or mode selection, sustainable mobility, smartphone usage, health, general transport behavior, or experience	Route or mode selection, sustainable mobility, smartphone usage

mobile phone data are spatially and temporally organized—but also integrated—constitute critical insights into mobility. Hence, given the importance of mobile phone data on the inquiry of gathering facts and evidence, we draft these central questions that need to be answered by researchers:

(i) What is the mobility value of the proximity of actors interested in mobile phone data and relevant products?

(ii) How would the integration and hybridity of mobile phone data relate to critical insights into transport behavior?

4.2. Pervasive User-Centric Design of Smartphone Apps. Design is a fertile field that focuses on attracting users and identifying user needs as a fundamental challenge to adoption [116]. Previous studies demonstrate the importance of the design phase taking into account expressed requirements [258]. In line with overtaking technological limitations, any information systems design should continue to realize a user-centric methodology for identifying opportunities from potential needs. The next step of research is expected to tackle issues of consistency, scalability, and recognizability around the visual communication of mobile information systems, a research problem that has not been fully addressed according to the literature.

Mobile-driven incentives and gamification elements are viable options for behavior stimuli. They can be associated with appealing features and contents. Most importantly, the application of gaming elements in a nongame context has been strengthened across domains over recent years. However, long-term behavioral outcomes as a consequence of pervasive computing's integration with riders' mobile life are not fully elucidated in the literature. The acquisition of information from ubiquitous media might point riders to the perception of being manipulated and therefore encounter negative experiences such as annoyance and loss of performance. Given the blur of the physical world and digitalization, a critical question is as follows:

(i) How will the design efficiency and effectiveness of smartphone apps be guaranteed?

4.3. Impact of Mobile Technology on Transport Systems. Mobile phone use is key to the temporal and spatial coordination of travel activities in networked societies. An increasing amount of mobile phone data drives quantitative studies on urban systems to explain the large variety of processes occurring with geographical constraints. Aguiléra et al. pointed out the difficulty of approaching the wealth and complexity of possible interactions between information and communication technology [238]. This was confirmed by examining the more recent literature. Most contributions of the work revolve around the representation of mobility and impact analysis. Experimental results show that it is possible for gathering route choice information on a large-scale road network based on route choice inference models for digital trace collection [27]. As Cats and Jenelius demonstrated, real-time information could facilitate the understanding of transport networks' vulnerability and disruptions [259]. The literature still lacks a coherent understanding of the dominant mechanism overarching the relationship between mobile phone use and mobility patterns in urban areas. In light of this, we posit the following research questions:

(i) What motivation will riders' major determinants of transport behavior provide for the usage of mobile phones?

(ii) How would riders adapt in transport systems after the long-term survival of a behavior change technique?

4.4. Freight Transport. A growing prevalence of mobile devices in delivery and logistics systems is observed and enabled. Our literature analysis discovered that previous studies did not emphasize simulation-based analytics supported by mobile data, which could be considered a promising future research topic. Despite a few qualitative studies in supply chains and logistics, mobile phone use is rarely mentioned in the quantitative analysis of goods movement and freight planning. Mobile data-driven models are promising for handling the inherent complexity of freighting through aggregation (using zoning systems and spatial clusters). It is worth encouraging supply chain trading partners to engage in the exchange of freight data but, more importantly, to reflect location intelligence. The following question needs to be addressed:

(i) How should freight zoning systems be reached in mobile data (considering aggregation into product groups based on distribution requirements)?

4.5. Adoption. Potential adoption is crucial to the relevance of carrying out research on a technical concept, in particularly given the history of failures at digitalization. With only a handful of publications addressing adoption, our analysis reveals the inadequacy of scholarly attention on this aspect to meet diverse requirements and realistic constraints of end users. Looking past the adoption of mobile technology outlines the barriers to adoption to be the external pressure and perceived benefits.

As technology permeates differently between organizations and cohorts, we argue that mobile phone use will be subject to cascades and a long-term interaction with transport systems. To this end, the research must consider it sufficiently beneficial for them to reflect the intentions, motivations, and behavioral factors; however, no holistic model addressing this incremental adoption is provided. Given the lack of research on adoption, we suggest that future research prioritize the overarching question on:

(i) What are the most important barriers and opportunities to mobile phone implementation and to making a translational impact?

5. Conclusions

This literature study offers an overview of current research, a critical discussion, and a research agenda for mobile technology in transport behavior studies. Through systematic analysis and a synthesis of works, a contribution to current research on smartphone apps and data systems is the summary of progress over the past two decades *t*. For researchers and developers, we recommend that further studies revolve around the interpretation of the value of mobile phone data from a brand-new scientific perspective focusing on pervasive user-centric design, impact on transport systems, application in freighting, and the adoption process. The research work on slow modes of transport and a diversified methodological viewpoint (the existing research is dominated by a few institutions) of the literature provide new insights for where to focus further efforts to continue exploring the revolutionary role mobile phone.

Mobile technology contributes to future adoption as a number of such issues have arisen. What is crucial to understand from a researcher's perspective is that currently, there are no well-established frameworks that illustrate how the move from the data gathered from riders to the application of mobile technology could ensue for the transport sector. We have also viewed the mobile phone's integration with transport systems as a positive scenario at scale rather than just the last mile of personalization. Standpoints of how mobile phones relate to mobility differ between stakeholders. Our analysis suggests an array of questions to be addressed in future research, stressing the importance of a cumulative approach. Addressing the current challenges of mobile phone conceptual development listed here would likely provide a solid ground for evaluating actual implementations in terms of its intended effects to solve the grand challenges in urban systems.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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