Chapter

Recent Progress in Activity-Based Travel Demand Modeling: Rising Data and Applicability

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Abstract

Over 30 years have passed since activity-based travel demand models (ABMs) emerged to overcome the limitations of the preceding models which have dominated the field for over 50 years. Activity-based models are valuable tools for transportation planning and analysis, detailing the tour and mode-restricted nature of the household and individual travel choices. Nevertheless, no single approach has emerged as a dominant method, and research continues to improve ABM features to make them more accurate, robust, and practical. This paper describes the state of art and practice, including the ongoing ABM research covering both demand and supply considerations. Despite the substantial developments, ABM's abilities in reflecting behavioral realism are still limited. Possible solutions to address this issue include increasing the inaccuracy of the primary data, improved integrity of ABMs across days of the week, and tackling the uncertainty via integrating demand and supply. Opportunities exist to test, the feasibility of spatial transferability of ABMs to new geographical contexts along with expanding the applicability of ABMs in transportation policy-making.

Keywords: activity-based models, travel demand forecasting, transportation planning, big data, transferability of transport demand models

1. Introduction

In recent years, behaviorally oriented activity-based travel demand models (ABMs) have received much attention, and the significance of these models in the analysis of travel demand is well documented in the literature [1, 2]. These models are found to be consistent and realistic in several fundamental aspects. They possess some significant advantages over the simple aggregated trip-based travel demand models [3]. To achieve this, ABMs consider the linkage among activities and travel for an individual as well as different people within the same household and place more attention to the constraints of time and space. In other words, these models are capable of integrating both the activity, time, and spatial dimensions. The comprehensive advantages of activity-based models in comparison to the trip-based models have been discussed in previous papers [4–8]. Activity-based models are suitable for a wider variety of transportation policies involving individual decisions such as congestion pricing and ridesharing. More especially, enabling the relationship between activity and behavioral pattern of trip making is one of the main reasons for the shift from the aggregate-level in trip based models to disaggregate-level provided by ABMs [9].

Activity-based travel demand models (ABMs) can be classified into two main groups: Utility maximization-based econometric models and rule-based computational process models (CPM). Utility maximization-based econometric models apply different econometric structures such as logit, probit, hazard-based, and ordered response models. While the logit models rely on different assumptions about the distribution of the error terms in the utility functions, hazard-based models use the duration of activity based on end-of-duration occurrence to generate activity schedules [10]. Rule-based computational process models apply different sets of condition-action rules and focus on the implementation of daily travel and ordering activities to mimic individuals' behavior when constructing schedules. In addition to the aforementioned models, other approaches can be employed either in combination with these models or separately to develop activity-based models. Examples include agent-based and time-space prism approaches. While an agent-based approach allows agents to learn, modify, and improve their interactions with other agents as well as their dynamic environment, time-space prisms are utilized to capture spatial and temporal constraints under which individuals construct the patterns of their activities and trips. **Figure 1** exhibits critical elements of ABM such as activity generation, activity scheduling, and mobility choices. It also provides a comparison among the notable existing travel demand models regarding their different elements. The development of activity-based travel demand models has been reviewed comprehensively in previous studies [10, 11]. **Table 1** provides a summary of the literature on the evolution of these models over time by introducing the notable existing developed models and highlighting their limitations.

Despite the existence of many models as listed in **Table 1**, ABM's abilities in reflecting behavioral realism are still limited [40]. The capability of ABM models

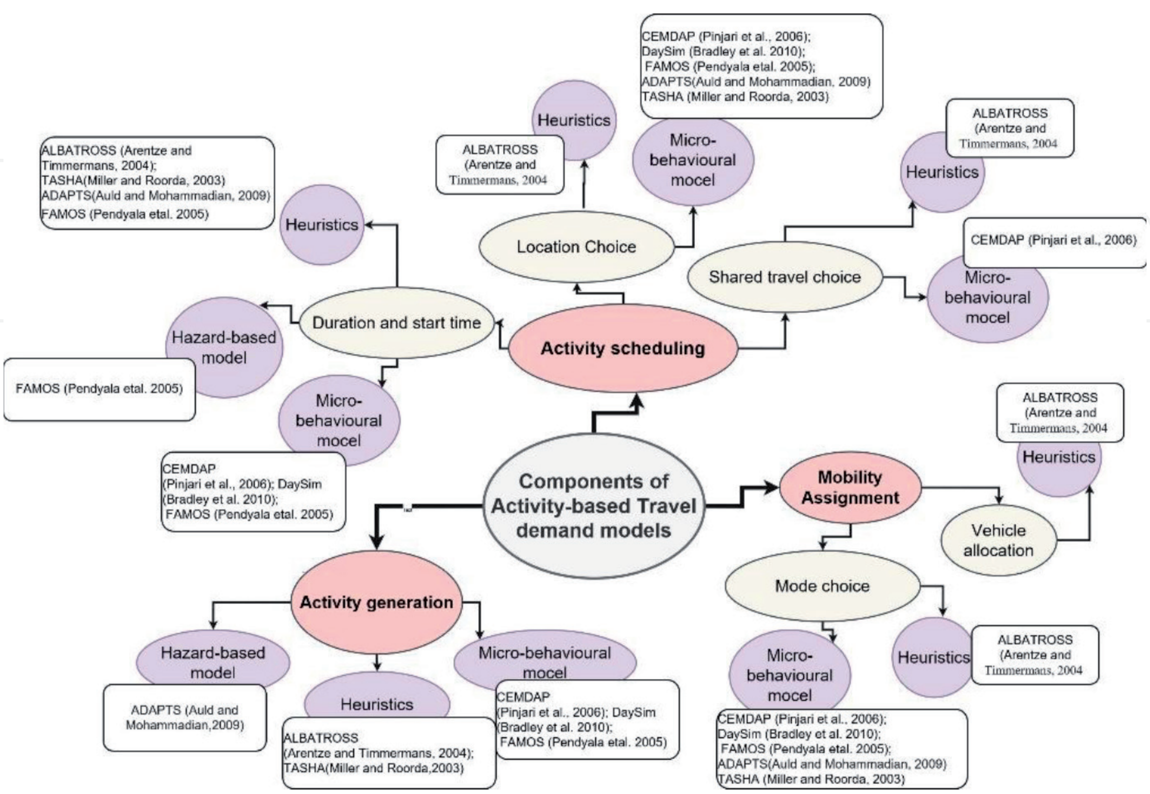

Figure 1.
Components of activity-based travel demand models.

ABM type + year of proposal	Examples	Model limitations
Constraint-based models 1967	PESASP [12]	Consider only individual accessibility, rather than household-level accessibility Some system features, like open hours and travel times, are considered fixed [11]
	CARLA [13]	
	BSP [14]	
	MAGIC [15]	
	GISICAS [16]	
Utility maximization-based models 1978	Portland METRO [17]	• Assume that all decision-makers are fully rational utility maximizers which are not realistic in practice [10] • Unable to reflect latent behavioral mechanisms in the decision processes [11]
	San Francisco SFCTA [18]	
	New York NYMTC [19]	
	Columbus MORPC [20]	
	Sacramento SACOG [21, 22]	
	CEMDAP [23, 24]	
	FAMOS [25]	
	CT-RAMP [26]	
Computational process models 2000	ALBATROSS [27, 28]	Focus more on scheduling and sequencing of activities than the underlying rules in decision-making [11]
	TASHA [29, 30]	
	ADAPTS [31–33]	
	Feathers [34]	
Agent-based modeling 2004	ALBATROSS [27, 28]	• High computational complexity • No transparency in the mechanical process of agents interacting with other agents and environment which depends on the parameters' values • Requires well-defined conditions and constraints • Non-reproducibility due to the non-streamlined process of calibrating and imputing parameters for the models [39]
	Feathers [34]	
	MATSim [35]	
	TRANSIMS [36]	
	SimMobilitiy [37]	
	POLARIS [38]	

Table 1.
ABM evolution over time.

in predicting individual travel movements can be evaluated from two perspectives of input (data) and output (applicability). Activity schedules are an essential input into the ABM model. From an input point of view, the necessity of deriving activity schedules from dynamic resources together with their challenges will be reviewed. From the applicability perspective, the application of ABM output in integration with dynamic traffic assignment (DTA) models, transferring to a new geographical context, and why and how it is applied in transport planning management will also be discussed. To this end, the first part of this paper will review the new real-time data resources revealing the pattern and traces of traveler's mobility at a large scale and over an extended period of time. The big data enables new ABM models to reflect mobility behavior on an unprecedented level of detail while collecting data over a longer period (e.g., more than one typical day) would improve the behavioral realism in trip making [41]. The second part of this paper looks into the applicability of ABM models. This part includes (i) gap investigation in enriching ABMs by integrating time-dependent OD matrices produced by ABMs with dynamic traffic assignment; (ii) investigation of ABMs' applicability in transferring from one region to another; and (iii) enriching the capability of ABMs by moving beyond the transportation domain to other such as environment and management strategies.

The remainder of the paper is organized as follows. Section 2 introduces new data sources such as mobile phone call data records, transit smart cards, and GPS data where the influence of new data sources on the planning of activities, formation, and analysis of the travel behavior of individuals will be investigated. This section also introduces activity-based travel demand models, which generates activity-travel schedules longer than a typical day. Section 3 describes the existing experiences in transferring utility-based and CPM activity-based travel demand models from one geographical area to another. This section also reviews the integration of ABM models with dynamic traffic assignment and other models such as air quality models. The possibility of using activity-based models in travel demand management strategies with a focus on car-sharing and telecommuting are considered as examples. The last section concludes the paper and identifies remaining challenges in the area of activity-based travel demand modeling.

2. ABMs and the emerging of big data

This section provides an overview of the role of big data in replacing the traditional data sources, and the changes in activity-based travel demand models given these newly available data.

2.1 Improvements in activity-based travel demand modeling

It is more than half a century that transportation planners try to understand how individuals schedule their activities and travel to improve urban mobility and accessibility. The evolution of travel demand modeling from trip-based to activity-based highlighted the need for high-resolution databases including sociodemographic and economic attributes of individuals and travel characteristics. Today, with the rapid advancements in computation, technology, and applications, the intelligent transportation systems (ITS) have revolutionized the analysis of travel behavior by having more accurate data, removing human errors, and making use of the vast amount of available data [42]. Tools such as GPS devices, smartphones, smart card data, and social networking sites all have the potential to track the movements and activities of individuals by recording and retaining the relevant data continuously over time. Most of the traditional travel survey data are rich in detail. However, it can result in biased travel demand models because of incomplete self-reports and inaccurate scheduling patterns. Therefore, in this section, the common tools used in collecting big data are introduced and the progress made in the area of extracting big data sources is discussed.

2.1.1 Cell phone data

A call detail record (CDR) is a data record produced by a telephone exchange and consists of spatiotemporal information on the recent system usage [40], which can track people's movements. This CDR data can be processed and applied in activity-based travel demand modelings to better understand human mobility and obtain more accurate origin-destination (OD) tables [43]. The first attempt using CDR data was a study of Caceres et al. [44], who applied mobile phone data to generate OD matrices. Their concept was then formalized by Wang et al. [45] to obtain transient OD matrices by counting trips for each pair of the following calls from two different telephone (cell) towers at the same hour. Afterward, using the shortest path algorithm, OD trips are assigned to the road network. In the area of urban activity recognition, Farrahi et al. [46] applied two probabilistic methods (i.e., Latent Dirichlet Allocation (LDA) and Author Topic Models, ATM) to cluster CDR trajectories according to their temporal aspects to discover the home and work activities. Considering the spatial aspect of CDR data, Phithakkitnukoon et al. [47] applied auxiliary land use data and geographical information database to find possible activities around a certain cell tower. And considering both the temporal-spatial aspect of CDR, Widhalm et al. [48] used an undirected relational Markov network to infer urban activities. They extracted activity patterns for Boston and Vienna by analyzing cell phone data (activity time, duration, and land use). Their results show that trip sequence patterns and activity scheduling observed from datasets were compatible with city surveys as well as the stability of generated activity clusters across time. In a more recent study, [49] an unsupervised generative state-space model is applied to extract user activity patterns from CDR data. Furthermore, it has been shown that the method of CDR sampling is as significant as survey sampling. For example, in one study [50], CDR and survey data is used during a period of six months to investigate the daily mobility for Paris and Chicago. The result shows that 90% of travel patterns observed in both surveys are compatible with phone data. In another similar study [51], a probabilistic induction was proposed using motifs (daily mobility network), time of day activity sequence, and land use classification to produce activity types. CDR data of Singapore was used by Jiang et al. [52] to produce activity-based human mobility patterns.

In the context of activity-based transport modeling, Zilske et al. [53] replaced travel diaries with CDRs as input data for agent-based traffic simulation. They first generated the synthetic CDR data, then the MATSim simulation software was used to identify every observed person as an agent to convert call information into activity. They fused the CDR data set with traffic counts in their next paper [54], to reduce the Spatio-temporal uncertainty.

In summary, the findings reported from different studies indicated the major implications of mobile phone records on the estimation of travel demand variables including travel time, mode and route choice as well as OD demand and traffic flow estimation; however; in practice, the information generated from CDR data are yet to be used widely in simulation models. This is mainly because of the conflict between either level of resolution or format and completeness of model and data [55].

2.1.2 Smart card data

Smart card systems with on- and off-boarding information gained much popularity in large public transport systems all over the world, and have become a new source of data to understand and identify the Spatio-temporal travel patterns of the individual passengers. The smart card data are investigated in various studies such as activity identification, scheduling, agent-based transport models, and simulation [56]. Besides, in other studies [57–59] smart card data was used as an analysis tool in investigating the passenger movements, city structure, and city area functions. Similarly, in the recent study [60], a visual analysis system called PeopleVis was introduced to examine the smart card data (SCD) and predict the travel behavior of each passenger. They used one-week SCD in the city of Beijing and found a group of "familiar strangers" who did not know each other but had lots of similarities in their trip choices. Zhao et al. [61] also investigated the group behavior of metro passengers in Zhechen by applying the data mining procedure. After extracting patterns from smart card transaction data, statistical-based and clustering-based methods were applied to detect the passengers' travel patterns. The results show that a temporally regular passenger is very probable to be a spatially regular passenger. The disaggregated nature of smart card data represents suitable input to multi-agent simulation frameworks. For example, the smart card data is used to generate activity plans and implement an agent-based microsimulation of public transport in two cities of Amsterdam and Rotterdam [62]. An agent-based transport simulation is developed for Singapore's public transport using MATSim environment [63]. Unlike Bouman's study, they considered the interaction of public transport with private vehicles. The study of Fourie et al. [64] was another research work to present the possibility of integrating big data algorithms with agent-based transport models. Zhu [65] compared one-week transaction data of smart cards in Shanghai and Singapore. They found feasibility in generating continuous transit use profiles for different types of cardholders. However, to have a better understanding of the patterns and activity behaviors, in addition to collecting the data from smart cards, one should integrate them with other data set.

2.1.3 GPS data

In travel demand modeling, it is important to have accurate and complete travel survey data including trip purpose, length, and companions, travel demand, origin and destination, and time of the day. Since the 1990s, the global positioning system (GPS) became popular for civil engineering applications, especially in the field of transportation as it provides a means of tracking some of the above variables. In the literature, methods of processing the GPS data and identifying activities can be classified according to different approaches such as rule-based and Bayesian model [66]; fuzzy logic [67]; multilayer perceptron [68]; and support vector machine learning [69]. Nevertheless, the disadvantages of using GPS data include the cost, sample size limitation, and the need to retrieve and distribute GPS devices to participate. Since smartphones are becoming one of the human accessories while equipped with a GPS module, they can be considered as a replacement of the GPS device to gather travel data. In this regard, CDR from smartphones is used [70] to estimate origin-destination matrices, or a smartphone-based application is used [71] to map the semiformal minibus services in Kampala (Uganda) and to count passenger boarding and alighting [72]. In the Netherlands, the Mobidot application is developed for analyzing the mobility patterns of individuals. To deduce travel directions and modes, this application uses the real-time data gathered by sensors of smartphones including GPS, accelerometer, and gyroscope sensors to compare them with existing databases [73].

Applying smartphones as a replacement of GPS however, holds several restrictions including the draining of smartphone battery and it is not possible to record travel mode and purpose.

2.1.4 Social media data

Today transport modelers, planners, and managers have started to benefit from the popularity of social networking data. There are different kinds of social media data such as Twitter, Instagram, and LinkedIn data, which consist of normal text, hash-tag (#), and check-in data. As hash-tag and check-in data are related to an activity, location or event, they can be used as meaningful resources in analysis of destination/origin of the activity [74]. According to the literature, social media has a great influence on different aspects of travel demand modeling [75]. Using social media instead of traditional data collection methods was investigated in different studies [76]. The way of processing these data to extract useful information is challenging as investigated in different studies [77, 78]. Various studies [79–82] also examined social media data to understand the mobility behavior of a large group of people. Testing the possibility of evaluating the origin-destination matrix based on location-based social data was researched [83] or in another similar studies [84, 85] where Twitter data was used to estimate OD matrices. The comparison between this new OD with the traditional values produced by the 4-step model proved the great potential of using social media data in modeling aggregate travel behavior. Social media data can be used in other areas such as destination choice modeling [86], recognizing activity [87], understanding the patterns of choosing activity [80, 88, 89], and interpreting life-style behaviors via studying activity-location choice patterns [90].

2.2 Dynamic ABM using a multi-day travel data set

Most existing travel demand modelers have applied the household survey data during the period of one day to construct activity schedules. However, longer periods such as one week or one month gained substantial importance during recent years. For simulating everyday travel behavior and generating schedules, a one-week period provides more comprehensive coverage because it includes weekdays and weekends and represents the weekly routines of individuals in making trips. Periods longer than one week can further provide detail on personal behavior as well as various usage of modes in different ways. So far only a few travel demand models covered a typical week as a studied period. For example rhythm in activity-travel behavior based on the capacity of one week was presented by applying a Kuhn-Tucker method [41]. Few works have been concentrating on the generation of multiple-day travel dataset. For example, by using large data and surveys, Medina developed two discrete choice models for generating multi-day travel activity types based on the likeliness of the activity [91]. a sampling method based on activity-travel pattern type clustering [92] was proposed to extract multi-day activity-travel data according to single-day household travel data. The results show similarities in distributions of intrapersonal variability in multi-day and single-day. MATSim is a popular agent-based simulation for ABM research [93, 94], however, it is not appropriate for modeling the multi-day scenarios because MATSim uses the co-evolutionary algorithm to reach the user equilibrium which is a time consuming particularly for multi-day plans. To solve these problems, Ordonez [95] proposed a differentiation between fixed and flexible activities. Based on different time scales, Lee examined three levels of travel behavior dynamics, namely micro-dynamics (24 hours), macro-dynamics (lifelong travel behavior), meso-dynamics (weekly/monthly/yearly basis) by applying different statistical models [96]. A learning day-by-day module in another agent-based simulation software SimMobility is proposed [97]. Furthermore, ADAPTS is one of the few activity-based travel demand models which depends on activity planning horizon data for a longer period than one day, for example, one week or one month [33].

As highlighted by the above literature review, applying one-day observation data in travel demand modeling provides an inadequate basis of understanding of complex travel behavior to predict the impact of travel demand management strategies. So multi-day data are needed to refine this process. Previously, it was not easy to collect multi-day data, however, today thanks to advantages to technology it is possible to extract data from GPS, smartphones, smart cards, etc. with no burden for the respondent. Models built based on GPS data have been found to be more accurate and precise due to having fewer measurement errors. Collecting call detail records from mobile phones provide modelers with large trip samples and origin-destination matrices, while smart card data are more useful in terms of validation.

3. ABM transferability

We now turn to the recent advances and ongoing research in ABM focused on testing and enhancing geographical transferability and capacity to predict a broader range of impacts than flows and performance of the transport network.

3.1 ABM transferability from one geographical context to another

The spatial transferability of a travel demand model happens when the information or theory of a developed model of one region is applied to a new context [98]. Transferability can be used not only as a beneficial validation test for the models but also to save the cost and time required to develop a new model. Validation of a model by testing spatial transferability beside other various methods such as base-year and future-year data set is a test of validity which represents the capability of activity-based models in predicting travel behavior in a different context [99]. The exact theoretical basis and behavioral realism of activity-based travel demand model make them more appropriate for geographic transferability in comparison to traditional trip-based models [100]. Testing the transferability of ABM was first investigated by Arentze et al. [101]. They examined the possibility of transferring the ALBATROSS model at both individual and aggregate levels for two municipalities (Voorhout and Apeldoorn) in the Netherlands by simulating activity patterns. The results were satisfactory except for the transportation mode choice. In the United States, the CT-RAMP activity-based model which was developed for the MORPC region then transferred to Lake Tahoe [102]. In another study, one component of the ADAPTS model showed the potential for having good transferability properties [31]. The transferability of the DaySim model system developed for Sacramento to four regions in California and two other regions in Florida was investigated in [103]. The results show that the activity generation and scheduling models can be transferred better than mode and location choice models. The CEMDAP model developed for Dallas Fort Worth (DFW) region was transferred to the southern California region [104]. Outside the U.S., the TASHA model system developed for Toronto was transferred to London [105], and also in another study [106] the transferability of TASHA to the context of the Island of Montreal was assessed. Activity generation, activity location choice, and activity scheduling were three components of TASHA that transferred from Toronto to Montreal. In general, TASHA provided acceptable results at (macro and meso-level) for work and school activities even in some cases better results for Montreal in comparison to Toronto area. The possibility of developing a local area activity-based transport demand model for Berlin by transferring an activity generation model from another geographical area (Los Angeles) and applying the traffic counts of Berlin was investigated [107]. In their research, the CEMDAP model was applied to achieve a set of possible activity-travel plans, and the MATSim simulation was then used to generate a representative travel demand for the new region. The results were quite encouraging, however, the study indicated a need for further evaluation. In one recent study [108], an empirical method was used to check the transferability of ABMs between regions. According to their investigations, the most difficult problems with transferability caused by parameters of travel time, travel cost, land use, and logsum accessibilities. They suggested that in the transferability of the ABM from another region, agencies should be aware of finding a region within the same state or with similar urban density, or preferably both in order to improve the results. The possibility of transferring the FEATHERS model to Ho Chi Minh in Vietnam is investigated [109]. FEATHERS initially is developed for Flanders in Belgium. After calibration of FEATHERs sub-models, testing results using different indicators confirmed the success of transferring the FEATHER's structure to the new context.

At the theoretical level, a perfect transferable model contributes to the transferability of its underlying behavioral theory, model structure, variable specification and coefficient to the new context. However, perfect transferability is not easy to achieve due to different policy and planning needs as well as the size of the regions, and the availability of data and other resources. Although the results of several transferred ABM model systems seem to have worked reasonably, it is equally important to assess how much accuracy is important in transferring models and how best and where to transfer models from.

3.2 ABM transferability to other non-transport domain

One of the advantages of the activity-based travel demand models over trip-based models is its capability to generate various performance indicators such as emission, health-related indicators, social exclusion, well-being, and quality of life indicators. Application of disaggregate models for the area of emission and air quality analysis was introduced by Shiftan [110] who investigated the Portland activity-based model in comparison to trip-based models. In another study [111], the same author integrated the Portland activity-based model with MOBILE5 emission model to study the effects of travel demand techniques on air quality. Regarding the integration of ABM with the emission model, the Albatross ABM model was coupled with MIMOSA (macroscopic emission model) [112] considering the usage of fuel and the amount of produced emission as a function of travel speed. A study in [113] added one dispersion model (AUROTA) to the previous integration of Albatross and MIMOSA to predict the hourly ambient pollutant. Albatross linked with a probabilistic air quality system was employed [114] in air quality assessment study. TASHA was another activity-based model, which has been extensively employed in air quality studies. For example, this model was integrated [29, 115] with MOBILE6.2 to quantify vehicle emissions in Toronto. In their study, EMME/2 was used in the traffic assignment part. The previous research was improved [116] by replacing EMME/2 with MATSim as an agent-based DTA model. This TASHA-MATSim chain was used in the research [117] with the integration of MOBILE6.2C (emission model) and CALPUFF (dispersion model). OpenAMOS linked with MOVES emission model [118], and ADAPTS linked with MOVES [119] together with Sacramento ABM model [120] are among recent studies which represented the application of activity-based models in analyzing the impacts of vehicular emissions.

Human well-being and personal satisfaction play an important role in social progression [121]. To understand the theory behind human happiness, transport policies concentrated on the concept of utility as a tool to increase activity, goods, and services [122, 123]. The issue of well-being as a policy objective is addressed in the literature and measured through various indicators, which show personal satisfaction and growth. For example, in the study by Hensher and Metz [124, 125], saving time which leads to engagement in more activities was introduced as one of the benefits of measuring transport performance. Spatial accessibility was another benefit of travel that provides a range of activities that can be reasonably reached by individuals [126]. A dynamic ordinal logit model was developed [127] based on the collected data on happiness for a single activity in Melbourne. The authors found different activity types, which have different influences on the happiness that each individual experienced. Well-being can be integrated into activity-based models based on random utility theory. In terms of modeling, a framework was introduced [122] considering well-being data to improve activity-based travel demand models. According to their hypothesis, well-being is the final aim of activity patterns. They applied a random utility framework and considered well-being measures as indicators of the utility of activity patterns, and planned to test their framework empirically by adding well-being measurement equations to the DRCOG's activity-based model.

The above literature review showed the importance of applying traffic models to generate input data to other models such as the air quality model. The accuracy of emission models is highly dependent on the level of detail in transport demand model inputs. Activity-based and agent-based models are supposed to describe reality more accurately by providing more detailed traffic data. Beyond measurement of air quality, well-being and health have drawn increasing attention. The health impact of changes in travel behavior, health inequalities, and social justice can be assessed within the activity-based platform [128]. With the help of geospatial data acquisition technologies like GPS, behavioral information with health data can be integrated into the development of an activity-based model to provide policies that affect the balance of transport and well-being.

3.3 ABM integration with dynamic traffic assignment

In parallel with the travel demand modeling, on the supply side, the conventional supply models used to be static, which import constant origin-destination flows as an input and produce static congestion patterns as an output. Consequently, these models were unable to represent the flow dynamics in a clear and detailed manner. Dynamic traffic assignment (DTA) models have emerged to address this issue and are capable of capturing the variability of traffic conditions throughout the day. It is evident that the shift of analysis from trips to activities in the demand modeling, as well as, the substitution of the static traffic assignment with dynamic traffic assignment in the supply side, can provide more realistic results in the planning process. Furthermore, the combination of ABM and DTA can better represent the interactions between human activity, their scheduling decision, and the underlying congested networks. Nevertheless, according to the study of [11], the integration of ABM with DTA received little attention and still requires further theoretical development. There are different approaches to the integration of ABM and DTA, which started with a sequential integration. In this type of integration, exchanging data between two major model components (ABM and DTA) happens at the end of the full iteration, to generate daily activity patterns for all synthetic population in an area of study, the activity-based model is run for the whole period of a complete day. The outputs of the ABM model which are lists of activities and plans are then fed into the DTA model. The DTA model generates a new set of time-dependent skim matrices as inputs to ABM for the next iteration. This process is continued until the convergence will be reached in the OD matrices output. Model systems applying the sequential integration paradigm can be found in most of the studies in the literature. For example, Castiglione [129] integrated DaySim which is an activity-based travel demand model developed for Sacramento with a disaggregate dynamic network traffic assignment tool TRANSIMS router. Bekhor [130] investigated the possibility of coupling the Tel Aviv activity-based model with MATSim as an agent-based dynamic assignment framework. Hao [116] integrated the TASHA model with

MATSim. Ziemke [107] integrated CEMDAP, which is an activity-based model with MATSim to check the possibility of transferring an activity-based model from one geographic region to another. Lin [131] introduced the fixed-point formulation of integrated CEMDAP as an activity-based model with an Interactive System for Transport Algorithms (VISTA). Based on the mathematical algorithm of household activity pattern problem (HAPP), ABM and DTA were integrated [132] by presenting the dynamic activity-travel assignment model (DATA) which is an integrated formulation in the multi-state super network framework.

In the sequential integration, the ABM and DTA models run separately until they reach convergence. At the end of an iteration, these models perform data exchange before iterate again. Therefore, this kind of integrated framework cannot react quickly and positively to network dynamics and is unable to adapt to real-time information available to each traveler. In addressing this limitation, integrated models that adopt a much tighter integration framework have been developed recently. This approach is quite similar to the sequential approach, however; the resolution of time for ABM simulation is one minute rather than 24 hours (complete day). Relating to this level of dynamic integration, Pendyala [133] investigated the possibility of integrating OpenAMOS which is an activity-travel demand model with DTA tool name MALTA (Multiresolution Assignment and loading of traffic activities) with appropriate feedback to the land-use model system. For increasing the level of dynamic integration of ABM and DTA models, dynamic integration having pre-trip enroute information with full activity-travel choice adjustments has been introduced. In this level of ABM & DTA integration, it is assumed that pre-trip information is available for travelers about the condition of the network. It means that travelers are capable of adjusting activity-travel choices since they have access to pre-trip and Enroute travel information. Another tightly integrated modeling framework was proposed in [134] to integrate ABM (openAMOS) and DTA (DTALite) to capture activity-travel demand and traffic dynamics in an on-line environment. This model is capable of providing an estimation of traffic management strategies and real-time traveler information provision. Zockaie et al. [135] presented a simulation framework to integrate the relevant elements of an activity-based model with a dynamic traffic assignment to predict the operational impacts related to congestion pricing policies. Auld et al. [38] developed an agent-based modeling framework (POLARIS) which integrates dynamic simulation of travel demand, network supply, and network operations to solve the difficulty of integrating dynamic traffic assignment, and disaggregate demand models. A summary of the current literature on ABM and DTA integration is presented in **Table 2**.

The above discussion illustrates that most of the model integration platforms between ABM + DTA work based on sequential integration. This loose coupling platform is the most straightforward and popular approach albeit is not responsive to network short-term dynamics and real-time information. Efforts to develop a comprehensive simulation model that can account for all components of dynamic mobility and management strategies continue. Further developments will have to deal with the implementation of an integrated ABM + DTA platform on a large network to support decision-makers, focus on the integration between activity-based demand models and multimodal assignment [143] as well as reducing computational efforts via better data exchange procedure and improving model communication efficiency. Defining practical convergence criteria is another issue which needs further investigations. Fully realistic convergence is normally never happened in sequential integration due to applying a pre-defined number of feedback loops in order to save model runtime.

Paper	ABM structure	DTA Structure	Method of integration	Insights
[136]	Kutter Model developed for the city of Berlin	Multiagent Simulation (MATSim)	Sequential	Discuss the disadvantages of the integration of ABM and DTA using OD matrices and link travel times
[137]	TASHA model	Multiagent Simulation (MATSim)	Sequential	Show the advantages of the microsimulation approach over conventional methodologies relying heavily on temporal or spatial aggregation
[138]	CEMDAP	(VISTA)	Sequential	Show the impacts of multiple time interval portioning and varying step size on reaching faster and more stable convergence results
[130]	Tel Aviv activity-based model	Multi-agent Simulation (MATSim)	Sequential	Show improved run times, the full activity list can be used directly, without creating origin-destination matrices
[129, 139]	DaySim ABM model developed for the Sacramento and Jacksonville	Disaggregate dynamic network assignment tool (TRANSIMS)	Sequential	Running time limitations prevent the models to realistically represent the impacts of network events or disruptions on activity-travel patterns
[140]	Agent-based Dynamic Activity Planning and Travel Scheduling (ADAPTS) developed for the Chicago region	Disaggregate dynamic network assignment tool (TRANSIMS)	Sequential	Choosing smaller time steps in the interaction of ABM and DTA makes integration more accurate
[133]	Simulator of travel, route, activity, vehicles, emission and land use (SimTRAVEL) that integrates land-use, activity-based travel demand with DTA models		Dynamic integration	Show the proposed model is capable of simulating the behavioral pattern of human activity in space, time, and networks
[134]	ABM (openAMOS) and DTA (DTALite)		Dynamic integration	Show the model is capable of providing an estimation of traffic management strategies and real-time traveler information provision
[132]	Formulation of a dynamic activity-travel assignment (DATA) model in the multi-state supernetwork framework combining ABM and DTA		Dynamic integration	Show the power of the model to capture multi-modal and multi-activity trip chaining at equilibrium states while sensitive to policy interventions
[141]	Integrated ABM-DTA framework to consider congestion pricing in a large-scale network		Dynamic integration	A user-based approach to evaluate equilibrium conditions

Paper	ABM structure	DTA Structure	Method of integration	Insights
[38]	POLARIS, which executes a continuous exchange of information between the ABM and DTA components		Dynamic integration	The resulting gains in computational efficiency and performance allow planning models to include previously separate aspects of the urban system
[92]	Advanced demand models (InSITE ABM)	Time-sensitive traffic network model (DTALite)	Sequential	Show the efficiency of the model over the static assignment-based ABM capturing behavioral changes at a finer time resolution
[142]	The ABM (CT-RAMP)	DTA (DynusT)	Sequential	Evaluate different convergence measurements: ABM demand, DTA in terms of a gap of costs

Table 2.
A summary of the empirical literature on ABM and DTA integration.

3.4 ABM and travel demand management applications

Travel demand management (TDM) strategies are implemented to increase the efficiency of the transportation system and reduce traffic-related emissions. Some examples include mode shift strategies (encouraging people to use public transport) [144], time shift (to ride in off-peak hours, congestion pricing), and travel demand reduction [145] (using shared mobility service or teleworking). Shared transport services including car sharing, bike sharing, and ridesharing have been implemented in most of the transport planning systems across the world. Applying activity-based travel demand models to study the optimal fleet size can be found in different studies in the literature [146, 147]. Parking price policies and their impacts on car sharing were investigated using MATSim in [148]. Results show shared vehicles use more efficient parking spaces in comparison to private vehicles. In the first attempt to model car sharing on more than one typical day [149] the agent-based simulation (mobitopp) was extended with a car-sharing option to study the travel behavior of the population in the city of Stuttgart in one week. In the recent study of [150], car sharing was integrated into an activity-based dynamic user equilibrium model to show the interaction between the demand and supply of car sharing. Among all the TDM strategies, telecommuting can be implemented in a shorter time [151–153]. The results of these studies present a reduction in vehicle-kilometers-traveled (VKT) during peak hours mainly because telecommuters change their trip timetable during these times. This plan rescheduling is also investigated and addressed in different studies [154] based on the statistical analysis of worker's decisions about choice and frequency of telecommuting. While the plan rescheduling leads to reducing commute travel, the overall impacts of telecommuting on the formation of worker's daily activity-travel behavior is challenging. For example, this policy reduced total distance traveled by 75% on telecommuting days while telecommuting could reduce the total commute distance up to 0.8% and 0.7% respectively [151, 155]. Based on the adoption and frequency of telecommuting, a joint discrete choice model of home-based commuting was developed for New York city using the revealed preference (RP) survey [156]. Their results show a powerful relationship among individuals' attributes, households' demographics, and work-related factors, and telecommuting adoption and frequency decisions. A similar study [157] estimated the telecommuting choice and frequency by using a binary choice model and ordered-response model respectively. In terms of using activity-based modeling, [158] POLARIS activity-based framework was applied to research telecommuting adoption behavior and apply MOVES emission simulator model to assess the consequences of implementing this policy on air quality. Their results show that considering 50% of workers in Chicago with flexible working time hours in comparison to the base case with 12% flexible time hour workers, telecommuting can reduce Vehicle Mile Traveled (VMT) and Vehicle Hour Traveled (VHT) by 0.69% and 2.09% respectively. This policy reduces greenhouse gas by up to 0.71% as well. Pirdavani et al. [159] investigated the impact of two TDM scenarios (increasing fuel price and considering teleworking) on traffic safety. In this work, FEATHERS model, which is an activity-based model, was applied to produce exposure matrices to have a more reliable assessment. The results show the positive impacts of two scenarios on safety (**Figure 2**).

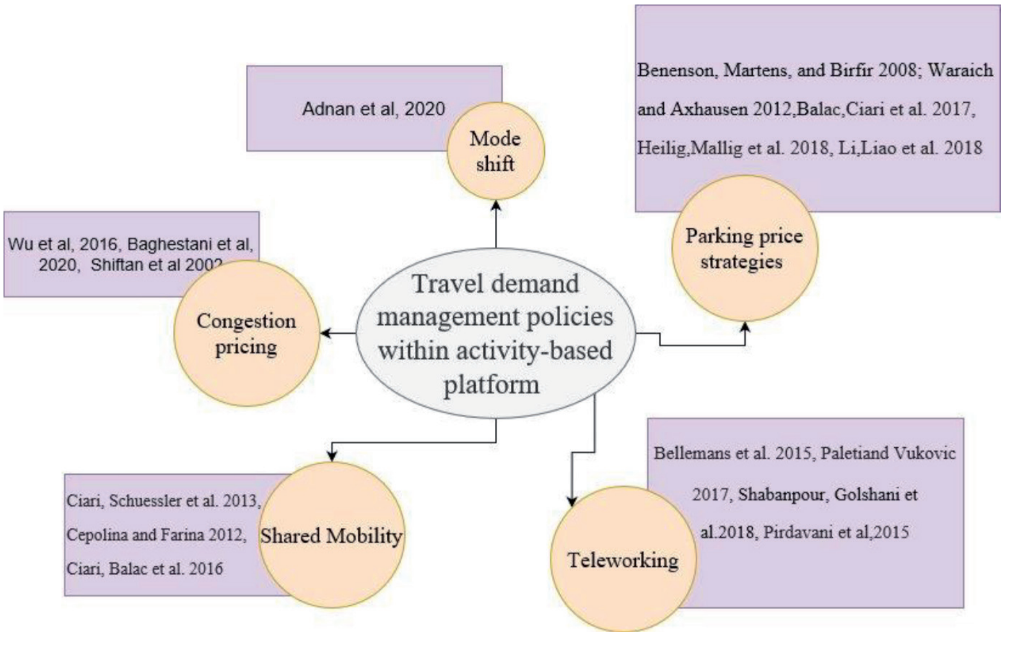

Figure 2.
Travel demand management policies within the activity-based platform.

The above section explores the relationship between transport demand management policies and travel behavior in the ABM context. The use of an activity-based travel demand model provides flexibility to employ a range of policy scenarios, and at the same time, the results are as detailed as possible to obtain the impact of policies on a disaggregated level. The finding highlights the importance of implementing different transportation policies management together to reach the most appropriate effect in terms of improving sustainability and the environment. The discussion emphasizes the need for considering more comprehensive transportation and environmental policies concerning sustainability to tackle travel planning in light of the increasingly diverse and complex travel patterns.

4. Summary and research directions

The use of activity-based models to capture complex underlying human's travel behavior is growing. In this paper, we began by introducing the components of activity-based models and the evolution of the existing developed ABM models. In the first part of this paper, the new resources of data for travel demand analysis were introduced. In the new era of travel demand modeling, we need to deal with a dynamic, large sample, time-series data provided from new devices, and as a result manage observation covering days, weeks, and even months. The outcome of the recent works revealed that since activity-based models originated from the concept of individual travel patterns rather than aggregate flows, they highly suited to these new big data sources. These big datasets, which document human movements, include the information about mobility traces and activities carried out. Based on the in-depth and critical review of the literature, it is clear that while these big datasets provide detailed insight into travel behavior, challenges remain in extracting the right information and appropriately integrating them into the travel demand models. In particular, extracting personal characteristics and trip information like trip purpose and mode of transport are still open problems as these big data resources which provide space-time traces of trip-maker behaviors. Research works along these lines have been started as it was reviewed in the first part; however, further researches should be conducted to handle the uncertainty of big data mobility traces in the modeling process. Also, new methods should be investigated to validate the results for each step of the data analysis and mining. The possibility of fusing data from different available datasets needs further investigation. For instance, to understand the mode inference both data from the smart card and CDRs can be analyzed simultaneously. Another challenging issue regarding the application of this rich new data in transport modeling is that the need for methodologies to extract useful information needed regarding the traveler's in-home and out-of-home activity patterns, which highlights the combination of data science, soft computing-based approaches, and transport research methods. It requires new Different algorithms such as statistical, genetic, evolutionary, and fuzzy as well as different techniques including advanced text and data mining, natural language processing, and machine learning.

The spatial transferability of activity-based travel demand models remains an important issue. Generally, it is found that the transferability of these models is more feasible than trip-based models, especially between two different regions with similar density or even between two areas in the same state. To date, most of the transferability research in activity-based travel demand modeling is motivated by a desire to save time, and very few studies that applied spatial transferability of activity-based models have undertaken rigorous validation of the results. While literature showed successful model transferability in terms of transferring activity/tour generation, time-of-day choice components, more studies are required on the model transferability regarding mode and location choice models as well as the validation test of activity-based models in different levels, i.e., micro, meso, and macro models.

As part of the second section of this study, this paper reviewed the progress made in the integration of activity-based models with dynamic traffic assignment.

Based on the literature, although evolution has occurred in DTA models, the loose coupling (sequential method) between ABM and DATA models still dominate the field. Two main challenges remain, namely poor convergence quality and excessively long run time. Replacing MATSim as a dynamic traffic assignment tool with other route assignment algorithms in recent years was a technical solution to loose coupling, which considered route choice as another facet of a multi-dimensional choice problem. MATSim provides not only an integration between the demand and supply side, but it can also act as a stand-alone agent-based modeling framework. However; MATSim potential drawbacks include being based on unrealistic assumptions of utility maximization and perfect information. To remove these unrealistic rational behavioral assumptions, applying other approaches such as a new innovative method of behavioral user equilibrium (BUE) is needed. This method helps trip-makers to reach certain utility-level rather than maximize the utility of their trip making [160]. Work along this approach has started (e.g., [161]).

The capability of activity-based models in generating other kinds of performance indicators in addition to OD matrices was also reviewed. Literature proved activity-based models generate more detailed results as inputs to air quality models, however; error rises from the accuracy of the information has a relevant impact on the process of integration. So it is necessary to do a comprehensive analysis of the uncertainties in traffic data. Literature proved that despite of the improvements in such disaggregate frameworks and the capability of these models in replicating policy sensitive simulation environment; there is yet to develop the best and perfect traffic-emission-air quality model. While the issue of health has drawn extensive attention from many fields, activity-based travel demand models have proved to have the potential to be used in estimating health-related indicators such as well-being. However, very few studies have been found to investigate the theories required to extend the random utility model based on happiness. While it is proved that mobility and environment have direct impacts on transport-related health [162], investigations on how travel mode preferences and air pollution exposure are related in this context are needed. Another area of research within ABM platform which is yet to be studied is the relationship between individual exposure to air pollution and mobility, especially in space, and time.

In the last part of this paper, the capability of activity-based models in the analysis of traffic demand management was investigated. Generally, the influence of telecommuting on both travel demand and network operation is still incomplete. Very few studies were found in which activity-based framework is used to simulate the potential impacts of telecommuting on traffic congestion and network operation where the real power of activity-based models lie.

In conclusion, while there are still open problems in activity-based travel demand models, there has been a lot of progress being made which is evidenced by the various recent and on-going researches reviewed in this paper. The review showed that by applying different methodologies in the modeling of different aspects of activity-based models, these models are becoming more developed, robust, and practical and become an inevitable tool for transport practitioners, city planners, and policy decision-makers alike.

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