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A Proposed Conceptual Framework for the Integration of Agent-based Microsimulation to Activity-Based Travel Demand Models

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ABSTRACT

Traffic patterns and related problems are changing due to population growth, calamities, among others. Transportation planning is crucial in finding solutions to these problems. Travel forecasting models such as activity-based demand and agent-based microsimulation ones are effective tools to simulate and evaluate transportation planning strategies. This paper aims to develop a framework in line with the advances and concepts from previous studies on transportation demand modelling. Numerous research from various countries in the past years that examine recent developments in agent-based microsimulation and activity-based travel demand models are investigated here. The integration of these models in the context of various scenario types are discussed. The findings and framework are envisaged to aid in the development of a microsimulation model that integrates both activity- and agent-based models.

Keywords: Agent-based microsimulation, Activity-based modeling, Transportation planning

INTRODUCTION

Major changes in travel patterns are brought about by recent occurrences like population growth, natural disasters, the COVID-19 pandemic, among others. These calamities have gravely affected travel activities due to socioeconomic and environmental conditions in the society (Molloy et al., 2020; Steenbruggen et al., 2012). People's decisions about whether to travel or not are affected, as to their plans to visit a specific destination (Lim et al., 2021: Chen et al., 2015). Transportation planning plays a fundamental role in these events. However, traffic engineers rely on experimentation due to the difficulty of planning, which is why traffic forecasting models are needed (Francis et al., n.d.; Palamariu and Tulbure 2021; Nor Azlan and Rohani, 2018). These scenarios highlight the necessity for models that can predict traffic patterns during the pandemic, look at potential solutions, and determine how much resource is needed to maintain economic activities (Kerr et al. 2021; Zhu et al., 2018; Jiang et al., 2014; Syed Abdul Rahman et al., 2021; Wolbertus et al, 2021; Collins et al., 2014).

Traffic forecasting models such as the activity-based travel demand and agent-based microsimulation models are used to study how potential advances in the population, economy, land usage, and transportation will affect the performance of the regional transportation network. The method of traffic simulation is frequently applied in research to plan for the development of traffic systems (Nor Azlan and Rohani, 2018). Activity-based travel demand models are designed to forecast individual tour choices through socio-demographic characteristics and behavioral factors (Ortuzar and Willumsen, 2011). This implies a behavioral approach in travel demand modeling, which provides a deeper knowledge on the factors influencing travelers, their travel, and their trip-making behaviors (Ortuzar and Willumsen, 2011; Malayath and Verma, 2012). Moreover, the significance of this method relies on its ability to predict changes in the travel choices of the corresponding household or individual, by just modifying variables that would affect their travel behavior (Horl et al., 2018). While activity-based travel demand modeling can provide alternative procedures in transport planning, it is limited by only predicting individual choices without considering factors from the transport environment itself (Chu et al., 2012; Horl et al., 2018). This means that when people encounter changes in the transportation environment, such as the incorporation of traffic management methods and increasing traffic volume as the model predicts more travelers along a given route, the basic procedure of the activity-based approach does not provide feedback (Ortuzar and Willumsen, 2011; Malayath and Verma, 2012; Chu et al., 2012; Horl et al., 2018).

There has been a developing research area in the integration of agent-based microsimulation procedures into activity-based travel demand models over the past decade. Through the development of agent-based microsimulations, researchers have explored means of providing spatiotemporal solutions for this gap within the activity-based approach. By having simulated agents adapt to the simulated transport environment, while the decision choices and transport environment parameters are constantly changing within the agent-based simulator, an equilibrated and optimized transport scenario can be achieved (Horl et al., 2018). This paper seeks to review prior works on the advancement and usage of an agent-

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based microsimulation integration to activity-based travel demand models. The selected literature was analyzed using the content analysis method to elicit common findings and develop the framework for integration of models. Content analysis is a research method used wherein common patterns from the analyzed topics under the literature are looked at. In doing so, the literature selected is gathered, common topic areas are put together, and work is focused on the analysis and understanding of the details presented in the materials reviewed. Words, themes, and concepts within the texts are analyzed. Then conclusions and recommendations are drawn. The findings and proposed framework can be applied as a learning background for the future development of new traffic forecasting models. Some of the data according to past studies still needs to be adjusted but the discrepancies are getting lowered. This calls for further development of forecasting models that provide better accuracy.

Activity-based Travel Demand Modelling

Activity-based travel demand modeling is driven by the concept of modeling transportation plans through derived travel demand from performing essential activities (Ortuzar and Willumsen, 2011). Before the activity-based travel demand became recognized, the four-step method (FSM) was widely used. The FSM has four sub-models that have different functions: trip generation, trip distribution, modal split, and trip assignment (Rodrigue, 2020; Ahmed et al., 2012). Trip generation includes the number of person trips inside a zone. While trip distribution consists of the number of travels between origin and destination zones. Modal split determines the number of travels on different modes, and trip assignment involves the assignment of traffic to a transportation network (Ahmed et al., 2012).

The concept of FSM had been scrutinized during the 1970s, while the activity-based travel demand has been developed (Rasouli and Timmermans, 2014). It was criticized that the FSM only analyzed spatial interactions through zonal trips, while the activity-based model heavily accounts for an individualistic approach in analyzing travel behavior (Rasouli and Timmermans, 2014). The FSM started its development during the 1960s, wherein it is generally represented by trip-based approaches and has always been the preferred method over activity-based approaches (Ortuzar and Willumsen, 2011; McNally, 2008). It evaluates the performance of transport networks and provides means for forecasting travel demands. This is made possible by initially determining study areas or Traffic Analysis Zones (TAZs), activity systems, and transportation systems. However, limitations of the trip-based approach in travel demand modeling have been a general topic of research throughout the years (Kim, 2021). This is mainly due to the inability of FSM to recognize interactions between trips made within trip chains (Kim, 2021). Moreover, this approach tends to become tedious in terms of added travel demand sub-models, which results in biases in demographic market segmentation, temporal scales, and spatial resolutions (Kim, 2021). Hence, activity-based approaches are on the rise in the field of research, as it provides more potential for travel demand sub-model developments. This potential allows for flexible representation in terms of travel behavior which could further address a larger scope of transport policies (Kim, 2021).

General frameworks for activity-based travel demand modeling are synthesized in various research and are collated in Figure 1 (e.g., Ortuzar and Willumsen, 2011; Malayath and Verma; 2013). Econometric models are widely used in this approach and are the bases for creating these frameworks (Malayath and Verma, 2013). The primary components of the framework inputs include land use transportation data, aggregate population statistics for the initial year, and policy actions for predicted years. The population synthesizer takes the aggregated population input as a reference to build a synthetic population that would account for the disaggregated behavior of the individuals within the population in the study. The daily activity pattern model, being the core phase of activity-based travel demand modeling would then process the synthetic population data by modeling inside and outside-home activities. Within these models, collaborative activities and tours can be evaluated or represented by considering constraints and intra-household interactions. The daily pattern activity model also incorporates the activity scheduling method, which forecasts the tour time of day option, mode, destination, supplementary tours, intermediate stops, and stop locations (Malayath and Verma, 2013). After predicting these choices, an output of a household or person's day/tour trip list can be formulated. This list contains the destination, mode, and time of travel choices that would be fed into a trip aggregator. Ortuzar and Willumsen (2011) have also added special trip generators, external trips, noise trips, and commercial vehicle trips into this aggregator. Special trip generators include long-distance trips such as those from an airport or any travel station. External trips are those trips that are not included in the initial aggregated data. Noise trips are supplementary trips added into the model to consider for infrequent trip cases such as trips that do not exactly have a constant activity or final location. Examples of these are lost drivers, people who just went out for a drive, among others. Moreover, commercial vehicle trips are those trips generated by logistics mobility such as deliveries. Once these trips are collected and evaluated, origin-destination matrices can be built according to spatial, temporal, and modal choices. These are then assigned to the transport network and resulting outputs from the model can be fed back to the population synthesizer and land use transport system models for a forecast year analysis. Further, an external analysis of emissions can be made through the network performance output. It should be noted that this framework still needs further validation by using actual travel behavior data, as the models presume heavily from preference surveys. Modifications are expected to streamline the generated framework according to the characteristics of prospective study locations.

Activity-based travel demand modeling is persistent in the past using several frameworks. According to Chu and Cheng (2015), more significant theoretical and procedural developments will be made in the activity-based travel demand modeling field. The advancements in activity-based modeling are summarized in Table 1.

Model development research has focused on the

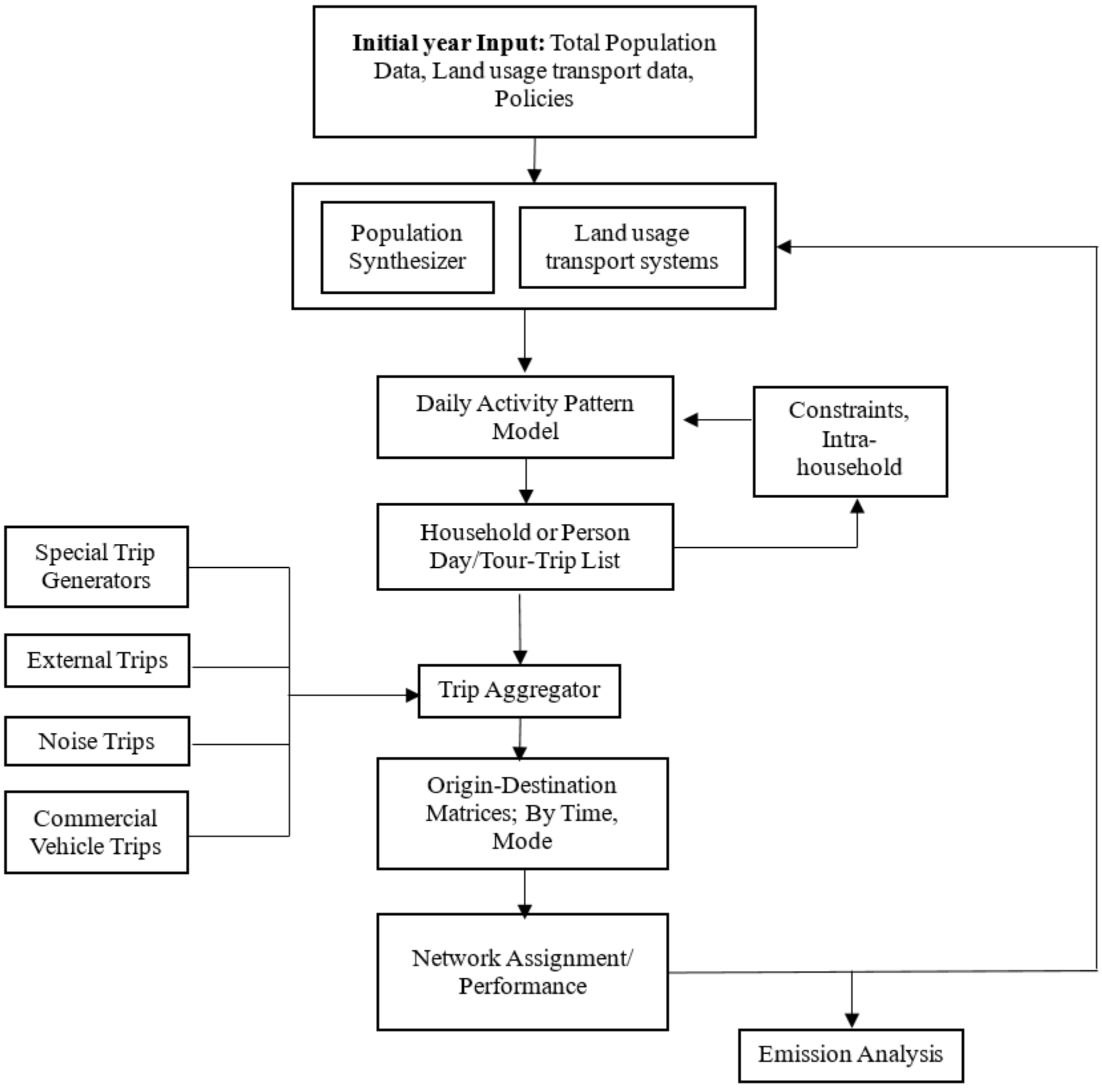

Figure 1. General Framework for Activity-based Travel Demand Modeling

Table 1. Summary of the development of activity-based travel demand modeling

Author/s	Country	Context of Research
Pinjari et al., 2006	U.S.A.	Model development (CEMDAP-II)
Nurul Habib et al., 2012	Canada	Model development (Parking type choice model)
Malayath and Verma, 2012	India	Review of an activity-based approach
Cho et al., 2015	South Korea	Model validation using smart-card data (Validation of FEATHERS – an activity-based simulator)
Lekshmi et al., 2016	India	Model development (Single activity tour generation model)
Yasmin et al., 2016	Canada	Model validation (Validation of TASHA)
Langerudi et al., 2017	Chicago	Optimization of ADAPTS, an activity-based model
Linh et al., 2019	Vietnam	Model transferability (Transferability of FEATHERS – an agent-based simulator)
Joubert and de Waal, 2020	South Africa	Model development using Bayesian networks
Hafezi et al., 2021	Canada	Model development (Random-Forest model)
Hamad et al., 2022	U.A.E.	Model development (Dormitory model)

development of an activity-based model for predicting travel behavior (e.g., Pinjari et al., 2006; Nurul Habib et al., 2012; Lekshmi et al., 2016; Malayath and Verma, 2012; Hafezi et al., 2021; Hamad et al., 2022). With the help of disaggregate models, Pinjari et al. (2006) created the Comprehensive Econometric Micro-simulator for Daily Activity-travel Patterns II (CEMDAP-II), which simulates activity-based travel modeling. The inputs of CEMDAP-II are the demographic dynamics of the population, long-term household choice behaviors, and economic markets. Then, to research the impacts of choices on types of parking on activity scheduling behavior, Nurul Habib et al. (2012) developed a parking type choice model. It was discovered that the choice of parking type has a significant impact on the method of activity scheduling and acts as an exogenous variable for mode selections. Furthermore, Lekshmi et al. (2016) created an activity-based trip generation model for the Indian city of Thiruvananthapuram. According to this model, the factors of distance, age, income, and presence of license are relevant to the travel demand in the field of study. This finding is corroborated in a review by Malayath and Verma (2012), who identified the important factors influencing travel behavior in India. It was determined from their research that individual and household socio-demographics, lifestyle, activity-travel environment, and communication technology are significant variables in individual travel behavior. Hafezi et al. (2021) built a Random-Forest modeling framework that predicts temporal attributes for activity-based travel demand models and combines the results from a series of regression decision trees. Additionally, Hamad et al. (2022) created a tour-based travel demand model for dormitory travel at Sharjah University City (SUC). This model demonstrated that home-based education and business travel have the highest mobility rates. It was also found that dormitory-based travelers are more likely to use private cars as destination trip distance and duration increase.

Due to these developments, model validation research has also been evident to test the capability and features of developed models (e.g., Joubert and de Waal, 2020; Cho et al., 2015; Yasmin et al., 2016). Cho et al. (2015) used smart-card data in Seoul from 2012 as a validation tool for the activity-based travel demand model Forecasting Evolutionary Activity-Travel of Households and their Environmental RepercussionS (FEATHERS). FEATHERS models the activity participation and travel of individual members of the population of a study region for a whole day. It predicts activity-travel patterns by Monte-Carlo simulation, where individuals take successive decisions based on 26 decision trees (Bellemans et al. 2010). It was found that FEATHERS performs better at anticipating the global pattern of public traffic needs than local patterns (Cho et al. 2015). Particularly, FEATHERS does not predict well in terms of local areas with mixed land-use types and multi-modal trips. From another study in 2020, Joubert and de Waal (2020) have shown the applicability of Bayesian networks in synthesizing activity and trip-chain structures. The study made it possible to use expert and data-driven inputs for structural and conditional probability. This provides an opportunity in focusing on low-frequency observations that would enable expert input that is difficult to obtain from small surveys. These low-frequency observations can pose helpful inputs for policymaking, especially in the case of developing countries.

Model transferability studies, on the other hand, investigated the compatibility and applicability of an activity-based travel demand simulator to the scenarios of developing countries (Yasmin et al., 2016; Linh et al., 2019). Yasmin et al. (2016) focused on using the spatial transferability test in validating the activity-based model Travel Activity Scheduler for Household Agents (TASHA). It was discovered that TASHA performs poorly when attempting to forecast the activity features of flexible activities like shopping. However, it performs well at the macro and meso-level of simulation. And then, Linh et al. (2019) investigated the transferability of FEATHERS to the area of Ho Chi Minh City in Vietnam. As FEATHERS is trained from developed countries' travel data, the researchers found the need to determine the model's applicability to developing countries such as Vietnam. The tests concluded that FEATHERS is indeed transferable to the study area, however, recalibrations must be performed on the sub-models of the simulator due to variability in the cultural settings. Additionally, it was found that mode of transport and choice of location models were shown to be the models that are least transferable because of the factors of land use patterns and personal location preferences.

The development of these models and simulators has also called for the need for optimizations, hence, studies that improve the performance of this methodology were also apparent. There have also been review studies on the subject matter that focused on collating recent developments. This implicates heavy significance in the advancement of this methodology. Langerudi et al. (2017) optimized the Agent-based Activity Planning and Travel Scheduling (ADAPT), an activity-based model, to result in conflict because of lacking notion dynamics in the activity scheduling process. In summary, model development, model validation, model transferability, model optimizations, and model reviews have been the main topics of research studies in activity-based travel demand modeling for the past decades. To determine the factors impacting travel behavior, models were developed, and their effectiveness was evaluated. The transferability procedure was used to examine the model's ability to adapt to different contexts. Finally, the features of the models were improved in some research studies.

Development and Applications of Agent-based Microsimulations

Several applications for the potent simulation modeling technique known as agent-based modeling have emerged in past years (Bonabeau, 2002; Collins et al., 2014; Zhu et al., 2018; Abdul Rahmen et al., 2021; Francies et al., n.d.; Wolbertus et al., 2021; Yedavalli et al., 2021). Agent-based microsimulation is simulating the responses per agent, wherein each agent captures the behavioral variables obtained from modeling methods and puts these agents within a simulated transport environment (Heard et al., 2015). This would then enable feedback for spatiotemporal optimization of decision choices. Further, agent-based simulation provides a set of autonomous

Table 2. Summary of reviewed literature on agent-based microsimulation		
Authors	Simulation Software	Application
Collins et al. (2014)	Repast Simphony	Building Disaster Evacuation
Zhu et al. (2018)	MATSim	Hurricane Evacuation
Francis et al. (n.d.)	LocalSim	Traffic management
Wolbertus et al. (2021)	R Software	Optimization of Roll-out Strategies
Yedavalli et al (2021)	MANTA	Transportation planning
Kerr et al. (2021)	CovaSim	Covid-19 agent-based microsimulation
Najmi et al., (2021)	SydneyGMA	Covid-19 agent-based microsimulation
Akyildiz et al., (2022)	Aimsun	National parks evacuation

persons (agents), where interaction between agents is allowed and where agents can consider the information before performing their next action (Gilbert and Troitzsch 1999). The design of the model, its implementation, and its evaluation are the three main processes in agent-based modeling (Abdulkareem et al. 2019). Growing research on the application of these agent-based traffic simulators has then been essential throughout the years. Table 2 presents a summary of reviewed literature on agent-based microsimulation that incorporates traffic simulators.

Researchers conducted a study on developing an agent-based microsimulation for forecasting the interactions of individuals during natural disasters (e.g., Collins et al., 2014; Zhu et al., 2018; Abdul Rahmen et al., 2021). Collins et al. (2014) used the Repast Simphony Software to create an agent-based model that includes groups of people that exit for evacuation. They concluded that this method is ineffective when the desire of people for group cohesion is low and produces a zigzag pattern of simulated movement. Furthermore, in the context of hurricane evacuation using the Multi-Agent Transport Simulation Toolkit (MATSIM), Zhu et al. (2018) proposed a calibrated behavior model with a simulation of agent-based evacuation to capture the evacuation behaviors of people from Northern New Jersey. According to MATSIM results, background traffic significantly slows down evacuation times. Then, in a 3D environment, Abdul Rahman et al. (2021) replicated in the Pathfinder simulator the required timings and user evacuation mobility conditions from the Campus Infrastructure Building. It was discovered that the ideal path planning, which separates the impact of the capacity of the user and the access factor, depends on the total evacuation time. Following that, Akyildiz et al. (2022) used the Aimsun to predict traffic flow and suggest a successful alternative evacuation in a variety of scenarios in Rocky Mountain National Park. The model was able to suggest alternative evacuation routes, and the agent-based microsimulation was able to replicate the traffic flow during the evacuation, despite the microsimulation requiring a lot of data as inputs.

Studies have also been developing agent-based microsimulations for traffic management (Francis et al., n.d.; Wolbertus et al., 2021; Yedavalli et al., 2021). Francis et al. (n.d.) validated the simulator developed by the University of the Philippines (UP), Localized Traffic Simulator (LocalSim). LocalSim is the first simulator developed in the Philippines. The model choices were based on traffic-related research done by UP. It is designed to explicitly replicate the driving behavior of the Filipino road user. Additionally, using R software, Wolbertus et al. (2021) investigated the effects of alternative implementation techniques for the infrastructure supporting the wide use of electric cars. In conclusion, the model has demonstrated its ability to simulate a variety of diverse deployment scenarios and evaluate these on many fronts. This aids decision-makers in making long-term decisions on these methods and making necessary adjustments. An expanded version of the Microsimulation Analysis for Network Traffic Assignment (MANTA) for adaptable transportation planning at the metropolitan level was created by Yedavalli et al. (2021). It is highly effective and can simulate actual traffic demand on very large-scale networks with a great level of precision.

The latest COVID-19 outbreak has a significant influence on travel behavior. Most studies also focused on the development of agent-based microsimulation for the pandemic. Kerr et al. (2021) developed the COVID-19 Agent-Based Simulator (CovaSim), which replicates the dynamics and interventions made during the pandemic. CovaSim has already been utilized by many countries to assess epidemic dynamics and inform policy choices. The software is subject to the typical restrictions that apply to statistical equations, and important limitations on the amount of accuracy that may be modeled. For instance, CovaSim must use incredibly basic algorithms to simulate unfathomably intricate human touch patterns. Furthermore, Najmi et al. (2021) utilized the SydneyGMA agent-based model to forecast the travel behavior in Sydney Australia during the COVID-19 pandemic and to evaluate how far alternative control techniques can prevent COVID-19 from spreading. They revealed that it is dangerous to resume regular travel and take public transportation in Sydney GMA, and they acknowledged that the model needs a lot of data to be adjusted.

From the above reviewed works, findings have shown that agent-based microsimulation is essential to transportation planning and optimizing roll-out strategies in the case of calamities and outbreaks. It is utilized to generate probable decisions based on what is shown in simulations. Maximizing the effectiveness of the activity-based travel demand model and agent-based microsimulation could develop better transportation plans.

4. Integration of Agent-based Microsimulation to Activity-based Travel Demand Models

Model development studies have integrated agent-based simulators into the concept of activity-based travel demand to account for spatiotemporal gaps. Some studies also involve the creation of frameworks that apply one model to another or the other way around, as well as the use of activity-based data from another device for agent-based simulation. Table 3 shows the summary of studies on the Integration of Agent-based Microsimulation to Activity-based Travel Demand Models from previous studies.

Researchers have been comparing and combining the features of the activity-based model into agent-based microsimulation to cover up the spatiotemporal gaps. Bekhor et al. (2011) investigated the possibilities of MATSIM and Tel Aviv activity-based model collaboration in a paper. The representation of individual supply from MATSim and the representation of disaggregate demand from Tel Aviv are both employed for this. The combined model executes in a decent period, according to the results. Furthermore, Ziemke et al. (2015) coupled MATSIM with FEATHERS. Despite being a demand-adaptation model, MATSim does not completely take into consideration activity-based demand, which forecasts activity-travel patterns based on a fictitious population with socioeconomic characteristics. This feature is added through the coupling with FEATHERS. Therefore, the linked model can be used to simulate scenarios where the population has increased, new neighborhoods have been added, or other spatial patterns have altered and require new activity-travel schedules. Additionally, Saleem et al. (2018) integrated MATSIM with SCAPER, an activity-based travel demand model that constantly considers temporal choices, to demonstrate how it can be used for more extensive simulations. Based on the basic service level matrices produced by MATSim, SCAPER develops travel patterns that include the trip amounts, mode of transport, travel destination, time of departure, and travel purposes. The demand is then simulated by MATSim using transport patterns created by SCAPER. SCAPER and MATSim continue to iterate in concert until convergence is reached. According to the results, the difference between the observed data in a location and simulated values in converged settings is very small. To simulate traffic flow, parking behavior, and vehicle energy use in Beijing, China, Zhuge et al. (2019) created MATSIM-Beijing, a sizable activity, and agent-based simulation. The model developed a detailed traffic network, parking areas, and the utilization of filling stations.

Some research also creates an activity-based model using the framework from an agent-based microsimulation and using different devices for inputs of activity behavior into agent-based microsimulation. Auld et al. (2011) implemented a fully integrated activity-based model using the frameworks from Polaris, an agent-based simulator. It has proven to have the ability to considerably boost efficiency and organize activity-based models and traffic flow simulations using agent-based modeling techniques. Bassolas et al. (2019) used records from mobile phones to acquire data from activity diaries in Barcelona for activity-based travel demand modeling, which they then used to develop a city transport MATSim model. This method has been demonstrated to be an effective way to create models that can be used to calculate the effects of traffic demand management strategies. The results obtained by the verification and calibration approach confirmed the accuracy of the activity-travel diaries data obtained from mobile phones and provide evidence in favor of the concept that other data sources can be used to satisfy the data requirements needed for agent-based modeling strategies.

Jafari et al. (2021) created an Activity-based and agent-based Transport model of Melbourne (AtoM). The mode choice coefficients for the different principal modes of transportation were modified to accurately reflect the mode sharing seen for actual journeys to major locations. The comparison with actual data also revealed that the model closely matches real-world peak hour car traffic volumes, public transport station utilization distributions, and realistic journey times and distances. To evaluate travel patterns of infected people during the pandemic, Shahrier and Habib (2021) integrated the

Table 3. Summary of studies of Integration of Agent-based Microsimulation to Activity-based Travel Demand Models

Author/s	Country	Context of Research
Bekhor et al., 2011	Israel	Integration of Tel Aviv and MATSIM
Auld et al., 2014	U.S.A	Implementing activity-based framework thru Polaris-an agent-based simulator
Ziemke et al., 2015	Poland	Integration of FEATHERS and MATSIM
Saleem et al., 2018	Sweden	Interfacing SCAPER, and activity-based model, to MATSIM
Bassolas et al., 2019	Spain	Mobile phone data for the activity-based demand model and MATSIM for analyzing toll policy
Zhuge et al., 2019	China	Integration of agent and activity base microsimulation (MATSIM-Beijing)_
Jafari et al., 2021	Australia	Activity-based and agent-based Transport model of Melbourne (AToM)
Shahrier, H. & Habib, M. (2021)	Canada	Coupling Epidemiological Model within an Activity-based Travel Modelling System

Shorter-term Decisions Simulator (SDS), an activity-based demand model, with the Susceptible-Infected-Recovered (SIR), an epidemiology model. The SIR model forecasts the percentages of infection and recovery as well as the amount of reproduction, whereas the SDS microsimulation model, on the other hand, makes predictions about the travel patterns in terms of several variables, including activity participation, mode preference, trip distance, route length, and vehicle allocation.

In summary of findings as discussed above, prior studies about the development of integration of activity-based demand models to agent-based microsimulation have shown the possibilities and innovations that will potentially serve as solution to the spatiotemporal gaps. The combination of these two could be applicable in different scenarios or environments and can significantly improve performance and standardize the structure of activity-based models and traffic flow simulations utilizing agent-based modeling methodologies. As the integration is being improved by different developers, it is shown that the discrepancies between the actual data and simulated data are being lowered.

Proposed General Framework for Integrating Agent-based Microsimulation and Activity-based Travel Demand Models

Based on the findings from the reviewed papers above, a general framework that describes this procedure is proposed and presented in Figure 2. The framework starts by introducing scenarios that call for evaluation, such as in the case of urban transport, pandemic, and evacuation. These examples are commonly observed in recent studies. After the provision of scenarios, variables relating to these scenarios can be modeled through different methods. Related literature has collated discrete choice, hazard duration, structural equations, rule-based simulation, and hybrid choice models as observed modeling methods in forecasting travel demand through an activity-based approach (e.g. Chu et al., 2012; Shah et al., 2022; Kim et al., 2014). These models provide significant behavioral variables as outputs, which are then used to predict or model the decisions of individuals. Destination, mode, evacuation, and activity-based output choices are the most found decision choices among previous activity-based travel demand research. Agent-based microsimulation is integrated by simulating the responses of individuals as agents. Each agent captures the behavioral variables obtained from modeling methods and puts these agents within a simulated transport environment. This would then produce outputs considering spatiotemporal optimization of decision choices.

Scenarios

The integration of agent-based microsimulation to activity-based travel demand models allows the replication of different scenarios that can proactively evaluate policy recommendations. Examples of scenarios include the application of this methodology for traffic problems, hurricane evacuation, fire disasters, building disasters, and optimization of roll-out strategies (e.g., Zhu et al., 2018; Jiang et al., 2014; Abdul Rahman et al., 2021; Wolbertus et al, 2021; Collins et al., 2014). Scenarios include the modification of variables that significantly affect the choices of respondents.

In many places across the world, traffic congestion is a serious issue (Ilahi et al., 2020). Harrou (2022) asserts that traffic congestion decreases traffic performance since it lengthens travel times and contributes to air pollution. The main issue is not traffic congestion, but rather the economic and educational systems that force individuals to commute to a job, schools, and other locations at the same time (Downs, 2014). On the other hand, fuel expenses, time, driver stress, and effects on physical and mental health are just a few of the costs that traffic congestion creates for society (Ng et al., 2021). According to a recent study, for individual drivers, the level of unhappiness with a 19% wage drop can be compared to the trip lengthening effect of 20 minutes (Chatterjee et al., 2017). Wasted output,

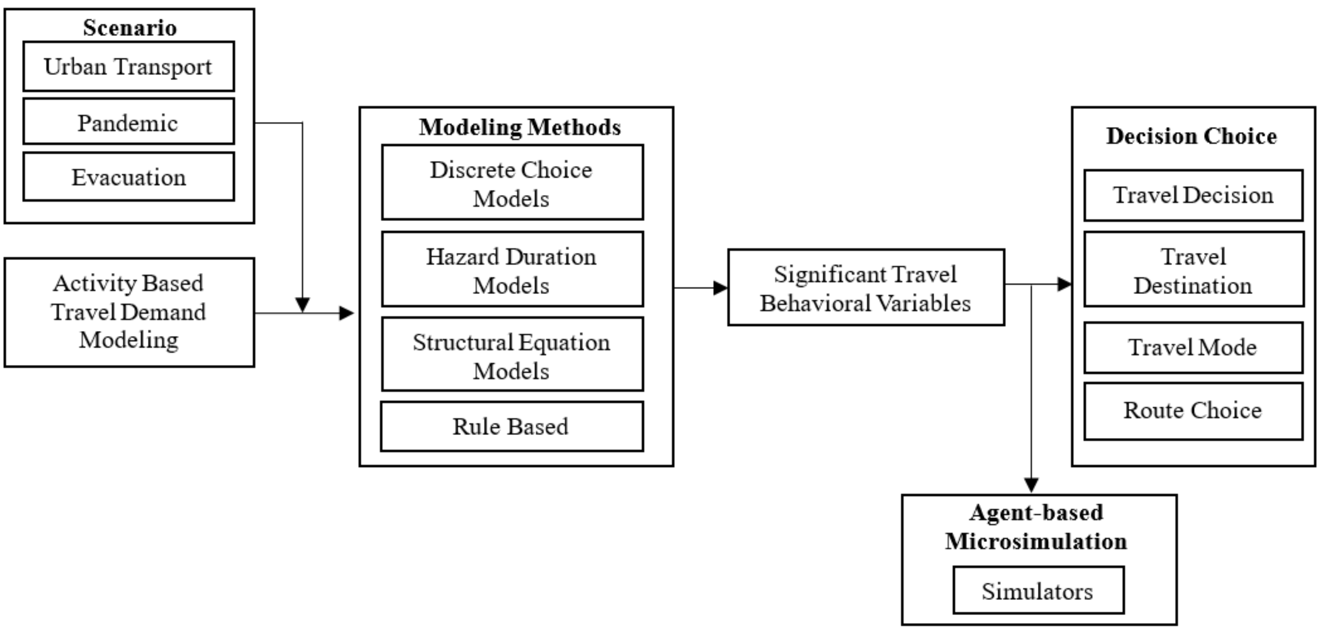

Figure 2. General Framework in Integrating Agent-based Microsimulation to Activity-based Travel Demand Models

noise, pollution, the likelihood of traffic accidents, the dangers to pedestrians, as well as the effects of emission of greenhouse gases on the environment, are some of the costs to society (Bilbao-Ubillos, 2008).

A study also found that natural disasters are one of the major accidents that affect transportation. Disaster affects traffic by having longer travel times, higher air pollution, and high risks of traffic accidents (Steenbruggen et al., 2012). The mobility of people is constrained not only by the need to pick up family members but also by the requirement to go to and from their places of employment. The interactions between family members, which are common during an evacuation, may significantly affect the evacuation process. Widespread use of activity-based modeling to predict daily traffic demand (Chen et al., 2015). According to Iida et al. (2020), the Great Hanshin-Awaji Earthquake uncovered problems with traffic management systems. Every aspect of travel behavior, including the selection of destination, frequency of travel, route selection, and mode selection, is impacted by the onset of a natural catastrophe, resulting in traffic patterns that are significantly different from typical ones. The traffic was in complete disarray after it because of the damage the earthquake caused.

Moreover, the recent COVID-19 pandemic had a huge effect on transportation because of social distancing and risk prevention. It is believed that the limits put in place by the government and people's fear of infection are the main reasons why travel preferences and behaviors alter significantly during pandemic scenarios compared to pre-pandemic situations (Abdullah et al., 2020). The closure of nearby physical companies has also resulted in a large reduction in trips made and distance traveled. With disparities between urban and rural populations, COVID-19 has resulted in a move away from multi-purpose vehicles and toward driving, walking, and biking. (Shaik and Ahmed, 2022). Hence, utilization of modeling tools considering such variables are also needed.

Modeling Methods of Activity-Based Travel Demand Approach

The various methods used in activity-based travel analysis are covered in this section, including rule-based models, hybrid models, hazard duration models, discrete choice models, and hybrid models. Discrete choice models are aimed to describe and forecast two or more choices of possible groups. Since the 1980s, it has been utilized to simulate complex trip behavior using activity-based modeling. (Chu & Cheng, 2012). It follows the premise that people are more likely to choose these observations depending on their socioeconomic status and how appealing the supplied choice is to them. (Ortuzar and Willumsen, 2011). The primary modeling method used in the activity-based approach is the discrete choice model (Chu et al., 2012; Joubert & de Waal, 2020; Hamad et al., 2022).

To include neural data in the model, hybrid choice models (HCM) are an appropriate framework. Hybrid choice models have been developed to extend discrete choice models, particularly multinomial logit models, and to include attitudinal variables. (Kim et al., 2014). Before now, HCMs have primarily been utilized to leverage measurable indicators to combine latent components, such as attitudes, views, or perceptions, with observable decisions in a single model structure (Ben-Akiva et al., 2002). The core of hybrid choice models is the estimation of an attitude formation model, which is added to the set of attributes that are frequently employed in discrete choice models, such as sociodemographic factors and attributes of the choices.

Another modeling method used is the Hazard-based duration model. Its concept is to model the probability of failures, given that the failures did not happen yet (Chu & Cheng, 2012). This model covers a class of analytical procedures that, if the duration has lasted for a predetermined period, are suitable for modeling data with a significant emphasis on an end-of-duration event (Mannering et al, 1994). The hazard-based duration is particularly helpful for activity-based travel demand analysis when simulating the length of activities and rest at home (Ettema et al., 1995; Mannering et al., 1992).

Inayat et al. (2014) created a structural equations model, a multivariate method used to evaluate theories for variable interaction. The major processes that this approach offers are factor analysis with regression to understand correlations between observed and unobserved variables. Instead of using exploratory factor analysis, it assesses relationships through confirmatory factor analysis. Several driving behavior indicators are converted into latent variables using the structural equations model, which is also utilized to investigate the relationships between crash severity, latent variables, COVID-19, and other relevant factors (Dong et al., 2002). The study of survey and clinical data, offers several benefits, including the capacity to model hidden characteristics that might not be immediately evident.

Rule-based models replicate the travel behavior of people by simulating daily travel and ordering activities using different sets of condition-action rules when creating schedules (Tajadinni et al., 2020). To comprehend or forecast a system's behavior and how it may be managed or altered, rules are modeled. Rule-based modeling assumes that the world may be viewed as a system of connected elements that behave predictably (Whitney, 2017). These models could be divided into two primary categories: switching models and activity schedule-building models (Jovicic, 2001). The switching models changed the predetermined schedule in response to proposed alterations, whereas the activity schedule building models create a schedule of activities from the beginning.

Travel Behavior Significant Determinants

Numerous studies have examined the effects of several factors on travel behavior. One factor that has been considered is the land usage pattern. Several land use attributes are highlighted in review studies (e.g., van Wee, 2002; Ewing and Cervero, 2001) from diversity and density measurements to the type of neighborhood and components of urban design. Results are often adjusted for socioeconomic characteristics, and some research also

Table 4. Significant variables that affect travel behavior according to past studies.		
Decision Choice	Authors	Significant variables
Travel decision	Chen et al. (2022), Shaikh et al. (2020), Lee et al. (2022), Wang (2022)	Security, safety, alternatives, travel risks, social media, travel-related apps, travel websites
Travel destination	Calumba et al. (2021), Lim et al. (2021), Shaer and Haghshenas (2021), Poli, (2021), Lakatos and Mandoki (2020)	purpose, reasons for the trip, socio-demographic behaviors, travel risks, distance
Travel mode	Bhaduri et al., (2020), Shakibaei et al. (2020), Arreeras et al., (2020), Harbering and Schluter (2020), Jiao and Azimian, (2021). Keyes and Brown, (2018), Arreeras et al., (2020)	Income, Vehicle ownership, safety and comfort, age, gender
Travel route	Cao et al. (2016), Anwari et al. (2021), Chen et al. (2020), Shelat et al. (2022), Marra et al. (2022)	The severity of traffic incidents, saving and delay time of alternate route, knowledge, route distance, and attitude of traveler

examines the perceptions, attitudes, and preferences of each participant (Witlox, 2009). Significant variables that affect the travel decision, travel destination, travel mode choices, and travel route choices based on past studies are summarized in Table 4.

Changes in circumstances have an impact on the decision to travel. In the Netherlands, Chen et al. (2022) investigated how the COVID-19 epidemic has affected travelers' behavior. Their findings indicate that the decision to travel is influenced by both their inclination to travel and their travel policy. Additionally, the importance of transit waiting time decreases during pandemic (Chen et al., 2022). Shaikh et al. (2022) conducted a study on the elements influencing Pakistani travelers' choices in other circumstances. The results demonstrate that tourists prioritize safety and security because of Pakistan's strict anti-terrorism laws. They utilize social media as well while making decisions. On the other hand, a study on the risk-related factors influencing travel decisions in South Korea was conducted by Lee et al. (2022). The research demonstrates that dangers associated with travel such as terrorism, natural catastrophes, and political instability, have a big impact on travel behavior. Further, with the increasing adaptability of social media applications, Wang et al. (2022) conducted research on the factors that influence the decision to travel. According to the research, social media travel websites and applications influence tourists' decisions to travel.

In terms of destination selection in various circumstances, numerous factors have also found to influence the choice. The choice of evacuation location in the case of natural disasters varies based on the socio-demographic or travel-related characteristics of the persons (Calumba et al. 2021; Lim et al. 2021). A received warning, being closer to the threat, and structural damage are statistically linked to the choice of evacuation destination after a natural catastrophe, all of which have a substantial impact on the evacuation process (Calumba et al. 2021). Lim et al. (2021) investigated the variables influencing evacuation destination decision behavior in Eastern Samar, Philippines. The findings indicate that the choice of destination is significantly influenced by gender, income, marital status, the number of evacuated family members, the position of the household leader, the mechanism and time of the evacuation, the amount of perceived risk, and the source of the information. On the other hand, for the COVID-19 context, Shaer and Haghshenas (2021) examined the impact of the outbreak on the trips of senior citizens and discovered that travel for work and groceries is more likely to influence the location of their trips. Longer travel distances may imply more tours in a trip, and thus more trips to be distributed (e.g. Poli, 2021; Lakatos and Mandoki, 2020). Poli (2021) found in his study that individuals decrease their distance traveled, so they go for destinations with lesser distance. It was supported by Lakatos and Mandoki (2020) in their study of long-distance transportation in Hungary. This could imply that people are reluctant to travel for an extended period during a pandemic. It is because there is a high chance of more prolonged exposure to many people during their travel.

For travel mode choices, respondents' age, income, and employment status are influencing factors in the context of India (Bhaduri et al., 2020). When gender and occupation characteristics are considered, the 35-44 age group is more likely to use private cars than others (Arreeras et al., 2020). It is supported by Jiao and Azimian (2021), who found that people aged 35 and up are much less inclined to utilize public transport. They also added that in terms of gender, men have a lower probability to travel by public transportation. This result is like that of Shakibaei et al. (2020) and Harbering and Schluter (2020), where it was revealed that females are more probable than males to take public transit and walk instead of driving. The negative coefficients associated with income had a significant impact on mode choice decisions. In addition, low and middle-income households show that they are more inclined to use public transit as they cannot afford to purchase a personal vehicle (Jiao and Azimian, 2021). The groups with higher income are less likely to use public transportation than low-income earners. The capacity of high-income earners to own a private car is linked to socio-economic factors. If all other factors are considered, income and car use are correlated with greater income linked with lower probability of deciding to take public transport or active mode rather than a car (Keyes and Brown, 2018, Arreeras et al., 2020).

As for choosing a route, the variables that affect such behavior include the socio-economic characteristics of the traveler, the severity of the traffic incident, the amount of time saved by taking an alternate route, the amount of time lost on the original route, road network knowledge, and the traveler's assessment and attitude toward traffic information (Cao et al., 2016). Pedestrians and vehicles differ in their route choice because of their difference in freedom of mobility in heavily congested areas. However, pedestrians without vehicles need more physical effort to take the transportation to reach their destination faster (Chen et al. 2020). Other studies of vehicle route planning during a pandemic, found that the trip destination, travel distance, and travel time all imply vehicle route choices. People who travel a shorter distance will have a relatively short travel time, which results in taking that route. Anwari et al. (2021) corroborated this previous study. Long-distance trips are closely attributed to the road a commuter will consider taking unless a shorter route can be accessed. Marra et al. (2022) reported the same results as other studies, indicating that the significant distinction in travel patterns during this outbreak depends on how people consider travel expenses and trip duration. Also, commuters do not have a definite best route for a regular trip, but they frequently take routes that will provide cheaper alternatives. However, they have suggested that this phase of transport planning needs more attention from studies and findings to understand better the factors in choosing their route alternatives. According to the studies, the most important thing to be considered in route choice is that people will want to reach their destination via the shortest route with the minimum cost as much as possible.

SUMMARY AND CONCLUSIONS

Transportation planning is significant in finding a solution to traffic problems due to population growth, calamities among others, and uncertain events such as the COVID-19 pandemic. Travel forecasting models such as activity-based demand and agent-based microsimulation are effective tools to simulate and evaluate transportation planning strategies. Development plans can be made through the help of simulations. Activity-based travel demand models are designed to forecast and analyze individual travel choices through socio-demographic characteristics and behavioral factors while agent-based microsimulation simulates responses per agents (e.g., Ortuzar and Willumsen, 2011; Malayath and Verma, 2012; Bonabeau, 2002). The limitation of the activity-based travel demand model is that it can only forecast individual decisions without taking the transportation environment into account (Chu et al., 2012; Horl et al., 2018). This is why past researchers recommend and take efforts to integrate the activity-based travel demand model into agent-based microsimulation.

Researchers have investigated ways to fill this gap by providing spatiotemporal solutions through the development of agent-based microsimulations. This paper includes the development of forecasting models over time. The activity-based model had undergone model development, model evaluation, model transferability, and optimizations. Growing research on the application of agent-based traffic simulators has then been essential throughout the years. It is developed for evacuation planning, optimization of roll-out strategies, transportation planning, and pandemic simulation. The simulation of many scenarios that can proactively analyze policy proposals is made possible by the integration of agent-based microsimulation with activity-based travel demand models. Researchers have been comparing and combining the features of the two models to cover the gap in the activity-based demand model. Through the integration of these models, frameworks were created.

Prior studies have collated the findings about the scenario, modeling methods, and significant variables affecting travel behavior and decision choices. The findings are integrated to create a framework that will be applied for the future development of models. The framework starts by introducing scenarios that call for an evaluation. And then, variables relating to these scenarios can be modeled through different modeling methods. These models provide significant behavioral variables as outputs, which are then used to predict or model the decisions of individuals. Destination, mode, evacuation, and activity-based output choices are the most found decision choices among previous activity-based travel demand research. Agent-based microsimulation is integrated by simulating the responses of individuals as agents. Each agent captures the behavioral variables obtained from modeling methods and puts these agents within a simulated transport environment. This would then enable feedback for spatiotemporal optimization of decision choices. The proposed framework is applicable in transportation planning to solve travel problems due to traffic congestion, disasters, and pandemic. This paper integrated agent-based simulators and activity-based travel demand to test further activity-type choices that would be essential for the improvement of policy recommendations. The further development of integrated travel forecasting models to be used for more applications of various situations, such as the COVID-19 pandemic, is a suggested topic for future study.

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