Literature Review of Accessibility Measures and Models used in Land Use and Transportation Planning in last 5 years

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Abstract: Since its inception accessibility has undergone various changes in the way it is defined, measured, and modeled. The paper reviews the recent advancements made in the accessibility measures along with the models used in different applications of accessibility related to land use and transportation. The measures of accessibility are grouped under infrastructure-based, location-based, and person-based measures. The paper finds that although the person-based measures are statistically robust and theoretically sound, they are less preferred than the location-based measure in the accessibility measurement. The review finds recent development such as web based mapping and use of location based data; image mapping through convolutional neural networks; and activity-time constraints modeling in the measures of accessibility. Further, the paper reviews literature from the last five years that have used accessibility to study travel mode choices and household location choices and finds the use of three types of modeling framework - Statistical, Neural Network, and Agent Based models. Based on the literature review, this paper suggests the inclusion of environmental sustainability and gender equity in the accessibility measurement framework and a shift towards model synthesis to enhance the model accuracy and to reduce the present complexities in model building.

Keywords: accessibility, travel behavior, household location choices, agent-based modeling, artificial neural network

1 Introduction

Livable cities are key to sustainable development (UN, 2014). A livable city is one where the local communities live a healthy life and are socially and economically prosperous. Accessibility can be labeled as the central component of livable cities, as it impacts different activities/components of city life such as people travel behavior, housing location choice (Yan, 2020; Morales et al., 2019), social equity (Allen and Farber, 2019; Özkazanç and Özdemir, 2017), neighborhood vibrancy (Lu et al., 2019), urban growth (Kasraian et al., 2017; Deng and Srinivasan, 2016), and environmental sustainability (Lee, 2020). With the cities transforming across the world, understanding of accessibility for sustainable urban development has become vital than ever before. The use of accessibility can be traced back to the 1920s where it was used in the location theory and transport network planning in a monocentric city pattern (Batty, 2009). From there onwards, the use of accessibility in the last 50 years has diversified to more complex city design patterns, incorporating new components and measures in the study of accessibility.

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With the advancement of geo-spatial techniques and the availability of microdata, accessibility is now being used to plan individual-level activity-travel patterns. Accessibility, being a multi-faceted concept, different fields such as spatial economics, urban geography, transport engineering, architecture, and planning, etc., have contributed to its conceptualization. Although this has enhanced the scope of accessibility, developing a unified theory and measure of accessibility has become a challenging task for researchers and planners (Handy, 2020). Accessibility has remained poorly defined and measured, which has impacted the correct usage of accessibility in its different applications (Geurs and Wee, 2004).

Several studies in the past have reviewed the developments in accessibility, the notable ones being Pirie (1979), Jones (1981), Handy and Niemeier (1997), Kwan (1998), Geurs and Wee (2004), Paez et al. (2012). Many of the earlier reviews of accessibility have looked at the theoretical developments in the way accessibility has been conceptualized and measured (Vale et al., 2014; Wang, 2012) while some of the reviews have discussed the impact of accessibility on travel mode choices and residential location choices (Liu et al., 2020; Delbosc and Currie, 2018; Stokenberga, 2014). The need for this literature review paper arises due to 3 reasons. First, with the advancement in geospatial technology and computation methods, the earlier measures of accessibility have been modified and thus, require a revisit. Second, new perspectives such as environmental sustainability and socio-economic equity have emerged in urban planning which can be added to the accessibility conceptual framework to make it more inclusive and comprehensive. Third, many studies in the last few years have examined the impact of accessibility on the city's land use and transportation under different models however, a review of such models is lacking in the literature of accessibility studies.

To fulfill this gap, our paper contributes to the existing literature on accessibility in the following two ways – First, the paper gives a conceptual context of the evolution of accessibility components and then links them with the accessibility measures. Looking at the strength and limitations of these measures, the paper highlights how these measures can be advanced using recent technological developments such as geospatial technology and machine learning. Also, the paper suggests how the existing measures of accessibility can be made more inclusive by including the component of environmental sustainability and gender equity. Second, the paper provides an insight into how the different modeling approaches have examined the impact of accessibility on individuals' travel behavior and residential location choices. The paper further suggests how model synthesis can overcome the limitations of these individual models and can incorporate complex measures of accessibility in a precise and meaningful manner. The inclusion/exclusion criteria followed to select relevant literature were as follows. First, as the paper reviews only the latest development in the accessibility measures and models, we have excluded research papers prior to the year 2015, with a maximum of our reviewed papers published during the years 2017-2020. Second, only papers written in the English Language were chosen for the review. Third, papers that have used a quantitative methodology to model the relationship between accessibility and land use and transportation, were chosen for the review. Fourth, to limit the scope of the paper, the paper focuses on studies that have chosen transit stations to examine the impact of accessibility on travel behavior and residential location choices. Few studies which have examined the impact of accessibility to other points of interest such as schools, parks, hospitals, job destinations, etc., on land use and transportation planning, are also highlighted. The scope of the journal is kept wide to include papers from multi-disciplinary areas.

The rest of the paper is organized as follows. Section II provides the conceptual context behind developments in accessibility. Section III talks about the accessibility measures and some recent developments in it. Section IV reviews the models used in accessibility applications and assesses their strengths and limitations. Section V provides the future research direction and section VI concludes the paper.

2 Conceptual Context

This section traces the evolution of accessibility by reviewing the different perspectives and dimensions attached to it. This may appear similar to what has been done by previous studies such as Ingram (1971), Geurs and Wee (2004), Paez et al. (2012), but our paper differs from them in the manner it has articulated the developments in accessibility in a progressive way. Accessibility is a combination of two words, access, and ability which means *"the fact of being able to be reached or obtained easily"* (Cambridge Dictionary). Hansen (1959) in his seminal paper '*How Accessibility Shapes Land Use'* defined accessibility as the "potential of opportunities for interaction", built over the concept of population potential developed by Stewart (1948). Here accessibility was seen in terms of the geographical distribution of activities, where more distant places were seen as less accessible. This gave a land use component to accessibility. The definition of accessibility was modified as new components and dimensions were added. Ingram (1971) defined accessibility as "inherent characteristic (or advantage) of a place with respect to overcoming some form of spatially operating source of friction". Building on this definition, Dalvi and Martin (1976) categorized sources of friction in terms of individual's ability and behavior, spatial variation of opportunities, and quality of transportation system. According to Dalvi and Martin (1976), the ability of the transportation system in terms of providing low cost and high-speed travel is an important determinant of accessibility. Burns and Golob (1976) defined accessibility as the "ease with which any land-use activity can be reached from a location using a particular transport system". Thus, transportation along with land use became the two main components of accessibility, and accessibility was defined as an output of the inter-mix of the geographical distribution of activities and transportation infrastructure (Paez et al., 2012).

Both the land use and transportation infrastructure provided the spatial or geographical dimension to accessibility. Accessibility also has an aspatial or social dimension related to individual socio-economic conditions such as age, gender, ethnicity, etc. (Khan, 1992).

Hagerstrand's (1975) paper "Space, time and human conditions" added a temporal perspective to the study of accessibility. In his concepts of time-geography, Hagerstrand discussed various constraints which consume an individual's time that could be allotted for different activities (Pred, 1977). This restricts the ability of the individual to reach the activity location at a specific time and diminishes his/her accessibility for that activity. Summarizing the above dimensions and components, one may say that accessibility is limited by spatial or locational constraints (distance, cost), aspatial or social constraints (age, gender), and temporal constraints (lack of time). Taking this constraint perspective Weibul (1980) defined accessibility as an "aspect of the freedom of action of individuals". On similar lines, Burns (1979) proposed accessibility as "freedom of individuals to decide whether or not to participate in different activities". The freedom thus provides choice to an individual to choose the alternative which maximizes his/her utility. This utility maximizing approach has given a behavioral dimension to accessibility, whereby an individual chooses that activity, location, and travel mode from which he/she can derive maximum benefit. Niemeier (1997) defined accessibility as "a value weighted approach whose values are subjective and based on the value of opportunities assigned by individuals". Thus, taking into account individual preferences and other barriers which restrict their movement, observed or realized accessibility may differ from the potential accessibility (Khan and Bhardwaj, 1994). While the observed or realized accessibility occurs when there is actual utilization of services, potential accessibility refers to accessibility in absence of any constraints (Wang et.al., 2020). Summarizing the different perspectives of accessibility, we find that accessibility has a positive correlation with the location of an activity along with individual freedom and willingness to perform that activity. Building on these observations, we propose accessibility as a degree of freedom and ability an individual has to perform a desirable activity to derive the maximum benefit out of it. We interpret the word freedom as the absence of any socio-economic restrictions and the word ability as the presence of physical (bodily) and economic resources that stops or facilitate an individual to step out of his/her place and visit a location through a desired mode of travel

Studies in past have used different components to study and measure accessibility. For example, Geurs and Wee (2004), have categorized accessibility under 4 components, i.e., Land Use, Transportation, Temporal and Individual. Building on the above discussion, this paper categorizes accessibility into 3 components - Land Use, Transportation, and Individual. All these components share either one or a mix of spatial, temporal, and behavioral dimensions. Table 1 highlights the accessibility dimensions under the three components. Among these three components, the individual component is specifically important as it makes accessibility a behavioral phenomenon and adds an element of individual heterogeneity in the measure of accessibility. We discuss the individual component in detail in the next sections.

Table 1: Accessibility components and dimensions

Component\Dimension	Spatial	Temporal	Behavioral

Land Use	+	-	-
Transportation	-	+	-
Individual	+	+	+

'+' means present,' –' means absent

3 Review of Accessibility Measures

In this section, based on the commonly used accessibility measurement criterion which has developed in the last 50-60 years, we have divided the different accessibility measures into 3 categories. Various studies such as Pirie (1979), Handy and Niemeier (1997), Geurs and Wee (2004), have reviewed different measures of accessibility. Our review of accessibility measures includes measures that have not been reviewed before. The key aspect of these measures may appear to be repetitive if compared to the past reviews but our focus in this section is to show how the different measures have evolved from one another. Moreover, this section provides a review of the latest developments in the measures of accessibility, which to the best of our knowledge has not been done before in the recent year.

3.1 Infrastructure based measures

Infrastructure based measures calculate the ease of travel by measuring the impedance occurring due to street infrastructure and availability of transportation. Street infrastructure is measured in terms of street design such as width, length, circularity, etc. The presence of cycling lanes, pedestrian lanes, footpaths, street greenery also counts in street infrastructure measurement. A direct measure of street infrastructure is via the use of geometric calculations using graph-based or space syntax methods. Space syntax method, developed by Hillier and Hanson (1984), is a method to measure urban morphology. A topological measure of accessibility, the space syntax method uses urban morphological relationships like street integration and connectivity to measure the accessibility of a street segment to all other street segments (Huang et al., 2020). Many studies in the recent past such as Badhan (2019), Huang et (2020), Öztürk (2018), Alkamali et al. (2017), Lee et al. (2020) have used the space syntax method to characterize street network and accessibility. A more in-depth discussion about the space syntax can be found in Yamu et al. (2020). With the advancement of remote sensing technology and machine learning tools, methods such as Convolutional Neural Network are being used to measure street design, using open street imagery platforms such as Google street view imagery. Recent studies like Weld et al. (2019), Zhang et al. (2019), Andrew et al. (2018) have used machine learning based image classification tools to measure the street quality and accessibility. An indirect measure of measuring street infrastructure is by examining the travel time, average speed, route length, road congestion levels, etc. This method is generally coupled with the location-based measures, discussed in the next section.

Another dimension related to travel infrastructure is the availability of public transportation. This may involve vehicle ownership, frequency of buses or metro rails along a particular route, waiting time at transit stations, parking time, etc. Since travel is an essential medium to reach a destination, swift travel reduces travel time with comfort to the travelers. This is a commonly used measure in transportation planning as it is easy to define and operationalize. However, this measure has one major limitation. Infrastructure based measures calculate accessibility without taking into account the need for travel. Since travel is a derived demand, measures of accessibility cannot be just confined to measuring travel impedance. Features of destination location need to be added in the measure of accessibility, as seen in location based accessibility measures discussed below.

3.2 Location Based Measures

Location Based Measures focus on the locational attributes of the destination. They largely involve 4 types of measures based on– distance, cumulative opportunities, gravity model, and supply-to-demand ratios. Distance based measures measure accessibility in terms of proximity between two points or a group of points using linear or shortest distance between the points. Studies have also calculated the proximity in terms of non-linear distance functions such as reciprocal function, negative exponential function, and gaussian function (Ingram, 1971). For accurate measurement of traveled distance, network or path-based distance has also been used in place of Euclidean distance. Further, some studies (Vickerman, 1974; Taaffe and Gauthier, 1973) have used topological measure which calculates the number of nodes in a network in place of absolute distance between two vertices as a measure of the proximity between two points.

Cumulative measure of accessibility is an aggregate measure that counts the number of opportunities that can be reached in a specified time or that falls within a specified radius (Wachs and Kumagal 1973; Wickstrom 1971; Pirie, 1979). Based on its simplicity and easy interpretation, this is a commonly used measure of accessibility. However, it is not a precise measure as it is subject to the choice of distance/time threshold beyond which accessibility becomes zero. The choice of this threshold may vary with the region and is dependent on the choice of travel mode. Also, this measure assumes that all the opportunities are equally desirable regardless of their type (Vickerman, 1974)

Gravity based models are one of the finest measures of accessibility which combines the distance based and cumulative based measures. First developed by Hansen (1959), Gravity based measures are built on Newton's Law of Gravity, which measures potential interaction between two spatial points. They are commonly expressed as,

$$A_i = O_j \sum_{j=1} f(c_{ij})$$

Where A_i denotes accessibility at a point i to all other points, O_j is factor or location attractiveness expressed in terms of size of opportunity (e.g., number of jobs) or product features (e.g., cost), $f(c_{ij})$ is the impedance function from i to j related to the travel attributes such as cost, time, or distance. Modifications in the gravity model have been done using different functional forms of impedance function such as inverse power, gaussian (Ingram, 1971), s-shaped, bell shaped, and logistic function (Vale and Pereira, 2016; Halas et al., 2014). Among these functions, the negative exponential function (Wilson, 1971) remains the most preferred functional form.

Morris et al. (1979) pointed out that one important limitation of location-based measures is their incapability to include a factor of competition for the available opportunities in the accessibility measurement. The factor of competition comes in when the demand to access a particular opportunity is greater than what can be supplied. Thus, competition limits the number of opportunities and the opportunity attractiveness which reduces accessibility. To address this limitation, studies have included the competition factor through different indicators such as demand potential (Weibul, 1976), quotient of opportunities (Shen, 1998), balancing factor (Wilson, 1970). More discussion about the competition factor can be found in Geurs and Wee (2004).

A widely used extension of the gravity model is the floating catchment area method (FCA). FCA measures accessibility for a location (e.g., Census tract) as the ratio of service providers to population falling in the catchment area of the location. FCA method uses a dynamic technique of buffering in GIS to construct floating boundary as against using any fixed or administrative boundary (Peng, 1997). As per Luo and Wang (2003), one major limitation of the FCA method lies in its assumption that service in a catchment area is fully available to the locations (or residents) within that catchment area. This assumption is not always true as the services lying within a catchment area may get distributed to the locations (or residents) of other catchment areas altering the demand-supply ratio and making the potential accessibility to differ from the observed accessibility. To overcome this limitation, Radke and Mu (2000) proposed a spatial decomposition method which was simplified by Luo and Wang (2003) under the method named two-step FCA method or 2SFCA. The 2SFCA method in the first step calculates the service to population ratio R_j for every service location 'j' by creating a catchment area of distance threshold 'd' centered at service location 'j', as shown in equation (1). In the second step, a catchment area with the same threshold distance 'd' is created for every population location 'i' and accessibility to the location 'i' is calculated as the summation of the service to population ratio for all the services located in the catchment area of the location 'i', as shown in equation (2)

$$R_j = \frac{S_j}{\sum_{i \epsilon \left| d_{ij} < d \right|} P_i} \tag{1}$$

$$A_i = \sum_{j \in |d_{ij} < d|} R_j \tag{2}$$

S_j is the number of services at location 'j' and P_i is the population at location 'i' which falls in the distance threshold $(d_{ij} < d)$. 2SFCA overcomes the limitation of traditional FCA in two ways. First, as it uses the catchment area centered at a service location in step 1, it makes all the residents in the catchment area have travel distance less than the threshold distance and thus, accessibility at location 'i' counts only those locations which fall within the threshold distance. Second, the use of a catchment area centered at a population location in step 2 makes the services to be used only by the residents within this catchment area and thus, the observed accessibility does not differ from the potential accessibility (Luo and Wang, 2003). 2SFCA has been used widely but has one major limitation i.e., it is a binary construct. It assumes every resident has equal access to a service only if they are within a catchment area and zero otherwise. Unlike the gravity model, it does not account for the impedance function (Luo and Qi, 2009). As highlighted in Tao et al. (2020) and Jamtsho et al. (2015) in the last two decades various modifications in the 2SFCA have been done by – (a) including impedance function such as kernel density (KD2SFCA, Guagliardo, 2004) and Gaussian (Alford et al., 2008) (b) varying the population location catchment area such as nearest neighbor method (NN-2SFCA, Jamtsho et al., 2015), base-population method (V2SFCA, Luo and Whippo, 2012), dynamic catchment sizes (McGrail and Humphreys, 2014) (c) including the supply demand side constraints such as competition effect (Modified 2FSCA, Delamater, 2013), adjusting population demand (Luo, 2014), minimizing service demand overestimation (Enhanced 2SFCA, Luo and Qi, 2009; 3SFCA, Wan et al., 2012) and (d) incorporating different travel behavior such as trip chaining (Commuter Based 2SFCA, Fransen et al., 2015), and use of public and private transportation (Multi-modal E2SFCA, Langford et al., 2016). The main concern with 2SFCA and other location based measures discussed above is that they use population data of macro-level areal units which gives an aggregated measure of accessibility (Bryant and Delamater, 2019). Spatial data aggregation errors make location based measures incapable to model the individual heterogeneity in terms of individual choices and preferences.

Recent advancements in location-based measures of accessibility include the use of web mapping platforms like Google Maps, Open Street Maps, and location-based services using mobile positioning data, and social network data. They are the preferred method over the complex network analysis as they precisely measure the location of spatial points along with the origin-destination travel time and travel route. Using application programing interface (API), these open access platforms provide a real time visualization with the accuracy of geographical data as compared to the traditional GIS based tools. They also have strong spatial analysis capabilities and can incorporate different layers such as traffic factors along different routes in the calculation of travel time. The use of web-based API can be found in recent studies like Cheng et al. (2016), Feilong et al. (2017), Niu et al. (2018), García-Albertos et al. (2018), Tao et al. (2018), Zheng et al. (2019) which have used web mapping API to calculate dynamic travel time and measure spatial accessibility to different destinations.

3.3 Person based measures

Person based measures can be classified into two groups – utility based and constrain based measures. Utility based measures are built on the random utility theory which assumes that an individual chooses the alternative which maximizes his/her utility. Activity based models are widely used to model the utility of activity-travel in terms of choices related to activity to be performed, destination location, travel mode, travel cost, and travel route choices. Personal and household level attributes are also incorporated in the activity-based models as these aspects affect the individual's activity-travel choices. Since choice modeling is an important component of activity-based model, discrete choice models such as Multinomial Logit Model (McFadden, 1978; Ben-Akiva and Lerman, 1985), Competing Destination Model (Fotheringham, 1986; Fotheringham et al., 2001), Nested Logit Model (Bradley et al., 2010), etc. are commonly used in the activity-based models. Maximizing the utility of an activity-travel is a way to enhance accessibility. At the same time, some constraints bound an individual in choosing a set of activity-travel.

Constrain based measures incorporate the spatial and temporal constraints of individuals in the accessibility measurement framework. Hagerstand (1970) space-time framework provides the constraints which limit the ability of the individuals to participate in different activities. Spatial-Temporal constraints in the calculation of accessibility have been incorporated using the space time prism (STP) framework. STP is an important conceptual framework to model human behavior. As defined by Miller (1991), "The space-time prism determines the feasible set of locations for travel and activity participation in a bounded expanse of space and a limited interval of time". Lenntrop (1976) has operationalized the space-time prism using inputs such as travel time, activity location, activity time duration, and hypothesized activity schedule to simulate the number of possible activity schedules that are regarded as the measure of accessibility (Miller, 1991). Traditional STP framework relies on geographical methods to calculate accessibility assuming constant travel speed, equitable distribution of opportunities, and using Euclidean distance measurement. To make the STP framework more realistic, it has been refined by the addition of network based approach using GIS (Burns, 1979; Miller, 1991), cognitive constraints (Kwan and Hong, 1998), and temporal constraints (Weber and Kwan, 2002; Kim and Kwan, 2003). Recent studies such as Wang et al. (2018), Lee and Miller (2019), Zhu and Diao (2020), Fu et al. (2020) have combined the temporal constraints in the activity-travel based accessibility measures.

Person based accessibility measures are considered more robust and theoretically sound to infrastructure and location-based measures as they can model individual heterogeneity and spatio-temporal constraints. However, the literature highlights that the use of person-based measures in accessibility measurement is limited due to two major challenges. First, in terms of model building and operationalization, it requires micro activity and travel data which is often not available especially in developing countries. Second, for utility-based model interpretations, it requires an understanding of complex theories which poses a challenge in its widespread applicability.

To conclude this section, we find that each of the above discussed measures of accessibility has its strengths and weaknesses. With the use of geospatial techniques and micro-data availability, it appears that measures of accessibility will be simplified in the future. No matter which measure of accessibility is used, accessibility will remain a means to an end and not an end in itself. That is, accessibility should not be seen in isolation but as an integral part of a larger socio-economic environment having ramifications on the city's economic and social development. In the following section 4, we review the models used in different accessibility applications.

4 Review of Accessibility Models on Land Use and Transportation Planning

Accessibility is a crucial parameter that is used extensively in the field of land use and transportation planning. In the context of land use planning, accessibility is considered as one of the five attributes of the built environment represented through the factor of Destination Accessibility. Density, Diversity, Design, and Distance to Transit are the other four attributes of the built environment. Destination accessibility, in the literature, has been measured for different types of destinations of which jobs and transit stations are common. This section is divided into three parts. In the first part, we review the different statistical and neural network models that have examined the impact of accessibility on land use and transportation planning using individuals' travel characteristics and household location choices in the last 5 years. In the second part we look at a micro-simulation model – agent-based models, which have emerged as a preferred simulation tool to model the complexity in human behavior in the literature of accessibility planning. In the third part of this section, we analyze the strength and limitations of these models.

4.1 Statistical and Neural Network Models

Statistical models employ regression techniques to analyze the relationship between dependent and explanatory variables. The literature review shows that statistical models are widely used in the field of land use and transportation planning to predict and analyze the travel mode choice or residential choice of households. Apart from accessibility, other factors of the built environment and socio-economic indicators are also used as explanatory variables in the statistical models. Based on the nature of data and study objective the statistical models have varied from simple linear regression models to discrete choice and structural equation models. In these studies, accessibility measures were found to be predominantly based on distance or cumulative opportunities.

Similar to statistical regression models, Artificial Neural Network (ANN) models can be considered a class of regression models that are used to model non-linear data. Advancements in machine learning algorithms and remote sensing technology have resulted in the wide application of Artificial Neural Network (ANN) models in the field of land use and transportation planning. ANN models consist of nodes called elementary neurons aggregated into different layers which receive inputs and convert them into outputs. Neural network modeling holds great potential in diverse applications such as ecological assessment and urban growth management (Zhang et al. 2018). Similar to statistical models, the parameter of accessibility in neural network models is also confined to two major applications - housing price and travel mode forecasting. In these applications, we found ANN models are used as a discrete choice model and are considered as a better alternative to the statistical regression models.

Based on our literature review of the past five years' studies, we look into two major applications of accessibility commonly used in statistical and neural network models.

4.1.1 Impact of accessibility on travel

Travel characteristics are generally determined by the mode of travel, travel time, and travel route. Studies, as highlighted below, show that accessibility has a profound impact on travel characteristics. Among the travel characteristics, accessibility to transit stations has been widely studied. Literature review shows that easy accessibility to transit stations makes public transportation a preferred mode of travel. At the same time, it also develops a walking/biking culture among people. People prefer to travel by metro rail or bus when the transit station is within a walking distance to their home or work location, thereby, incentivizing them to walk or bicycle to reach the transit station. Using structural equation modeling, Cheng et al. (2020) find that origin destination (OD) transit accessibility has a significant impact on transit mode choice while OD travel distance has no significant impact. Lu et al. (2018), using a multilevel regression model, reports accessibility to transit stations has a positive impact on the walking behavior while the other factors of the built environment have negative or no effect. Wu et al. (2020) have used a spatial regression model to find that higher accessibility to subway stations from bike stations results in more use of bikes and develop bike sharing networks. Using multivariate logistic regression, Guan et al. (2019) find higher accessibility to transit stations incentivizes households to use low carbon transport modes such as walking and cycling. Lee et al. (2017) find that good transit accessibility at job (destination) site make people use public transportation while the local urban characteristics at trip’s origin were less significant in promoting the use of public transportation. Liu et al (2016) have used structural equation modeling to find that higher accessibility to transit stations makes people choose low carbon travel modes. Pang and Zhang (2019) use hierarchical linear models to show that better transit accessibility reduces vehicle miles travel. Mahmoudi & Zhang (2018) use a mixed effect regression model and find that higher drive highway accessibility and transit-drive accessibility discourage walking. Using structural equation modeling, Chen and Akar (2017) find that access to public transportation at tour destination make people take complex tours and travel more distances.

Apart from accessibility to the transit station, studies have found accessibility to other destinations also has an impact on travel characteristics. Using multi-level logistic regression, Lu et al. (2018) find that accessibility to retail stores and urban centers makes people prefer to walk and take public transportation while density and diversity have little effect on their commuting mode choice. Jin (2019) finds higher job accessibility decreases commuting time. Nasri et al. (2020) find job accessibility via transit contributes to the bike share demand.

In the last five years, we find that few studies have used neural network models to study the impact of accessibility on travel characteristics. Yu et al. (2016) used bus accessibility to predict the bus passenger trip flow and found the model accuracy better than the non-linear regression models. Zuo et al. (2021) have used a neural network model to predict the individual accessibility to bus stations. Kaewwichian et al. (2019) build a household car ownership demand model using accessibility and other socio-economic variables and finds it better than discrete choice models. Mishra and Sarkar (2017) modeled commuting choice behavior using accessibility to public transport and found the model better than the binary logistic model.

4.1.2 Impact of accessibility on household location choices

Accessibility is one of the important factors that affect household location choice. Easy accessibility to attractive destinations such as job centers, parks, schools, and other public amenities plays an important role in household location choice. Earlier models of urban growth found accessibility to the central business district as an important factor of household settlement patterns. The Alonso-Muth-Mils model was one of the first such models which discussed that in a monocentric urban form, population density declines as one moves away from the central business district. With the decline in density from the city center, the land price also declines, and thus, for low-income households, areas away from the city center become a preferred location. Contrary to the monocentric model, the polycentric model of new urban economics (White, 1999) recognizes the existence of multiple job clusters in an urban area. The existence of multiple commercial centers and industrial centers in a city provides an effective alternative to the central business district. The polycentric model hypothesizes that population density does not decline with the increase in distance to CBD rather increases near to sub-centers (Muniz et al., 2008).

Many studies have proved that apart from distance to CBD and sub-centers, variations in household location choice can be attributed to other important factors such as proximity to urban amenities. One such frequently studied urban amenity is transit stations. Concerns about sustainable urbanization have resulted in many cities adopting policies of transit-oriented development. This has pushed the growth of public transportation especially metro rails to provide better accessibility to different destinations. Proximity to transit stations is thus valued by households, especially by those who belong to a middle or lower economic group. AlQuhtani and Anjomani (2021) use a multiple regression model to study the impact of the proximity of residential blocks to rail transit and find that it has a positive impact on the block population density. Li et al (2018) analyzed the housing price in the inner city and suburban areas of Shanghai and found that accessibility to amenities such as parks, schools, hospitals, entertainment, etc. impacts the land price in the inner-city region while in the sub-urban areas accessibility to transit stations is valued by the property buyers. Using the discrete choice model, Yan (2020) finds transit accessibility to jobs has a positive impact on the residential location choice. Saghapour & Moridpour (2019) used an ordered logistic regression model and found that public transport accessibility has a significant contribution in explaining the residential location choice of households. They note that accessibility has a greater impact than other built environment factors on the household re-location choice. Using vector autoregression, Song and Kim (2015) found that increase in subway accessibility (due to subway network expansion) resulted in population change and land rents in the measured region. Guan and Peiser (2018) performs hedonic regression and find that metro accessibility has a significant impact on housing price which discourages low-income households to live near metro stations. Morales et al. (2017) studies the impact of accessibility to multiple destinations on land values and found that accessibility to CBD has the greatest impact on the land value compared with accessibility to other destinations. Interestingly, they found accessibility to jobs has a negative impact on land value, which they hypothesized due to the negative externalities such as pollution and congestion caused by increasing accessibility.

Within the category of household location choices, the paper finds the use of neural network models in predicting house prices. Ruo-Qi and Jun-Hong (2020) use a genetic algorithm back propagation (GA-BP) neural network model to study the impact of accessibility to rail transit on the change in house prices. Wu et al. (2018) use an artificial neural network model to study the impact of accessibility to different public facilities on housing prices. They find the ANN model has better accuracy than the hedonic linear regression and geographically weighted regression models. Hu et al. (2019) use different machine learning algorithms including the multi-layer perceptron neural network (MLP-NN) model and find accessibility to job destinations and health centers have a significant impact on the household rental price in Shenzhen, China. Apart from housing prices, the application of accessibility can be seen in modeling built-up areas and urban form. Using a neural network model, Al-Sayed and Penn (2017) use street accessibility to forecast the urban form in terms of street width, building height, block density, and retail land use. Using a generalized estimating equation, Kasraian et al. (2017) find both road and rail accessibility have a significant positive impact on the urban built-up area. Similarly, studies such as Kasraian et al. (2020), and Koopmans et al. (2012) find that proximity to existing population centers has a greater impact on the built-up area as compared to accessibility to transit stations.

4.2 Agent Based Models

Agent based modeling is a bottom-up approach that micro-simulates discrete agents in an interacting environment (Babakan and Alimohammadi, 2016). The use of agent-based models in the field of land use and transportation planning has grown in the last decade with the advancement in micro-simulation techniques. Agent based models are being used to study the interrelationship between different variables such as transportation and residence location choices (Babakan and Taleai, 2015), gentrification and displacement (Eckerd et al., 2019), urban sprawl, and income segregation (Guo et al., 2017), and mobility and urban development (Leao et al., 2017). In all these studies, the thrust is to stimulate the behavior and examine the evolutionary dynamics between different agents and the environment. The agents, acting as the primary unit of study, include mainly the individuals as employees or residents. In a few studies, non-movable agents such as households and buildings have also been used (Fosset et al., 2016;

Marini et al., 2019). The crucial component of an agent-based model lies in the way the behavior of agents is modeled. This is typically done by defining a set of rules which the agents follow. The paper finds that in most of the studies the rules are built on a utility function or algorithm build on some statistical models like the logit model. Apart from equation-based modeling, studies elsewhere have also used cognitive frameworks such as BDI (Rao and Georgeff, 1991), PCES (Schmidt, 2002), ODD+D (Müller et al., 2013), Modelling Human Behavior (Schlüter et al., 2017) to decide agents' behavior rules. However, to the best of our knowledge, none of the papers have used such behavior modeling to study accessibility.

Various agent-based models have been used to study how changes in land use and transportation policies have impacted household residential choices for different socio-economic groups (Tomasiello et al., 2020). However, only a few studies have used accessibility as one of the model inputs. One of the earliest agent based residential location choice models which have used accessibility as a model input is UrbanSim (Waddell, 2000). The model uses local and regional accessibility to jobs and other facilities to simulate urban growth and real estate price. Babakan and Taleai (2015) find that the development of new transport services such as highways, BRT stations, and metro stations enhances the accessibility to different services and amenities which impact the household rent for different socio-economic households. Zhuge et al. (2016) use an agent based Residential Location Choice – Real Estate Price (RLC-REP) model to forecast real estate prices taking accessibility and house price as key input parameters. Tomasiello et al. (2020) use an agent-based model, ACCESS, to explore the job inequalities for different socio-economic groups. The model helps in understanding the impact of different housing and transport policies on the residential location choice and job accessibility of individuals. We now shift our focus on analyzing the strength and limitations of the statistical, neural network and agent based models.

4.3 Models Analysis

Statistical vs ABM: Based on our literature review, we find that the application of statistical models is widespread than agent based and neural network models in accessibility based land use and transportation models. Statistical models offer various advantages such as robust calibration and validation techniques, and easy interpretation and application of results. However, they are not very robust in modeling the individual measure of accessibility (Hunter et al., 2018). Due to this reason, there has been a growing interest in the agent-based models in the accessibility literature as they can model agent's behavior at a local level, and thus account for the heterogeneity and complexity in human behavior (Li and Gong, 2016). These models hold the potential to incorporate complex measures of accessibility occurring due to spatial and temporal changes in land use and transport policies (Tomasiello et al., 2020). Inspite of these advantages, we find that the use of agents-based models in applications of accessibility is still very limited. As outlined in various studies such as Heppenstall et al. (2021), Manson et al. (2020), Schulze et al. (2017), the key challenges in ABM lie in model parameterization, formulating agents' behavior rules, model calibration, and validation. What should be the appropriate behavioral rule for the agents, and should all the agents be governed by the same rule, or can there be a different rule for different groups of agents? Formulating behavioral rules require agents' daily activity data and a very acute understanding of agents' socio-economic conditions and their surrounding environment which is often not available. In addition, most agent-based models use the same behavioral function for every agent to model the agent's behavior (Dahlke et al., 2020). For example, in studies such as Tomasiello et al. (2020) and Babakan and Taleai (2015) to find optimal household location choices, all agents were modeled to maximize their accessibility to public services, which may not be a preferred choice for all agents. As noted by Macal (2016) such a representation of agents makes the simulation unrealistic and limits the agent's adaptability to the changing environment. Another major limitation of the ABMs is their limited capacity to calibrate and validate the results (Lee et al., 2015; Zhang et al., 2020). Due to complex model design and many parameters, calibration becomes essential so that all the parameters are fitted as per the model data. Model validation is also required to check the consistency of the model result with the real-world data. As the simulation of individual activities is a very detailed and complex phenomenon, it becomes a challenging task to validate the results as a large amount of information is needed which is often not available for the entire region (Huang, 2017). According to Heppenstall and Malleson (2020), validation of agent-based model remains a "dark art at worst and haphazard at best". This puts a question mark on the model's efficiency and decreases the credibility of the simulation result. To strengthen the ABMs, the paper finds that studies combine them with Neural Network models.

Statistical vs ANN: Application of ANN models in land use and travel choice modeling is preferred due to their better accuracy (Shukla et al., 2016) and ability to model complex nonlinear relationships in urban design (Lee et al., 2018; Feng et al., 2015). These models are known to provide a better prediction, unlike statistical models which decrease estimation error, ANN models decrease prediction error (Kaewwichian et al., 2019). ANN models use a hidden layer that captures the complexity or non-linearity of the dataset which statistical models are unable to do. Comparing discrete choice analysis model with ANN models, Lee et al. (2018) find that ANN models outperform the Multinomial Logit Model (MNL) with a prediction accuracy of 80% compared with 70% for MNL. Also, ANN models do not require many data distribution assumptions like normality and Independence to Irrelevant Alternatives (IIA) unlike their statistical counterparts (Lee et al., 2018). This makes ANN models a preferred choice over statistical models for predicting unknown data. However, statistical models are still relevant and should not be replaced completely. They give better insight into how each variable affects the model outcome, unlike ANN models which appear to operate in a 'black box' posing a challenge in result interpretability (Ha et al., 2019). In statistical modeling, it is easy to eliminate the variables which do not contribute to the model fit and there is the scope of hypothesis testing between dependent and independent variables. Furthermore, it requires a huge quality dataset to train the ANN models. These challenges in ANN models have restricted their widespread use in accessibility modeling.

5 Future Research Directions

This section discusses the future research direction that lies in the measures of accessibility and the models that are used to study the impact of accessibility.

(a) Gender Equity and Environment Sustainability

Today accessibility is seen as a crucial parameter in the design of a city's physical form. However, a value-neutral approach in enhancing accessibility can be counter-productive. The question we ask here is - does an increase in accessibility is always desirable, especially when it comes at the cost of increased environmental degradation and social-economic inequity? At the conceptual level accessibility need to be defined and measured by including its impact on the environment and social-economic equity. With the availability of high resolution spatial data, use of disaggregated measures or person based measures of accessibility is going to increase. While many of the accessibility measures incorporate the individual preferences to travel, they do not explicitly capture the inequity in accessibility arising due to socio-economic factors such as age, gender, income, etc. Ignoring such individual characteristics in accessibility measures masks the inequity that exists within different socio-economic groups (Dixit and Sivakumar, 2020). Limiting the scope of the paper to one of the socio-economic factors, we found that only a few studies have examined the gender inequity in accessibility measures. A study by Lecompte and Pablo (2017) in Bogota shows that women spend more time commuting than men for the same distance and have lower job accessibility per capita. They further suggest that this accessibility inequity becomes stronger in lower socio-economic groups. Kwan and Kotav (2015) in their survey in Bulgaria find that the daily travel time of women is higher than men because women in the sample used public transportation instead of a private vehicle as their primary mode of travel.

In our literature review, we found the measures of accessibility so far developed are largely male biased or at best gender neutral as they do not factor explicitly women perception towards the mode of travel and destination location which can be different from men. The case of gender based inequity in accessibility is very important to measure especially in patriarchal societies where women face different barriers to travel. To make the accessibility measures more inclusive they need to be modified taking into account those factors which impact women's preference of travel mode and travel location. This includes transport safety, security, comfort, reliability, cleanliness, and factors like a perceived threat of violence or harassment at the traveled location (Pirra et al., 2021). Thus, women's accessibility differs from men's accessibility as it is not just confined to factors of time, cost, and availability of opportunities but also includes other factors of safety and security to which women give more preference than men (Lecompte and Pablo, 2017).

Apart from gender equity, our review suggests environmental sustainability is a potential area of research in accessibility studies. As discussed in a previous section different perspectives in accessibility – transportation, land use, and individual - have evolved in the last 60 years. Today, with an increase in vehicular emissions and their negative impact on the environment there is a need to have an environment centric approach in accessibility as the environmental issues have been either avoided or addressed implicitly in the past studies of accessibility (Kinigadner et al., 2021; Määttä-Juntunen et al., 2011). The concerns of environmental sustainability in the study of accessibility arises as an individual's utility maximization approach can have a negative impact on the environment (Johansson-Stenman and Martinsson, 2006). To maximize accessibility, an individual may choose a travel mode that provides the highest utility in terms of travel cost and travel time. However, the choice of travel mode also decides the extent of damage to the environment occurring through vehicular greenhouse gas emissions and other pollutants (Inturri et al., 2017; Woodcock et al., 2007). Thus, the environmental cost of the travel mode (or the external travel cost) should be taken into account in the measure of accessibility along with different travel attributes like time, cost, and comfort (Kinigadner et al., 2020; Vasconcelos and Farias, 2012). If environment sustainability becomes a component of accessibility measures, then non-motorized travel will contribute to enhancing accessibility scores. However, the overall accessibility with non-motorized travel might still be less if the travel time or cost involved in such travel modes is higher than the motorized travel.

(b) Model Synthesis

Looking at the scope of these models, recent studies show that model efficiency can be enhanced with the coupling of statistical / machine learning (ML) models with agent-based models. Gore et al. (2016) build a novel approach of statistical debugging to enhance the efficiency of trace validation and verification of agent-based models. Zhang and Vorobeychik (2019) in their review of different categories of agent-based models discuss the use of machine learning models to calibrate and predict human behavior in agent based models. They find that although only a few studies have incorporated machine learning models in ABM simulations, advancement in data analytics is a positive development to solve the issue of model calibration and validation. Carrella et al. (2019) use a simple linear regularized regression to calibrate agent-based model. Studies such as Lamperti et al. (2018), Zhang et al. (2020) have performed calibration of ABM through surrogate modeling techniques using machine learning algorithms. By combining techniques of intelligent iterative sampling and machine learning, a surrogate of the ABM is built which makes the calibration of the model easier and less time consuming. Crooks et al. (2020) highlight how different studies have used machine learning models at different stages of agent-based model formulation such as model parameterization or to set decision rules for the agents or to carry out model optimization and estimations. In their review of agent-based models using machine learning algorithms, Dahlke et al. (2020) find that agents' behavior can be made more realistic by making them learn their behavior during the simulation through the use of Multi Agent Reinforcement Learning (MARL). Some studies in energy sector such as Kofinas et al. (2018), Wang et al. (2019) have used Q-learning algorithm to carry out Multi Agent Reinforcement Learning. Edali & Yucel (2018) have used random forest metamodels and sequential sampling to understand the input output relationships in the agent-based simulation models. Similarly, through the use of other ML algorithms such as genetic algorithm deep nets, decision trees, and inverse re-enforcement learning, studies have obtained better realistic simulations (Van der Hoog, 2019; Ramchandani et al., 2017; Negahban, 2017; Laite et al., 2016). The use of such ML algorithms makes agents learn and adapt their behavior to the changing environmental conditions. This suggests that model synthesis can bring significant changes in making the model result more efficient and robust.

We end this section with a cautious note about the use of ML in ABM. ML models will certainly enhance the explanatory power of ABM in the coming future; however, the focus should not be on making the model grand but on its simplification and meaningfulness. That will happen only when modelers keep an eye on the model processes and not just on the model efficiency. Understanding *what goes in, what comes out, and what happens in between* should be the guiding torchlight in ML based simulations. To put it in other words, modelers using ABM should understand the need of using the ML and the associated cause and effect in the simulation, otherwise as noted by Dahlke et al. (2019), the use of ML can result in the creation of "intelligent yet black box ABMs".

6 Conclusion

As cities are complex entities that evolve organically with time, a critical understanding of accessibility measures and models related to different applications of accessibility can help the policy makers to solve many challenges of urban development. This literature review was aimed at understanding how accessibility has been measured and modeled in the past. The review found that many studies have defined accessibility using different dimensions and components such as land use, transportation, spatial and temporal. The study defines accessibility as "the degree of freedom and ability an individual has to perform a desirable activity to derive the maximum benefit out of it". The study reviewed the measures of accessibility and categorized them under infrastructure based, location based, and person based measures. Within each such measures, recent advancements were highlighted. Three notable advancement includes - use of machine learning tools to measure street forms, use of web-based mapping software and location based data to measure precise travel and activity location, and accounting temporal variations in activity based measures. The measures of accessibility have a normative purpose as they specifically focus on what policy planning measures can be taken to improve accessibility. The study suggests the use of environmental sustainability and gender equity as crucial factors that should be included in the measure of accessibility, as a future research direction.

The paper reviewed two major applications of accessibility along with the models used in these applications. The models are used as an explanatory tool to study the impact of accessibility on travel mode and household location choices. Many studies report that accessibility to transit stations makes public transportation a preferred mode of travel and is considered an important factor in household location choice. Noting the strength and weakness of these models, statistical models are found to be widely used as they are statistically robust and easy to interpret, but do not account for heterogeneity at the individual level. Neural Network models are preferred over statistical models as they account for non-linearity in the data and have better prediction accuracy. Challenges of big data requirement and interpretability of results restrict the wide use of neural network models in accessibility modeling. Agent based models are known to simulate the heterogeneity in individual behavior but have issues related to behavior simulation, calibration, and validation. The paper finds that studies in the recent past have combined statistical/neural network models with agent-based models. This suggests that model synthesis can bring significant changes in making the model result more efficient and robust. With easy access to micro-data and advancement in modeling software, complete integration of the three models can result in better operationalization of the accessibility measures in its different applications, which to the best of our knowledge has not been reported in the accessibility literature so far and thus, holds potential for future research.

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