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Article

Integrated Accessibility and Service Substitution in Urban Systems: A Multi-Layer Simulation Approach

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Abstract

Urban accessibility is increasingly shaped by the interaction between physical mobility, digital service accessibility, and social relationships. However, most existing urban simulation models primarily focus on physical transportation networks and rarely incorporate digital accessibility or social interaction mechanisms. This limitation restricts the ability of conventional models to capture emerging behavioral patterns associated with digital service adoption and changing urban lifestyles. To address this gap, this study develops a multi-layer Social Dynamics Simulation (SDS) model that integrates three interdependent network layers: a real network representing physical accessibility, a virtual network representing digital accessibility, and a social network representing interpersonal relationships. The model introduces an integrated accessibility index that combines physical and digital accessibility based on a probabilistic service choice framework estimated using survey data (n = 6,210). The proposed model is applied to a virtual city experiment to examine how digital service usage and social interaction preferences influence long-term urban dynamics. Simulation results indicate that digital accessibility partially relaxes spatial constraints imposed by transportation networks, enabling households to maintain acceptable service access even in locations with lower physical accessibility. However, transportation accessibility remains a dominant factor shaping residential concentration around transit nodes. The results further demonstrate that digital service substitution can reduce travel demand while reinforcing accessibility differences across population groups. The proposed framework contributes to computational urban systems modeling by incorporating digital service substitution and social interaction effects into a multi-layer simulation environment. The results highlight the importance of representing non-physical accessibility processes when evaluating urban dynamics in increasingly digitalized cities.

Keywords: multi-layer urban simulation; integrated accessibility; digital service substitution; social dynamics simulation; urban microsimulation; land-use and transportation modeling; service choice behavior

1. Introduction

Urban structures are increasingly shaped by the interaction between physical mobility, digital connectivity, and social relationships. The rapid expansion of Information and Communication Technologies (ICT), accelerated by events such as the COVID-19 pandemic, has significantly transformed how individuals access services, interact socially, and make residential and mobility decisions. Activities that were traditionally dependent on physical mobility, such as shopping, working, and communication, can now be partially or fully conducted through digital platforms. While this transformation offers benefits such as reduced travel costs, improved time efficiency, and enhanced accessibility to services [1], it also introduces new spatial and social dynamics [1, 2] that influence urban structure and sustainability outcomes [3].

Previous studies have examined behavioral changes related to online shopping, teleworking, and digital service usage, particularly during periods of mobility restriction. These studies have

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shown that digital services can substitute for or complement physical activities, thereby altering travel demand, accessibility patterns, and residential preferences. However, most empirical studies have focused on short-term behavioral responses or single activity domains, rather than examining the broader urban dynamics generated by these behavioral changes over time. For example, an existing study [4] focused on changes in internet-based consumer behavior due to the decrease in outings caused by COVID-19. Conducting an online survey in Tokyo's 23 wards and Okayama City, Okayama Prefecture, they found a strong tendency for women and younger people to increase their online activity. The results indicated that the reasons for online shopping varied depending on the size of the city, with the motivation for reducing travel hassle in the metropolitan area and for supplementing the availability of physical stores in rural areas. Furthermore, existing studies [5] analyzed the impact of changes in working patterns [6] and shopping behavior [7] during the COVID-19 pandemic on urban structure and suggested that the traditional concept of commuting has collapsed. Furthermore, Daimon [8] investigated the impact of advances in telework and online shopping on residential choice in urban and rural areas, particularly illuminating how smart cities affect relocation behavior. These studies have provided significant insights into the relationship between information network usage, transportation behavior, and residential choice. Similarly, a study by Mutahari et al. [9] has further investigated the substitutability of physical services with digital alternatives and connected the service access substitutability to an individual`s quality of life and decarbonization effort.

To understand long-term urban transformation, researchers have developed a variety of urban simulation models, particularly within the field of land-use and transport interaction modeling [10, 11]. Representative examples such as UrbanSim [12], TLUMIP [13], PECAS [14,15], ILUTE [16], ILUMASS [17, 18], PUMA [19], and SelfSim [20] simulate interactions between households, land use, and transportation systems. These models have significantly advanced the ability to evaluate urban policies and predict spatial development patterns. Nevertheless, their analytical frameworks largely focus on physical transportation networks and land-use interactions, while the role of digital accessibility and social interaction networks remains insufficiently represented.

Recent developments in complex network science highlight that urban systems can be better represented through multi-layer networks, where different types of relationships, such as spatial proximity, communication, and social networks, interact simultaneously, and network analysis has been widely applied to the analysis of complex social structures [21]. In this context, Social Dynamics Simulation (SDS) model [22] has been proposed to capture temporal changes in population attributes, household composition, and facility access through a multi-layer network representation of urban entities. Existing SDS applications have demonstrated the ability to simulate interactions between individuals, households, zones, and facilities, thereby reproducing important aspects of urban dynamics.

Existing studies have applied the SDS model to a virtual city by incorporating attributes of a real city to examine its applicability to large and complex urban spaces. The model describes individuals, households, and urban space using a multi-layer network and expresses social dynamics as temporal transitions in population attributes, household composition, and facility access. The model was applied to a virtual city under multiple facility distribution scenarios, and its behavior was verified through changes in household location and traffic conditions. The multilayer network structure follows a layer-breaking k-partite network, in which individuals, families, zones, and facilities are represented as nodes across multiple layers. For example, Nakatani et al. [23] applied a multi-layer network model to a real city, describing entity attributes, land use changes, and physical accessibility to facilities. They applied an urban microsimulation model in an actual city to evaluate urban policy, considering the temporal changes. However, to dynamically and comprehensively evaluate the individual behavioral changes and factors identified in these studies as a process of long-term urban structural change through interactions between people across the city, it is necessary to expand the framework of conventional models and adopt an integrated approach that deals with multiple layers. In particular, there is a lack of research that comprehensively analyzes the complex interactions between different layers, such as physical networks (transportation network, physical accessibility), virtual networks (ICT network, digital accessibility), and social networks (human interpersonal

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relationships), using a single model. A challenge with conventional urban simulation models is that they are unable to adequately represent the social dynamics, considering temporal changes in the virtual network and social network via individual behavior. Considering the importance of sensitivity analysis of urban models, such as the SDS model, an existing study [24] has performed parameter setting examinations on the SDS model to check the sensitivity and applicability of the model. The results confirmed that the SDS model is stable under different parameter settings and is applicable for evaluating urban policies and predicting future urban conditions under different scenarios.

Despite these advances, two key limitations remain in the current literature. First, most urban microsimulation models consider only physical accessibility, ignoring the growing importance of digital accessibility in determining service access and behavioral choices. As digital services increasingly complement or substitute physical activities, neglecting virtual accessibility may lead to incomplete representations of urban behavior. Second, the interaction between accessibility conditions and social relationships has rarely been incorporated into urban simulation models. Social networks influence how individuals exchange information, form connections, and access opportunities, which in turn affects mobility patterns, service choices, and residential location decisions. Without explicitly modeling these social interactions, the ability of simulation models to reproduce realistic urban dynamics remains limited.

To address these gaps, this study develops a multi-layer network SDS model that integrates three interdependent systems:

- Real network representing physical accessibility through transportation systems
- Virtual network representing digital accessibility through ICT infrastructure
- Social network representing interpersonal relationships between individuals

Within this integrated framework, the study introduces two key methodological innovations. First, an integrated accessibility index is developed to combine physical and digital accessibility measures, enabling the model to represent hybrid service access environments where individuals may choose between physical and virtual services. Second, a behavioral service choice model based on a binomial logit model is incorporated to capture the probabilistic decision process through which individuals select either physical or digital services depending on accessibility conditions and social interaction factors.

By integrating these mechanisms into a multi-layer SDS model, the proposed model enables simulation of the co-evolution of residential location, service access mode choice, mobility demand, and social network structure over time.

The main contribution of this research is therefore threefold:

- Conceptual contribution: introducing an integrated framework linking physical, digital, and social networks within urban microsimulation models.
- Methodological contribution: developing a multi-layer SDS model incorporating integrated accessibility and service choice behavior.
- Analytical contribution: demonstrating how digital accessibility and social interactions jointly influence urban spatial dynamics through a controlled virtual city experiment.

By extending the existing SDS model to incorporate digital and social dimensions of accessibility, the proposed model provides a new analytical tool for evaluating sustainable urban development, equity in service access, and emerging smart-city policies.

The remainder of this paper is organized as follows. Section 2 describes the methodology and modeling framework. Section 3 introduces the virtual city experiment used for model application. Section 4 presents the simulation results. Section 5 discusses the implications of the findings. Finally, Section 6 summarizes the main conclusions and outlines directions for future research.

2. Materials and Methods

2.1. Representation of Urban Space by a Multi-Layer Network

A new descriptive image of urban space by a multilayer network is shown in Figure 1, where a layer-breaking K-partite network [25] has been used. The individuals, their families, and the spaces

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in the cities are represented in multiple layers. Nodes of each layer represent attributes of individuals, households, and urban spaces such as age, gender, parent-child relationship, marital relationships, urban facilities, etc. The addition of a digital service layer to the multi-layer network redefines the individual's accessibility and service choice behavior.

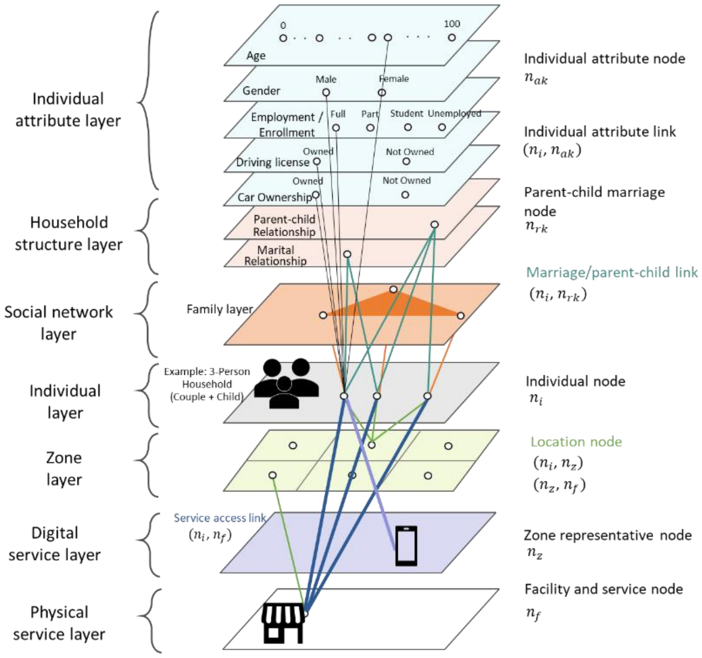

Figure 1. Description of urban space by a multi-layer network

As can be seen in Figure 1, a new virtual space layer and social network layer are added to the existing multi-layer network model to describe urban space. Additionally, the study develops a model that integrates the three layers of physical space, virtual space, and social network. Figure 1 shows a description of how urban space will be represented at a specific point in time within this framework. In addition to traditional accessibility assessments that rely solely on physical networks, the study developed an extended integrated accessibility index that reflects the impact of digital accessibility and social networks on the behavioral choices of individuals. The virtual space (digital service) layer is expressed in correspondence with the real space (physical service) layer of the existing model and describes service locations that do not involve physical movement. The connection relationship between the two layers is expressed as link weights determined by a choice model, which will be described in the latter part of this manuscript.

To simplify the representation of the social network layer, this study does not explicitly model the network structure based on specific interpersonal connections but instead adopts an approach that describes each individual's "psychological importance placed on human relationships" as link weights. This factor directly affects the utility values of the physical space and virtual space and influences the probabilistic decisions made about service choices.

2.2. Social Dynamics Simulation (SDS) Model

This study modifies the framework of the existing SDS model [22] by considering behavioral choices in real space and virtual space and the impacts of the social network involved in the service choice. The structure of the SDS model is shown in Figure 2. At each simulation time step, processes such as reassigning links between nodes are performed, changing the shape of the multi-layer network, and representing these transitions.

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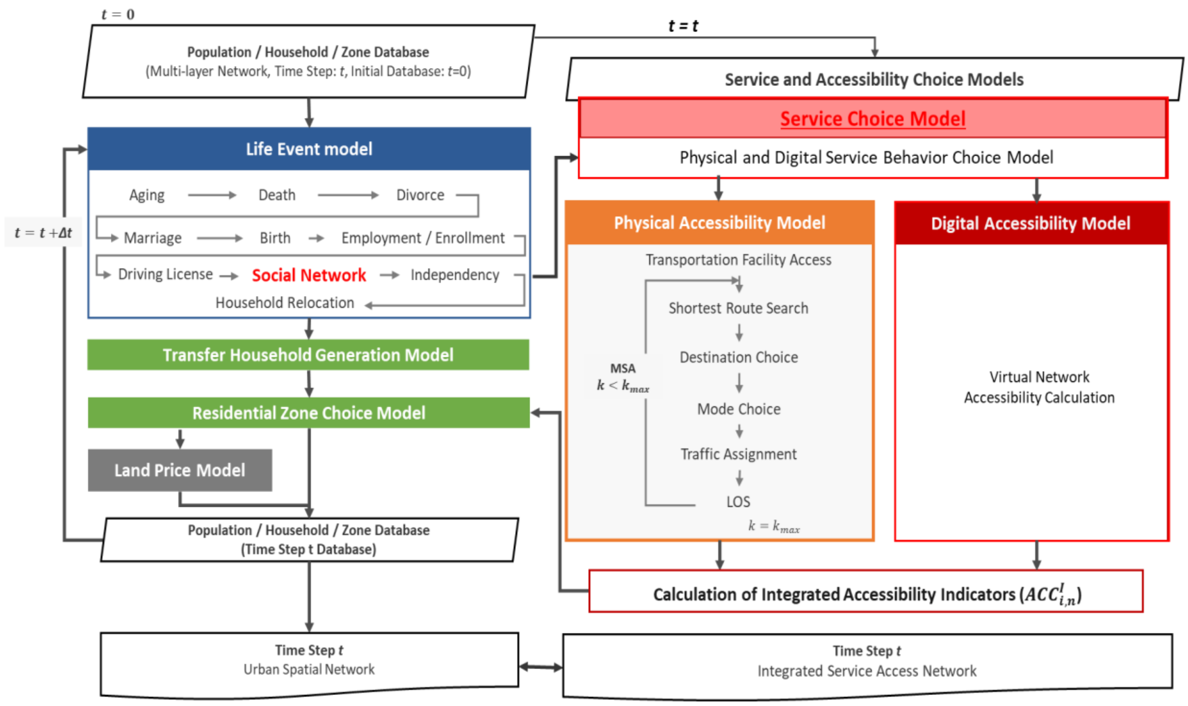

Figure 2. Basic structure of the SDS model

The service choice model determines the probability that an individual will choose real space or virtual space based on their attributes. The physical accessibility model represents individual facility choices and accessibility and allocates traffic volume using user equilibrium allocation, taking into account the urban population and household distribution and the transportation network at each simulation time step. Meanwhile, the digital accessibility model determines the accessibility of services in virtual space based on factors such as individual attributes (e.g., age, gender) and values (importance) regarding virtual networks. This physical accessibility and digital accessibility are integrated using the choice probability determined in the service choice model as a weight to define integrated accessibility. The integrated accessibility calculates the transportation LOS and the generalized costs associated with individual facility (destination) access.

The life event model represents changes in individual and household attributes, as well as resulting in independence and household relocations, by stochastically generating various life events (aging, death, divorce, marriage, birth, employment, independence, relocation, etc.) at each simulation time step. The importance placed on individuals' relationships changes based on personal attributes such as age, gender, marital status, and occupation, using a social network update model incorporated into this life event model. Additionally, location changes for relocating households are represented by a residential zone selection model that incorporates integrated accessibility indicators for real space and virtual space. Finally, land prices in each zone are updated using a land price model.

2.3. Service Choice Model

The service choice model uses a binary logit formulation to estimate the probability of choosing virtual space (P_n^D) versus physical space (P_n^R) for service access. The service choice model expresses the probability that an individual will select a service in real space or in virtual space. The individual's choice probability is determined by the difference between the utility in the real space, $V_n^R$and the utility of the alternative action in the virtual (digital) space, V_n^D. Here, by normalizing the utility in the virtual space to 0, the choice probability in the real space relative to the information space is defined as follows:

$$P_n^R = w_n^R = \frac{1}{1 + exp\,(V_n^D - V_n^R)} = \frac{1}{1 + exp\,(-V_n^R)} \tag{1}$$

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$$V_n^R = \sum_i \alpha_k X_{kn} + \beta_0 \tag{2}$$

$$w_n^D = 1 - w_n^R \tag{3}$$

where
P_n^R : Probability of selection of real space for individual category n
w_n^R : Link weights for real-space layers
w_n^D : Link weights for virtual (digital) space layers
V_n^R : Utility of real space for individual category n
V_n^D : Utility of virtual space for individual category n
α_k : Estimated parameters
X_n^k : Attribute k of individual category n
β_0 : Constant term

The utility of real space and the virtual space is defined using individual attributes and social networks as explanatory variables. The weights w_n^R and w_n^D of the links to facilities in the real space and services in the information space are determined by the selection probability P_n^R and reflected in the multi-layer network. The systematic utility function V_n^D for the virtual space alternative is specified as:

$$V_n^D = \beta_0 + \alpha_1 \cdot \mathrm{Age} + \alpha_2 \cdot \mathrm{Male} + \alpha_3 \cdot \mathrm{Married} + \alpha_4 \cdot \mathrm{Employed} + \alpha_5 \cdot \mathrm{IMP}_{\mathrm{work}} + \alpha_6 \cdot \mathrm{IMP}_{\mathrm{internet}} \tag{4}$$

where β_0 is the alternative-specific constant, α_i are the estimated coefficients, Age is the individual's age in years, Male is a gender dummy (1 = male), Married is a marital status dummy (1 = married), Employed is an employment dummy (1 = employed), $\mathrm{IMP}_{\mathrm{work}}$ is the importance of workplace relationships (1-7), and $\mathrm{IMP}_{\mathrm{internet}}$ is the importance of internet relationships (1-7).

2.4. Physical Accessibility Model

To calculate accessibility indices in real space, the study uses a transportation network user equilibrium allocation model using a logit model for user mode choice [22]. In this model, the available transportation modes for individual category n are $m \in M_n${auto; public transportation; bus/rail; walking; walk; household ride sharing; RS}. Individual category n is classified based on individual attributes (e.g., age, available transportation modes). Furthermore, the transportation network within the urban space is assumed to be specified exogenously and is not endogenously adjusted within the model. Using this model, the study calculates LOS by allocating OD traffic volume by mode to the transportation network within the urban space, and then calculates the generalized cost and accessibility index for individual category n's OD route.

First, an individual residing in zone i and choosing a facility in zone j selects the route with the lowest generalized cost between OD(ij). The shortest route, weighted by link cost, is calculated for each mode of transportation. In addition, the OD route cost at this time is the generalized cost ($gc_{ij,n}^m$) when using transportation mode m for individual category n, and is expressed as the sum of link costs as equation (5).

$$gc_{ij,n}^m = \sum_a \delta_a^{ij} c_{a,n}^m + \zeta_n^m \tag{5}$$

where
$c_{a,n}^m$: Link cost for transportation mode m, personal category n, and road link a
δ_a^{ij} : Path connection matrix between ij
ζ_n^m : Constant for transport mode m and individual category n (reflecting vehicle ownership costs and insurance fees, as well as category n specific resistance to the use of transport mode m).

In addition, the link costs by transportation mode, $c_{a,n}^m$ are as follows.

$$c_{a,n}^{Auto} = \tau_n t_a^{Auto} + cf\, d_a \tag{6}$$

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$$c_{a,n}^{RS} = \tau_n \, t_a^{Auto} + cf \, d_a \tag{7}$$

$$c_{r_l,n}^{PT} = \tau_n \left(t_{r_l}^{PT} + cc_{r_l} + \frac{1}{2f_l} \right) + ca_{r_l} + ct_{r_l} + cd_{r_l}, \quad (r_l \in a) \tag{8}$$

$$c_{a,n}^{Walk} = \tau_n \, t_a^{Walk} \tag{9}$$

where

τ_n : Time value of individual category n
t_a^{Auto} : Road link a ride time
d_a : Distance of road link a
cf : Vehicle driving cost
r_l : Public transportation links in system l $(r_l \in a)$
$t_{r_l}^{PT}$: Ride time for public transport links, r_l.
cc_{r_l} : Congestion of public transportation links, r_l. (time cost).
f_l : Frequency of operation of system l
ca_{r_l} : Transfer penalty associated with public transport link r_l (applied only to the first public transport link).
ct_{r_l} : Terminal charge for route l and public transport link r_l (Considered only for the first public transport link)
cd_{r_l} : Distance charge for route l and public transport link r_l
t_a^{Walk} : Walking time on the road link a

For public transport, the model does not use actual frequency or fares, but rather charges are incurred for each distance and terminal, and frequency is variable depending on the number of users.

Based on the above, the study calculates the OD traffic volume for each purpose and mode of transport within the network. First, the destination selection probability $P_{ij,n,k}$ for the purpose k of individual category n between ij is expressed as follows: The accessibility index between ij for individual category n ($ACC_{ij,n}$) in here is expressed as a log-sum variable using the utility function $V_{ij,n}^m$ when personal category n uses mode m between ij in the transport mode choice model in equation (15), as follows:

$$ACC_{ij,n} = \frac{1}{\mu} ln \left(\sum_{m \in M_n} av_n^m exp\,(\mu V_{ij,n}^m) \right) \tag{10}$$

$$V_{ij,n,k} = ps_{n,k} \, S_{j,k} + pa_n \, ACC_{ij,n} \tag{11}$$

$$P_{ij,n,k} = \frac{exp(V_{ij,n,k})}{\sum_{j' \in J_n} exp(V_{ij',n,k})} \tag{12}$$

where

μ : Scale (dispersion) parameter of the stochastic error term
av_n^m : Individual category n mode of transportation m availability
$S_{j,k}$: Customer attraction index for facility (destination) j by purpose k
$V_{ij,n,k}$: Utility between ij for individual category n
ps_n, k : Customer attraction index parameters
pa_n : Accessibility Metrics Parameters

The traffic volume of the purpose k of the individual category n is calculated using the following formula as $T_{i,n,k}$., OD traffic, $T_{ij,n,k}$. is the destination selection probability, $P_{ij,n,k}$.

$$T_{ij,n,k} = T_{i,n,k} \cdot P_{ij,n,k} \tag{13}$$

In addition, the probability of choosing transportation mode m for individual category n between ij, $P_{ij,n}^m$, is expressed as follows:

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$$V_{ij,n}^{m} = pgc_n \, gc_{ij,n}^{m} \tag{14}$$

$$P_{ij,n}^{m} = \frac{av_n^m \, exp\,(V_{ij,n}^{m})}{\sum_{m' \in M_n} av_n^m \, exp(V_{ij,n}^{m'})} \tag{15}$$

where
$V_{ij,n}^{m}$: Utility of using transportation mode m for individual category n between ij
pgc_n : Generalized Cost Parameters
av_n^m : Availability of transportation mode m for individual category n

In this case, the availability of transportation mode (av_n^m) is expressed as follows, taking into account the individual's availability of transportation mode, walking distance, and generalized cost threshold. Therefore, (av_n^m) takes values between 0 and 1.

$$avnm=av\_mnm \times av\_wnm \times av\_cnm \tag{16}$$

where
av_n^m : Availability of transportation mode m for individual category n
$av\_m_n^m$: Availability of transportation mode m for individual category n (ownership of transportation mode) (Available → 1, Unavailable → 0, Ride sharing with other household members → 0 to 1)
av_w_n : Walking accessibility considering the walking distance of individual category n (walking distance < walkable distance → 1, walking distance ≥ walkable distance → 0)
$av\_c_n^m$: Accessibility considering generalized cost threshold ($gc\_thr_n^m$), ($gc_{ij,n}^{m} < gc\_thr_n^m \rightarrow 1$, $gc_{ij,n}^{m} \geqq gc\_thr_n^m \rightarrow 0$)

If the availability of all transportation means for a facility (destination) (av_n^m) is 0, the number of accessible facilities is changed by excluding that facility (destination) from the J_n choice set. The OD traffic volume by purpose and transportation means $T_{ij,k}^{m}$ is calculated using the transportation means selection probability $P_{ij,n}^{m}$ using the following formula.

$$T_{ij,k}^{m} = \sum_n P_{ij,n}^{m} T_{ij,n,k} \tag{17}$$

The calculated OD traffic volume by transportation mode is allocated to the link traffic volume x_a^m using the following formula.

$$x_a^m = \sum_k \sum_i \sum_j \delta_a^{ij} \, T_{ij,k}^{m} \tag{18}$$

The LOS is calculated based on the allocated link traffic volume by the following formula. First, the road link travel time, t_a^{Auto} is calculated by the following BPR function.

$$t_a^{Auto} = t_{a,0}^{Auto} \left(1 + \alpha \left(\frac{x_a^{Auto}}{K_a} \right)^{\beta} \right) \tag{19}$$

where
$t_{a,0}^{auto}$: Free running time on the road link a
K_a : Traffic capacity of road link a
α, β : parameter

In addition, the frequency of public transportation services, f_l , is calculated by the following formula, taking into account the link traffic volume (number of users) and the maximum and minimum frequency.

$$f_l = min\left(max\left(\frac{max\{x_{r_l}^{PT}\}}{K_l}, minf_l \right), maxf_l \right) \tag{20}$$

where
$x_{r_l}^{PT}$: Traffic volume of the public transport link r_l
K_l : Public Transit System Capacity

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$minf_l$: Minimum frequency of the public transportation system l
$maxf_l$: Maximum frequency of the public transportation system l

In addition, public transportation congestion, cc_{r_l} is considered the time cost and calculated by the following formula.

$$cc_{r_l} = \gamma \left(\frac{x_{r_l}^{PT}}{SK_l}\right)^{\eta} \tag{21}$$

where
SK_l : Public transport system l seating capacity
γ, η : parameter

In this model, the traffic volume is evenly distributed by adopting the MSA method, and the generalized cost by means of transportation for the LOS of the transportation network and the individual category n is calculated by the above calculations for each iteration of the MSA.

$$x_a^{m,p+1} = \frac{p}{p+1} x_a^{m,p} + \frac{1}{p+1} x_a^{m,p'} \tag{22}$$

where
p : Number of iterations
$x_a^{m,p+1}$: Link traffic after update (p+1)
$x_a^{m,p}$: Link traffic before update (p)
$x_a^{m,p'}$: Link traffic volume after redistribution at iteration p

Based on the traffic volume and LOS after allocation, the accessibility index ($ACC_{ij,n}$) between ij of personal category n is calculated using equation (9) and assigned as the weight of the facility access link connecting the personal node and the facility node. In this case, to avoid the weight becoming negative, the accessibility index is normalized using the following equation.

$$ACC_{ij,n}^{R} = \frac{ACC_{ij,n} - ACC_{ij,n,min}}{ACC_{ij,n,max} - ACC_{ij,n,min}} \tag{23}$$

where
$ACC_{ij,n}^{R}$: Accessibility index between *ij* of the standardized personal category *n*
$ACC_{ij,n}$: Accessibility index between *ij* of personal category *n*
$ACC_{ij,n,min}$: The minimum value of $ACC_{ij,n}$
$ACC_{ij,n,max}$: The maximum value of $ACC_{ij,n}$

2.5. Digital Accessibility Model

In this study, digital accessibility (ACC_n^D) represents the extent to which an individual can effectively use digital services, defined as the interaction between potential digital access (digital infrastructure and devices) and digital friction arising from individual-level constraints such as knowledge, trust, security concerns, etc. Unlike the physical (transportation) accessibility index ($ACC_{ij,n}^R$), this index does not depend on spatial facility location or travel costs between zones, but rather varies depending on factors such as individual attributes (e.g., age, gender) and digital access friction (knowledge, trust, security, etc.) for digital services. Therefore, (ACC_n^D) has different values for each individual depending on the individual's attribute and their knowledge and concerns towards digital service usage, regardless of residential zone. The digital accessibility (ACC_n^D) can be formulated as equation (24).

$$ACC_n^D = \alpha V_n^D . e^{-\beta \emptyset_{ns}} \tag{24}$$

Where V_n^D is the available digital infrastructure and digital devices, which the study assumes are fully available (1). $\emptyset_{ns}$ is the digital service friction (the ability and concern of individuals towards digital service usage). The α and β are parameters.

2.6. Definition of integrated accessibility index

The integrated accessibility index ($ACC_{i,n}^I$) proposed approach in this study quantifies the overall attractiveness of a residential zone when an individual considers the service choices between real

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space and virtual space. Integrated accessibility is defined as a linear combination of the physical (transportation) accessibility in real space and the digital (ICT) accessibility in virtual space, weighted by the probability of choosing each space. Equation 25 quantifies the integrated accessibility index as follows.

$$ACC^{I}_{ij,n} = P^{R}_{n} \cdot ACC^{R}_{ij,n} + P^{D}_{n} \cdot ACC^{D}_{n} \tag{25}$$

where

$ACC^{I}_{i,n}$: Integrated accessibility of individual category n in zone i

ACC^{D}_{n} : Digital accessibility of individual category n in zone i

P^{R}_{n} : Probability of choosing real space for individual category n

P^{D}_{n} : Probability of choosing the virtual space for individual category n

Although digital services may partially replace certain activities, the proposed framework in this article treats digital accessibility as complementary to physical accessibility. Digital accessibility does not depend on spatial impedance or facility locations and therefore cannot substitute for physical travel. Instead, it modifies individuals' service choice probabilities. Physical accessibility continues to determine spatial differentiation across zones, while digital accessibility raises the baseline level of access uniformly.

2.7. Life Event Models

At each simulation time step, processes such as reassigning links between nodes are performed, changing the shape of the multi-layer network to represent the transition of urban structure. The life event model stochastically generates life events (aging, death, divorce, marriage, birth, employment, schooling, license status, independence (leaving home), and relocation) at each simulation time step to represent changes in individual and household attributes and the resulting relocations. The life event model is based on the existing SDS model [22]. Location changes due to household relocations are represented using a residential zone choice model.

2.8. Social Network Updates

Social networks are defined by the importance assigned to each individual's relationships, such as the workplace and online relationships. These important attributes are incorporated as explanatory variables in the utility functions of the aforementioned real-space and virtual space behavioral choice models, designed to allow individuals' psychological tendencies to indirectly influence behavioral choices.

At the start of the simulation (t=0), the importance of each relationship is assigned as an attribute. This is assigned based on the distribution of the importance of each relationship using statistical data. In this model, changes in the social network over time are triggered by changes in attributes when life events (aging, marital status, and employment status) occur, and the importance of relationships is updated appropriately based on the average attribute distribution. In the microsimulation model, we added two new functions to define the social interaction and update the social interaction.

Social interaction of each individual is assigned to them based on their attributes (age, gender, marital status, and employment status) and the degree they place in the social interaction type. As the study took shopping behavior as a focal activity, the significant relationship types are relationships with colleagues (workplace), and relationships formed online (internet relationship). Each simulation time step updates the necessary relationship type of the individuals. Social networking is used in the service choice model, accessibility, and zone choice model.

2.9. Residential Location Choice Model

In the existing SDS model, the physical accessibility index (ACC^{R}_{ih}) is used to measure the attractiveness of a residential area. However, this article instead uses the integrated accessibility index (ACC^{I}), which integrates real space and virtual space, to describe residential choice that reflects changes in individuals' lifestyles. Location links are reassigned to individual nodes belonging to households that are moving. The destination zone is selected using a multinomial logit model, which selects one zone from each zone within the target area. Furthermore, if the residential zone choice set

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for household h is Z_h, the multinomial logit model and utility function for the probability of selecting zone i are as follows:

$$V_{ih} = \sum_k \alpha_k X_{ik} + \beta ACC^I_{ih} + \gamma\, LP_i + c \tag{28}$$

$$P_{ih} = \frac{e^{V_{ih}}}{\sum_{i' \in Z_h} e^{V_{i'n}}},\quad (i \in Z_h) \tag{29}$$

where
$\alpha_k,\ \beta,\ \gamma$: Parameters
X_{ik} : Zone conditions (distance from city center, distance to nearest station, etc.)
ACC^I_{ih} : Synthetic accessibility of household h
LP_i : land prices

In addition, ACC_{ih} is defined as the average value of personal accessibility within a household and is expressed as follows:

$$ACC^I_{ih} = \frac{1}{HS_h} \sum_{a_h=1}^{HS_h} ACC^I_{iah} \tag{30}$$

$$ACC^I_{iah} = ACC^I_{in},\quad Cat(a_h) = n \tag{31}$$

where
ACC_{ia_h} : Accessibility of the individual a_h in zone i
HS_h : Number of people in household h
$Cat(a_h)$: Individual category of individual a_h who belongs to household h

2.10. Land Price Model

For each simulation time, the land price as an attribute value of Zone i is calculated by a regression model. The land price model is as follows.

$$LP_i = \sum_k \gamma_k X_{ki} + \delta D_i + c \tag{32}$$

Here, γ_k, δ, and c are parameters that update land prices (LP_i) by taking into account zone conditions (X_{ki}) such as distance to the city center and distance to the nearest station, and location density (D_i). This updates the land prices used in the residential zone selection model for the next period.

3. Application of Social Dynamics Simulation Model to a Virtual City

3.1. Target Activity Behavior

This study utilizes the analysis results from an existing study [3] about the substitutability of physical service access with digital alternatives, which were extracted from a web-based questionnaire survey conducted in November 2023, with 6,210 valid samples. Considering a higher substitution of physical shopping with online shopping [3], this study selects the shopping behavior as a focal digital substitutability and investigates the choice behaviors of individuals through real and virtual networks. Using the incorporated social network and integrated accessibility indices in the microsimulation model, the study investigates the service choice behavior of individuals. In the shopping behavior, the significant relationship type parameters were relationships in the workplace and the internet. Therefore, this study introduces these two types of relationships to the social relationship (interaction) type of microsimulation model.

3.2. Virtual City Configuration

The virtual city environment allows for controlled experimentation to examine the internal mechanisms of the proposed model without confounding real-world data limitations. The objective

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is not empirical replication but verification of behavioral and structural interactions within the modeling framework.

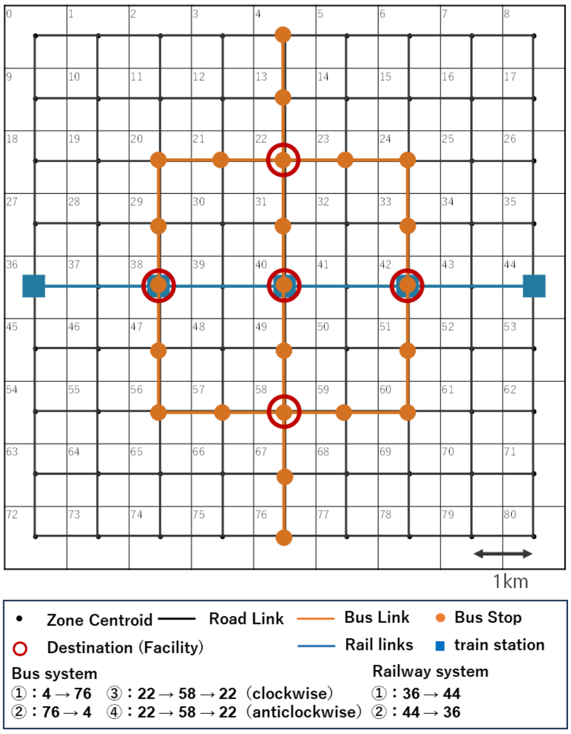

Figure 4. Setting of a virtual city

The constructed multi-layer network model is applied to a virtual city. The shape of the virtual city is shown in Figure 4. The virtual city consists of 9 × 9 = 81 zones, each of which is a square with sides measuring 1 km. Residents are assumed to reside at the centroid of each zone. The transportation network within the virtual city also includes roads and public transportation (rail and bus). The road network is represented by connecting adjacent zone centroids with bidirectional links. Buses run on the road network, with bus stops located at zone centroids. Railroads run on a network composed of rail links, with rail stations located at zone centroids. Traffic volume allocation and accessibility index calculations for the virtual city are based on this transportation network. Furthermore, five facilities serving as individual destinations are placed in the virtual city. The facility placement zones are fixed at 22, 38, 40, 42, and 58.

3.3. Parameter Setting

3.3.1. Parameter Estimation of Service Choice Model

Parameter estimation for the physical and digital service choice model was performed using the web-based questionnaire survey data described. In addition to individual and household attributes, the importance of interpersonal relationships was incorporated as an explanatory variable. The study extracted information on respondent demographics, shopping behavior (physical vs. online shopping frequency), and social interaction importance ratings on a 7-point Likert scale from the survey and estimated the model parameters. Table 1 shows the parameter estimation for the service choice model, which is incorporated into the SDS model.

3.3.2. Transportation Network Conditions and Model Parameters

This study utilizes the values defined by Sugiki et al. [22] for model parameters such as attributes by individual category, transportation network conditions, occurrence probability of each life event, residential zone selection model, and land price model. The transportation network conditions and main model parameters used in the SDS model are similar to those in the existing study [22].

Table 1. Parameter estimation results of the service choice model.

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Variable	Coef.	Std. Err.	t-stat	p-value	Sig.
Constant (β_0)	-1.142	0.034	-33.17	<0.001	***
Age (α_1)	-0.010	0.001	-14.49	<0.001	***
Male (α_2)	+0.104	0.048	2.18	0.029	**
Married (α_3)	-0.061	0.044	-1.38	0.168	
Employed (α_4)	+0.111	0.047	2.37	0.018	**
$IMP_{workplace}$ (α_5)	-0.309	0.052	-5.90	<0.001	***
$IMP_{internet}$ (α_6)	+0.297	0.071	4.19	<0.001	***

Note: *** p<0.01, ** p<0.05. n=6,210.

3.4. Virtual City Simulation

3.4.1. Simulation Prerequisites

The simulation covers a 30-year period and is performed with a one-year time step. Based on a life event model, events (births, deaths, relocations, etc.) occur probabilistically in each period, dynamically updating population and household attributes and locations. Key evaluation perspectives include temporal changes in the integrated accessibility index ($ACC^I_{i,n}$) by zone and attribute, and the distribution of population and household locations in response to changes in residential location selection probability.

3.4.2. Simulation Setting Under Integrated Accessibility and Social Network

The integrated accessibility index ($ACC^I_{i,n}$) developed in this study is applied within the virtual city simulation to evaluate how physical accessibility, digital accessibility, and social network factors jointly influence individual behavior and the evolution of urban structure. By embedding this index into the residential location and service choice model of the SDS model, the simulation captures the dynamic interactions between virtual space, social relationships, and spatial organization over time.

4. Results

This section presents the results of applying the proposed multi-layer SDS model to the virtual city environment. The objective is to examine whether integrating digital accessibility and social network factors produces plausible urban dynamics in terms of service usage, residential distribution, mobility demand, and accessibility evolution.

4.1. Digital Service Adoption Dynamics

Figure 5 presents the simulated share of digital service usage across age groups over the 30-year simulation period. The results reveal a clear generational gradient in digital service adoption. Younger individuals (0–20 years) exhibit the highest share of digital service usage at approximately 25%, followed by the 21–40 age group at approximately 21%. Adoption gradually decreases with age, reaching approximately 13–14% among individuals aged above 80.

This pattern directly reflects the behavioral parameters estimated in the service choice model. In particular, the negative coefficient for age indicates that older individuals have a lower probability of selecting virtual services. At the same time, the positive coefficient associated with internet relationship importance increases the likelihood of digital service usage. As younger individuals tend to have stronger online social interactions, these behavioral characteristics reinforce the observed age-based differences in digital service adoption.

Importantly, digital service usage remains relatively stable across the simulation period. This stability indicates that the behavioral parameters governing service choice generate persistent cohort-based differences rather than temporary fluctuations. The model therefore reproduces a realistic behavioral mechanism in which generational preferences toward digital services remain stable over time.

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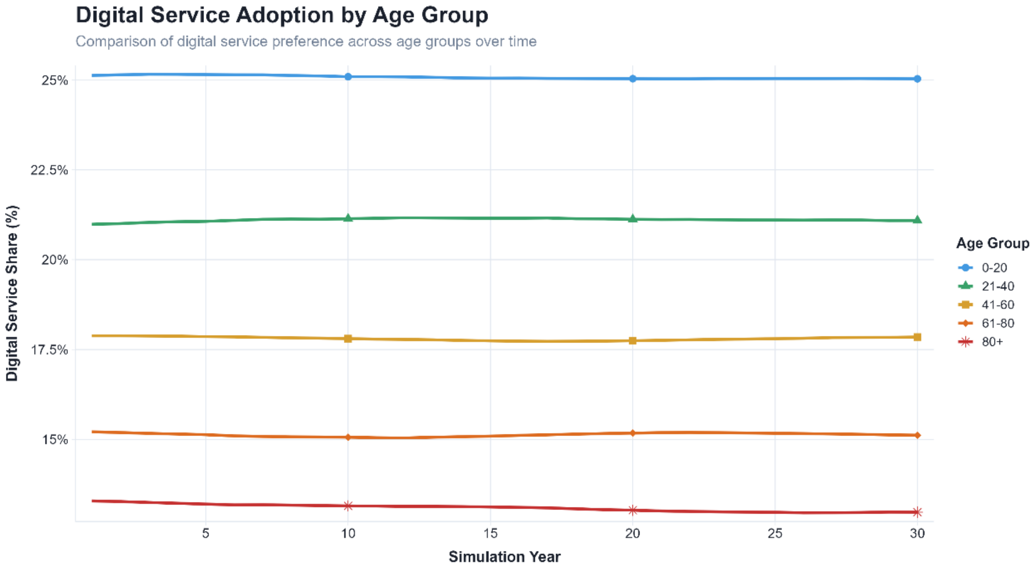

Figure 5. Digital service usage by age over 30 TS

The temporal stability of these adoption rates across all age groups indicates that the service choice model captures persistent generational preferences rather than transient behavioral patterns. This finding aligns with the parameter estimates with existing study [9], where age was found to have a significant negative effect on physical service utility (α_1 = -0.010, p<0.001), suggesting that younger individuals are inherently more inclined toward digital alternatives. The consistency of adoption rates over the simulation period suggests that cohort effects dominate over period effects in service choice behavior.

4.2. Population Redistribution

The spatial population distribution at the end of the simulation period (T31) is shown in Figure 6. Population concentration emerges around zones 36 and 44, which correspond to major rail transit nodes in the virtual city. Secondary concentrations appear near zones 38 and 42 where multimodal connectivity between rail and bus networks exists.

This concentration pattern reflects the residential location choice model embedded in the SDS framework. Households evaluate potential residential zones based on integrated accessibility, land prices, and spatial characteristics. Zones located near public transport hubs provide high levels of physical accessibility while maintaining relatively moderate land prices compared to the central zone. Consequently, these locations become highly attractive residential areas.

Interestingly, the city center itself does not exhibit the highest population density despite its central location. This outcome is largely explained by the land price component in the residential location choice model. Higher land prices reduce the probability of selecting the central zone, pushing households toward nearby transit-accessible zones that offer a more favorable trade-off between accessibility and housing cost.

Simulation results show that residential location patterns are influenced by both physical and digital accessibility. Areas with high physical accessibility continue to attract households that rely strongly on physical service access. However, zones with lower transport accessibility but relatively high digital accessibility maintain or gain population, particularly among households with higher digital substitution tendencies. This result indicates that digital accessibility partially relaxes the dependence of residential location choice on transportation accessibility. While physical accessibility remains a key determinant, the integrated accessibility index allows households to maintain acceptable service access levels even in less transport-accessible locations. Consequently, population distribution becomes more spatially dispersed than would be expected in a purely transport-based model. These outcomes confirm that the integrated accessibility framework is functioning consistently within the SDS model and that digital accessibility plays a meaningful role in shaping long-term urban spatial structure.

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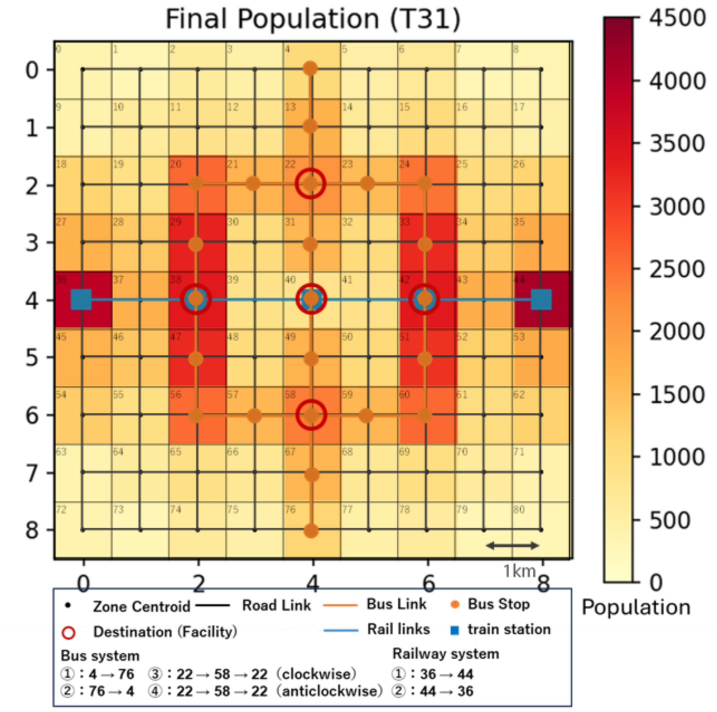

Figure 6. Population distribution in 31 TS

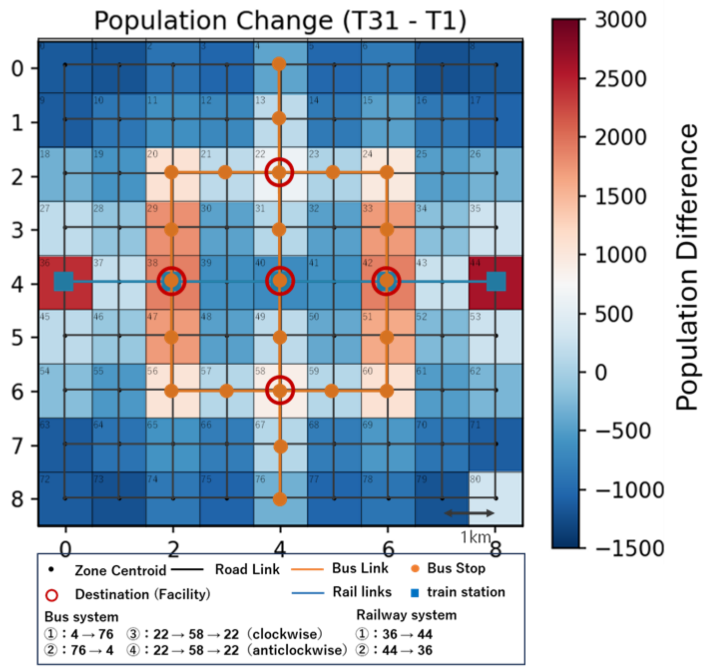

Figure 7. Population change distribution

Figure 7 illustrates the spatial distribution of net population change over the 30-year simulation period. The results show a pronounced polarization pattern. Zones located near major transportation nodes experience significant population growth, exceeding 3,000 residents in some areas, while peripheral zones experience population decline of up to 1,500 residents.

This pattern reflects the combined effects of accessibility and land price dynamics. The integrated accessibility index increases the attractiveness of zones with strong transport connectivity while digital accessibility allows some households to maintain acceptable service access levels even outside the most accessible areas. As a result, the urban structure evolves toward a configuration characterized by clustered residential growth around transport hubs combined with moderate spatial dispersion. These dynamics demonstrate how the integration of digital accessibility modifies, but

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does not replace, the traditional influence of transportation infrastructure on residential location choice.

4.3. Household Spatial Patterns

Figures 8 present the spatial distribution of elderly and non-elderly households at the end of the simulation period. Both groups show concentration patterns around zones with high accessibility; however, the intensity of clustering differs between groups. Non-elderly households display stronger concentration around transit nodes. This reflects their higher reliance on commuting and service access, making accessibility a more influential factor in residential decision-making. Elderly households also concentrate in accessible zones but exhibit a more dispersed pattern.

This difference can be explained by differences in mobility needs and life-cycle characteristics. Working-age households are more sensitive to accessibility conditions due to employment-related travel and daily service needs. In contrast, elderly households face lower travel demand and therefore demonstrate greater residential flexibility.

Figure 8. Elderly households in 30 TS (a); non-elderly households in 30 TS (b)

4.4. Transportation Network Dynamics

Figures 9 and 10 compare road network traffic conditions between the initial year and the end of the simulation period. Although the population becomes more spatially concentrated over time, overall traffic congestion decreases. The minimum travel speed in the most congested links increases from approximately 15 km/h to 24 km/h. This improvement is primarily driven by the overall population decline assumed in the simulation environment, which reduces total travel demand. Additionally, partial substitution of physical shopping trips with digital services contributes to moderating travel demand. The improvement in traffic conditions further enhances physical accessibility in highly connected zones. This creates a feedback mechanism within the model: improved accessibility increases residential attractiveness, which reinforces population concentration in well-connected areas.

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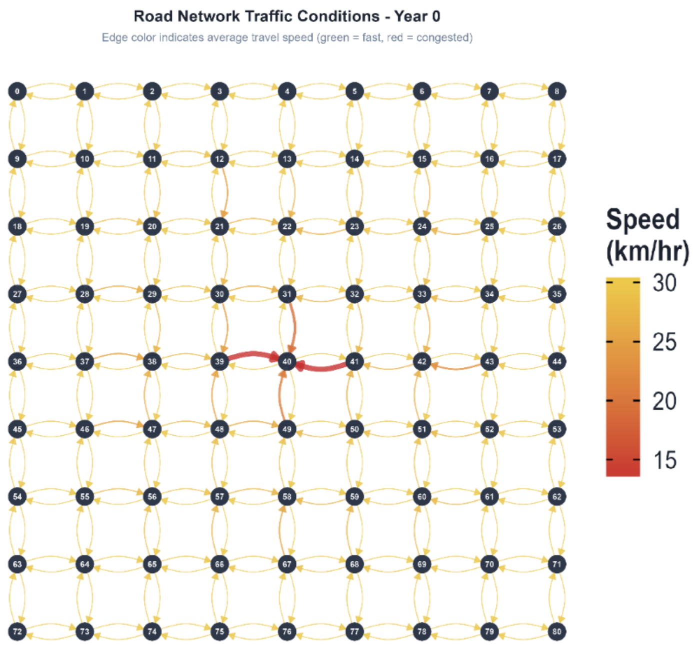

Figure 9. Road network traffic condition in 0 TS

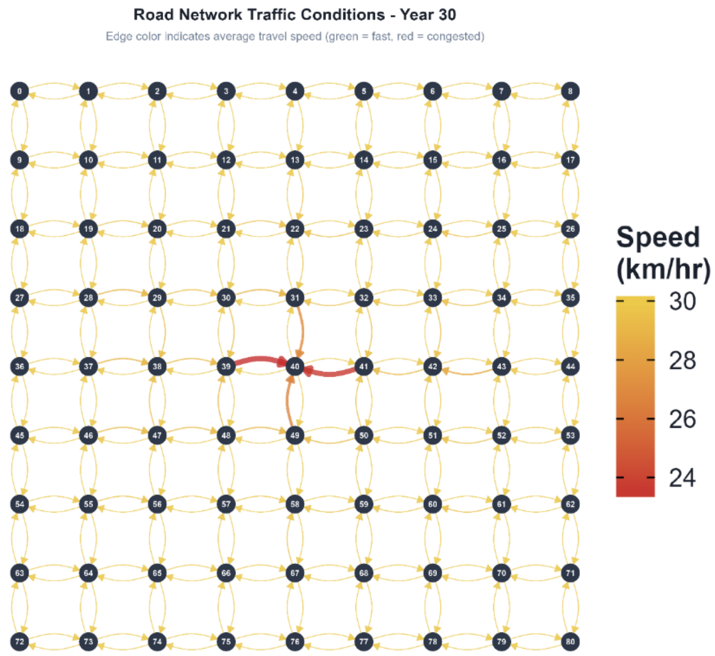

Figure 10. Road network traffic condition in 30 TS

At Year 0, as shown in Figure 9 traffic congestion is concentrated around the central node (node 40), where travel speeds decrease to approximately 15 km/hr on the links connecting nodes 39–40, 40–41, 31–40, and 40–49. The remainder of the network operates at free-flow conditions with speeds approaching 30 km/hr.

By Year 30, as shown in Figure 10, the congestion pattern persists at the central node but with improved overall traffic conditions. The minimum travel speed has increased from approximately 15 km/hr to 24 km/hr, representing a 60% improvement in the most congested links. This counterintuitive finding, population concentration alongside traffic improvement, can be attributed to overall population decline reducing total traffic demand, despite increased concentration in accessible zones, and dispersed population distribution. The improved traffic conditions create a positive feedback loop: reduced congestion enhances physical accessibility, which reinforces the attractiveness of central locations for residential choice.

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4.5. Modal Shifts

Figures 11 and 12 illustrate the change of public transportation frequency and modal choice patterns throughout the 30-year simulation time steps. Figure 11 presents public transport service frequency evolution for bus and rail lines. Bus service frequency increased from an average of approximately 6–8 vehicles per hour at Year 0 to approximately 9–10 vehicles per hour by Year 30. Rail service frequency showed even more dramatic improvement, increasing from approximately 2 vehicles per hour to 4–5 vehicles per hour. This adaptive increase in service frequency reflects the model's assumption that public transportation providers respond to demand concentration by improving service levels in high-ridership corridors passing through attractive zones such as zones 36 and 44.

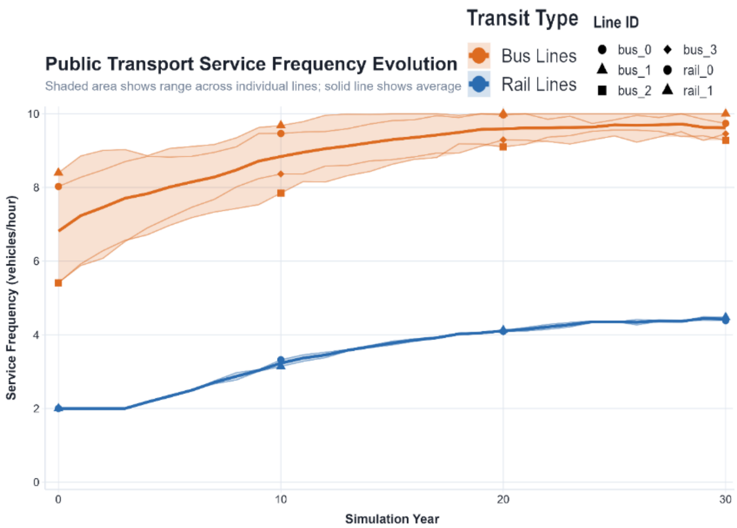

Figure 11. Public transport service frequency in different TS

Figure 12 displays the absolute number of users by transport mode over 30-year time steps. As can be seen in the figure, private car usage declined most substantially, from approximately 42,000 users at Year 0 to 35,000 users at Year 30 (a 17% reduction). This could be because of an aging population. Public transit usage remained relatively stable, declining only marginally from 27,000 to 25,000 users (7% reduction). Carpool usage decreased from 14,000 to 9,000 users (36% reduction), while walking maintained consistent but minimal usage around 1,000 users.

These modal trends demonstrate that population decline does not uniformly reduce transportation demand across modes. The relatively stable public transit ridership, combined with increased service frequency, suggests that population concentration in transit-accessible areas has maintained transit viability despite overall population decline. The sharper decline in private car and carpool usage reflects both population reduction and the concentration of remaining residents in areas where non-automobile modes are competitive alternatives.

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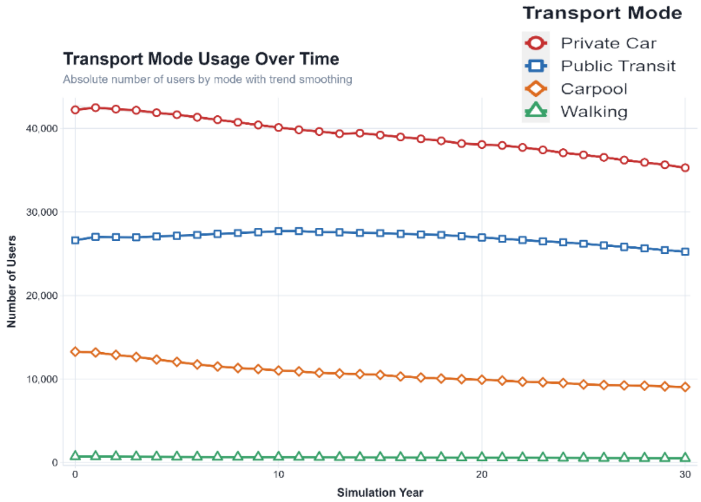

Figure 12. Transport mode usage in different TS

4.6. Accessibility Evolution

Figures 13–15 illustrate the evolution of individual accessibility measured through eigenvector centrality within the urban network. Over time, the distribution of accessibility shifts toward higher values, indicating increasing concentration of the population in zones with stronger network connectivity. Accessibility outcomes vary significantly across user categories. Individuals without personal mobility resources, particularly elderly residents without vehicle access, maintain the highest accessibility levels throughout the simulation. This reflects a spatial selection effect in which individuals with limited mobility must reside in highly accessible locations in order to maintain service access.

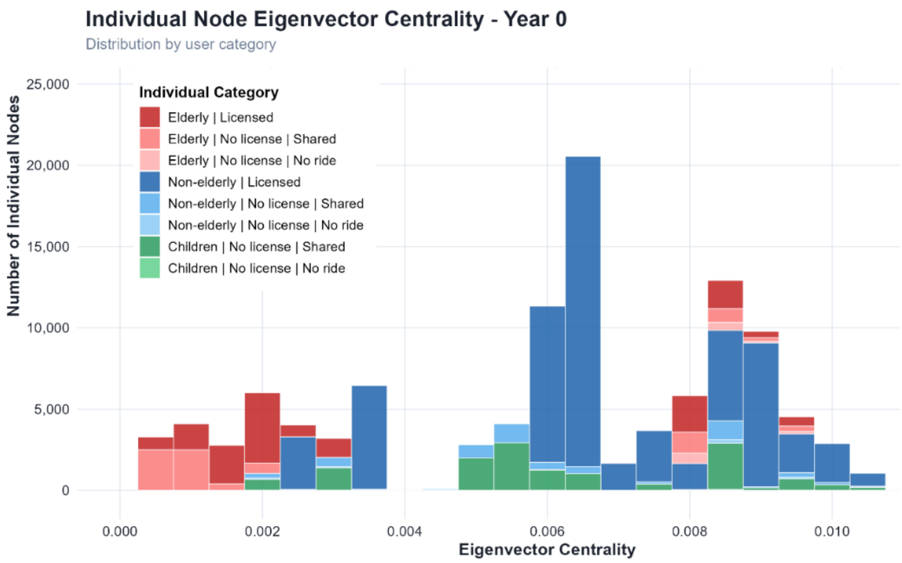

Figure 13. Individual node EC in 0 TS

Conversely, individuals with private vehicle access demonstrate lower average accessibility values. Their greater mobility flexibility allows them to reside in locations with weaker network connectivity. These findings indicate that accessibility inequality emerges from the interaction between infrastructure distribution, mobility resources, and behavioral preferences. By incorporating social networks, service choice behavior, and integrated accessibility into the SDS framework, the model captures these heterogeneous accessibility dynamics across population groups.

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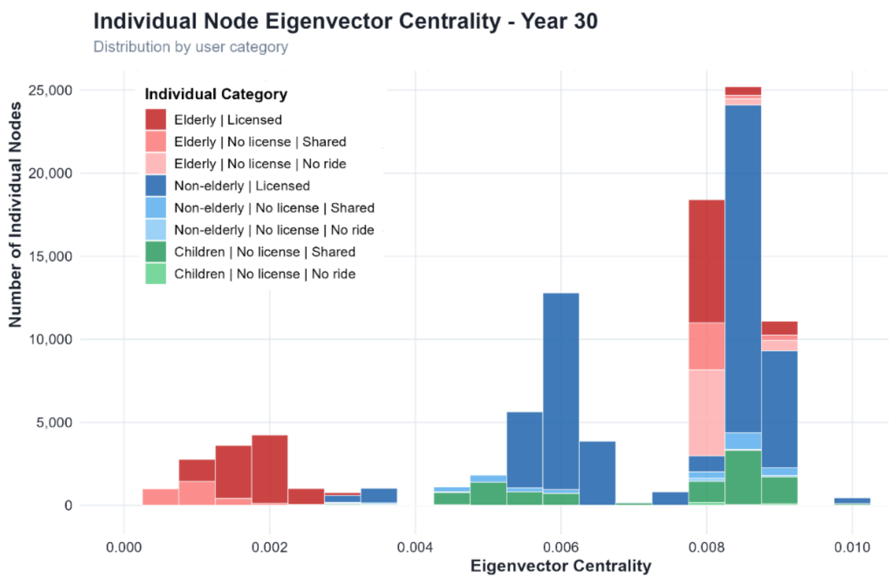

Figure 14. Individual node EC in 30 TS

Figures 13, 14, and 15 illustrate individual-level eigenvector centrality (EC), a network-based accessibility index, across different population segments and time periods. Figure 13 presents the distribution of individual EC at the Year 0 timestep, disaggregated by user category (age group and mobility resources). The distribution shows substantial variation, with EC values ranging from approximately 0.001 to 0.011. The peak of the distribution occurs around EC = 0.006–0.007, where approximately 20,000 individuals are concentrated. Non-elderly licensed individuals (shown in dark blue) dominate the higher EC ranges, reflecting their initial distribution across zones with better network connectivity. Lower EC values (0.001–0.003) show a more diverse composition, including elderly and children with limited mobility resources.

Figure 14 displays the corresponding distribution at Year 30. The distribution has shifted rightward, with the peak now occurring at approximately EC = 0.008 and containing approximately 25,000 individuals. This rightward shift indicates that over the simulation period, the remaining population has concentrated in zones with higher network accessibility. Simultaneously, the population in lower EC zones (0.001–0.004) has substantially diminished, reflecting out-migration from less accessible areas.

Figure 15 synthesizes these patterns by tracking mean EC over time for each user category. Several notable findings emerge: First, elderly individuals without personal vehicle access ("Elderly No ride") maintain the highest mean EC throughout the simulation, approximately 0.008. This finding appears counterintuitive but reflects a selection effect: elderly residents without transportation options must locate in highly accessible areas to maintain their quality of life. Those who cannot do so likely relocate or are filtered out of less accessible zones over time.

Second, the mean EC for non-elderly licensed individuals increases steadily from approximately 0.0068 to 0.0073 over the 30 years. This trend reflects the gradual concentration of the working-age population in accessible zones, driven by the integrated accessibility index in the residential location choice model. Third, elderly licensed individuals show the lowest but increasing mean EC (from 0.0039 to 0.0048). This group has the greatest residential location flexibility due to automobile access, allowing them to reside in less accessible zones where housing may be more affordable.

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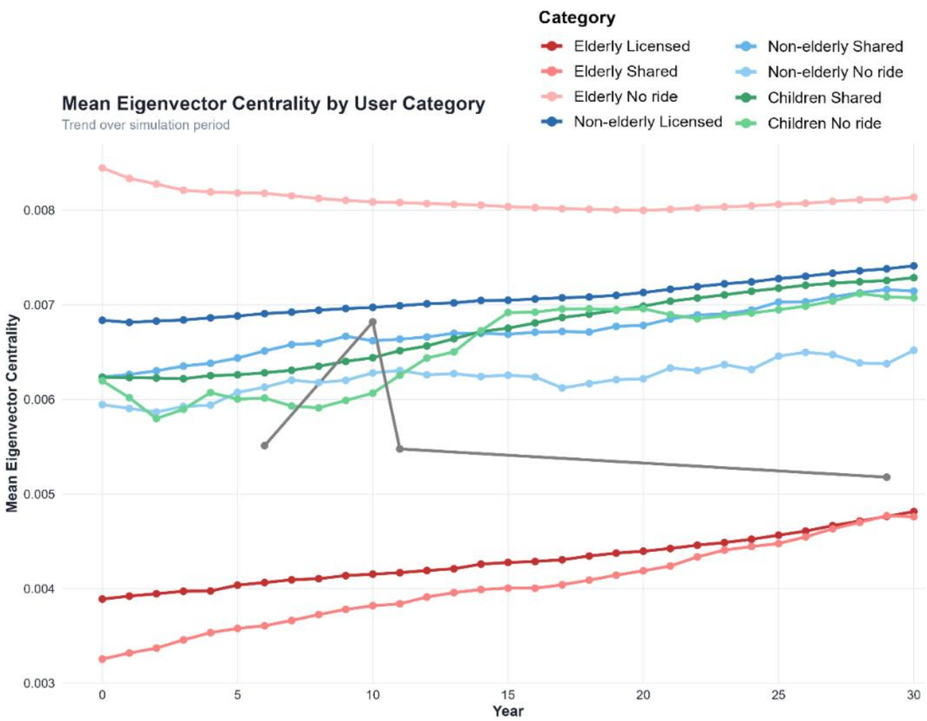

Figure 15. Mean EC by user category in different TS

These accessibility dynamics demonstrate that the integration of integrated accessibility and social network factors into the SDS model captures meaningful differentiation in how various population segments experience and respond to urban spatial structure. The model successfully predicted the residential location decisions across diverse population groups while incorporating the social network, service choice model, and integrated accessibility model.

5. Discussion

The results of the simulation demonstrate that integrating digital accessibility and social interaction mechanisms into the SDS model significantly changes the way urban accessibility, mobility behavior, and residential patterns evolve over time. The findings highlight the importance of considering the combined effects of physical, digital, and social networks when analyzing long-term urban structural dynamics.

5.1. Role of Digital Accessibility in Service Choice Behavior

The simulation results show that digital service usage differs systematically across age groups and remains relatively stable throughout the simulation period. Younger individuals exhibit the highest levels of digital service adoption, while older age groups demonstrate lower digital service usage. This pattern reflects the estimated service choice model parameters, where age negatively influences the likelihood of selecting virtual services.

The persistence of these age-related differences suggests that digital service adoption is strongly influenced by cohort-based behavioral preferences rather than short-term external conditions. Even though digital infrastructure is assumed to be universally available in the model, individual attributes such as age and social interaction preferences continue to shape service choice decisions. These findings are consistent with empirical observations reported in previous studies indicating that younger individuals are more comfortable engaging with digital platforms and are therefore more likely to substitute certain physical activities with digital alternatives.

At the same time, the results indicate that digital services do not fully replace physical services. Instead, digital accessibility primarily modifies the probability of selecting between physical and digital services. Consequently, physical accessibility remains a critical determinant of activity behavior, while digital accessibility acts as a complementary factor that expands the range of available service options.

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5.2. Implications for Urban Population Distribution

One of the most significant findings of this study is that integrating digital accessibility into the SDS framework alters the spatial distribution of population over time. The simulation results show that residential concentration continues to occur in zones with high transportation accessibility, particularly around major public transport nodes. However, the integrated accessibility index enables households to maintain acceptable service access levels even in locations with relatively lower physical accessibility.

This mechanism leads to a more spatially dispersed urban structure compared with models that rely solely on physical accessibility indicators. In traditional land-use–transport models, residential location choices tend to concentrate strongly around highly accessible transportation hubs. In contrast, the proposed integrated accessibility framework allows households with higher digital service substitution tendencies to reside in zones that would otherwise be considered less attractive in purely physical accessibility (transport)-based models.

These findings suggest that digital accessibility can partially relax the spatial constraints imposed by transportation infrastructure. Nevertheless, the results also indicate that digital accessibility does not completely eliminate the importance of physical accessibility. Transportation hubs continue to attract population due to their combined advantages of mobility access, service availability, and moderate land prices. Therefore, digital accessibility acts as a moderating factor rather than a dominant driver of urban spatial structure.

5.3. Mobility Impacts and Transportation System Dynamics

The simulation also reveals important interactions between population distribution, service choice behavior, and transportation demand. Despite the concentration of residents in highly accessible zones, the overall traffic conditions improve over time. This improvement can largely be attributed to the declining total population within the virtual city, which reduces overall travel demand.

Modal choice patterns further illustrate how demographic and behavioral factors influence transportation demand. Private automobile usage decreases substantially over the simulation period, while public transportation usage remains relatively stable. The decline in automobile use appears to be driven partly by demographic aging, as older populations tend to travel less frequently and may rely more on accessible residential locations rather than long-distance travel.

At the same time, public transport systems adapt to demand concentrations by increasing service frequency along heavily used corridors. This adaptive response reinforces the attractiveness of transit-accessible zones and contributes to maintaining the viability of public transportation services despite overall population decline.

The interaction between digital service usage and mobility demand is also noteworthy. As digital services substitute for certain physical trips, particularly shopping activities, the pressure on transportation networks is reduced. This effect suggests that digital service accessibility may indirectly contribute to more sustainable transportation systems by moderating travel demand.

5.4. Accessibility Inequality Across Population Groups

The analysis of individual-level accessibility, represented by eigenvector centrality, provides additional insight into how different population groups experience urban spatial structure. Over time, the distribution of accessibility shifts toward higher values, indicating that the population increasingly concentrates in areas with stronger network connectivity.

However, the results also reveal important differences between user groups. Individuals with limited mobility resources, particularly elderly residents without vehicle access, tend to reside in highly accessible zones throughout the simulation period. This pattern reflects a spatial selection mechanism: individuals who rely heavily on public transport or walking must locate in areas where accessibility is already high.

Conversely, individuals with greater mobility flexibility, such as those with private vehicle access, are able to reside in less accessible zones where housing costs may be lower. This

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differentiation suggests that accessibility inequalities are shaped not only by infrastructure distribution but also by individual mobility resources and behavioral preferences.

The incorporation of social network attributes further contributes to these dynamics by influencing service choice behavior and residential location preferences. Individuals who place greater importance on workplace interactions tend to rely more on physical services, while those with stronger internet-based relationships show higher digital service usage. These behavioral differences reinforce the heterogeneous accessibility outcomes observed across population groups.

5.5. Implications for Sustainable Urban Planning

From a broader planning perspective, the results of this study highlight the importance of incorporating digital accessibility into urban policy evaluation frameworks. As digital services become increasingly integrated into daily life, traditional accessibility measures based solely on transportation infrastructure may no longer adequately capture the true service opportunities available to residents.

The proposed integrated accessibility model provides a more comprehensive representation of urban accessibility by explicitly accounting for the interactions between physical mobility systems, digital service networks, and social relationships. This integrated perspective is particularly relevant in the context of ongoing digital transformation, where remote services, online commerce, and virtual social interactions are increasingly influencing urban lifestyles.

For urban planners and policymakers, these findings suggest that investments in digital infrastructure may play an important role in shaping future urban spatial patterns. However, digital accessibility should be viewed as complementary to, rather than a replacement for, traditional transportation infrastructure. Balanced development of both physical and digital access systems is therefore essential for promoting equitable and sustainable urban environments.

6. Conclusions

This study developed an extended multi-layer SDS model that integrates physical accessibility, digital accessibility, and social networks within a unified urban simulation modeling system. By introducing an integrated accessibility index and a behavioral service choice model, the proposed framework captures how individuals dynamically choose between physical and digital services and how these choices influence residential location, mobility demand, and social interactions over time.

The application of the model to a virtual city environment demonstrates that urban structure emerges from the interdependent evolution of accessibility conditions, individual behavior, and social networks. Simulation results indicate that digital accessibility can partially relax spatial constraints associated with physical transportation networks, thereby expanding the range of viable residential locations. However, physical accessibility remains a critical determinant of urban activity patterns, suggesting that digital services primarily complement rather than fully substitute traditional urban functions.

The results also highlight important social equity implications. Individuals with greater mobility and accessibility advantages tend to occupy more central positions within the evolving social network, while mobility-constrained populations remain relatively peripheral. This suggests that differences in both physical and digital accessibility may reinforce disparities in social connectivity and access to opportunities within urban systems.

From a policy perspective, the proposed urban simulation model provides a new analytical tool for evaluating integrated urban policies in the context of digital transformation. In particular, the model can support policy assessment in areas such as digital infrastructure investment, sustainable mobility planning, accessibility equity evaluation, and smart-city development strategies. By explicitly representing interactions between transportation systems, digital service environments, and social networks, the SDS model enables policymakers to explore how emerging digital services may reshape urban spatial structures and accessibility patterns.

This study contributes to the literature on urban simulation and sustainable urban development in several ways. First, the research proposes a conceptual extension of urban simulation models by integrating physical accessibility, digital accessibility, and social interaction networks within a

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unified multi-layer framework. While traditional land-use and transport interaction models primarily focus on physical mobility, this study explicitly incorporates digital service access and social relationships as key determinants of urban dynamics. Second, the study introduces a methodological innovation through the integrated accessibility index, which combines transportation accessibility and digital accessibility based on probabilistic service choice behavior. This formulation allows accessibility conditions to evolve dynamically as individuals choose between physical and digital services. Third, the research advances behaviorally grounded microsimulation modeling by incorporating an empirically estimated service choice model derived from survey data. By embedding this behavioral component within the SDS framework, the model captures heterogeneous responses to accessibility conditions across demographic groups. Fourth, the application to a virtual city demonstrates the analytical potential of the proposed framework for examining long-term urban evolution. The results show how digital accessibility can partially relax spatial constraints while maintaining the importance of transportation accessibility in shaping population distribution, mobility patterns, and social network structures. Together, these contributions provide a foundation for future research on the interaction between digital transformation, accessibility equity, and sustainable urban development.

However, several limitations remain. The current implementation focuses primarily on shopping behavior and does not yet incorporate other major activity domains such as commuting, education, or leisure activities. Additionally, the model was tested in a virtual city environment rather than a real-world case study. Future research should therefore extend the model to multiple activity types and apply the model to empirical urban contexts in order to evaluate real policy scenarios.

Despite these limitations, the study demonstrates that integrating physical, digital, and social dimensions of accessibility within a multi-layer simulation model provides a promising direction for advancing urban sustainability analysis. The proposed SDS model establishes a foundation for future research on air-front smart city environment evaluation models [26], and equitable access to services in digitally connected cities.

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