Integrated Evaluation of Real and Virtual Networks for Air-front Smart Cities

（臨空スマートシティのための実ネットワークと仮想ネットワークの統合評価）

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Abstract

The Air-front Smart City is an emerging urban development concept that seeks to integrate airport functions and Digital Transformation (DX) technologies with development not only within the city but also in hinterland regions. The air-front smart cities focus on the enhancement of quality of life (QOL), economic competitiveness, and environmental sustainability by utilizing DX technologies and improving airport functions, while considering the strength and uniqueness of the city. The expansion of digital technologies has already enabled the substitution or complementarity of physical activities with digital alternatives. Understanding of how these transformations reshape service access, social behavior, and urban spatial dynamics has become critical for designing future sustainable cities and air-front smart cities. This thesis addresses these challenges by developing an integrated evaluation methodology for air-front smart cities to consider the substitutability and complementarity of physical service access findings using a social dynamics simulation model. The developed integrated evaluation model in this thesis is expanded to evaluate urban living and business environments within the air-front smart cities.

Chapter 1 introduces the research background, the growing importance of DX, and the necessity of integrating real and virtual interactions into urban planning. The chapter clarifies the research problem: despite rapid digitalization, existing urban evaluation frameworks cannot jointly assess real and virtual networks, social dynamics, and policy impacts. The research objectives, significance, and structure of the thesis are presented accordingly.

Chapter 2 reviews the literature on the Air-front Smart City concept, real and virtual network theory, social dynamic simulation, and QOL evaluation. The chapter positions this study within existing research and highlights its novelty: (1) integrating behavioral substitutability and complementarity into urban simulation, (2) developing a multi-layer network model that represents real and virtual interactions simultaneously, and (3) constructing a comprehensive evaluation system linking the integrated accessibility index to QOL and quality of business (QOB) for policy analysis.

Chapter 3 investigates the substitutability and complementarity between physical and digital services using a web-based survey. The chapter provides a systematic analysis of behavioral substitution ratios across 5 activity categories, revealing variations by age, gender, mobility resources, residential location, and social relationship types. The results disclose that younger individuals show higher substitution tendencies, while older individuals rely more on physical networks. Cluster analysis identifies seven social relationship groups, demonstrating that online-oriented individuals adopt more digital alternatives, whereas community-oriented individuals maintain strong physical activity patterns. The chapter further examines residential relocation choices and shows that digital accessibility influences location choice primarily in urban areas. These findings offer fundamental behavioral insights necessary for understanding how real and virtual networks interact within Air-front Smart Cities.

Chapter 4 develops a multi-layer social dynamics simulation model that represents urban space through interconnected real and virtual layers. The model incorporates real and virtual accessibility, land price, household generation, life events, residential location choice, and the service choice model. Additionally, the chapter incorporates a social network layer to life event models to assess its impact on service choice. A virtual city is constructed to verify the model's ability to replicate population distribution, service usage, and network interactions. This chapter demonstrates how integrated accessibility and social interactions affect service choice and residential location choice, providing a tool for projecting future urban developments.

Chapter 5 presents the total concept and methodological foundation of this thesis by constructing an integrated accessibility-based evaluation framework for both QOL and QOB. Based on insights from Chapters 3 and 4, the chapter develops accessibility indices that incorporate physical and virtual service accessibility. The QOL and QOB models are enabled to evaluate urban living and business environments for different stakeholders of business within the air-front smart city context. The chapter showcases indicator definitions and scenario settings (Aichi startups, Baguio agriculture, and Phuket tourism), which illustrate how the framework can be applied to diverse contexts. This chapter establishes the core evaluation methodology for air-front smart cities.

Chapter 6 applies this methodology to an air-front smart city policy evaluation case study in Aichi, Japan. Using survey data, open access regional data, parameter estimation, and integrated accessibility calculations, the chapter evaluates how policy interventions affect startups' QOB, business partners' QOL, residents' QOL, and overall urban performance. Furthermore, the chapter applies the methodology to Singapore and Munich using the parameters estimated in Aichi and compares startup ecosystems within these three regions.

Finally, Chapter 7 summarizes the major findings and discusses future research opportunities. The results show that sustainable air-front smart city development requires a balanced approach where digital services complement, rather than replace, physical accessibility. Policies that integrate DX, human mobility, social interactions, and spatial planning are essential for ensuring resilience, inclusivity, and environmental sustainability.

Overall, this thesis provides a comprehensive empirical and methodological foundation for evaluating air-front smart cities. By integrating substitutability and complementarity analysis, social dynamics simulation, and QOL–QOB accessibility evaluation, the study offers practical guidance for policymakers aiming to create adaptive and human-centered urban environments in the digital era.

Acknowledgement

I would like to express my sincere and profound gratitude to my primary supervisor, Professor Nao Sugiki, for his rigorous academic guidance, insightful comments, and continuous support throughout my doctoral studies. His expertise, critical perspective, and commitment to academic excellence were essential in shaping the conceptual framework, methodological approach, and overall quality of this dissertation. I am also sincerely grateful to my co-supervisors, Associate Professor Kojiro Matsuo and Professor Hiroyuki Shibusawa, for their valuable comments, constructive suggestions, and support throughout the course of this PhD program.

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Statement of Original Authorship

I, Mustafa Mutahari, hereby declare that this dissertation, entitled “Integrated Evaluation of Real and Virtual Networks for Air-front Smart Cities,” represents my own original research. This work was carried out under the guidance and supervision of Professor Dr. Nao Sugiki and is submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy (PhD) at Toyohashi University of Technology (TUT).

I further declare that this dissertation has not been previously submitted, either in whole or in part, for the award of any degree or diploma at this or any other institution. All publications arising from this doctoral research that form the basis of this dissertation have been included with the necessary permissions obtained from the respective publishers. All sources of information, data, and intellectual contributions from others have been appropriately acknowledged and cited in accordance with academic standards.

Dedication

This dissertation is dedicated to my beloved family, whose unwavering support and encouragement have been fundamental to the completion of this work.

It is dedicated to my father, Qasim Ali Sherzad, whose wisdom, guidance, and steadfast encouragement have continually inspired me to pursue excellence and to persevere in the face of challenges. His principles and example have profoundly shaped both my personal values and academic aspirations.

It is also dedicated to my mother, Safora Sherzad, whose boundless love, sacrifices, and unwavering belief in me have been the enduring source of my strength and resilience throughout this journey.

I dedicate this work to my wife, Khatera Mutahari, and to my daughters, Elsa Mutahari, Sana Mutahari, and Kiana Mutahari, for their patience, understanding, and unconditional support. Their love and presence have provided constant motivation and meaning during the most demanding periods of my doctoral studies.

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Table of Contents

Table of Figures

List of Tables

Chapter 1

Introduction

The purpose of this chapter is to introduce research topics, outlining the significance of the study in urban and transportation planning. It presents the background of the issues, including the growing importance of DX technologies and the necessity of integrating real and virtual interactions into urban planning. It also explains why Air-front Smart Cities are crucial in regions where airports with DX technologies act as economic and logistical hubs, enabling high levels of mobility and digital connectivity. The chapter clarifies the research problem: despite rapid digitalization, existing urban evaluation frameworks lack the ability to jointly assess real and virtual networks, social dynamics, and policy impacts. The research objectives, significance, and structure of the thesis are presented accordingly.

1.1. Backgrounds

Rapid advances in Digital Transformation (DX) technologies have fundamentally reshaped daily life, economic activities, and urban functionality. The proliferation of digital services, such as online shopping, teleworking, e-treatment, e-learning, food delivery, and virtual social networks, has increasingly substituted or complemented traditional physical services and interactions. This shift accelerated significantly during the COVID-19 pandemic, forcing societies to transition many socio-economic activities and services from physical to virtual networks. As a result, individuals' activity patterns, service access behavior, and social relationships have become deeply intertwined with digital service adaptation.

Smart city policies around the world have positioned DX technologies as key instruments for improving urban performance, optimizing resource consumption, and enhancing residents' Quality of Life (QOL). However, smart city initiatives typically focus on optimizing conditions within municipal boundaries, paying limited attention to broader spatial and functional relationships among cities. This city-centric approach contradicts the functional nature of urban systems, which depend on regional interactions, integrated infrastructure, and shared socio-economic networks. Cities operate not as isolated entities but as interconnected nodes within larger metropolitan and regional systems. This oversight becomes more pronounced in regions where airports play central economic, logistical, and mobility roles.

Additionally, while smart cities emphasize the utilization of advanced technologies and digital services to enhance residents' QOL, excessive reliance on digital solutions introduces new social and equity challenges. These include risks to mental and physical health, reduced social interaction, and potential exclusion of populations with limited digital access or literacy. Furthermore, digitalization can contribute positively to environmental sustainability, such as by reducing certain types of mobility, lowering carbon emissions, and enabling more efficient resource management. Current smart city models rarely integrate the utilization of DX technologies with a holistic consideration of human well-being and long-term economic development; instead, they tend to prioritize technological optimization over balanced socio-economic and environmental outcomes.

On the other hand, airports increasingly function as gateways for global connectivity, trade, and economic development. Their integration with DX technologies and adjacent hinterlands offers new opportunities to create highly connected, competitive, and sustainable urban systems.

The air-front smart city concept, which tackles the challenges associated with current smart cities, is an emerging urban development concept that seeks to integrate airport functions and DX technologies with industrial innovation unique to each specific region, to promote decarbonization and balanced regional development while maintaining a higher QOL not only within the city but also in hinterland regions. As smart cities have primarily focused on the enhancement of QOL by utilization of DX technologies within the city, the air-front smart cities focus on the enhancement of QOL, economic competitiveness, and environmental sustainability by utilizing DX technologies and improving airport functions. The expansion of digital technologies has already enabled the substitution or complementarity of traditional physical services and social interaction with digital alternatives.

Understanding how these transformations reshape service access, social behavior, and urban spatial dynamics has become critical for designing future sustainable cities and Air-front smart cities. Additionally, mathematical analysis models are required to quantitatively evaluate the effects of air-front smart city policies on urban living environments and urban business environments, considering the substitutability and complementarity of physical services with digital alternatives. Such evaluation tools were not identified in the literature survey conducted in this thesis.

1.2. Research Problem

While digital technologies are reshaping how people live, work, and interact, current urban evaluation and planning frameworks are not equipped to capture these transformations comprehensively. Conventional smart city models emphasize technological efficiency and infrastructure optimization, but they rarely consider how digital services affect social networks, behavioral patterns, residential location choices, and overall urban spatial structure. Additionally, the same definition of smart city development is applied to all regions without considering their potential strength and characteristics of that region, which may result in the loss of the uniqueness of that region. Furthermore, existing evaluation methods separate physical and digital accessibility and therefore cannot account for their substitutability or complementarity.

In the context of air-front smart cities, this limitation becomes more critical. Airports serve as major economic, mobility, and logistics hubs, yet most smart city frameworks do not integrate airport functions into evaluations of living and business environments or long-term urban and economic development. Even fewer studies attempt to model how real and virtual networks jointly influence individual decisions, business performance, and regional socio-economic outcomes.

Additionally, empirical evidence is lacking regarding how different demographic groups adopt digital services, how digital accessibility influences residential location choices, and how these shifts manifest in social dynamics and urban evolution. The existing social dynamic simulation (SDS) model does not capture multi-layer interactions involving real and virtual networks.

The core research problem addressed in this thesis is the absence of an integrated analytical framework capable of evaluating the combined effects of real and virtual networks, and behavioral substitutability and complementarity, on QOL and QOB. Without such a framework, policymakers lack the tools to assess how rules and regulations, infrastructure, and DX technologies should be coordinated to design sustainable and human-centered air-front smart cities.

1.3. Research Objectives

This thesis addresses this academic gap by developing an integrated evaluation methodology for Air-front smart cities, but not limited to, to consider the substitutability and complementarity of physical service access while evaluating air-front smart city policies. The thesis investigates the substitutability and complementarity of physical services with digital alternatives to understand which services can be substituted and analyze their impacts on social relationships and urban structure. Using the results of the substitutability analysis, the thesis develops an integrated accessibility index that indicates individuals' accessibility to services through physical accessibility (transportation) and digital accessibility (ICT). The integrated accessibility model is incorporated into the social dynamic simulation (SDS) model developed by an existing study [Sugiki et al., 2021] to improve the efficiency and applicability of the SDS model and holistically forecast the future situation of a city. Additionally, the thesis develops Quality of Life (QOL) and Quality of Business (QOB) evaluation models using the integrated accessibility index to evaluate urban living and business environments, respectively, within an air-front smart city. The developed evaluation model is applied to assess different air-front smart city policies in the case of a startup ecosystem in Aichi, Singapore, and Munich.

Therefore, to address the research problem, this thesis pursues the following objectives, which will be tackled by each chapter of this thesis:

1. To empirically identify the substitutability and complementarity between physical and digital activities across various socio-demographic groups and social relationship types.
2. To develop a multi-layer social dynamics simulation model that represents real and virtual accessibility, social network, behavioral choice, land use, household generation, and long-term urban evolution.
3. To construct an integrated accessibility-based evaluation framework for assessing QOL and QOB in Air-front Smart Cities.
4. To apply the QOL and QOB framework to real-world policy evaluation, with a focus on Aichi, Japan, to analyze how DX, mobility, regulatory measures, and airport-related developments affect social and economic outcomes.
5. To provide a comprehensive methodological foundation that guides future planning of Air-front Smart Cities in diverse geographical and sectoral contexts.

1.4. Research Questions

This thesis is guided by the following research questions:

1. How do digital services substitute or complement traditional physical activities among different population groups?
2. How do changes in digital accessibility influence service usage, social interactions, and residential location decisions?
3. How can real and virtual networks be jointly represented in a multi-layer simulation model of urban behavior and long-term spatial development?
4. How can integrated accessibility indices be constructed to evaluate QOL and QOB for households, businesses, startups, and other regional stakeholders?
5. What policy insights can be derived by applying this integrated model to air-front smart city development in Aichi and other contexts?

1.5. Significance of Study

One of the significant aspects of this study is providing the first comprehensive framework for jointly evaluating real and virtual networks within the context of air-front smart cities. By combining large-scale empirical analysis of behavioral substitutability and complementarity, a multi-layer social dynamics simulation model, and an integrated accessibility-based QOL–QOB evaluation system, the research overcomes critical limitations in existing smart city assessments that focus only on physical or digital accessibility to the services, and produces a highly applicable SDS model. The study offers policymakers and planners an evidence-based methodology to understand how different policies on rules and regulations, infrastructure, and DX technology affect human well-being and business environments. The key contributions of this thesis to urban planning, air-front smart city policy, and digital transformation research can be as follows:

- Empirical Contribution: Provides a large-scale, nationwide analysis ($n = 6{,}210$) of behavioral substitution and complementarity between physical and digital services across multiple activity categories in Japan.
- Theoretical Contribution: Establishes a conceptual foundation for understanding urban systems as interconnected real–virtual networks rather than purely physical structures.
- Methodological Contribution: Develops a multi-layer social dynamics simulation

model that integrates physical and digital accessibility, land use, and long-term urban dynamics.

- Evaluation Contribution: Introduces an integrated accessibility framework that links physical and digital accessibility to QOL and QOB, enabling more comprehensive policy evaluations for the air-front smart city.
- Practical Contribution: Offers evidence-based policy insights for promoting industrial innovation unique to the characteristics of each region within the concept of an air-front smart city.

1.6. Structure of the Thesis

The outline of the thesis is shown in Figure 1.1. This thesis has two topics: utilizing integrated accessibility into the SDS model and developing the QOL and QOB model for air-front smart city policy evaluation. As the opening of this thesis, Chapter 1 explains the background and research objective. Chapter 2 presents related work and research positioning. The rest of this thesis is organized based on the author's publications, as follows.

- Chapter 3: Presents empirical analysis of substitutability and complementarity of physical services with digital alternatives using a web-based questionnaire survey and investigates its impacts on human relationships and urban structure (Mutahari et al, 2025a, and Mutahari et al., 2025b). This chapter provides data and insight for SDS model modifications, QOL and QOB model development, and QOL and QOB model application presented in subsequent chapters.
- Chapter 4: Modifies the SDS model (Mutahari et al., 2025c) by incorporating a newly developed integrated accessibility model and social networks, and validates its applicability by applying it to a virtual city.
- Chapter 5: Develops the integrated accessibility-based QOL and QOB evaluation models and demonstrates applications across various regions and sectors (Mutahari et al., 2025d).
- Chapter 6: Applies the methodology to air-front smart city policy evaluation in Aichi, Singapore, and Munich.
- Chapter 7: Concludes the thesis, summarizes contributions, and identifies future research directions.

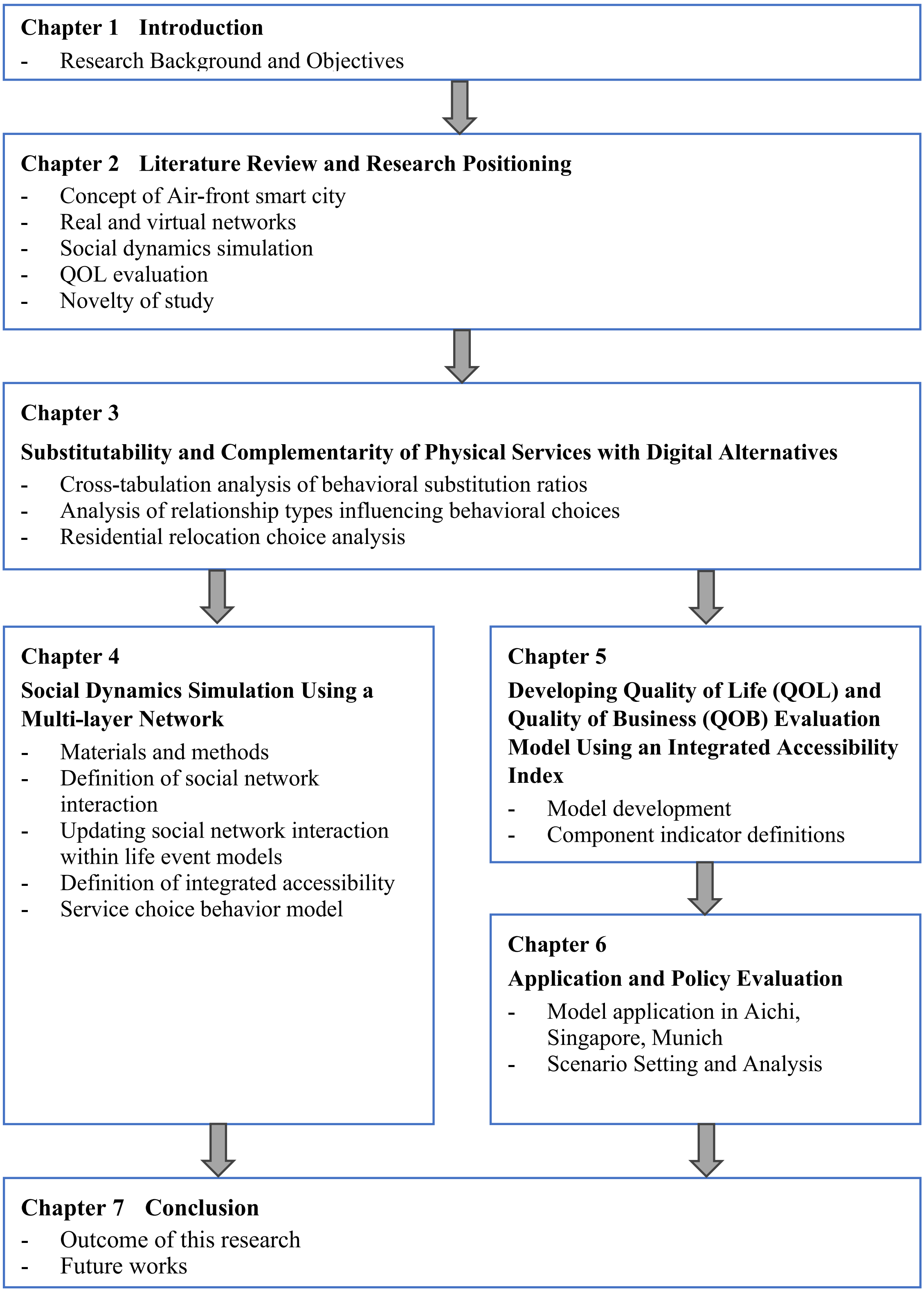


Figure 1.1. Outline of thesis.

Chapter 2

Literature Review and Research Positioning

This chapter reviews the literature on the air-front smart city concept, real and virtual network theory, social dynamic simulation, and QOL evaluation. The chapter positions this study within existing research and highlights its novelty: (1) integrating behavioral substitutability and complementarity into urban simulation, (2) developing a multi-layer network model that represents real and virtual interactions simultaneously, and (3) constructing a comprehensive evaluation system linking the integrated accessibility index to QOL and Quality of Business (QOB) for policy analysis.

2.1. Concept of Air-front Smart City

2.1.1. Smart city and role of airport in economic development

Technological progress, combined with the integration of digital services into everyday life, has reshaped the cultural, social, and economic activities and impacted urban structures. Technological advancements have created opportunities for global interaction that allow people and businesses from various economic backgrounds to engage with numerous virtual space activities and services. The COVID-19 pandemic greatly accelerated this development by forcing businesses and people to adjust to new conditions, which led to numerous socio-economic activities and services moving from physical space to virtual space (Lu et al., 2020; Shakibaei et al., 2021; Abu-Rayash and Dincer, 2020). The growing adoption of technology in everyday life, along with pandemic-related transformations like COVID-19, has led to advanced technological solutions delivering services through both spaces to improve individuals' Quality of Life (QOL) (Sheng et al., 2022). Furthermore, the development of smart cities aims to solve urbanization challenges while improving sustainability efforts and enhancing QOL through innovative urban development strategies (Chang and Smith, 2023) and utilizing cutting-edge technologies to improve urban performance and efficiency (Ejaz and Anpalagan, 2019; Chen et al., 2024) while enhancing the QOL of people as described by Vodak et al. (2021). Provision of services through real and virtual networks is the core principle of smart city development. Smart cities, which are founded on six pillars: smart governance, smart economy, smart mobility, smart environment, smart living, and smart people (John et al., 2025), are specifically designed to deliver such services by leveraging advanced technologies (Ejaz and Anpalagan, 2019; Chen et al., 2024), aiming to enhance the QOL of people (Vodak et al., 2021).

The concept of smart cities has evolved through multiple generations, shifting from technology-driven implementations in Smart City 1.0 (Cohen, 2015) toward city authorities-driven in Smart City 2.0 (Cohen, 2015), and more participatory, citizen-centered, and sustainability-oriented models in Smart City 3.0 (Cohen, 2015) and Smart City 4.0 (Makieła et al., 2022). Recent discourse further highlights Smart City 5.0 (Svitek and Kozhevnikov, 2023), which emphasizes human-centric innovation, social inclusion, and the integration of digital technologies with societal well-being rather than purely technological efficiency. Although the priorities of smart cities shift or will shift through each smart city generation, from smart city 1.0 to smart city 5.0, still, excessive utilization and integration of technologies into daily life services may harm human-centric urban structures and their functionality. Moreover, usually smart city development plans are implemented in a region without considering the uniqueness and potential strength of that area for economic development, gross regional happiness improvements, and contribution to environmental sustainability.

Numerous studies have been conducted to systematically review the smart city transformation process (Dai et al., 2024; Zhao et al., 2021) and to investigate smart cities' functionality and efficiency concerning people's QOL (Hartley, 2023; Madakam et al., 2023; Janaina et al., 2018; Hsiaoping, 2017). These papers investigate how smart city policies affect the QOL of residents, through analysis of perceptions of individuals about smart cities, how technologies are prioritized over users' satisfaction, issues of ICT and IoT (Internet of Things) related to security and privacy for residents and built-in environments. Studies by Wang and Hao (2023) and An et al. (2024) demonstrate how smart cities, due to reliance on ICT, reduce carbon emissions.

Similarly, existing studies covered the multiple aspects of smart cities such as environmental sustainability (Li et al., 2024; Wu et al., 2023), governance (Hartley, 2023; Hämäläinen, 2020), urban service and infrastructure (Sharifi et al., 2024; Larrinaga et al., 2021; Soyata et al., 2019), accessibility (Mora et al, 2017; Rashid et al, 2017), decision making (Osman et al., 2022), United Nations SDGs (Furtado et al, 2023), economic trajectories (Marchesani et al., 2023) and so on. There are several existing studies that criticize the smart city development policies for prioritizing technologies over human-centric urban development (Oliveira and Campolargo, 2015), social inclusion and inequality (Kruhlov and Dvorak, 2025; Jonek-Kowalska and Wolny, 2025; Lingli et al., 2024), user satisfaction (Janaina et al., 2018), and human rights concerning privacy (Flak and Hofmann, 2020), which are the key components of QOL evaluation.

We can understand from these studies that excessive reliance and utilization of technologies and provision of digital services may negatively impact an individual`s QOL, may raise critical concerns on social inclusion and inequality, which will question the sustainability of urban development and the United Nations Sustainable Development Goals (SDGs) agenda. It is important to comprehensively analyse the substitutability of physical services with digital alternatives and their impacts on urban structures and the QOL of individuals during smart city policy evaluation.

The author also investigated the role of airports in economic growth, which directly or indirectly affects the QOL of individuals within smart cities through a literature study. Vojkovic and Milenkovic (2024) investigated the relationship between smart cities and airport development. The study highlights the potential improvements of the smart city paradigm through the integration of airports and argues that the integration may generate synergistic advantages and deliver more efficient services for both residents and visitors. No further studies were found to concretely discuss and link the airport developments and smart city policies with economic growth.

However, research studies by Hui and Tingting (2023), Addie (2014), and Xue-Ming and Joyce (2010) demonstrate how the advancement of airport infrastructure, together with its operational capabilities, supports urban expansion and economic development while boosting global city competitiveness. Expanding global access through airports plays a transformative role in reshaping existing industries, fostering the development of new ones, and building more inclusive and diverse urban environments (Ke et al., 2023; Bilotkach, 2015). These advancements extend beyond the immediate airport areas to impact surrounding hinterland regions and their existing industries (Tang et al., 2021). Additionally, an existing study (Alam et al., 2020) that investigated the relationship between transport infrastructure and economic development argues that economic development is often regarded as a key factor in improving the living standards of people.

Through this literature, it was witnessed that a sufficient number of existing studies have been conducted to investigate different aspects of smart cities, and all underscoring the role of technology in improving QOL and optimizing resources. Also, we could understand that economic growth can be stimulated by airport function improvements, and the role of airports has become substantial in urban policy evaluation by functioning as essential transit hubs that facilitate the movement of passengers, freight, and services.

What can not be seen sufficiently within the existing studies is the joint utilization of airport functions and DX technologies for the enhancement of social well-being, economic growth, and decarbonization within smart cities and sustainable urban development policies. The air-front smart city concept, which is introduced by e-Asia air-front smart city JRP (Air-front smart city, 2025), can address the aforementioned challenges of smart cities.

2.1.2. Description of the air-front smart city

Expanding global access through airports plays a critical role in transforming existing industries and fostering the creation of new ones, ultimately contributing to the development of more inclusive and diverse urban environments. This transformation reaches beyond the immediate airport areas, influencing the economic and industrial landscapes of surrounding regions. Hence, to address the stagnation of industries in developed countries and stimulate economic growth in developing countries while maintaining a higher quality of life for people and contributing to decarbonization, and overall considering the United Nations SDGs, the concept of air-front smart cities with three pillars, economic competitiveness, decarbonization, and Gross Regional Happiness (GRH), is introduced. Air-front smart cities are argued to connect airport functions with urban and industrial innovation, tailored to the unique characteristics of each region, focusing on the impacts not only within the city but also on hinterland areas, on a regional level. This concept connects not only cities with airports but also hinterlands through a combination of physical transportation and digital infrastructures. By creating synergies between global gateways and their hinterlands, this approach seeks to promote sustainable urban planning, industrial growth, and contribute to several UN SDGs, especially SDGs 8, 9, 10, 11, and 13.

The air-front smart city development concept redefines airports as hubs not just for transport, but also for industrial innovation, information exchange, and sustainable development. Incorporating advanced digital technologies such as AI, IoT, and machine learning, these cities seek to link airports with nearby urban areas and hinterlands, fostering economic growth, attracting new industries, and promoting environmentally friendly and socially inclusive urban spaces with a higher QOL for residents, workers, and visitors.

The discussion of smart cities is often about the introduction of similar services and technologies to any development in any location, which can lead to a loss of uniqueness and diversity of the city. Figure 2.1 illustrates the creation of synergies between global gateways and the hinterland region by the air-front smart city concept. Additionally, an air-front smart city considers spillover effects not only to the development site but also to the hinterland region and its existing industries, in order to identify the suitability of introducing technologies and services according to the city's characteristics, as shown in Figure 2.1.

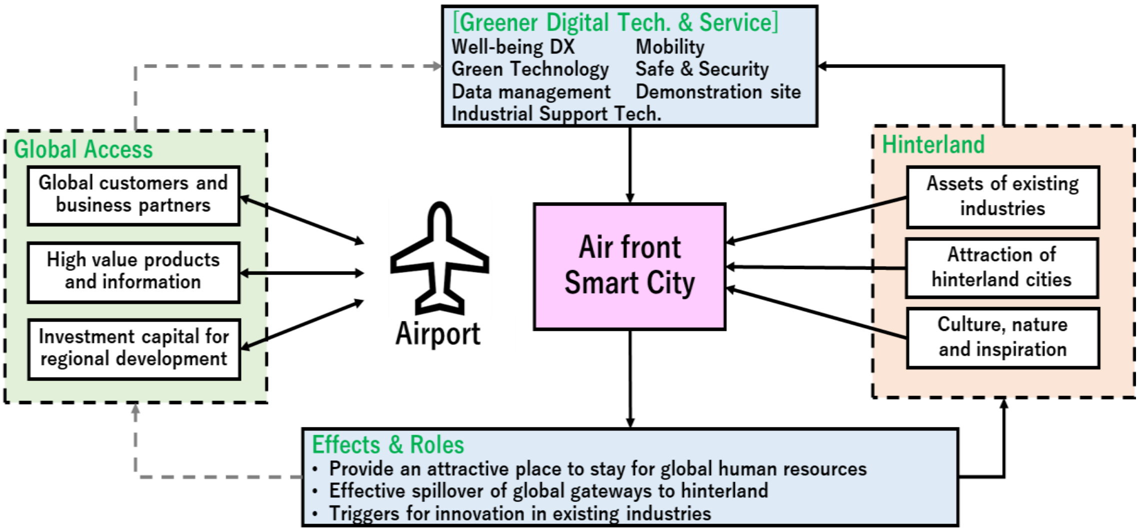


Figure 2.1. Air-front smart city concept.

Figure 2.2 shows the sustainability initiatives of the air-front smart city concept. In an era of global competition, climate emergency, and well-being, the air-front smart city seeks comprehensive sustainability consisting of three pillars: competitiveness (happiness for business), decarbonation (happiness for planet), and quality of life (happiness for people), as was shown in Figure 2.2. Regenerative economy, which considers human and natural capitals in industry, tourism, and agriculture, is the other concept that is utilized with the air-front smart city development. Regenerative economy enhances the competitiveness of businesses and urban living environments, and at the same time creates the base for decarbonization, leading to a higher quality of life, which further attracts international interest and investment. However, the regenerative economy and decarbonization are out of the scope of this thesis, but the thesis will refer to them while discussing urban air-front smart city policies.

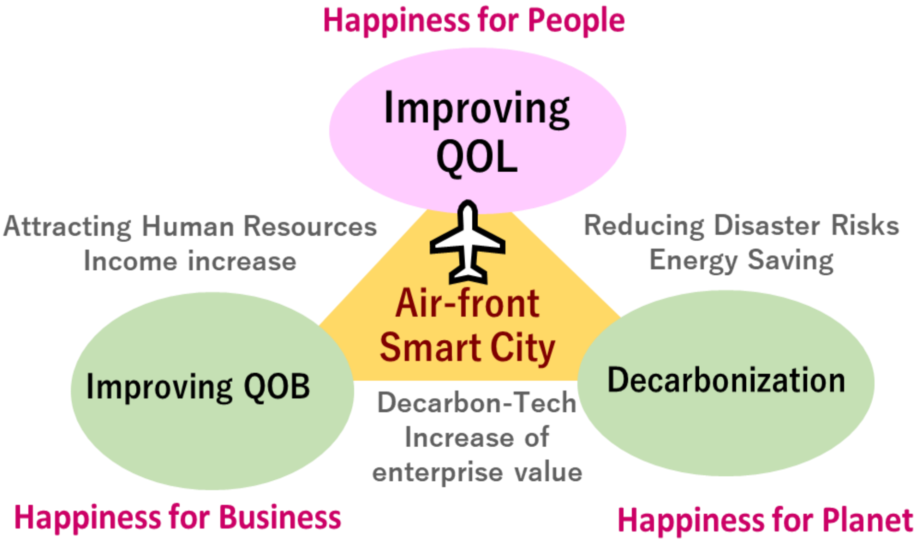


Figure 2.2. Sustainability initiatives of the air-front smart city.

2.1.3. Air-front smart city evaluation system

As was explained previously, at the core of air-front smart city development are three essential pillars: economic competitiveness, decarbonization, and improved QOL. These cities are designed to meet the unique needs of each region by combining airport-driven growth with localized industrial innovations. The integration of DX technologies enables air-front smart cities to provide tailored services that suit the specific economic stages of different regions. Furthermore, these cities prioritize the evaluation of Quality of Business (QOB) and QOL metrics to ensure that industrial growth aligns with improving residents' well-being, enhancing environmental sustainability, and supporting long-term economic success. This multi-faceted approach fosters balanced regional development, promotes sustainable planning, and enhances the overall quality of urban life.

The air-front smart city evaluation system framework is shown in Figure 2.3, which illustrates how the air-front smart city is going to be evaluated through the three pillars: economic growth, decarbonization, and Gross Regional Happiness (GRH), considering the integration of physical space (real network) and cyberspace (virtual network). As can be seen in Figure 2.3, accessibility indices (physical accessibility index and digital accessibility index) are used to measure QOL and QOB. Whereas the QOL and QOB will be used as input for the regional evaluation model in the smart city evaluation system. The regional evaluation system focuses on economic growth, decarbonization, and gross regional happiness. The integration of physical and digital accessibility while accessing

QOL and QOB within the air-front smart cities ensures equity and sustainability of living and business environments.

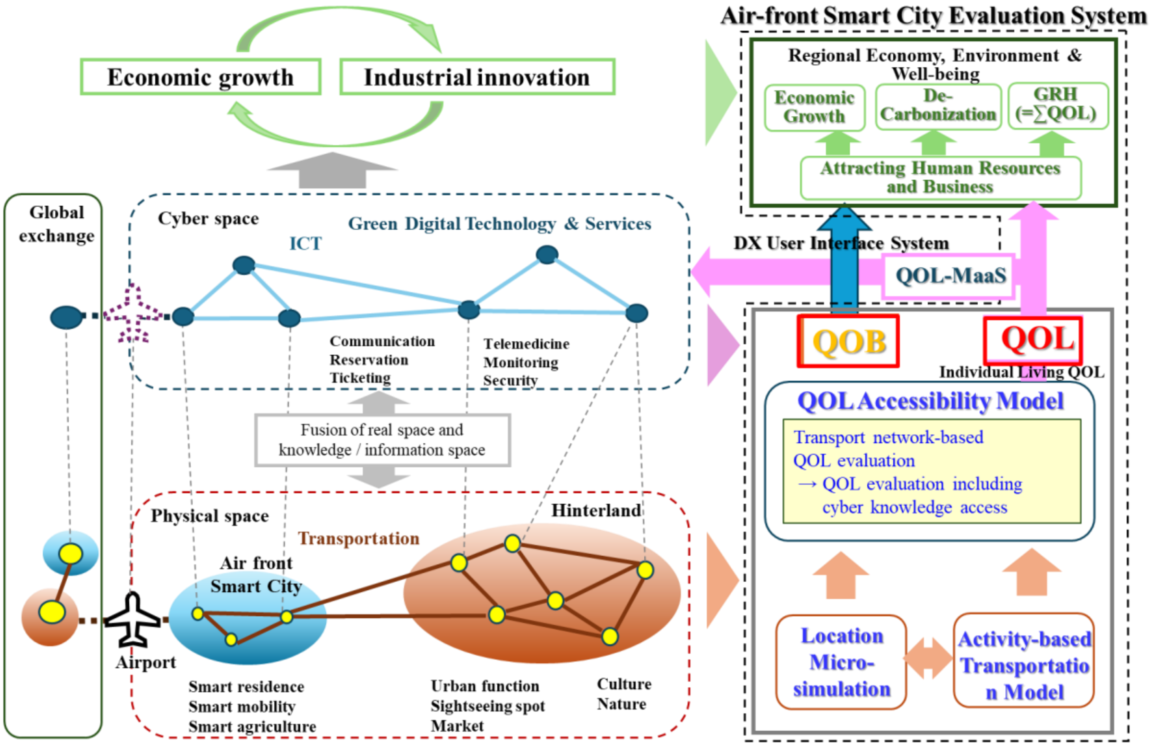


Figure 2.3. Air-front smart city evaluation system framework. (Mutahari et al., 2025d)

2.1.4. Study area and selection of industry

The e-Asia air-front smart city project, which initially introduced the concept of the air-front smart city, has selected three cities in different economic development stages, having different industrial problems as shown in Figure 2.4. For instance, Aichi in Japan, whose economy has already matured heavily dependent on the mechanical car industry and is in a stagnation period, has been selected. The startup is believed to boost the economic development within Aichi. Phuket in Thailand, which is suffering from over-tourism despite economic growth, has been selected. The selected industry of Phuket is tourism, which is tied to the economic growth of the city. The last city is Baguio in the Philippines, which lacks the basic infrastructure to protect from flood disasters, and faces traffic issues that further disturb economic growth. The selected industry in Baguio is the post-harvest agriculture. Table 2.1 represents the evaluation objective of the e-Asia air-front smart city project, where three cities with three different economic development stages and three industries are involved to solve the industrial problem while maintaining a higher QOL for residents, referring to the concept of air-front smart city.

However, no study has been conducted on the concept of air-front smart cities, and mathematical tools have not been developed to quantitatively assess living environments for people and business environments for industries based on the concept of air-front smart cities. Analytical tools are required to assess living and business environments, evaluate different air-front smart city policies, and assess their impacts on the QOL of people and QOB of business owners.

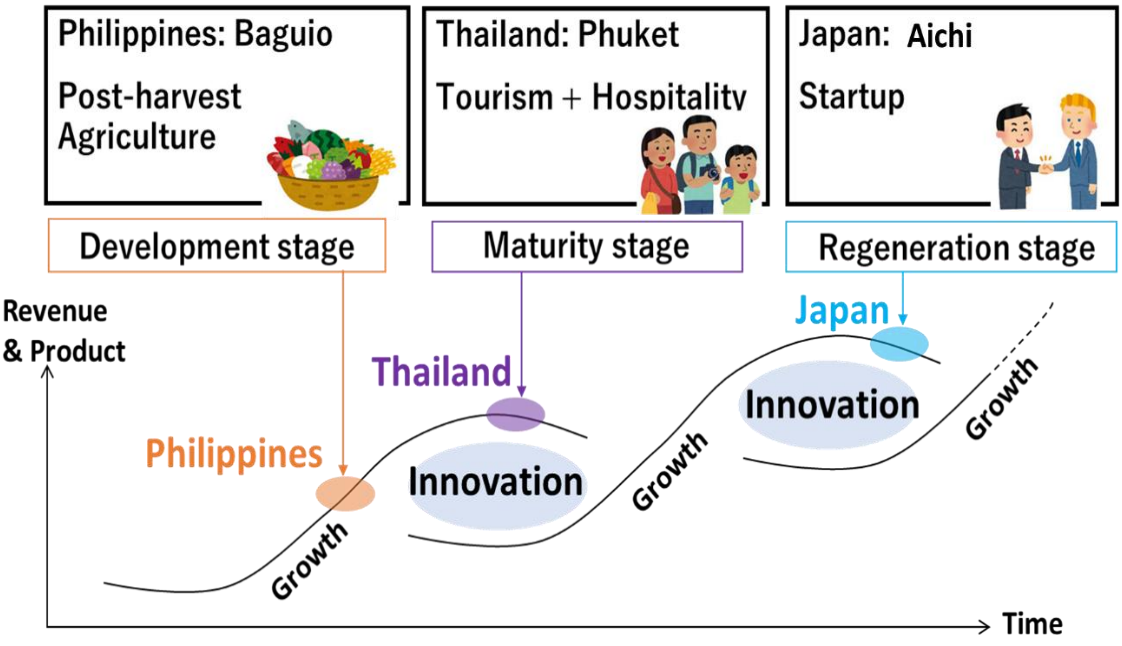


Figure 2.4. Study area with different economic stages and industries.

Table 2.1. Evaluation objective of the e-Asia air-front smart city project

Cities	Objective	Evaluation Model	Economic Stage
Aichi	Promote startup	Developing a model to evaluate policies regarding startup promotions	Stagnation
Phuket	Reduce over-tourism	Developing a model to evaluate policies regarding over-tourism, developing new cities near airports to reduce congestion and CO2 emissions	Maturity
Baguio	Improving post-harvest agriculture	Developing a model to evaluate policies regarding improving post-harvest agriculture production and distribution	Development

2.2. Real and Virtual Networks

The merging of real networks and virtual networks, which rely on transportation and ICT, respectively, has dramatically changed different aspects of living environments, including cultural and socio-economic activities. These technological advancements have facilitated global engagement, allowing individuals from diverse regions and socio-economic characteristics to participate in a wide range of activities and receive services through both real and virtual networks. Additionally, the rapid spread of COVID-19 and its announcement as a global pandemic [WHO, 2020] also impacted socio-economic activities and urban structures [Lu et al., 2020] and contributed to the acceleration of digital transformation. The lockdowns during pandemics made individuals adapt to a new environment, shifting daily activities and services from physical spaces to cyberspaces.

Although pandemics have historically affected different socioeconomic activities and urban structures [Matthew and McDonalds, 2006], COVID-19 showcases how pandemics can accelerate the transition to digital alternatives where services are offered in cyberspace through virtual networks using ICT. The traveling restrictions during the COVID-19 pandemic led to drastic changes in urban mobility as governments enforced lockdowns and promoted remote work, resulting in a significant reduction in commuting and personal travel [Abu-Rayash & Dincer, 2020; Beria & Lunkar, 2021; Bucsky, 2020; De Vos, 2020; Shakibaei et al., 2021]. Similarly, public transportation saw a decline due to challenges associated with maintaining physical distance in crowded spaces [Hu et al., 2021; Politis et al., 2021; Sun & Zhai, 2020]. Existing studies also show that the environmental impacts of these lifestyle shifts are significant. For instance, a study [Le Quéré et al., 2020] shows global CO2 emissions dropped by 17% during the pandemic, whereas a pollution reduction of around 30% was seen in heavily affected regions like Wuhan, Italy, Spain, and the United States [Gautam, 2020; Muhammad et al., 2020; Wang et al., 2020]. Noise pollution in urban areas also decreased considerably (Basu et al., 2021; Rumpler et al., 2020; Sharifi and Khavarian-Garmsir, 2020).

The COVID-19 pandemic underscored the importance of access to information and services during crises, prompting research on analyzing the effects of COVID-19 during disaster evacuation [Noda et al., 2024] and the role of information accessibility during evacuations with its implications for future resilience planning [Merchant and Nicole, 2020; Tang et al., 2020]. The shift from physical services to digital alternatives, such as online shopping, remote work, and virtual meetings, reduced the need for physical travel and face-to-face interactions, thereby alleviating pressure on transportation systems and decreasing CO2 emissions [Zu et al., 2023]. The shift toward online shopping, already gaining momentum before the COVID-19 pandemic, has seen an accelerated adoption in response to restrictions on mobility [Abu-Rayash and Dincer, 2020]. Similarly, the rise in e-learning, supported by Information and Communication Technologies (ICTs), has allowed many students to attend online classes from home [Shakibaei et al., 2021]. The case is similar to teleworking, which has emerged as a critical component of modern work–life flexibility, reducing physical commuting and offering substantial environmental benefits by lowering CO2 emissions [Le Quéré et al., 2020]. With this transition, access to services began to rely more on virtual networks rather than traditional transportation networks, bringing new challenges and opportunities for researchers, urban planners, and policymakers.

Considering this digital transformation, it is essential to examine the substitutability of physical services with their digital alternatives, which individual categories are more prone to substitute physical services with digital services, and what services can be substituted. Additionally, it is vital to assess the impacts of digital service substitution on social networks and urban and regional structures. An existing study [Ohata and Ujihara, 2022] has investigated the changes in online consumption behavior using surveys in Tokyo and Okayama, revealing that the frequency of in-person shopping declined during the pandemic. Findings suggest that women and younger individuals were more likely to engage in online shopping, with motivations differing based on city size. In the Tokyo metropolitan area, time savings were a key factor, while in rural areas, online shopping served as a complement to physical stores. The study suggests age has an effect on online shopping substitution, meaning that younger individuals are more likely to do online shopping, whereas the elderly are less likely to do online shopping. This raises questions about social inclusion if physical service access is substituted with digital or virtual service access. For instance, the elderly and individuals with limited digital literacy may find it difficult to access digital services.

Kruhlov and Dvorak (2025) investigated access equity to digital services, who classified vulnerable population groups into elderly people, people with disabilities, low-income individuals, and residents of remote areas. Considering the inequality in digital accessibility, they categorize the digital divide into access, digital skills, and the ability to derive socio-economic benefits. Silva et al. (2018) propose a conceptual framework considering physical accessibility and digital accessibility to predict activity travel behavior of individuals. The study argues that substitutability of physical activities with digital ones depends on at least five aspects: 1) the ownership of a digital device, 2) network coverage and network subscription, 3) digital literacy or technology savviness (the ability or knowledge to use a digital device and its functions), 4) ability to conduct an activity in virtual space (some activities can not be conducted in virtual space, where presence of individuals are necessary), and 5) the availability of time to do a specific behavior in virtual space. These five factors significantly influence the substitutability of behavior or service access.

Similarly, Studies by Matous (2017) and Kenyon (2003) investigate the substitutability and complementarity of physical accessibility with digital accessibility. Both studies confirm that some physical activities can be substituted with digital activities, whereas digital accessibility can enhance and complement physical accessibility. Also, existing studies (Omori, 2022; Daimon, 2022; Kuse, 2003) have examined the impact of ICT on transportation behavior, work patterns, and urban structure.

However, these studies did not comprehensively explore how digital service substitution influences social networks and urban structure, and how to develop a mathematical model to evaluate the QOL of individuals and QOB of businesses through an integrated accessibility (physical accessibility and digital accessibility). The result of substitutability analysis and the development of an integrated accessibility index can be incorporated into QOL evaluation models to holistically evaluate urban living environments. Additionally, such investigations' results can be incorporated into land-use-transport modes, such as social dynamics simulation models, to holistically evaluate different urban policies and scenarios and predict a realistic future situation of a city.

2.3. Social Dynamics Simulation

Studies have been conducted to develop models that can express, analyze, and evaluate social and urban structures. Various urban models (land use and transportation models) have been developed to evaluate various urban policies that consider the integral relationship and interaction between land use and transportation. Wegener (2003; 2005) has systematically summarized the characteristics and development history of urban and transportation models. In recent years, urban models using micro-simulation have been actively developed as an analytical method to describe temporal changes in land use and transportation, such as Urbansim (Waddell, 2002), 2nd generation model of TLUMIP (Hunt et al., 2001), PECAS (Abraham, 2005; Hunt and Abraham, 2009), ILUTE (Salvini and Miller, 2005), ILUMASS (Moeckel et al., 2003; Strauch et al., 2005), PUMA (Ettema et al., 2007), and SelfSim (Chengxiang et al., 2016).

Urban micro-simulation models use individual and household micro-data for the analysis, and probabilistic choice behaviors related to changes in individual attributes and household composition, location choice, moving choice, and transportation mode choice were modeled. Hence, urban microsimulation models can be used in urban microscopic analysis and policy evaluation by considering the attributes of individuals and households. In addition, these models are quasi-dynamic models, from which the land use distribution of the next simulation time step is obtained from the simulation result of the land use distribution and traffic conditions in the current simulation time step.

Furthermore, several studies used network analysis for complex social structures and analyzed the characteristics of social structure mathematically. Relationships between people and organizations (human relationships, intercompany relationships, individual–community relationships, etc.) are modeled in many studies using networks and analyzed from the perspectives of Graph Topology and Network Science (Social Network Analysis) in various fields (Newman, 2010). A social network is a group of individuals in a society, organization, or any collective social unit (Wasserman and Faust, 1994). Social network analysis can analyze human relationships visually and mathematically and can be used to quantify human relationships in a network (Jamali and Abolhassani, 2006).

Jamali and Abolhassani (2006) have discussed some properties of social networks, considered web and web blogs as social networks, and applied SNA on the web. Alex Bavelas (1949) used network centrality phenomena to understand human community structure by developing a mathematical model. Uchida et al. (2006) estimated the network structure model of SNS by focusing on the centrality of nodes in propagation dynamics. Tsugawa and Ohsaki (2015) have focused on social interaction networks and investigated the strength of interaction locality in large-scale social networks. Mehmet and Hakan (2017) used SNA to examine the usage and popularity of social media such as Facebook pages and groups related to open education in Turkey. Camarasa et al (2020) used SNA methods to map a full network of stakeholders involved in the decision-making process and showed their degree and interactions in the selection of technologies.

Maskil-Leitan et al. (2020) have used the social network analysis measures for the assessment of the integration of stakeholders for green Building Information (BIM) Modeling and management. Guancen et al. (2021) used SNA to investigate the spatial relationship of housing prices in different cities in China by developing a modified gravity model. He et al. (2021) used SNA to explore the effects of High-Speed Rials (HSR) on the spatial structure of economic networks, including nodal centrality and community structures. Jiao et al. (2021) used SNA to find the key influence factors of urban rail transit station resilience against disasters caused by rainstorms. Kim et al. (2011) used SNA to calculate the expertise index in the introduced Knowledge Brokering System (KBS).

Almahmoud and Doloi (2015) used the SNA to evaluate a proposed dynamic assessment model, which was developed using sustainability and equity theories. Wang et al. (2018) used SNA to assess the potential application of SNA for improving social sustainability in construction projects. Loosemore (1998) used SNA to analyze the management of construction crises and concluded that both quantitative and qualitative methods are needed to understand the complexity of people's changing social roles, positions, and behaviors. Yie et al. (2021) applied SNA to cluster characteristics of COVID-19. Kim et al. (2021) measured the subjective happiness of nursing students using centrality in social networks in addition to individual psychological perception.

SNA can be used to analyze relationships and interactions between organizations (Camarasa et al., 2020; Maskil-Leitan et al., 2020). Senaratne et al. (2021) examined the possibility of improving the knowledge management process between construction project teams through social network analysis. Tamura et al. (2005) analyzed the relationship between social capital and regional revitalization by focusing on the density and order of networks between regional groups and the centrality of eigenvectors. Gomyo (2013) performed a social environment analysis of remote islands using a network evaluation index.

SNA is a methodology that captures social characteristics by focusing not only on the attributes of the entities but also on their relationships. Network analysis can mathematically express and consider complex relationships between entities, and several complex network analyses have been developed. In addition, various analysis methods for the investigation of complex large networks and phenomena caused by their structures have been proposed (Wasserman and Faust, 1994; Masuda and Konno, 2010).

In the field of transportation, studies have been conducted to analyze road networks from the viewpoint of network theory. Nakaminami et al. (2018) proposed a method for estimating vulnerabilities in emergency transport road networks. Ando and Kurauchi (2020) examined the applicability of eigenvector centrality to road network connection vulnerability assessment. Ando et al. (2021) also evaluated the impact of road maintenance on road network functions from a long-term perspective.

Furthermore, social cooperation tendency within the region during a disaster (Kuwano, 2014), the relationship between individuals that defines the degree of life safety (Kuwano et al., 2016), accessibility to daily life facilities (Kuwano and Fukuyama, 2015), urban structure (Porta et al., 2008), etc., have been analyzed using social networking techniques. By using basic statistics, like order distribution, cluster coefficient, and eigenvector centrality, it is possible to analyze network characteristics, such as connectivity between regions and individuals, with a small computational load.

The above existing research results disclose that it will be easy to express complex and large-scale urban structures and evaluate them from network theory perspectives by describing the interrelationships between entities in urban space with a network. Moreover, it will be possible to develop a method for expressing the social dynamics of a network and evaluating various policies for the realization of a sustainable city by positioning the temporal change of the urban structure as network dynamics and using the urban micro-simulation model for illustration.

The Social Dynamics Simulation (SDS) Model (Sugiki et al., 2021) has been developed and applied to a virtual city by taking attributes of a real city to check if such models can be applied to large and complex urban spaces. The author used a multi-layer network to describe the attributes of individuals and households and the urban space in which they are located. Social dynamics are expressed by modeling the transition over time, such as population attributes, household composition, and facility access, as the dynamics of a multilayer network by using an urban micro-simulation model and a transportation network equilibrium, as shown in Figure 2.5.

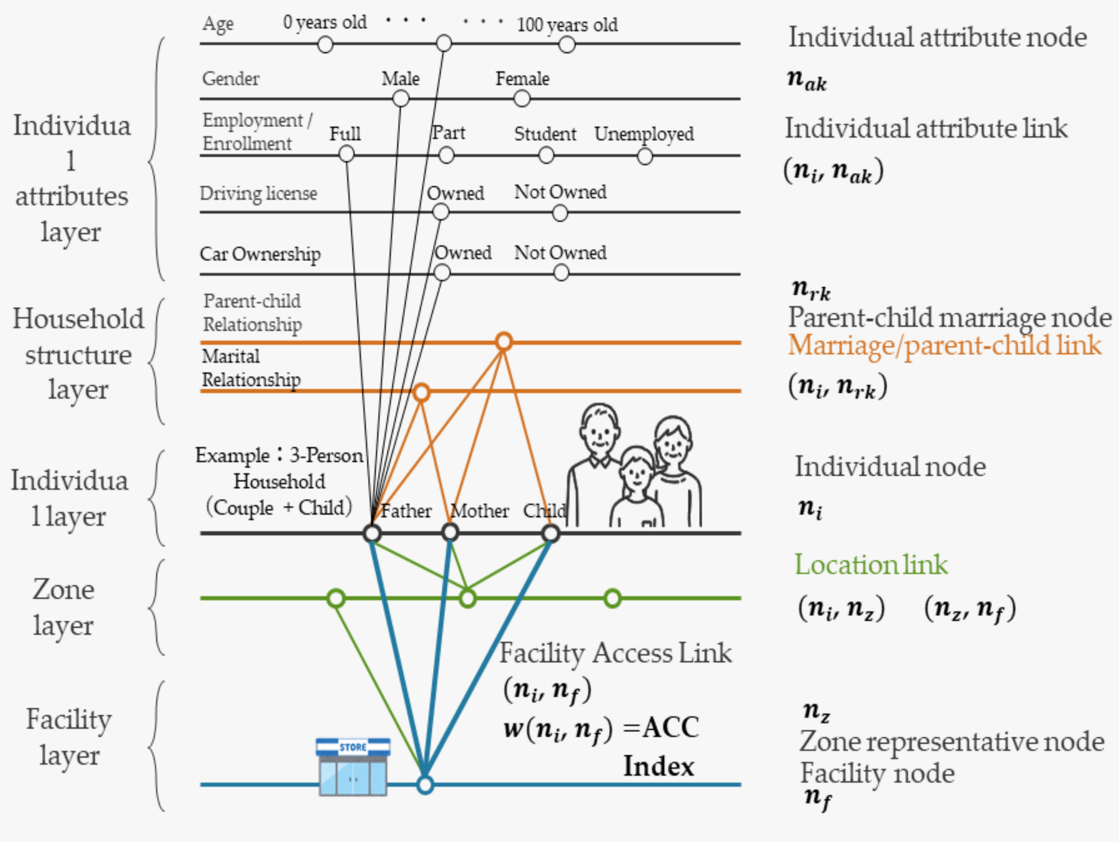


Figure 2.5. Description of urban space by a multi-layer network. (Sugiki et al., 2021)

The dynamic model in the developed multilayer network is applied to a virtual city in which the population and household composition are adjusted to a real city, and simulations over time are carried out under multiple facility distribution cases. The behavior of the model is verified by the temporal behavior of the household location and traffic conditions. The paper focuses on individual facility access, examines what kind of interpretation is possible for network indicators, and discusses the availability of social dynamics networks for urban analysis. The shape of the multilayer network in that study refers to the layer-breaking k-partite network (Kivelä et al., 2014). The individuals, their families, and the spaces in the cities have been presented in multiple layers. Nodes belonging to each layer express attributes, such as age and gender, parent-child relationships, marital relationships, individuals, zones, and urban facilities, indicated in each divided zone.

Knowledge of sensitive input parameters is beneficial for model development and application. It can lead to a better understanding and better-estimated values and thus reduce uncertainty (Lenhart et al., 2002). Sensitivity analysis as an instrument can be used for the assessment of the input parameters concerning their impact on model output and is useful not only for model development but also for model validation and reduction of uncertainty (Hamby, 1994). El-Fadel et al (2002) have performed a model sensitivity analysis to parameter variation to check the model`s efficiency while conducting simulations to predict future noise exposure along the highways. Lenhart et al. (2002) have investigated two simple approaches to sensitivity analysis by varying one parameter and keeping the other parameters. Therefore, it is crucial to investigate whether SDS models can evaluate different urban policies, scenarios, and alternatives to help decision-makers and contribute to sustainable urban development.

The sensitivity and stability of the SDS model have been tested by Mutahari et al. (2025c). The study examined the behavior of the simulation models associated with the city`s demography, land use, and transportation system. Additionally, the study investigates the correlation between the birth rate, land prices, and transportation costs with the future situation of the city by analyzing the social dynamic model`s simulation results. The result of the study showed that the SDS models can evaluate different urban policies, such as changes in the population, land prices, and transportation accessibility.

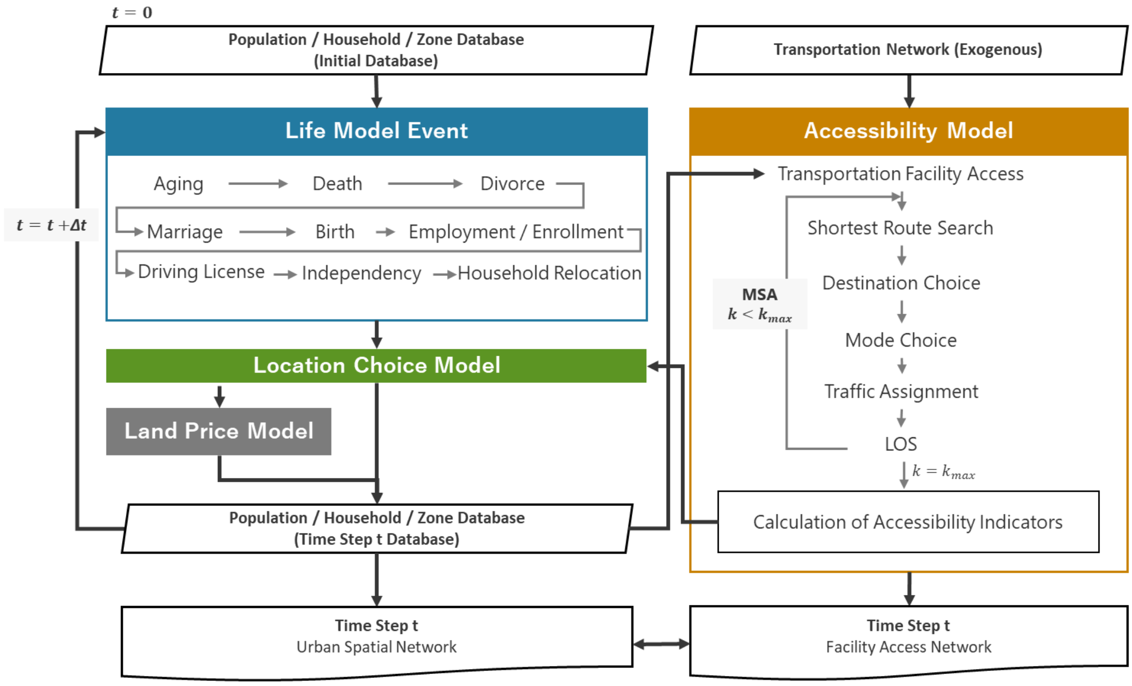


Figure 2.6. Basic structure of network dynamic model. (Sugiki et al., 2021)

Additionally, the Developed SDS model (Sugiki et al., 2021) has been developed only considering physical accessibility, as shown in Figure 2.6, whereas digital accessibility has not been considered while developing the model for urban policy evaluation. Incorporating digital accessibility, as was discussed previously, can greatly enhance the applicability of such SDS models. Furthermore, the impacts of social networking on human beings on urban structure, which is an integral part of society, have not been studied widely within the existing studies. Incorporating social networks into SDS models alongside a newly defined integrated accessibility index can greatly improve the applicability of SDS models.

2.4. QOL Evaluation

Quality of Life (QOL) has a long intellectual history spanning psychology, healthcare, social sciences, welfare economics, and urban studies. Since its emergence in the early twentieth century, QOL has been viewed as a multidimensional construct reflecting the physical, psychological, social, and environmental conditions that shape human well-being. A key driver behind the modern development of QOL concepts was the "paradox of affluence," which observed that technological advancement and economic growth alone do not automatically lead to improved well-being (Pacione, 2003; Lever, 200). This recognition led scholars and policymakers to develop alternative indicators capable of capturing more holistic dimensions of health, welfare, and life satisfaction beyond economic metrics alone.

Early conceptualizations of QOL built heavily on the World Health Organization's (WHO) definition of health as "a state of complete physical, mental, and social well-being", not merely the absence of disease or infirmity (WHO, 1948). Building on this definition, the WHOQOL instrument established a comprehensive framework for evaluating health-related QOL (WHO, 2012). Subsequent measures, such as EuroQol EQ-5D (EuroQol Group, 1990), the Short-Form Six-Dimension (SF-6D) (Brazier et al., 2002), and the Health Utilities Index (HUI) (Feeny et al., 1995), further advanced standardized QOL assessment in healthcare. These measures were primarily developed in the healthcare field to evaluate health outcomes, disability impacts, and functional ability, but they contributed significantly to the methodological foundations of QOL research.

In policy contexts, QOL gained importance when U.S. presidents Johnson and Nixon introduced it into public-policy agendas during the 1960s (Calder, 1982), created a "Quality of Life Committee" to study interrelated QOL variables such as consumer and environmental interests, industrial requirements, and safety aspects, and emphasized transparency and multidimensional evaluation in public administration (Tozzi, 2011). At the same time, philosophical and economic perspectives contributed to broadening the concept. Nussbaum and Sen's capability approach framed well-being as the ability of individuals to achieve valued functions, shifting attention toward the conditions that enable people with diverse capabilities to lead fulfilling lives (Nussbaum and Sen, 1993). These historical developments demonstrate that QOL is not a single-domain concept but rather a multidimensional construct shaped by physical health, psychological well-being, social relationships, economic stability, environmental conditions, and, in some cases, spiritual or personal beliefs.

Across disciplines, QOL has therefore been conceptualized as a multifaceted term encompassing physical health, psychological well-being, social relationships, economic resources, environmental conditions, and in some cases, spiritual or personal beliefs. As shown in previous studies, these domains can be grouped into four overarching categories: (a) physical status, (b) psychological status, (c) social interactions, and (d) the surrounding environment. These categories capture both the internal conditions of individuals (health, ability, emotions) and their external contexts (family, community, economy, and physical environment). Importantly, these dimensions are deeply interrelated; changes in one category can significantly influence others. For example, poor environmental conditions may affect physical health, which in turn affects psychological well-being and social participation.

The relevance of QOL to urban studies has grown substantially as scholars have sought to understand how living environments shape well-being. Urban-related QOL research focuses particularly on the social and environmental dimensions of well-being, including housing, neighborhood conditions, safety, employment, community cohesion, mobility, environmental quality, and access to public services. International frameworks such as the Human Development Index (HDI) (UNDP, 1990), the OECD Better Life Index (OECD, 2011), the WHO Urban Health Index (UHI) (WHO Kobe Centre et al., 2014), and UN-Habitat's City Prosperity Index (CPI) (UN-Habitat, 2016) illustrate the multidimensionality of QOL in urban contexts. These frameworks incorporate health, education, income, housing, community cohesion, civic engagement, environmental quality, safety, mobility, and subjective well-being.

More recent empirical studies have analyzed QOL determinants at the regional or municipal levels, incorporating factors such as household resources, social inequality, housing quality, environmental health, safety, green space access, commuting conditions, neighborhood satisfaction, and participation in community activities. For instance, a study by Murgaš & Klobuční (2016) studies the QOL within the domain of health, family, life, and job, whereas another study (Mittal et al., 2021; Mouratidis, 2020; Zhan et al., 2018; Aroca et al., 2017; Martín and Mendoza, 2013; Ülengin et al., 2001) further expands the QOL domains.

While numerous studies have evaluated living environment, QOL in physical spaces by evaluating perceived accessibility through transportation networks (Segev-Jacubovski, 2025; Birenbaum et al., 2025; Kim, 2024; Gu et al., 2016; Takano et al., 2023; Nakamura et al., 2014), relatively few have examined the impact of substitutability of service access and ICT on QOL (Alfaro-Navarro et al., 2024; Alhassan and Adam, 2021). Also, studies exist that studied the value of physical interactions within digital service environments (Palmié, 2022), a literature review on impacts of digital technology on the QOL of elderly people (Vincek et al., 2024), or impacts of perceived accessibility of travel behavior (Mehdizadeh and Kroesen, 2025). Another study (Lavieri et al., 2018) proposes a framework integrating physical and digital accessibility to analyze how ICT usage, accessibility, and demographics jointly affect engagement of individuals in physical and digital activities.

Hayashi (2023) introduced a perceived physical accessibility based QOL evaluation, which evaluates QOL of individuals considering their preferences for the services and the access cost to reach the service. The author argues that the value of the services differs for each individual category depending on their age, gender, social status, and so on, and needs to be considered while estimating QOL for that individual category. Additionally, the study considers the access cost to the services, which further diminishes the existing value of the services. The equation model developed by Hayashi (2023) is as follows:

$$QOL_i^k = \sum W^{mk} A_{ij}^m \tag{2.1}$$

$$A_{ij}^m = V_j^m \cdot e^{-\alpha c_{ij}} \tag{2.2}$$

Where m is the QOL factor, i is the place where the individual lives, j is the place where the objective value of QOL factor m exists, α is the impedance parameter for traveling between i and j, cij is the travel or communication cost between i and j. α. V_j^m is the existing value of the QOL factor m that exists in j, A_{ij}^m is the accessible value of V_j^m for individuals living in *i, k* is the individual category with a specific attribute, W^{mk} is the weight of the QOL factor m for individual category k among all factors, and QOL_i^k is the perceived value, which is QOL for individual category k living in *i.* This model is also developed to consider only physical accessibility.

Whereas no study has fully developed a comprehensive methodology to evaluate QOL based on accessibility to services through both real and virtual networks. Such an approach is critical for ensuring equity and promoting sustainable urban development in the digital age. Despite advancements in DX technology and digitalization, traditional QOL evaluation frameworks still focus largely on physical environments and socio-economic conditions. They generally assume that access to services and opportunities occurs through physical networks and do not fully account for the role of digital accessibility, online services, or virtual social interactions. In the era of rapid digital transformation, however, individuals increasingly rely on both real and virtual networks to fulfill daily needs. Telework, online shopping, e-treatment, and social media have reshaped how people access services, interact socially, and navigate urban environments. As a result, existing QOL models, which were designed primarily for pre-digital urban systems, are insufficient for evaluating well-being in digitally integrated smart cities or in emerging Air-front Smart City contexts where airport connectivity and digital services jointly influence daily life and business performance.

Considering the complexity of modern urban systems, QOL evaluation must go beyond conventional physical-environment-based indicators to incorporate behavioral changes, digital service adoption, digital accessibility, and multi-layer interactions between real and virtual networks. These gaps underscore the need for an integrated evaluation framework capable of capturing the combined effects of digital transformation, airport-driven regional connectivity, and evolving social dynamics on human well-being. Addressing this need is a central contribution of the present dissertation. Additionally, one of the major challenges of incorporating digital accessibility into the QOL evaluation model is quantifying the digital accessibility cost, unlike the physical accessibility, which relies on the transportation network, and accessibility cost estimation methods have been developed by existing studies. Mostly, existing studies state that digital accessibility depends on at least three aspects: 1) the ownership of a digital device, 2) subscription to a network provider and its network coverage, and 3) digital literacy (the ability or knowledge to use digital devices and their functions, also called technology savviness). Quantifying these factors and incorporating them into the QOL evaluation model is another academic gap that needs to be addressed.

2.5. Novelty of Study

This thesis offers several novel contributions at the intersection of digital transformation, airport-integrated urban development, and urban simulation. Additionally, the thesis contributes to at least the 4 pillars of smart city: smart people (analyzing social network), smart living (developing QOL model), smart economy (developing QOB model), and smart mobility (integration of transport and ICT networks to QOL, QOB evaluation, and urban microsimulation model).

First, it provides the first empirical examination of behavioral substitutability and complementarity between physical and digital service access across diverse socio-demographic and social relationship groups using a large-scale nationwide questionnaire survey.

Second, the thesis proposes a new integrated accessibility index that unifies physical (transportation) and digital (ICT) access to services, offering a quantitative representation of real–virtual interaction mechanisms that have not been addressed in prior smart city research.

Third, it develops a social dynamics simulation (SDS) model that explicitly integrates real, virtual, and social networks, enabling dynamic representation of how digital accessibility, physical mobility, and social relationships jointly shape long-term urban and regional structures. This constitutes a methodological advancement beyond existing SDS and land-use–transport models, which consider only physical networks.

Fourth, it establishes the first comprehensive QOL and QOB evaluation framework grounded in integrated accessibility and tailored to the Air-front Smart City concept, thereby enabling simultaneous assessment of living and business environments at the regional scale.

Fifth, the developed integrated accessibility based QOL and QOB evaluation method serves as a base for regional evaluation models and regenerative economy models used to evaluate air-front smart cities. However, both topics, the regional evaluation model and regenerative economy, are out of the scope of this thesis.

Finally, by applying this integrated framework to policy scenarios in Aichi, Singapore, and Munich, the study generates new insights into how air-front smart city policies can jointly improve well-being and economic competitiveness, demonstrating the practical value of an evaluation approach that treats physical and digital networks as interconnected components of future Air-front Smart Cities.

Chapter 3

Substitutability and Complementarity of Physical Services with Digital Alternatives

This chapter investigates the substitutability and complementarity between physical and digital services using a nationwide Japanese web-based survey (n = 6,210). The chapter provides a systematic analysis of behavioral substitution ratios across six activity categories, revealing variations by age, gender, mobility resources, residential location, and social relationship types. Younger individuals show higher substitution tendencies, while older individuals rely more on physical networks. Cluster analysis identifies seven social relationship groups, demonstrating that online-oriented individuals adopt more digital alternatives, whereas community-oriented individuals maintain strong physical activity patterns. The chapter further examines residential relocation choices and shows that digital accessibility influences location choice primarily in urban areas. These findings offer fundamental behavioral insights necessary for understanding how real and virtual networks interact within Air-front Smart Cities. Some parts of this chapter are published in the Sustainability journal (Mutahari et al., 2025a; Mutahari et al., 2025b).

3.1. Introduction

The rapid integration of digital technologies into daily life, further accelerated by the COVID-19 pandemic, has significantly altered patterns of service access, mobility, and social interaction. While digital alternatives such as online shopping and teleworking have reduced the need for certain physical activities, existing evidence suggests that their impacts on urban structure, social networks, and residential behavior are complex and heterogeneous. Digital services often coexist with, rather than fully replace, physical services, raising important questions about their long-term implications for sustainable urban development.

Previous studies have examined ICT impacts on consumption behavior, travel demand, work patterns, and quality of life. However, most have analyzed these dimensions in isolation and have not jointly addressed how digital service substitution interacts with social networks and residential location choice to influence urban structure. In particular, the interconnected effects of individual characteristics, social relationships, and digital accessibility remain insufficiently understood.

To address this gap, this chapter aims to investigate how digital service substitution and social networks affect residential location choices and result in changes in urban structure. Specifically, the chapter examines: (1) the behavioral patterns of digital alternative usage across different socio-demographic categories, (2) how the adoption of digital service alternatives, such as online shopping, teleworking, etc., affects social interaction patterns, and (3) the factors influencing the intention to relocate, including the effects of substitutability and social networks. By analyzing these relationships, the study contributes to a deeper understanding of digital substitution policy implications for sustainable urban development. The findings of this chapter contribute to the developments in chapters 4 and 5 of this thesis.

The chapter, using factor and cluster analyses, explores the relationships between individual attributes, residential location, and social networks to understand the broader implications for urban sustainability. A web-based questionnaire survey was conducted to examine the substitutability of access to daily life services through ICT networks, considering relationships within social networks. The analysis focuses on how sociodemographic factors such as age, gender, and place of residence, as well as the strength of social networks, influence these behaviors through cross-tabulation, factor analysis, and cluster analysis, ultimately identifying the factors affecting residential location choice through binomial logistic regression analysis.

The overall objective of this chapter is to fill the academic gap, providing urban planners and policymakers with insight into digital service usage and contributing to sustainable urban development by proposing a tradeoff between physical and cyberspace service usage and supply. As stated in Chapter 2, it is believed that excessive usage of either will have negative impacts on social environments, well-being, and urban structure, and contribute to overall QOL reduction. To this end, the chapter comprehensively studies the individual's preferences and behaviors toward digital service adaptation and investigates the impacts on residential location choice. The result of this study suggests that urban structures will be affected by digital service substitution and urges urban planners and policymakers to carefully plan for future sustainable urban development through rules and regulations at the policy level; thus, access to physical services and digital services shall be traded off and balanced based on individual needs.

Figure 3.1 presents the conceptual framework of the interrelationship between digital service substitution, social networks, and urban structure. In this thesis, digital service substitution refers to the replacement of physical activities or services in the real network that rely on transportation systems, such as shopping, working, etc., with digital activities or services in the virtual network that rely on ICT, such as online shopping, teleworking, etc. As can be seen in Figure 3.1, individuals, based on their preferences and characteristics, will choose either a transportation network or an ICT network to reach a service. If the individual uses a transportation network to reach a service, that service is called a physical service. Whereas, if the individual uses an ICT network to reach a service, the service is called a digital service. The potential to replace physical services with digital services is called digital service substitutability. However, the term service access complementarity in this thesis refers to complementing or enhancing the physical service access by utilizing ICT, meaning that rather than substituting the physical accessibility with digital accessibility, the physical accessibility can be enhanced by using ICT, and jointly digital and physical service access can be used for smart city model developments and policy evaluations.

Silva et al. (2018) identifies six principal effects of digital activities on individual physical activities and travel: substitution, where a location-based activity is replaced by a tele-activity and travel is eliminated; complementarity, whereby virtual activities generate additional location-based activities; modification, in which virtual activities alter the timing, duration, or location of physical activities; neutrality, indicating no observable impact on location-based activities; activity fragmentation, referring to the division of activities into smaller components performed at different times and places enabled by continuous digital access; and multitasking, the concurrent performance of multiple activities within the same time period. However, in this thesis, the author investigates the substitution and complementarity effects of digital service access. Based on the findings, the thesis develops an urban microsimulation model in Chapter 4 and QOL and QOB evaluation models in Chapter 5 of this thesis. This chapter investigates the effects of this substitutability on social networks and residential relocation choice, which, as a result, affect the urban structure.

The remaining parts of this chapter are as follows: After the introduction, Section 3.2 provides an overview of the data acquisition process, analyzes the survey, and presents the survey results. Sections 3.3, 3.4, and 3.5 service choice behavior analysis detail the analysis methods, corresponding findings of a cross-tabulation analysis of behavioral substitution ratios, and human relationships affecting behavioral choices, respectively. Subsequently, Section 3.6 discloses the methodology and briefly discusses the residential relocation choice analysis. Section 3.7 discloses the main findings of this study, whereas Section 3.8 opens a discussion based on the findings. Finally, Section 3.9 offers conclusions and suggests directions for future research.

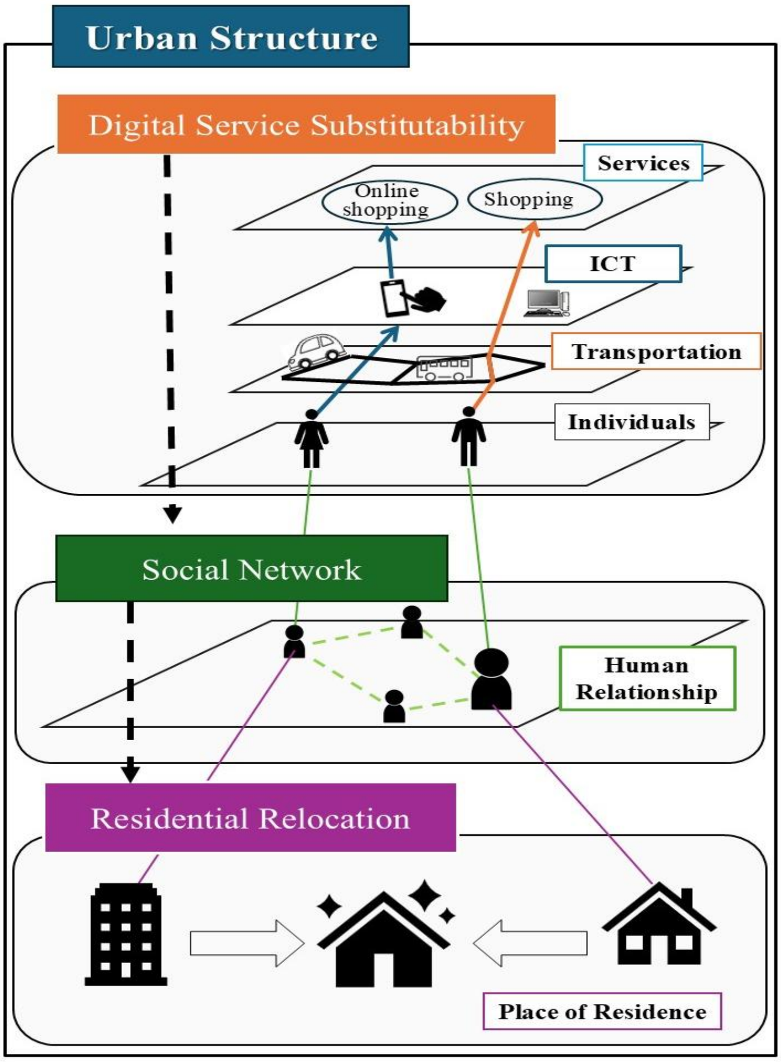


Figure 3.1. Interrelationship between digital service substitution, social networks, and urban structure. (Mutahari et al., 2025a)

3.2. Materials and Methods

3.2.1 Survey outlines

This chapter investigates the substitutability and complementarity of physical services with digital alternatives using a web-based questionnaire survey conducted all over Japan. The survey aims to gather information about people's preferences and behaviors while participating in activities and receiving services in both physical space and cyberspace. The web-based questionnaire survey by this study gathered information that is hard to obtain through other methods, such as how people access services through ICT networks and social networks, and how these factors affect their residential relocation choice. The ability to reach a wide range of respondents and collect reliable data efficiently across a large area are the main reasons that the author used a web-based questionnaire survey in this thesis. The survey was conducted on 24 and 25 November 2023, and 6,210 valid responses were received. The survey questions were divided into five main sections: personal characteristics, life behaviors, service access, use of information network services, social connections, and relocation choices.

The first section collected demographic information to understand how household characteristics affect access to both physical services and digital services. In this thesis, the author considered 5 basic daily life activities or services, such as shopping, dining, working, schooling, and healthcare visits, as shown in Figure 3.2. Dining refers to eating outside, such as in restaurants, where individuals use an actual mode of transportation, either walking, cycling, a private car, or public transport, to reach the facility and receive the services. Whereas food delivery refers to ordering food from a restaurant and eating at a place of residence, where individuals use a mode of ICT to reach the virtual facility and receive the service. Food delivery is a digital alternative to dining in a restaurant. Similarly, online shopping, teleworking, e-learning, and e-medical consultation are digital alternatives for in-store shopping, in-office working, in-school learning, and in-hospital treatment, respectively.

These activities can be performed in physical space and cyberspace, and the author named them physical activities and digital alternatives, respectively. Physical activities rely on transportation systems to reach the facilities or venues to perform the activity. For instance, to shop, eat outside, work, study, and visit a hospital, someone may use an actual mode of transportation to go to designated places to perform the activities. On the other hand, to perform activities in cyberspace (digital alternatives), people may use ICT to reach the virtual venue of activities to perform the activities, and will not use the actual transportation systems. The thesis defines digital alternatives as an alternative to physical activities that use ICT rather than the transportation system. The second section of the questionnaire survey provided us with information on how frequently individuals perform physical activities or digital alternatives.

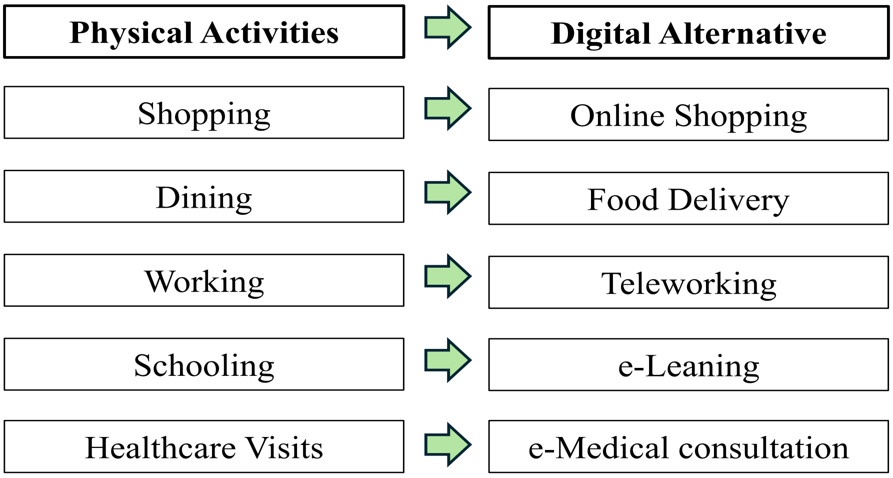


Figure 3.2. Physical activities and their digital alternatives. (Mutahari et al., 2025a)

Additionally, the third section of the survey provided us with information on how people use digital platforms and what might prevent them from using these services. The social connections section of the survey asked about satisfaction with personal relationships, comparing in-person and online interactions to see how virtual engagement affects social relationships. Lastly, the survey investigated how access to both physical and digital services influences people's decisions regarding residential relocation, along with the obstacles they may encounter in making such decisions. The survey could provide us with this information to study the substitutability of the services from physical to digital alternatives. Table 3.1 represents an overview of the questionnaire survey.

Table 3.1. Web-based questionnaire survey summary. (Mutahari et al., 2025b)

Items	Contents	
Target area	All 7 regions of Japan (Hokkaido, Tohoku, Kanto, Chubu, Kansai, Chugoku-Shikoku, Kyushu)	
Date	November 24 to November 26, 2023	
Number of samples	6,210 responses	
Survey data category	1. Basic personal attributes	
	2. Daily life activities	2.1 Shopping activities
		2.2 Dining activities
		2.3 Working activities
		2.4 Schooling activities
		2.5 Hospital visit activities
		2.6 Entertainment activities
	3. Virtual network usage	
	4. Social network (Interaction with other people)	
	5. Residential location choice	

The questionnaire survey was segmented and evenly distributed based on gender, age, and place of residence, based on the population distribution characteristics, as shown in Figure 3.3. This balanced distribution was carefully considered to improve the quality and reliability of the survey results and remove biases. Although the author carefully looked into removing potential biases through survey segmentation, there might have been some bias within the elderly (70s and older) age group, who may not have been capable of using smart devices to answer the online questionnaire survey. However, this bias was insignificant in this study. As one of the objectives of this thesis, the author discusses the future urban structure, where younger individuals are the target, who have the capability to use smart devices and receive digital services. Therefore, the potential bias with elderly responses cannot be considered a limitation of this study.

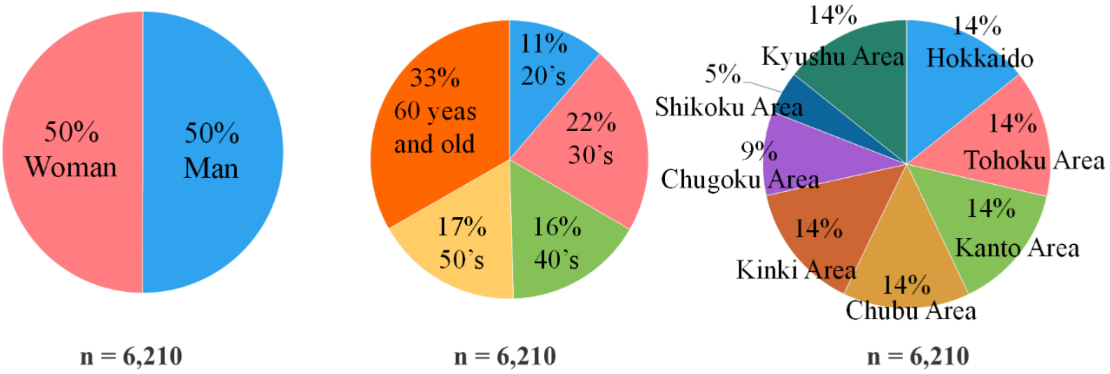


Figure 3.3. Demographic distribution of survey respondents by gender, age, and place of residence. (Mutahari et al., 2025a)

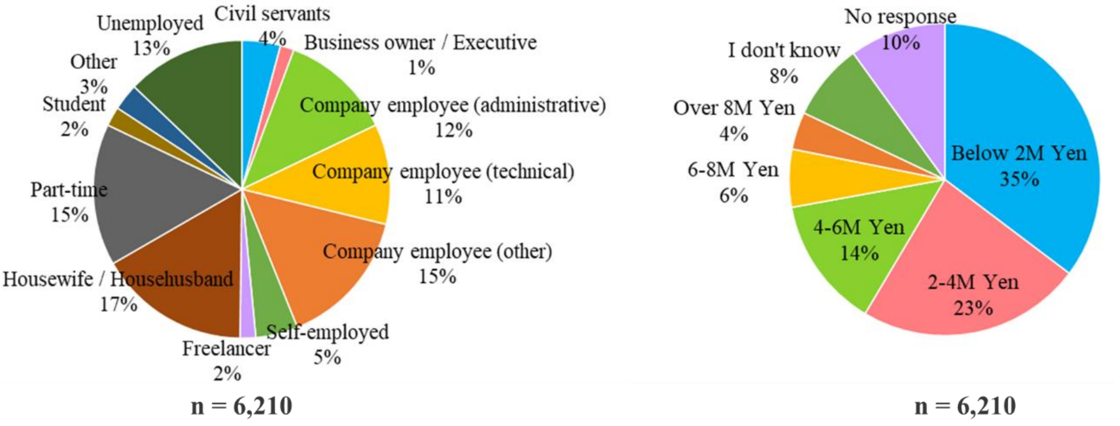


Figure 3.4. Demographic distribution of survey respondents by employment type and income. (Mutahari et al., 2025a)

Although the author has gathered information about individuals' income and employment type, as shown in Figure 3.4, the thesis has not used these variables in its analysis. The focus of the thesis is to consider major socio-demographic variables such as age, gender, and place of residence.

3.2.2. Substitutability analysis

This section presents a comprehensive analysis of average substitutability between physical activities and their digital alternatives across various daily life activities using the web-based questionnaire survey data. To evaluate the substitutability of physical activities with their digital alternatives, the thesis analyzes the primary activities: "shopping," "dining," "working," "schooling," "hospital visits," and "entertainment." The goal of this analysis was to determine how frequently people engage in these activities in the real network compared to their virtual counterparts to assess the substitutability of certain activities.

The " average substitution ratio" is calculated by comparing how often individuals engage in real activities and their digital counterparts. Figure 3.5 illustrates the average substitution across the five activity categories and their error bar based on the survey results. Survey results disclose clear variations in substitutability. Shopping and schooling exhibited significantly higher levels of substitution ratios up to 16% and 14%, respectively. Whereas, working and hospital visits exhibit the lowest levels of substitution, with only about 5% of participants frequently opting for digital alternatives. This low substitution rate is likely due to the inherent nature of these activities, which often require physical presence (e.g., attending medical appointments or physically being present at work).

Additionally, the analysis revealed that young adults are more likely to substitute physical shopping and dining with digital alternatives, driven by factors such as convenience and increased familiarity with e-commerce. Interestingly, the gender gap in substitution behavior was witnessed to widen with age, with older men showing a higher tendency to shift to digital alternatives compared to women. Men consistently exhibit higher substitution rates for dining, such as food delivery, while elderly individuals still prefer in-person dining at restaurants due to the social aspects of the experience. This study confirms that age and gender play significant roles in determining the likelihood of replacing physical activities with digital alternatives. In healthcare, younger men in their 20s are the most likely to adopt virtual consultations such as e-medical treatment, while older adults, who require more complex medical care, are less inclined to substitute hospital visits with online services. Interestingly, it was witnessed that entertainment behaviors, such as playing games and watching movies, have a higher digital substitution rate, while e-tourism remains less common, reflecting the need for physical presence in travel experiences, as shown in Figure 3.5, while healthcare visits and working remain resistant to substitution, activities like shopping, schooling, and entertainment show higher flexibility for digital alternatives.

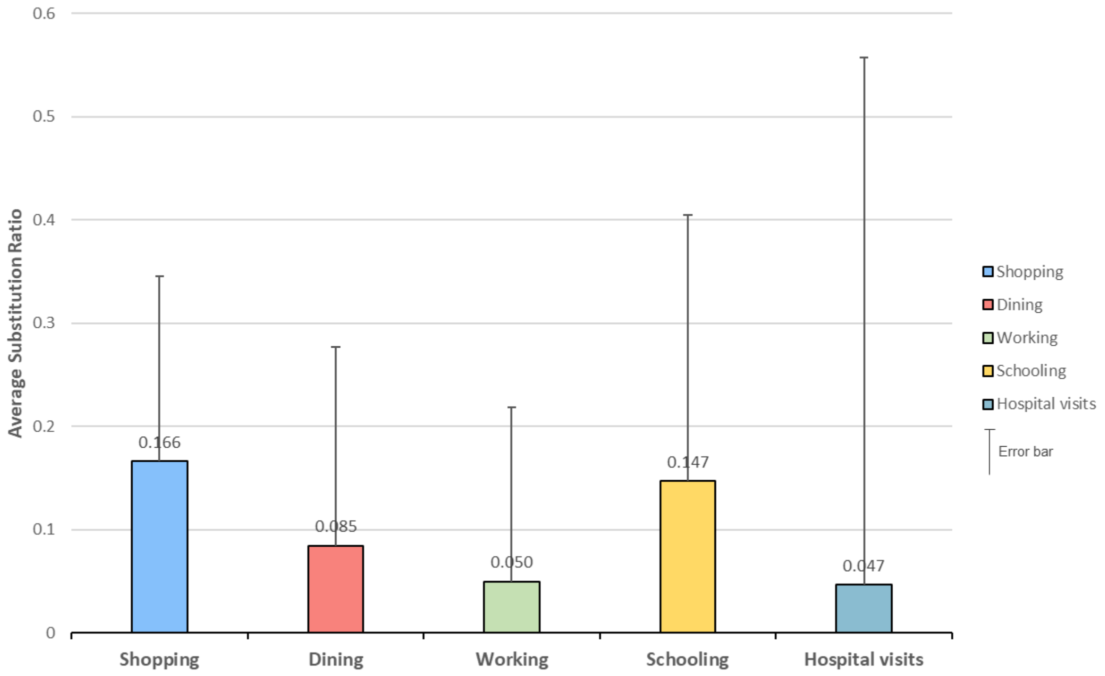


Figure 3.5. Average substitution of shopping, dining, working, schooling, and hospital visits. (Mutahari et al., 2025b)

Figure 3.6 shows the average substitution of entertainment activities by digital alternatives and their error bar. Games exhibit the highest average substitution ratio (0.719), indicating that gaming activities are largely transferable to digital alternatives. Movies also display a relatively high substitution ratio (0.619), suggesting substantial acceptance of online or digital viewing options such as YouTube, Netflix, etc. In contrast, concerts show a much lower substitution ratio (0.280), reflecting the continued importance of physical presence and live social interaction. Tourism has the lowest substitution ratio (0.056), implying that it is minimally substitutable by digital services and remains strongly dependent on physical mobility and place-based experiences.

These findings suggest significant variability in substitutability across different behaviors and demographic groups. These insights offer guidance for urban planners to design flexible systems that integrate both real and virtual networks, create sustainable urban systems that enhance individual QOL, and support global sustainability and De-Co2 goals by optimizing both physical and digital infrastructure.

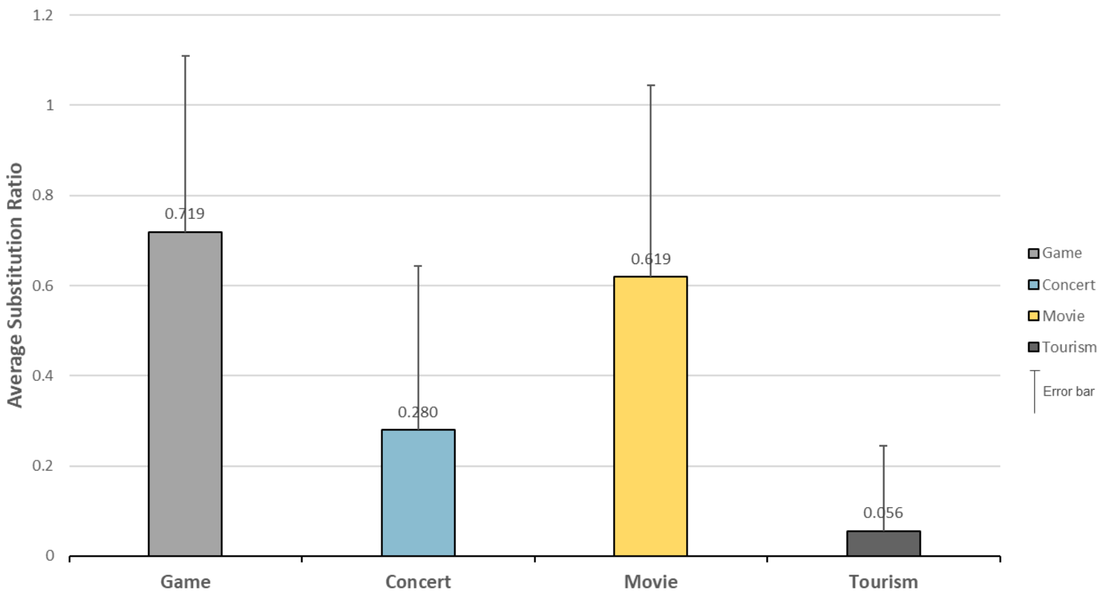
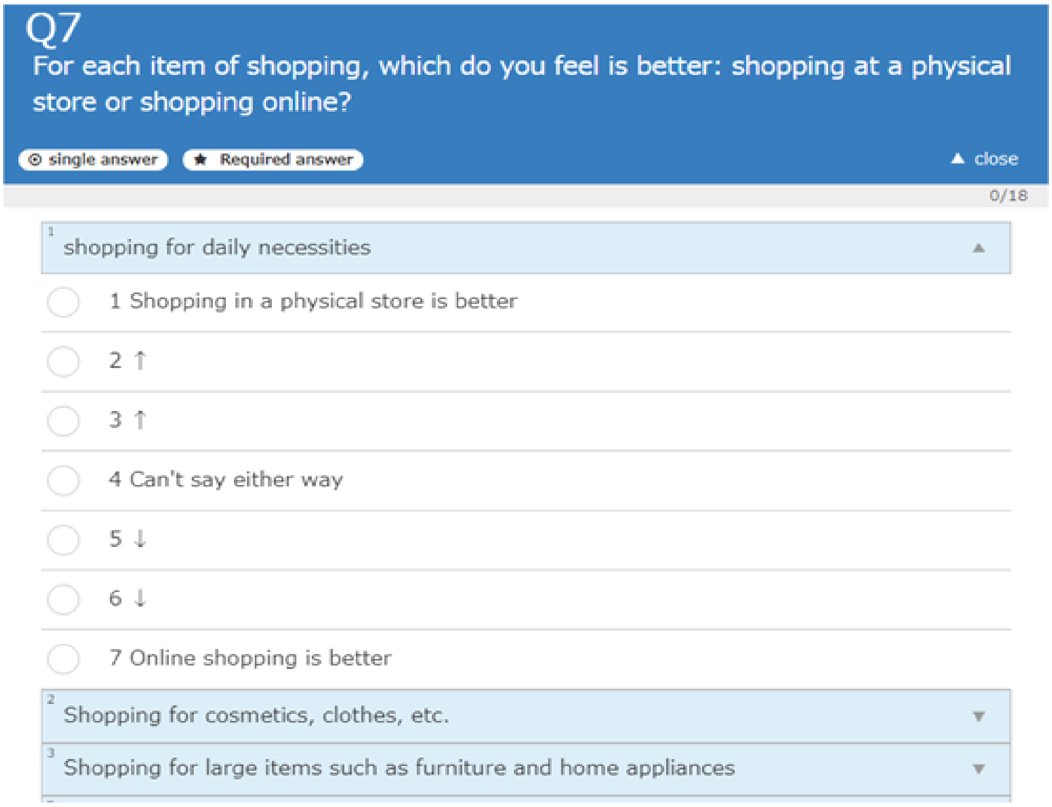


Figure 3.6. Average substitution ratio of entertainment. (Mutahari et al., 2025b)

3.2.3. Service value evaluation

The survey analysis results provided insightful findings about the substitutability of several activities from physical space to virtual space. However, the value of activities and services is different in both spaces. For instance, comparing online shopping with physical store shopping, physical store shopping will give an opportunity to closely inspect the products before purchasing, whereas a similar opportunity is limited in the case of online shopping. On the other hand, online shopping might be convenient due to relying on ICT networks or might be preferred by individuals due to contributing to the De-CO2 efforts. Considering these factors, this study evaluates the value of the activities or services in real and virtual networks based on the stated preference of individuals using the web-based questionnaire survey conducted in Japan. The study conceptualized a method to evaluate the value of the services by asking individuals to express their preferences over physical and digital alternative activities, considering several items dedicated to each activity by answering single-choice 7-point Likert scale questions, as shown in Figure 3.7.



Q7

For each item of shopping, which do you feel is better: shopping at a physical store or shopping online?

1 shopping for daily necessities ▲

○ 1 Shopping in a physical store is better

○ 2 ↑

○ 3 ↑

○ 4 Can't say either way

○ 5 ↓

○ 6 ↓

○ 7 Online shopping is better

2 Shopping for cosmetics, clothes, etc. ▼

3 Shopping for large items such as furniture and home appliances ▼

Figure 3.7. Shopping service-related survey question. (Mutahari et al., 2025b)

The respondents were asked if services offered in physical space are better, or if services offered in cyberspace are better, considering several items such as travel time, cost, stress, quality, convenience, etc. For instance, as shown in Figure 3.7, respondents were asked “For each item of shopping, which do you feel is better: shopping at a physical store or shopping online?” where several shopping considerations were listed such as shopping for daily necessities, shopping for cosmetics, shopping for large items, cost other than shopping, shopping time, travel stress, etc. Subsequently, to numerically calculate the value of physical and digital alternative services based on each service item, numbers 1 to 7 are assigned to -3 to 3 as shown in Figure 3.8. This analysis provides insightful data to be used for SDS model improvements in Chapter 4 of this thesis and QOL-QOB model developments in Chapter 5 of this thesis.

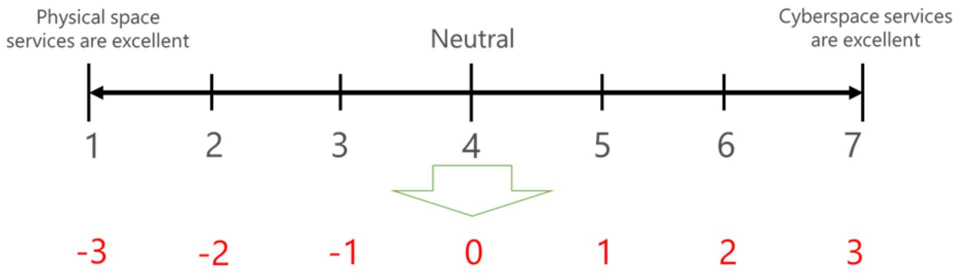


Figure 3.8. Service value estimation for a physical and digital alternative. (Mutahari et al., 2025b)

3.3. Service Choice Behavior Analysis

3.3.1. Physical services and digital alternatives value analysis

Using the data gathered from the web-based questionnaire survey, this chapter further explored the value of services provided in physical space and virtual space based on the preferences of individuals, considering several evaluation items. To evaluate the service values and analyze factors affecting the service value and preference of individuals, respondents were asked questions regarding their preference for physical and digital services, considering several items. Subsequently, the responses for each activity and service are aggregated and analyzed to understand the service choice behavior of individuals through real and virtual networks. The analysis in this section is carried out to analyze the service choice behavior of individuals and investigate major factors influencing people to substitute their activities from real networks to virtual networks.

Shopping

Figure 3.9 illustrates the result of the survey analysis for physical and online shopping services, and it is found that online shopping is preferred by individuals considering accessibility-related evaluation items such as shopping time, travel stress, location restrictions, and time constraints. In contrast, physical shopping is weighted higher in the case of non-accessibility-related evaluation items such as the type of shopping items, service satisfaction and convenience, and social interactions. The result confirms that accessibility-related factors can be the potential drivers of the substitution of physical services for digital alternatives in the case of shopping.

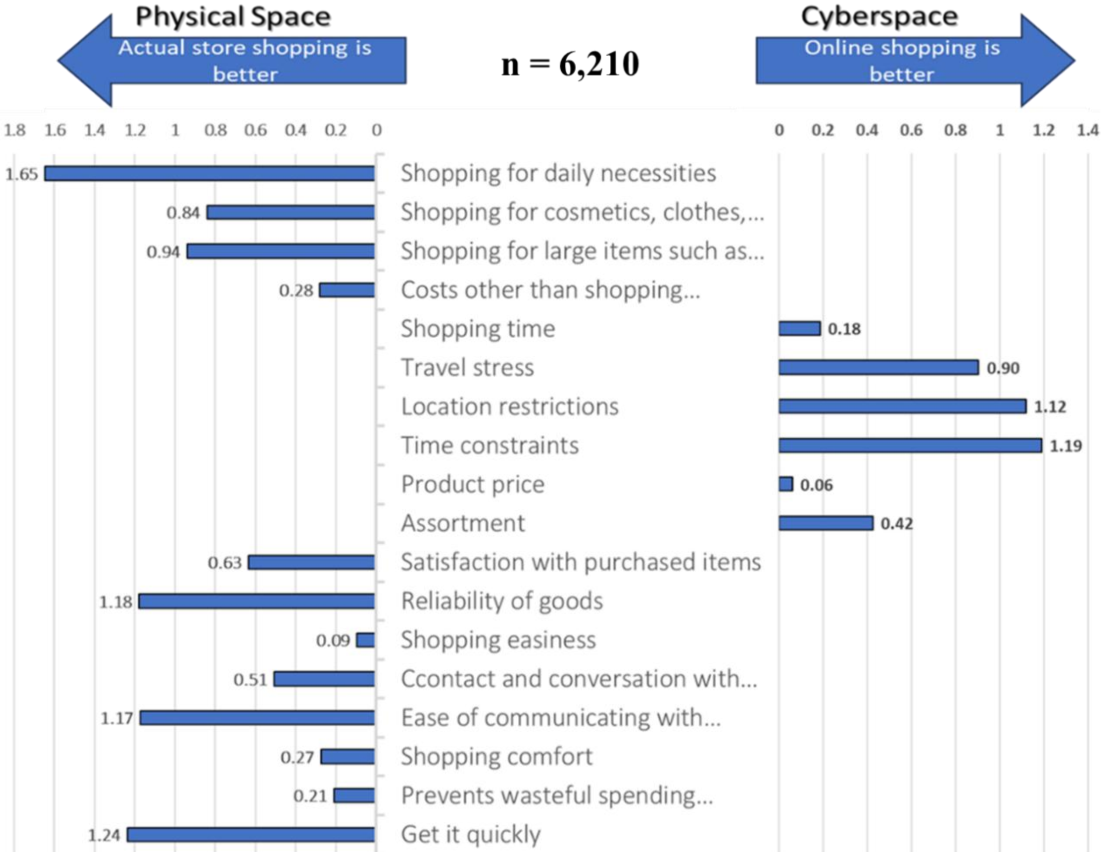


Figure 3.9. Individual's physical (in-store) shopping service and digital alternative (online shopping) preferences. (Mutahari et al., 2025b)

Dining

Individuals were asked if they feel physical (in-restaurant) dining is better or if online food delivery is better, considering several evaluation items. Physical (in-restaurant) dining refers to dining activities performed outside of the home. As shown in Figure 3.10, the survey results disclose that, similar to shopping, online food delivery is preferred considering accessibility-related items such as travel time, travel stress, location, and time constraints. Whereas dining in actual restaurants is preferred, considering the non-related accessibility items such as costs, quality, reliability, convenience, and social interactions. The result confirms that, similar to shopping, the digital alternative substitution is highly influenced by accessibility-related factors in the case of dining.

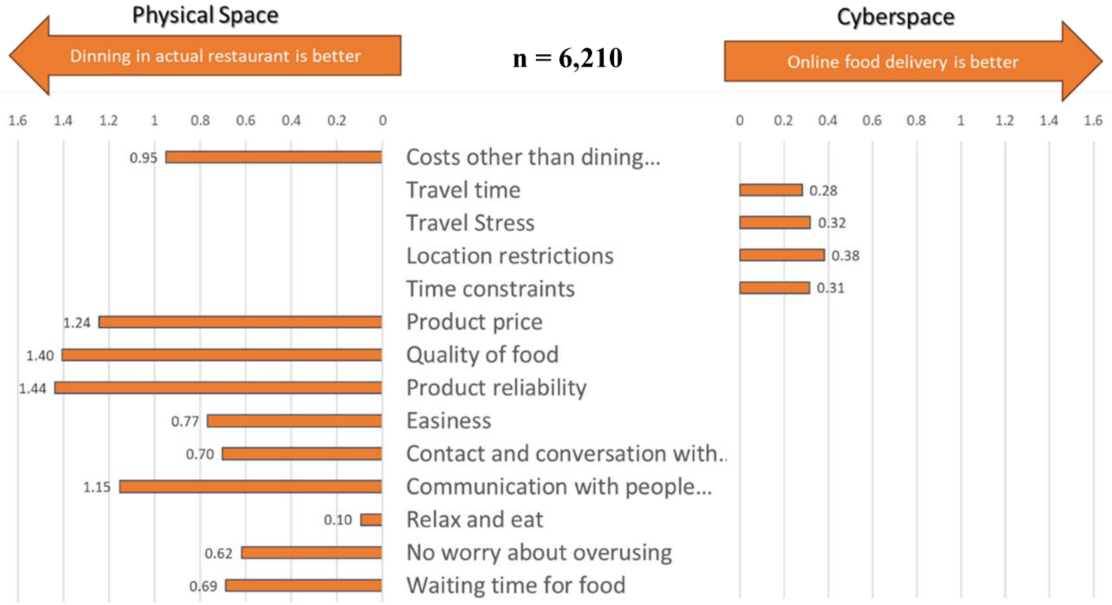


Figure 3.10. Individual’s physical (in-restaurant) dining service and digital alternative (food delivery) preferences. (Mutahari et al., 2025b)

Working

Through the web-based questionnaire survey, individuals were asked if they feel physical (in-office) working is better or if telework is better, considering several evaluation items. The results disclosed that teleworking is weighted higher by varying degrees, considering the accessibility-related items as shown in Figure 3.11. Whereas physical (in-office) working is weighted higher considering non-accessibility-related factors such as working while commuting, work productivity, self-management, and social interactions.

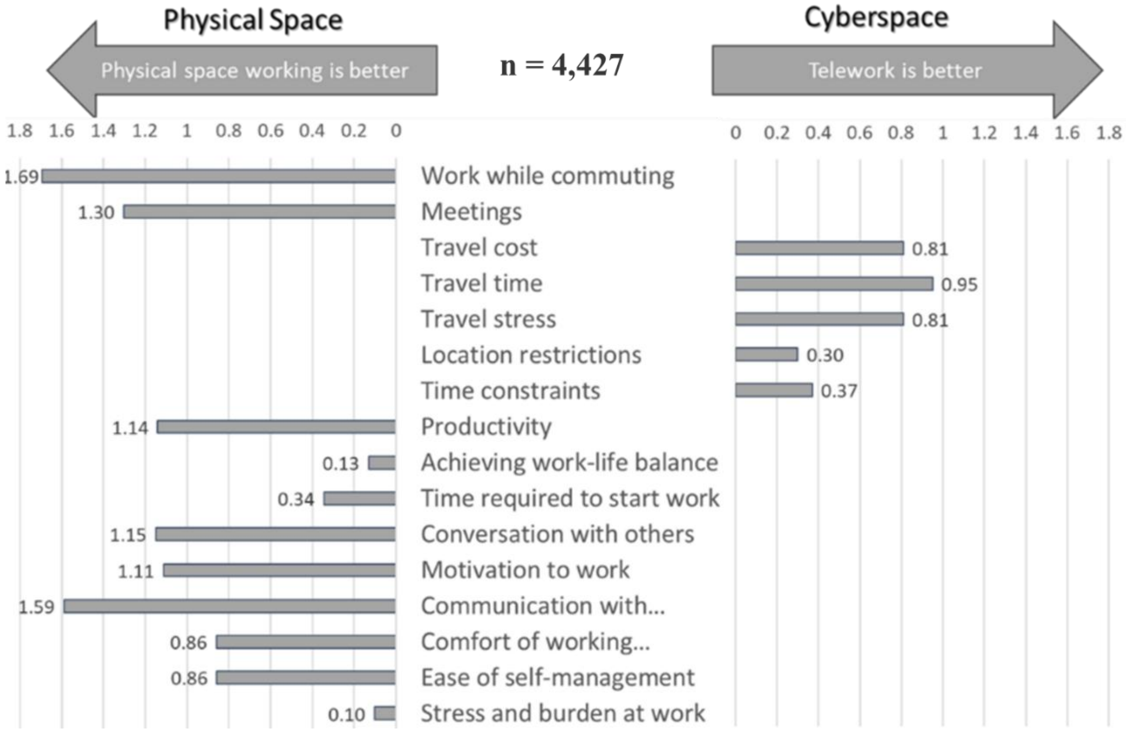


Figure 3.11. Individual’s physical (in-office) working service and digital alternative (telework) preferences. (Mutahari et al., 2025b)

Schooling

Through the web-based questionnaire survey, individuals were asked if they feel physical (in-school) learning is better or if e-learning is better, considering several evaluation items. Similar to shopping, dining, and working, the results disclosed that respondents prefer e-learning considering the accessibility-related items, but physical learning value is weighted higher considering social interaction in the school, learning effectiveness, satisfaction with tuition fees, motivation, self-management, and convenience, as shown in Figure 3.12. The result discloses that accessibility-related factors can be a potential driver for digital alternative substitution in the case of schooling as well.

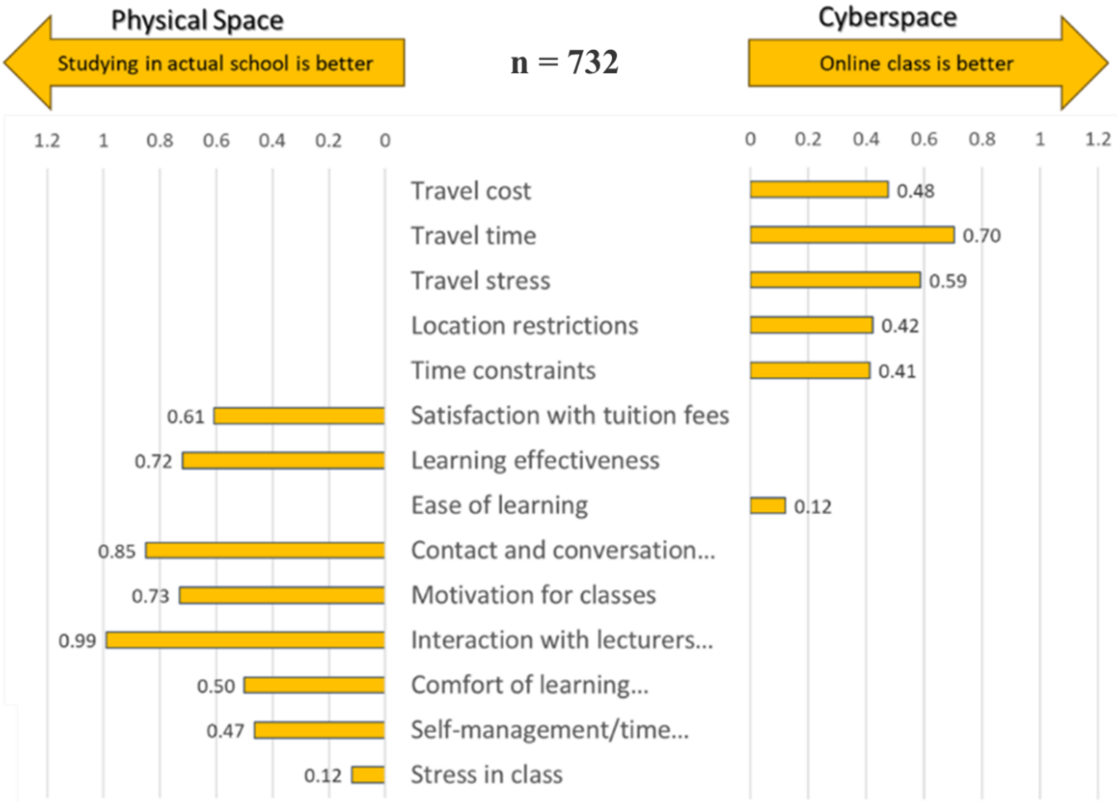


Figure 3.12. Individual’s physical (in-school) learning service and digital alternative (e-learning) preferences. (Mutahari et al., 2025b)

Hospital Visit

Through the web-based questionnaire survey, individuals were asked if they feel physical (in-hospital) treatment is better or if online treatment is better, considering several evaluation items to evaluate the value of the services and factors affecting it. The result discloses that, in addition to accessibility-related factors, avoiding contact with others and waiting time are the other factors that weigh more heavily on the online treatment, as shown in Figure 3.13. In contrast, service quality, social communication, treatment price, and convenience are factors influencing individuals to prefer physical (in-hospital) treatment.

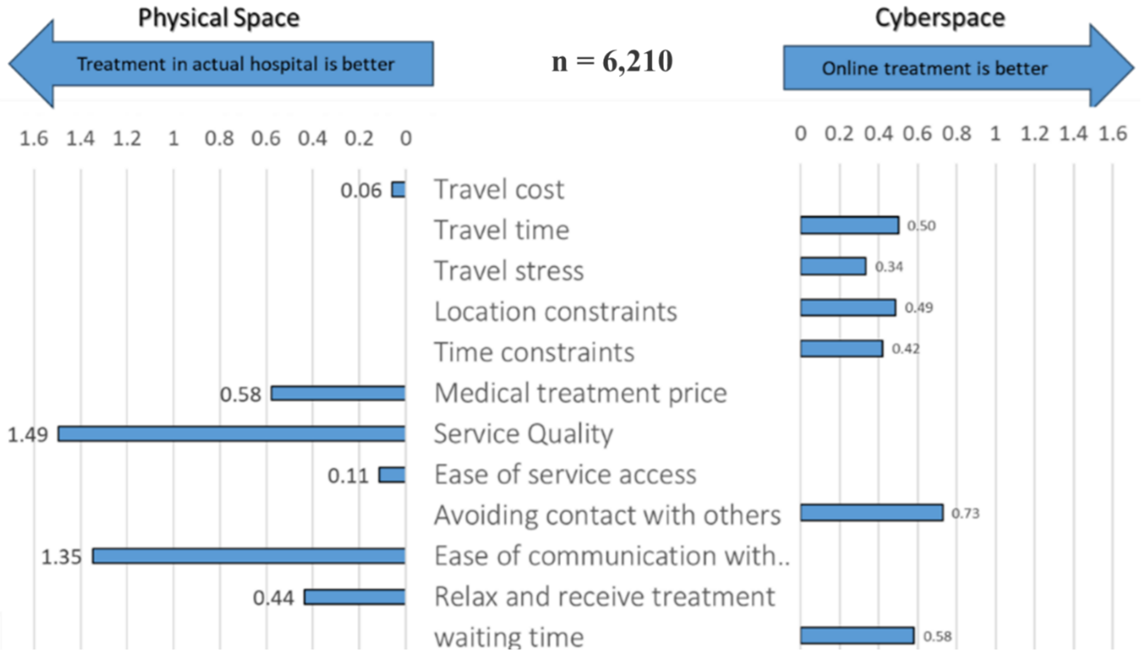


Figure 3.13. Individual's physical (in-hospital) treatment service and digital alternative (online treatment) preferences. (Mutahari et al., 2025b)

Tourism

Through the web-based questionnaire survey, individuals were asked if they feel physical (in-spot) tourism is better or if e-tourism (virtual tours) is better, considering several evaluation items to evaluate the value of the services and factors affecting it. It was found that, similar to hospital visits, the individuals prefer e-tourism because of accessibility-related items, avoiding contact with others, and ease of service access, as shown in Figure 14. In contrast, the preference of individuals towards physical hospital visits was strongly influenced by service quality and social interaction items. The result confirms that accessibility-related factors, in addition to avoiding contact with others, positively affect the substitutability of actual tourism for a digital alternative, whereas the strong reluctant factors are service quality and social communication.

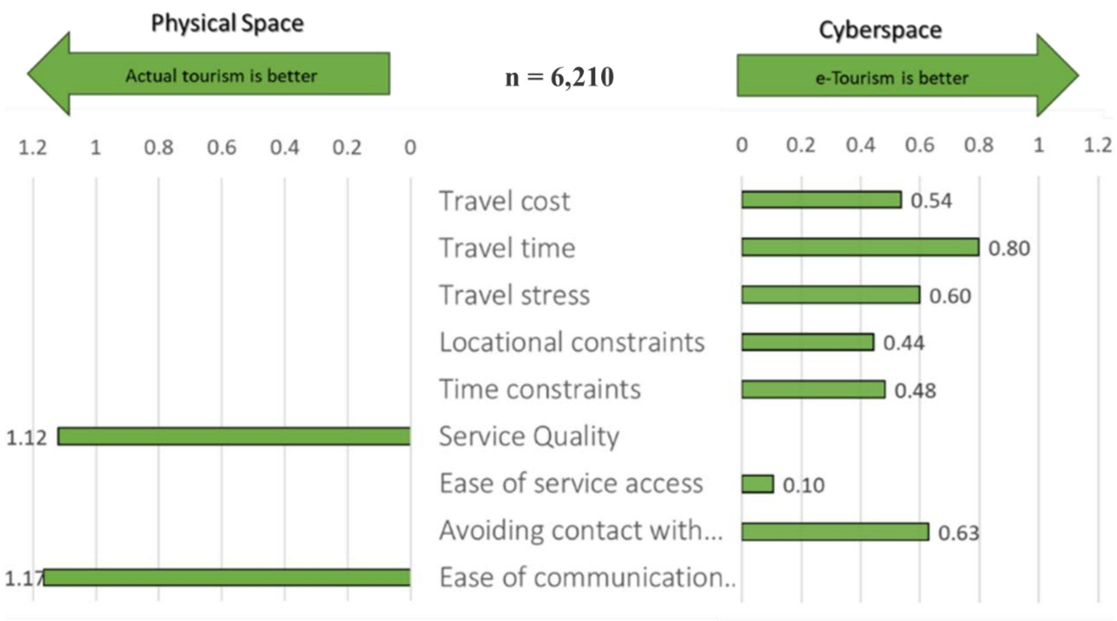


Figure 3.14. Individual's physical (in-spot) tourism service and digital alternative (e-tourism) preferences. (Mutahari et al., 2025b)

3.3.2 Socio-economic and demographic factors affecting substitutability

This section investigates the factors affecting substitutability (preference of individuals for physical services or their digital counterparts) of the six primary services (shopping, dining, working, schooling, treatment, and watching movies) with their digital counterparts, as shown in Table 3.2. The study conducted Multiple Linear Regression (MLR) Analysis, where the substitution rate for services is kept as a dependent variable, while the age, sex, driving license, household income, and employment status are kept as independent variables. For the dummy variables, the coding was set as follows: Gender (0 = Male, 1 = Female), Driver's License (0 = No, 1 = Yes), and Employment Status (0 = Unemployed, 1 = Employed). Accordingly, the regression coefficients represent the change in the substitution rate relative to the reference (0) category.

Factors affecting the substitutability of shopping

Table 3.2 presents the results of the multiple linear regression (MLR) analysis examining the factors influencing the shopping substitution ratio, which indicates the extent to which individuals replace in-person shopping with online shopping (digital alternative). The results show that age, gender, and employment status have significant effects on substitution behavior.

The coefficient for age is negative and highly significant ($\beta = -0.00167$, $p < 0.001$), demonstrating that younger individuals are substantially more likely to substitute traditional shopping with digital alternatives, while older respondents tend to maintain physical shopping behavior. Similarly, gender is highly significant and negative ($\beta = -0.0208$, $p < 0.001$), suggesting that female respondents engage less frequently in online shopping substitution compared with males. This difference may reflect variations in product preferences, digital purchasing confidence, or risk perception between genders.

Employment status also exhibits a significant negative relationship ($\beta = -0.0191$, $p = 0.007$), indicating that those in stable employment positions are less likely to shift to online shopping, possibly due to habitual purchasing routines. Conversely, driving license ownership and household income do not significantly influence shopping substitution, implying that digital purchasing behavior is shaped more by socio-demographic and lifestyle factors than by mobility or income levels.

Overall, these findings highlight that the digital substitution of shopping activities is most prominent among younger, male, and more flexible workers, reflecting the influence of the elderly`s digital literacy and differing lifestyle patterns of men and women in the transition toward virtual shopping environments.

Table 3.2. Results of MLR analysis on factors affecting the shopping substitution ratio. (Mutahari et al., 2025b)

Variables	Coefficient (β)	Std. Error	t value	p value
Age	-0.00167	0.00016	-10.17538	0.0000 ***
Gender (F)	-0.02079	0.00505	-4.11514	0.0000 ***
Driving license (Y)	-0.00561	0.00767	-0.73158	0.464
Household income	0.00054	0.00089	0.60618	0.544
Employment status (Emp.)	-0.01910	0.00711	-2.68561	0.0072 **

Note: *** indicates highly significant ($p<0.001$), and ** indicates moderately significant ($0.001 \leq p < 0.01$)

Factors affecting the substitutability of dining

Table 3.3 presents the results of the MLR analysis examining factors affecting the dining substitution ratio, which measures the tendency to replace dining out with digital alternative options (food delivery). The analysis indicates that age, driving license, and employment status significantly and moderately influence dining substitution behavior, respectively. Specifically, age has a negative coefficient ($\beta = -0.00147$, $p < 0.001$), suggesting that older individuals are less likely to substitute dining out with alternatives. This could be because of elderly put a higher importance on face-to-face communication (social interaction) or lack of digital literacy (inability to use digital devices to reach virtual services).

Similarly, having a driving license ($\beta = -0.03503$, $p < 0.001$) is associated with a lower substitution ratio, indicating that individuals with easier access to transportation are more likely to continue dining out. Employment status (β = -0.02246, p = 0.012) also shows a negative effect, meaning that employed individuals tend to have a lower dining substitution ratio than unemployed individuals. In contrast, gender (β = 0.00210, p = 0.722) and household income (β = 0.00116, p = 0.281) do not have statistically significant effects on dining substitution. Overall, the findings suggest that age, employment, and driving ability play a more substantial role in influencing dining substitution behavior than gender or income.

Table 3.3. Results of MLR analysis on factors affecting the dining substitution ratio. (Mutahari et al., 2025b)

Variables	Coefficient (β)	Std. Error	t value	p value
Age	-0.00147	0.00019	-7.66351	0.0000 ***
Gender (F)	0.00210	0.00590	0.35553	0.722
Driving license (Y)	-0.03503	0.00977	-3.58690	0.0003 ***
Household income	0.00116	0.00107	1.07925	0.281
Employment status (Emp.)	-0.02246	0.00891	-2.52009	0.011 *

Note: *** indicates highly significant ($p<0.001$), ** indicates moderately significant ($0.001 \leqslant p < 0.01$), and * indicates marginally significant ($0.01 \leqslant p < 0.05$).

Factors affecting the substitutability of working

Table 3.4 presents the results of the MLR analysis examining the factors influencing the working substitution ratio, which represents the degree to which individuals substitute physical work activities with virtual work (reaching the work using virtual accessibility). The results show that gender, household income, and employment status have statistically highly and marginally significant effects on the working digital substitution ratio, respectively. Specifically, the coefficient for gender is negative and highly significant (β = –0.027, p < 0.001), indicating that female respondents tend to have a lower working substitution ratio compared to males. This is consistent with an existing study (Silva et al., 2018), which suggests women are performing less telework than men due to a lower degree of virtual accessibility.

Household income exhibits a positive and significant relationship (β = 0.0026, p = 0.019), suggesting that higher-income groups are more likely to engage in telework. Employment status also shows a negative but marginally significant effect (β = –0.033, p = 0.046), implying that those in more stable or traditional employment arrangements are less likely to substitute physical work with digital alternatives. Age (p = 0.052) and possession of a driving license(p = 0.270) do not significantly influence substitution behavior.

Table 3.4. Results of MLR analysis on factors affecting the working substitution ratio. (Mutahari et al., 2025b)

Variables	Coefficient (β)	Std. Error	t value	p value
Age	0.00042	0.00021	1.94386	0.052
Gender (F)	-0.02712	0.00596	-4.55016	0.0000 ***
Driving license (Y)	-0.01240	0.01124	-1.10304	0.270
Household income	0.00262	0.00113	2.33005	0.019 *
Employment status (Emp.)	-0.03323	0.01660	-2.00104	0.045 *

Note: *** indicates highly significant ($p<0.001$), and * indicates marginally significant ($0.01 \leqslant p < 0.05$).

Overall, these findings suggest that digital substitution in working activities is more prevalent among higher-income and male respondents, while employment status still limits the diffusion of teleworking. This highlights the socio-economic heterogeneity in the transition toward hybrid and digital work styles.

Factors affecting the substitutability of hospital visits

Table 3.5 presents the results of the MLR analysis examining the factors influencing the hospital visit substitution ratio, which reflects the extent to which individuals replace in-person medical consultations with online or telemedicine alternatives. The results indicate that age and gender are the primary determinants of substitution behavior for healthcare services, while other socio-economic variables such as income, employment status, and driving license ownership show no statistically significant effects.

The coefficient for age is negative and highly significant ($\beta = -0.00069$, $p < 0.001$), suggesting that younger individuals are more likely to use digital healthcare services, whereas older respondents remain strongly dependent on traditional, face-to-face consultations. This result is consistent with the known digital divide in health technology adoption, where older populations face greater barriers related to digital literacy, virtual accessibility, and trust in remote medical systems. Similarly, gender shows a significant negative association ($\beta = -0.0110$, $p < 0.001$), indicating that female respondents are less likely than males to substitute physical hospital visits with telemedicine options. This may reflect greater risk aversion or a stronger preference for direct, interpersonal care interactions among women.

The lack of significant effects for income, employment status, and driving license ownership suggests that the choice between physical and online medical consultations is driven more by personal and demographic factors, such as age and gender, than by economic or mobility constraints. Overall, these findings underscore that digital healthcare substitution remains limited among older and female populations, highlighting the need for inclusive e-health policies that promote accessibility, trust, and literacy in telemedicine platforms to reduce disparities in healthcare access.

Table 3.5. Results of MLR analysis on factors affecting the hospital visits substitution ratio. (Mutahari et al., 2025b)

Variables	**Coefficient (β)**	**Std. Error**	**t value**	**p value**
Age	-0.00069	0.00010	-6.95573	0.0000 ***
Gender (F)	-0.01101	0.00309	-3.56915	0.0003 ***
Driving license (Y)	-0.00386	0.00459	-0.84021	0.401
Household income	-0.00011	0.00055	-0.20067	0.841
Employment status (Emp.)	-0.00353	0.00411	-0.85956	0.39

Note: *** indicates highly significant ($p<0.001$)

Factors affecting the substitutability of schooling

Table 3.6 presents the results of the MLR analysis examining the factors influencing the schooling substitution ratio, which represents the extent to which individuals or households replace physical, in-person education with online or remote learning alternatives. The analysis shows that none of the examined socio-economic or demographic variables, age, gender, driving license ownership, household income, or employment status, have statistically significant effects on the schooling substitution ratio ($p > 0.05$ for all variables).

Table 3.6. Results of MLR analysis on factors affecting the schooling substitution ratio. (Mutahari et al., 2025b)

Variables	**Coefficient (β)**	**Std. Error**	**t value**	**p value**
Age	-0.00002	0.00131	-0.01201	0.99
Gender (F)	-0.00772	0.03299	-0.23389	0.815
Driving license (Y)	0.02429	0.04860	0.49974	0.618
Household income	-0.00083	0.00531	-0.15591	0.876
Employment status (Emp.)	0.04528	0.04148	1.09158	0.276

Factors affecting the substitutability of watching movies

Table 3.7 summarizes the results of the MLR analysis examining the factors influencing the watching-movie substitution ratio, which represents the degree to which individuals replace cinema visits with online viewing (Netflix, Disney+, etc). The analysis reveals that age and household income are the most influential variables, both showing statistically significant negative relationships with the substitution ratio.

The coefficient for age is negative and highly significant ($\beta = –0.00235$, $p < 0.001$), indicating that younger respondents are considerably more likely to substitute physical cinema experiences with online streaming or digital platforms, while older individuals tend to maintain traditional in-person viewing habits. Similarly, household income displays a negative and moderately significant effect ($\beta = –0.0093$, $p = 0.009$), suggesting that individuals with higher incomes are less likely to prefer digital substitutes, possibly because they can more easily afford the cost and leisure associated with physical movie outings.

Other variables, including gender, driving license possession, and employment status, show no statistically significant relationships ($p > 0.05$), implying that these factors do not substantially influence the choice between online and in-person movie watching.

Overall, these results highlight that digital substitution for entertainment activities such as movie watching is driven primarily by age and income differences; younger and lower-income groups are leading the shift toward digital platforms, reflecting generational preferences, cost sensitivity, and differing lifestyle patterns within the ongoing digital transformation of leisure behavior.

Table 3.7 Results of MLR analysis on factors affecting the watching movie substitution ratio. (Mutahari et al., 2025b)

Variables	Coefficient (β)	Std. Error	t value	p value
Age	-0.00235	0.00062	-3.80557	0.0001 ***
Gender (F)	-0.01618	0.01976	-0.81868	0.413
Driving license (Y)	-0.02434	0.03216	-0.75680	0.449
Household income	-0.00931	0.00356	-2.61489	0.009 **
Employment status (Emp.)	0.02595	0.02809	0.92405	0.356

Note: *** indicates highly significant ($p<0.001$), and ** indicates moderately significant ($0.001 \leqslant p < 0.01$)

3.3.3. Findings and discussion

Building on the regression results, the findings indicate that socio-economic and demographic factors, particularly age, gender, income, and employment status, play a critical role in shaping individuals' adoption of digital alternatives across service types. Younger, higher-income, and more flexible workers tend to substitute physical services with virtual ones more readily, while elderly and traditionally employed individuals remain more reliant on physical services through physical accessibility (physical network). The service choice behavior analysis further revealed that digital alternatives are mainly preferred for activities where accessibility-related constraints, such as travel time, cost, or schedule inflexibility, are significant. In particular, shopping, working, and dining activities show higher substitution tendencies when convenience, reduced contact, and time savings are valued. Conversely, activities that rely on service quality, social interaction, and tangible experience, such as hospital visits or entertainment, demonstrate lower levels of substitutability.

For example, the advantages of online shopping, such as the ability to purchase goods at any time and from any location, while avoiding travel and queuing, illustrate how certain daily tasks can be efficiently conducted in virtual networks. However, the physical experience of evaluating product quality, engaging in social interactions, and the immediacy of obtaining goods remain critical factors sustaining physical shopping demand. Likewise, the regression results showed that younger males and unemployed individuals exhibit significantly higher online-shopping substitution ratios, whereas older and female respondents show lower adoption levels, emphasizing the heterogeneity of digital inclusion.

Similar trends were found in working and entertainment activities. Higher-income and male respondents were more likely to engage in remote working, whereas having a permanent employment status limited teleworking adoption. In contrast, younger and lower-income groups displayed higher substitution ratios for movie-watching through virtual networks, reflecting their greater familiarity with streaming platforms and cost sensitivity toward cinema visits.

These findings confirm that while digital transformation enhances accessibility and efficiency, its benefits are not uniformly distributed among social groups. Overall, the findings suggest that service substitutability is activity- and group-specific, determined by the trade-off between convenience and physical experience. Services with strong spatial or social components remain less substitutable, reinforcing the importance of hybrid service models that integrate both real and virtual networks. Such integration not only enhances overall accessibility but also mitigates digital inequality, contributing to sustainable and inclusive urban development. Hence, the subsequent proposed QOL evaluation framework in Chapter 5 incorporates these differentiated substitution patterns to assess how physical-virtual accessibility jointly influences individuals' well-being and the sustainability of urban service systems.

3.4. Cross-Tabulation Analysis of Behavioral Substitution Ratios

3.4.1. Substitution ratio for each behavior

This section examines the substitutability of physical activities for digital alternatives across five daily life activities, such as shopping, dining, commuting, schooling, and medical visits. For example, the section examines to what extent shopping in physical space can be substituted by online shopping, considering several factors such as age, residential location characteristics, and license ownership. The "substitution ratio" is calculated by comparing the frequency of performing physical activities with their digital alternatives, within 5 categories: "0, 0-10%, 10-20%, 20-50%, and 50-100% of substitution, as shown in Figure 3.15.

Figure 3.15 presents the substitution ratio for these activities, highlighting tendencies toward digital alternatives. The survey analysis results disclose that shopping exhibits a higher substitution ratio toward digital alternatives, with only 25% of respondents reporting no adoption of digital alternatives, whereas 75% indicated varying levels of substitution. This result confirms that shopping has a higher substitution ratio toward its digital alternative than other activities. This trend suggests a transformation in consumer behavior, where digital network accessibility increasingly changes the shopping behavior of individuals. Considering the higher substitution ratio of shopping behavior and its direct relevance to transportation demand and urban land use, the chapter selects shopping behavior as a focal activity for substitution ratio analysis. This chapter mainly focuses on analyzing the factors influencing the choice of shopping digital alternatives and investigates the main cause of these behavioral shifts.

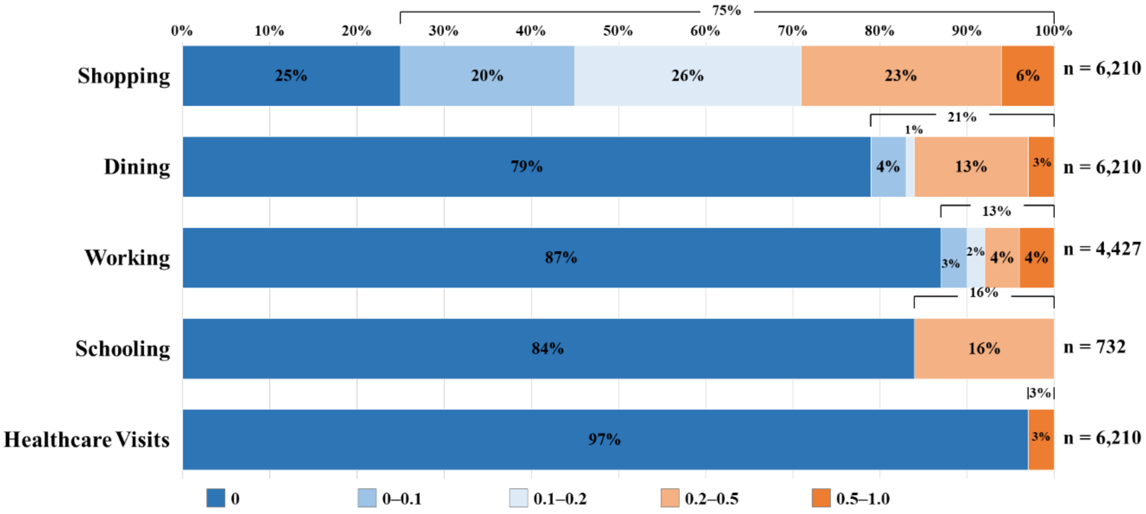


Figure 3.15. Distribution of substitution ratio by activities. (Mutahari et al., 2025a)

3.4.2. Impact of age on shopping substitution behavior

Figure 3.16 illustrates the percentage of shopping substitution across different age groups, highlighting key trends in the adoption of digital alternatives. The survey results disclose that the tendency of shopping digital alternative behavior decreases with age. It is found that younger generations (20s) are engaging more in online shopping compared to other age groups. However, even among the elderly (60+ years old), approximately 69% reported using online shopping as a substitute for traditional in-store purchases. A total of 80% of individuals belonging to the 20s age group reported online shopping to varying degrees. The trend is 78%, 77%, 76%, and 69% for age group 30s, 40s, 50s, and 60+, respectively. This finding emphasizes the widespread adoption of online shopping across all age groups, emphasizing the substitutability of access to physical shopping with its digital alternative, even among the elderly.

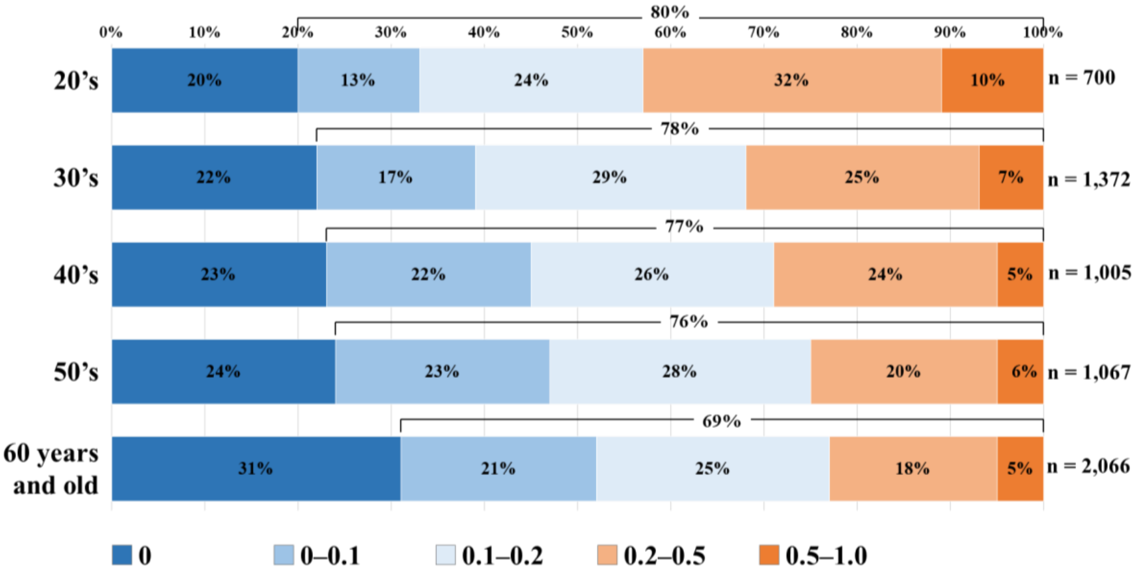


Figure 3.16. Distribution of substitution ratio by age. (Mutahari et al., 2025a)

3.4.3. Impact of residential location on shopping substitution behavior

Figure 3.17 demonstrates the relationship between residential location and the shopping substitution ratio. Residential characteristics were categorized according to responses to the question: 'Please select the option that best describes your residential area'. Five residence categories, including city center, city center surrounding, suburbs, rural areas, and nature-rich areas, were listed hierarchically for the respondents.

The analysis results reveal that the average shopping substitution ratio, ranging from 0.1 to 0.2, was slightly higher among respondents living in the city center. This may suggest that residential environments may slightly influence shopping substitution behavior. However, as can be seen in Figure 3.17, no significant difference can be witnessed in online shopping frequency across various residential areas. In contrast, it can be witnessed that, regardless of residential locations, online shopping has a higher substitution ratio. The survey results disclose that individuals tend to do online shopping at an average rate of 25.2%, regardless of their place of residence.

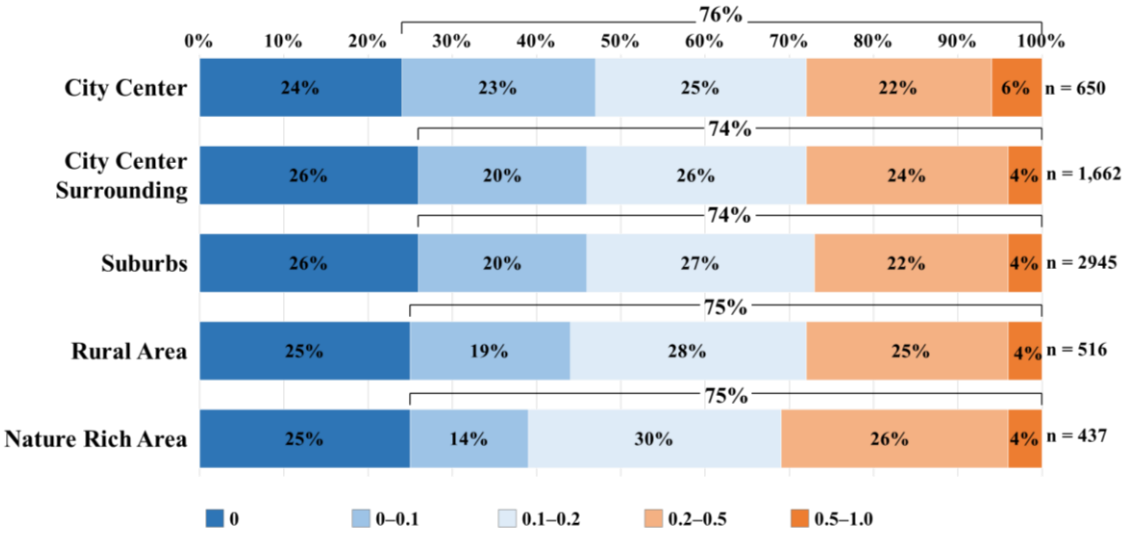


Figure 3.17. Relationship between place of residence and shopping substitution ratio. (Mutahari et al., 2025a)

3.4.4. Impact of license possession on shopping substitution behavior

Figure 3.18 illustrates the relationship between license possession and the shopping substitution ratio. Although it was assumed that people without driving licenses might do more frequent online shopping compared to people with driving licenses due to convenience and delivery options, the result of this study shows otherwise. The survey results show that individuals with a driver's license tend to do more online shopping. Almost 75% of individuals with a driving license engage in online shopping, whereas only 66% of individuals without a driving license engage in online shopping. However, the substitution ratio of 0.5–1.0 is higher by 2% among individuals without a driving license.

Findings on the relationship between license possession and online shopping may suggest that licensed individuals, while having the option to use private vehicles for investigating and checking the products in an actual store, may prefer online shopping due to convenience and lower prices. The result of this study emphasizes that mobility and digital alternatives can coexist, and the presence of a driving license does not necessarily reduce the use of digital alternatives. Additionally, the result emphasizes that online shopping may not necessarily reduce traffic congestion or private vehicle usage.

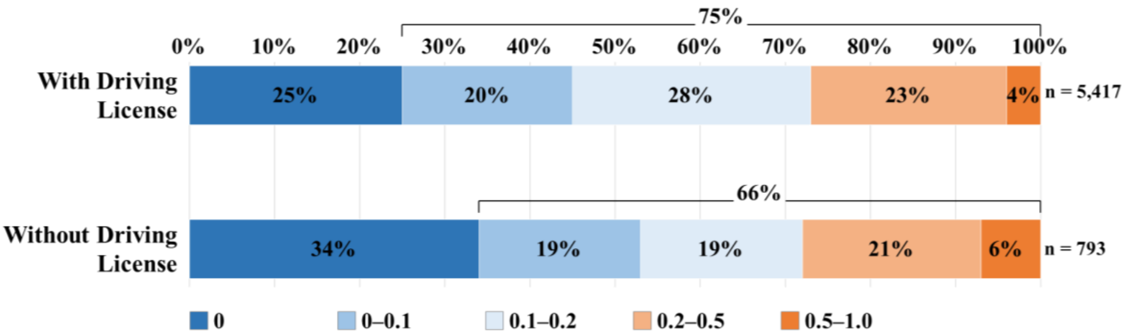


Figure 3.18. Relationship between license possession and shopping substitution ratio. (Mutahari et al., 2025a)

3.4.5. Impact of social relationships on shopping substitution behavior

This section examines how personal relationships affect the adoption of digital alternatives. Respondents were asked to rate the importance of relationships across three categories: family, friends, and internet acquaintances, using a seven-point Likert scale, where one indicates “not at all important” and seven indicates “very important”. In this thesis, the author divided the relationships into two categories: “neighbors” in real networks and “internet acquaintances” in virtual networks, such as social media, to investigate the relationship between social relationships and digital substitution. Figure 3.19 illustrates the relationship between the perceived importance of “Internet acquaintances” and the shopping substitution ratio. Respondents were grouped into three categories based on their relationship importance: “less important” (ratings 1–3), “neutral” (rating 4), and “important” (ratings 5–7).

The results show that the “important” group, which places a higher importance on relationships with internet acquaintances, had the highest shopping substitution ratio. This indicates that individuals who place more value on their online relationships are more likely to prefer digital alternatives, such as online shopping. Consequently, a stronger emphasis on online communication correlates with an increased tendency to adopt digital shopping behavior. This means people who are exposed to more online communication tend to do more online shopping and have a higher digital substitution ratio.

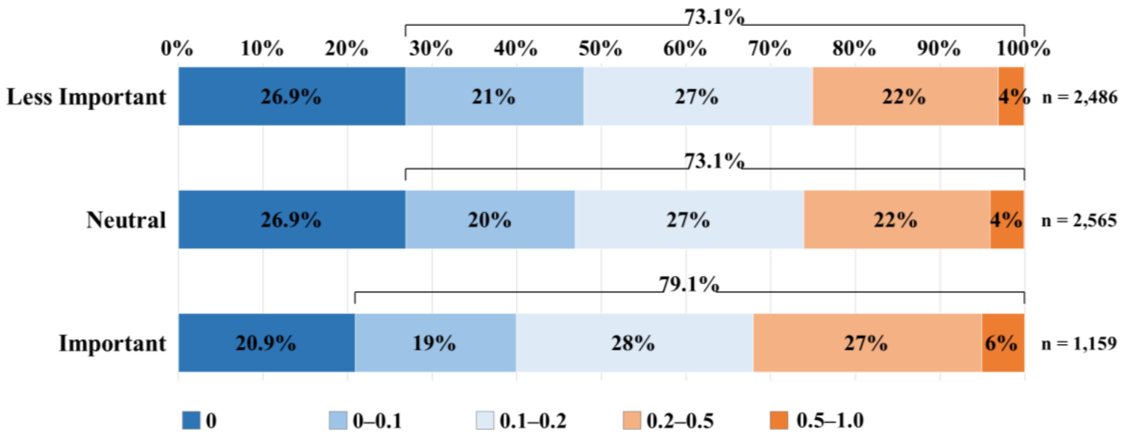


Figure 3.19. Relationship with internet acquaintances and shopping substitution ratio. (Mutahari et al., 2025a)

Figure 3.20 illustrates the relationship between personal relationships with neighbors and the adoption of digital shopping behavior. The results reveal that respondents who placed less importance on personal relationships with neighbors in physical space were more likely to have higher engagement with digital alternatives. The results of this study confirmed that people who stated that relationships with neighbors are less important shopped online more frequently compared to the other two groups, who found relationships to be "neutral" or "important". Individuals who responded that relationships and interactions with neighbors were important or remained neutral engaged in online shopping less, by 74.3% and 72%, respectively, compared to the other group, at 77.7%. The substitution ratio of 0.5–1.0 was higher among the less important category by 2% compared to the important category. Combining the results from Figures 3.19 and 3.20, it can be suggested that social networks, either in real networks or virtual networks, affect the digital substitution ratio accordingly.

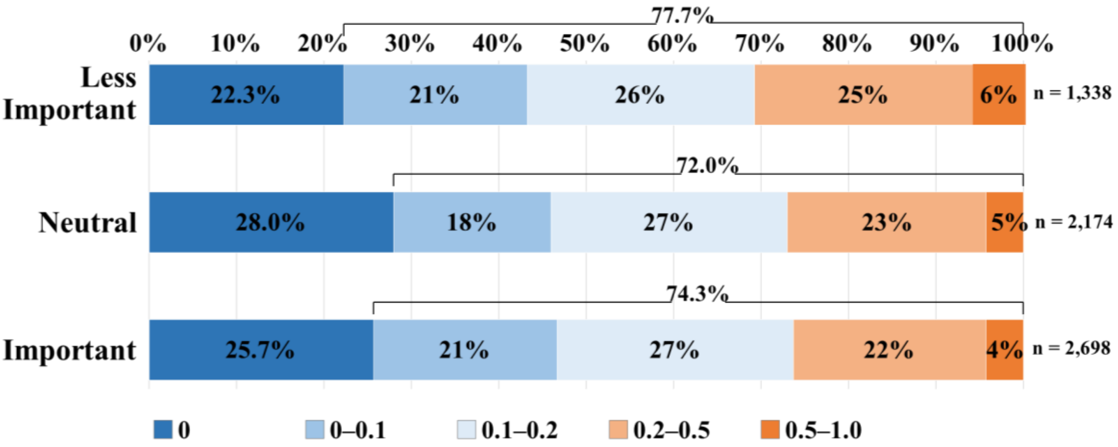


Figure 3.20. Relationship with neighbors and shopping substitution ratio.
(Mutahari et al., 2025a)

3.5. Analysis of Relationship Types Influencing Behavioral Choices

3.5.1. Factor analysis of relationship types influencing behavioral choices

To understand the significance of various relationships by respondents, an exploratory factor analysis was conducted. The maximum likelihood method was employed for factor extraction, with Promax rotation applied to accommodate correlations between factors. Factors were retained based on an eigenvalue of at least 1 and a factor loading of at least 0.40. This analysis identified five items and four distinct factors, which together accounted for approximately 62% of the total variance. The factor loadings and eigenvalues of the extracted factors are presented in Table 3.8. The resulting factors were interpreted and labeled as "Family-Oriented Relationships" (emphasizing the importance of family and relatives), "Workplace/School Relationships" (emphasizing the significance of workplace and school connections), "Community Relationships" (emphasizing the neighborhood and community ties), and "Internet Relationships" (emphasizing the relationships formed in virtual networks).

Table 3.8. Factor analysis results. (Mutahari et al., 2025a)

Item	**Factor Loadings**			
	1	**2**	**3**	**4**
Relationships with family members	1.08	−0.07	−0.09	−0.24
Relationships with relatives	0.69	−0.12	0.19	0.02
Relationships at work or school	−0.12	1.02	0.07	−0.14
Relationships in the neighborhood or community	0.02	0.08	0.83	0.05
Relationships with acquaintances and friends on the internet	−0.12	−0.09	−0.05	0.73
Relationships with friends	0.39	0.26	0.11	0.08
Relationships with loved ones	0.35	0.20	−0.15	0.28
Eigenvalue	1.80	1.09	0.87	0.57
Factor contribution ratio	0.258	0.157	0.125	0.081
Cumulative contribution ratio	0.258	0.415	0.540	0.621

3.5.2. Cluster analysis of respondents and behavioral characteristics

This section presents a cluster analysis using the K-means method, applied to the factor scores derived from the factor analysis represented in Table 3.8. K-means clustering was selected due to its computational efficiency and suitability for large datasets such as ours (n = 6,210). Compared to hierarchical clustering, which can become computationally intensive and less scalable with larger samples, K-means can offer faster convergence and clearer interpretability, especially when the number of clusters is predefined or empirically estimated (Jain, 2020). The thesis used the elbow method (Syakur et al., 2018) to determine the optimal number of clusters, resulting in seven distinct clusters. Each cluster's proportion of alternative behaviors, particularly those related to shopping, was calculated and standardized to serve as an explanatory variable. This clustering approach allowed us to capture meaningful behavioral profiles reflecting different levels of digital service usage and social interaction preferences across respondent groups. Figure 3.21 reveals the result of the cluster analysis.

The section further examined the characteristics and proportions of digital alternative behaviors within each cluster, providing insights into how respondents' behavioral tendencies align with their factor scores and residential location attributes. This classification highlights digital alternative behavior across various respondent groups, offering a deeper understanding of the factors driving these behaviors. The results of cluster analysis and each cluster characteristic are shown in Figure 3.21 and Table 3.9.

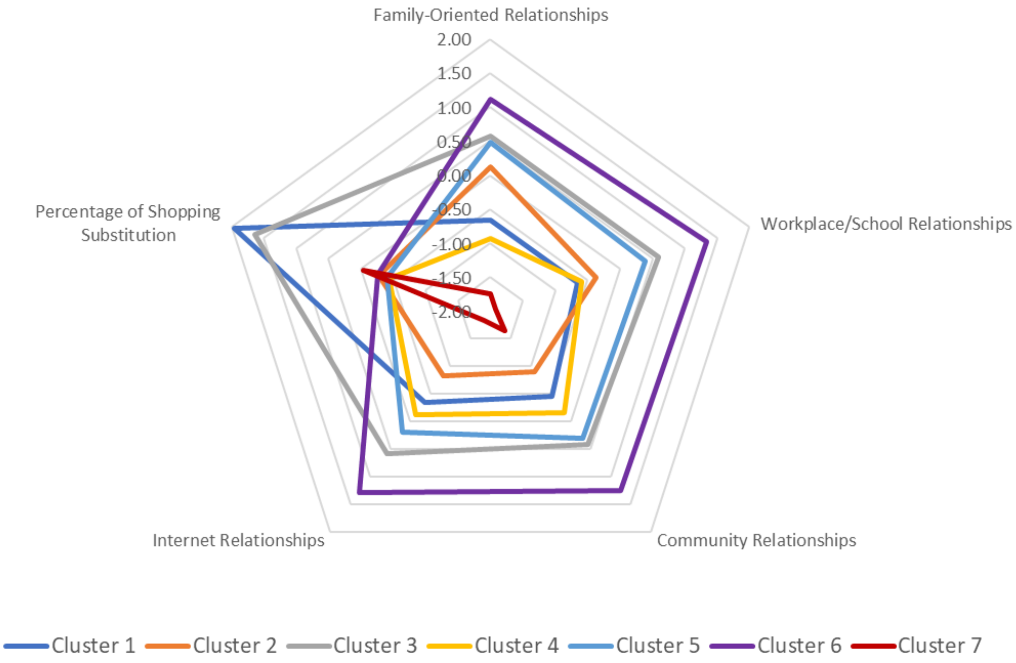


Figure 3.21. Cluster analysis result of shopping substitution vs. social network importance. (Mutahari et al., 2025a)

Following the cluster analysis, respondents were grouped into distinct clusters based on their factor scores and the proportion of digital alternative behaviors, particularly in relation to shopping. The following clustering provided us with an in-depth explanation of the characteristics and behavioral patterns observed within each cluster, shedding light on how human relationships, preferences for digital alternatives, and shopping behaviors intersect across different respondent groups.

Cluster 1

Cluster 1 consists of individuals who assign minimal importance to human relationships, both in physical space and cyberspace. These respondents seem to prioritize their needs over daily social interactions and prefer online shopping. The behavioral tendencies of this group suggest that they rely on digital alternatives to a significant extent, potentially due to their low emphasis on social networks.

Cluster 2

Similar to Cluster 1, respondents in Cluster 2 also place little importance on social networks. However, in contrast to Cluster 1, this group exhibits a low proportion of shopping digital substitution. Instead, they show a preference for shopping at physical stores, which can potentially suggest that, despite their reluctance to engage in social relationships, they still prefer to do their shopping in physical stores.

Cluster 3

Cluster 3 is composed of individuals who place a relatively high value on social relationships, both in their physical space and cyberspace. Despite the emphasis on human interactions, they also actively engage in online shopping. This can suggest that respondents in this group are capable of efficiently performing both physical activities and their digital alternatives, as they can make strategic use of digital alternatives for shopping while maintaining social interactions across various networks.

Cluster 4

In Cluster 4, although the respondents exhibit a low level of importance placed on social relationships, especially within the family, they tend to rely more on physical stores for shopping. This can suggest that there might be external factors (such as convenience, familiarity, or personal preferences) that influence their shopping choice behaviors. Additionally, it can be witnessed that this cluster's strong tendency towards physical shopping rather than digital alternatives.

Cluster 5

Although respondents in Cluster 5 valued social relationships to varying degrees, their shopping behaviors are not strongly influenced by giving importance to social relationships. Their low shopping substitution ratio indicates a preference for physical stores, potentially driven by the direct interaction they have with their environment and the people around them. This cluster may reflect individuals who engage in shopping activities as part of their social experience, valuing face-to-face interactions.

Cluster 6

In Cluster 6, while respondents show a high level of importance placed on relationships, their shopping substitution rate remains low. This suggests that, like Cluster 5, these individuals prefer physical stores despite their value on social interactions. The emphasis on direct human connections may play a significant role in shaping their shopping preferences, where the in-person experience is preferred over digital alternatives.

Cluster 7

Cluster 7 is characterized by individuals who do not place significant emphasis on any of their social relationships. These respondents have a moderate shopping substitution ratio, suggesting that they are somewhat indifferent toward both physical shopping and digital alternatives. This group may have a more passive approach toward shopping and social interactions, showing a general reluctance to engage in both social interactions and shopping digital alternatives.

Table 3.9 provides an overview of cluster analysis by gender, age group, and driver's license status. As can be seen in Table 3.9, clusters 2 and 4 have a higher percentage of men and women, and huge significant differences cannot be witnessed in the age distribution among the clusters. Regarding age distribution, Clusters 1 and 3 have a higher concentration of respondents in their 20s and 30s, with respondents in these clusters showing a higher substitution ratio but varying importance placed on social networks, while Cluster 2 shows a greater proportion of older age groups, with respondents in this cluster ascribing higher importance to social networks and showing a lower substitution ratio. As previously shown in Figure 3.16, younger individuals are more likely to adopt digital alternative behaviors, such as online shopping, whereas older individuals tend to prefer physical shopping. However, Cluster 5 has a higher proportion of respondents with a driver's license compared to those without. Since this cluster appears to favor physical shopping, the author infers that access to private vehicles may facilitate their preference for physical shopping.

Table 3.9. Characteristics of each cluster. (Mutahari et al., 2025a)

Item		**Cluster 1**	**Cluster 2**	**Cluster 3**	**Cluster 4**	**Cluster 5**	**Cluster 6**	**Cluster 7**
		n=936	n=1292	n=492	n=1237	n=630	n=618	n=1004
		15.1%	20.8%	7.9%	19.9%	10.1%	10.0%	16.2%
Gender	Men	15.2%	21.2%	7.5%	20.3%	10.0%	9.8%	15.9%
	Women	15.0%	20.4%	8.3%	19.5%	10.3%	10.1%	16.4%
Age	Average Age	48.5	51.1	47.5	50	49.2	49.5	48.9
	20s	17.4%	16.1%	10.0%	18.7%	10.4%	10.1%	17.1%
	30s	16.4%	19.9%	9.1%	20.8%	9.6%	8.9%	15.2%
	40s	14.9%	19.8%	8.5%	20.2%	10.3%	10.5%	15.7%
	50s	13.5%	22.8%	5.9%	19.1%	11.7%	11.6%	15.3%
	60 and over	14.7%	22.9%	7.3%	20.6%	9.4%	9.4%	15.6%
Driving License	Yes	15.0%	20.8%	7.9%	19.8%	10.6%	9.9%	16.0%
	Men	15.2%	21.2%	7.5%	20.3%	10.0%	9.8%	15.9%

3.6. Residential Relocation Choice Analysis

3.6.1. Overview of residential relocation choice

This section investigates the respondents' intentions to relocate from their current place of residence. The five residence categories described earlier are recategorized into urban and rural areas. Residences such as the city center and its surroundings fall into urban areas, whereas suburbs, rural, and nature-rich areas fall into rural areas. Figure 3.22 illustrates the relocation intention of the respondents obtained from the survey analysis. The results indicate that 35.9% of respondents in urban areas and 30.8% in rural areas expressed an intention to relocate, whereas 59.2% of respondents living in urban areas and 64.2% of respondents living in rural areas expressed no intention of relocation. However, about 5% of respondents living in both residence categories had already changed their place of residence. These findings confirm that the residential relocation intention is lower by 5% in rural areas compared to urban areas. The subsequent part of this paper will disclose what kinds of factors affect the residential relocation intention.

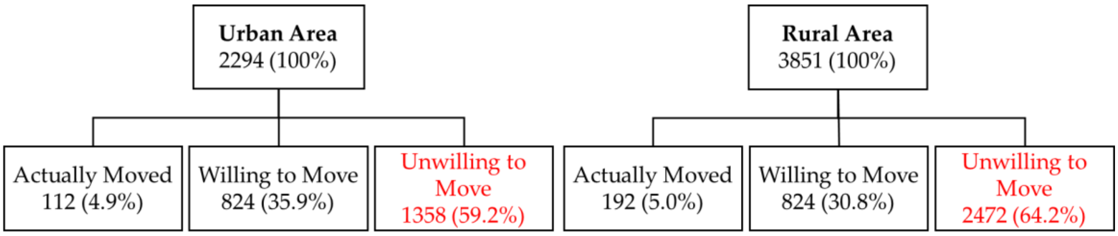


Figure 3.22. Residential relocation intentions in urban and rural areas.
(Mutahari et al., 2025a)

3.6.2. Factors influencing residential relocation choice

To further analyze the determinants of residential relocation, a binomial logistic regression analysis was performed, with the intention of changing residence as the dependent variable. Explanatory variables included gender, age, possession of a driver's license, attachment to place of residence, and the percentage of shopping substitution. The analysis results are shown in Table 3.10 for urban areas and Table 3.11 for rural areas.

The analysis result of this study reveals that age had a significant negative impact on the residential relocation choice of individuals in both urban and rural areas: as individuals age, their likelihood of relocating their residential place decreases. This may be attributed to older residents' preference for maintaining their established living environments and avoiding relocation inconveniences.

Similarly, attachment to one's residential place also showed a significant negative impact on the residential relocation choice of individuals in both urban and rural areas. The analysis results disclosed that a higher attachment to the current residential location is associated with a reduced intention to relocate, reflecting the importance of local community satisfaction and familiarity with the surrounding environment. However, the impact of attachment to residential places on residential relocation choice is stronger in rural areas, suggesting that community ties in rural settings play a more substantial role in relocation.

Table 3.10. Factors affecting residential relocation choice in urban areas. (Mutahari et al., 2025a)

Survey Item	**Urban Areas**					
	Regression Coefficient	**Standard Error**	**Odds Ratio**	**95% Confidence Interval**	**Significance**	
Age	−0.04536	0.38384	0.95565	0.94955–0.96169	1.60 × 10−44	***
Sex	−0.02446	0.00324	0.97584	0.80443–1.18366	0.803878	
Driving license	0.19685	0.09845	1.21756	0.92918–1.60155	0.156044	
Attachment to the place of residence	−0.34296	0.13877	0.70967	0.65198–0.77173	1.50 × 10−15	***
Shopping substitution rate	1.13927	0.26456	3.12450	1.86155–5.25563	1.66 × 10−5	***

Note: *** indicates statistical significance at $p < 0.001$.

Table 3.11. Factors affecting residential relocation choice in rural areas. (Mutahari et al., 2025a)

Survey Item	**Rural Areas**					
	Regression Coefficient	**Standard Error**	**Odds Ratio**	**95% Confidence Interval**	**Significance**	
Age	−0.04632	0.00275	0.95474	0.94957–0.95984	6.95×10^{-64}	***
Sex	0.00012	0.07725	1.00012	0.85955–1.16360	0.998740	
Driver’s license	0.13059	0.13737	1.13950	0.87249–1.49557	0.341771	
Attachment to the place of residence	−0.40555	0.03282	0.66661	0.62489–0.71069	4.38×10^{-35}	***
Shopping substitution ratio	0.19790	0.21480	1.21884	0.79853–1.85411	0.356874	

Note: *** indicates statistical significance at $p < 0.001$.

Additionally, the impact analysis of shopping substitution on residential location choices in this study disclosed some differences between urban and rural areas regarding the impact of shopping substitution on residential relocation choices. In urban areas, the odds ratio was 3.12, meaning the shopping substitution ratio has a higher impact on residential choice in urban areas, compared to the odds ratio of 1.21 in rural areas. It can be argued that the availability of alternative shopping options, such as online shopping, can increase residential retention in urban areas. This may suggest that improved accessibility to goods and services through ICT and transportation networks enhances the convenience of urban environments. In contrast, in rural areas, the odds ratio was 1.21, and the effect was not significant. This may suggest that in rural areas, shopping substitution has a limited impact on relocation choices. This may be due to established lifestyles that rely on car travel, where physical store accessibility remains an integral part of daily life.

3.7. Results

3.7.1. Behavioral substitution ratios

The analysis results of digital behavior substitutability in this study confirm the possibility of substitution of different physical activities with digital alternatives, especially shopping behavior. The substitution is reduced by orders from shopping, dining, schooling, working, and hospital visits. Only a 3% substitution was witnessed for the hospital visit digital alternative. Younger individuals show a significant substitution ratio in shopping for digital alternatives, whereas the shopping substitution ratio reduces as people age. However, older adults and the elderly also demonstrate a considerable substitution ratio in shopping for digital alternatives. Furthermore, the study discloses that the impacts of residential location on the substitution ratio are insignificant. Respondents living in urban areas show an insignificant, only 0.33% higher substitution ratio compared to the respondents living in rural areas.

Assuming the individuals who have a driver's license can drive a private vehicle and their choice of transportation mode is greater, they will do more in-store shopping than online shopping. However, the study discloses that mobility, such as having a car, can influence digital alternative behavior, with individuals holding a driving license favoring online shopping, implying that access to transportation does not necessarily reduce the substitution ratio. In contrast, having a car enhances online shopping by giving individuals an opportunity to use their private vehicle to inspect products in a physical store and purchase products online at a lower price, which may increase traffic congestion and private vehicle usage.

Additionally, the study reveals that social relationships, particularly virtual network relationships, affect digital shopping behavior, and emphasizes the growing influence of virtual networks on online shopping. Furthermore, the result of this study confirms that digital substitution affects social and cultural environments, considering the tendency of people to favor digital alternatives but place less importance on face-to-face interaction. These findings show that digital alternatives affect social networks and urban infrastructures.

3.7.2. Relationship Types Influencing Behavioral Choices

The clustering analysis of this study, based on the K-means method and the elbow technique, identified seven distinct respondent groups, each characterized by different levels of emphasis on human relationships and shopping digital alternative behaviors. The results disclosed that younger individuals, particularly in clusters 1 and 3, are more inclined toward online shopping, while older respondents in cluster 2 exhibit a stronger preference for physical shopping. Additionally, it was found that respondents putting higher importance on social relationships, as seen in clusters 3 and 6, tend to have a higher and lower substitution ratio, respectively. This means that although clusters 3 and 6 value social relationships, their shopping behaviors are different. In contrast, respondents who place less importance on social relationships, such as Cluster 1, prefer more digital alternatives.

It was also found that mobility factors also influence these digital alternative behaviors, with Cluster 5 preferring physical shopping and having a higher proportion of respondents with a driving license, indicating that access to a private vehicle supports physical shopping for some individual groups. These findings highlight the diversity in shopping digital alternative behavior shaped by social interactions, social network usage, and mobility, providing valuable insights for businesses, policymakers, and urban planners.

Cluster analysis of this study, which categorized respondents into distinct groups based on their digital alternative behavioral tendencies and factor scores, reveals different levels of digital substitution ratio. Some clusters show a strong preference for shopping digital alternatives, often due to minimal emphasis on social relationships, while others prefer physical stores despite being socially active. The findings of this study disclose that social relationships, mobility, and age significantly influence the digital substitution ratio. This classification provides valuable insights into understanding how different respondent groups navigate their activity paths in both real and virtual networks. These findings can contribute to discussions on the integration of digital technologies in daily life, the substitutability of access, and proposing a tradeoff between physical activities and digital alternatives to enhance overall QOL.

3.7.3. Residential relocation choice

The analysis result of this study discloses that residential relocation intentions are shaped by multiple factors such as age, attachment to the place of residence, and the availability of shopping alternatives. Younger individuals and those with weaker community ties are more inclined to relocate, and the impact of shopping substitution differs between urban and rural areas. In urban areas, digital shopping alternatives enhance residential convenience, and they affect the residential location choice. Whereas, in rural areas, traditional mobility patterns and local attachments remain dominant determinants of relocation choice behavior, and digital shopping alternatives have less impact on residential choice. The result of this study confirms that digital substitution affects sustainable urban structures, considering residential relocation, changes in land use and transportation, and population distribution. These changes will require new facilities to meet the people's demands. Therefore, the result of this study suggests that sustainable urban planning requires a tradeoff between services offered in physical space and cyberspace to contribute to the development of sustainable urban structures, considering the needs of each individual and their well-being.

3.8. Discussion

The result of this chapter reveals that urban structure, including land use and social interactions, will be affected by digital service substitution. The findings of the study suggest that individuals who have a higher digital service substitution ratio are less likely to give importance to actual human relationships formed in physical space, such as those between families or relatives; in contrast, they are more likely to place higher importance on acquaintanceships and friendships formed in cyberspace, such as social media. The increase in digital service substitution will weaken in-person relationships and can potentially affect the strength, stability, and connectedness of communities over time. Individuals with a higher digital service substitution ratio tend to be more comfortable and active in digital environments. This digital lifestyle naturally extends to social behavior, where online communication becomes not just a supplement but a primary mode of social interaction. Due to this, individuals who value virtual relationships more are more likely to have a higher digital service substitution ratio. These findings redefine social networks and emphasize long-term implications for community cohesion by addressing potential challenges related to disaster response and evacuation, social inclusion and mental health, public safety and crime prevention, and overall sustainable behavior and shared resources.

Additionally, in line with existing studies (Shao et al., 2016; Siikavirta et al., 2002) that have argued that online shopping reduces traffic congestion and greenhouse gas emissions, our study reveals an unexpected finding that individuals with driving licenses and cars are approximately 9% more likely to engage in online shopping compared to those who do not have cars. The reason behind this could be that having a car eases goods inspection for individuals when purchasing, while enjoying the convenience and lower prices of online shopping. For instance, one of the factors that could diminish online shopping service value is in-person product inspection. In physical stores, individuals have the opportunity to actually look closely at the product, but in online shopping, such an opportunity is limited. However, online shopping is said to be convenient and has a lower price. The author believes these factors are associated with the shopping choice behavior of individuals, and the results suggest that online shopping may not necessarily reduce traffic congestion or private vehicle usage. These insights have policy relevance for sustainable urban development and smart cities.

The findings of this chapter also highlight important digital inequalities. Older adults and rural residents were found to engage less in digital service substitution, which may reflect barriers such as limited digital literacy, lower access to high-speed internet, or reduced exposure to online platforms. These disparities can lead to unequal access to public digital services, digital commercial goods, and virtual social interaction opportunities. In the context of sustainable and inclusive urban development, especially targeting SDG 11 (Sustainable Cities and Communities), it is essential that policymakers address these gaps by investing in digital infrastructure, education, and support systems that ensure all populations—regardless of age or geography—can benefit from the digital transformation of services and social life to have a higher gross regional happiness.

Considering the findings of this study, the authors of this paper argue that physical services need not be substituted for digital alternatives, completely considering their consequences. However, the author believes that digital services should be complementary to physical services, which would enhance service access and result in user satisfaction and a higher overall QOL, ensuring equity and sustainability. Additionally, the study suggests making a tradeoff between physical and digital alternative service usage. Excessive usage of either of them will negatively impact the sustainable urban structure, social environment, and overall QOL. For instance, excessive usage of digital services will contribute to more social isolation and reduce face-to-face communication and mobility, which will affect physical and mental health. On the other hand, there is a need for digital services for different reasons, such as increasing accessibility for all, including disabled people, demand and preference of individuals, and opportunities for businesses to innovate, expand their reach, and generate revenue in an increasingly digital economy. In contrast, physical activities generate more CO_2 due to relying on transportation, and consume more resources, e.g., facility construction, maintenance, etc., but they enhance face-to-face social and cultural interactions, promote individual mobility, and diminish the negative effects of digital service usage.

Based on the findings of this chapter, the author urges urban planners and policymakers to address both the negative and positive impacts of digital service substitution for future sustainable urban planning and smart city developments. This chapter suggests making a tradeoff between physical and digital service usage and should be considered at policy- and strategy-making levels to have a larger positive socio-economic impact aligned with the United Nations Sustainable Development Goals (SDGs) and reduce the negative impact of either of them.

3.9. Conclusions

3.9.1. Summary

This chapter initially explored trends in the frequency of digital alternative usage, examining how these behaviors correlated with factors such as gender, age, and driving license status. The analysis result confirmed that socio-demographic factors significantly influence the adoption of digital alternatives. A cross-tabulation in this study further investigated the relationship between the emphasis placed on interpersonal relationships and the frequency of digital alternative usage. The analysis results suggest that the value placed on human relationships in real space will negatively affect digital alternative behavior choices.

Subsequently, factor analysis was performed to investigate the importance respondents placed on different relationships, identifying key factors and their influence on digital alternative behaviors. Using these results, respondents were classified into distinct clusters, with specific attributes and digital alternative behavior patterns explained through the percentage of alternative behaviors within each cluster. The analysis results disclosed that individuals who frequently use digital alternatives place less importance on human relationships and face-to-face interaction, and confirmed that digital alternative substitution has impacts on social and cultural environments.

A binomial logistic regression analysis of age and residential attachment in this study confirmed that both factors significantly affect residential relocation choices. The impact of attachment was especially strong in rural areas, where personal ties to the community are more pronounced. Additionally, the study disclosed that in urban areas, digital alternative substitution affects residential relocation choice, while in rural areas, it has no clear impact, likely reflecting the differences in lifestyle and mobility across residential locations. The result of this chapter suggests that sustainable urban structure, land use, transportation, and population distribution are affected by digital alternative substitution to some extent; therefore, they need to be integrated into the land-use transport models.

This chapter contributes to several Sustainable Development Goals, particularly

SDG 11 (Sustainable Cities and Communities), by informing digital-age urban planning strategies. It also supports SDG 9 (Industry, Innovation, and Infrastructure) and SDG 10 (Reduced Inequalities) through its insights on digital access, behavioral shifts, and inclusive service design. Furthermore, the environmental implications of reduced physical mobility align with the objectives of SDG 13 (Climate Action).

3.9.2. Policy recommendations

Based on the chapter`s findings, four actionable recommendations to balance digital innovation with inclusive, sustainable, and human-centered urban design are suggested below for urban planners and policymakers, which can guide sustainable urban planning in the digital era:

- Design well-balanced city development that integrates both digital and physical infrastructure to support diverse lifestyles. Urban planners should ensure that digital services complement, rather than replace, essential in-person services such as healthcare, tourism, and community centers.
- Promote digital service substitution only as a means of improving efficiency, reducing environmental impacts, and enhancing service accessibility, particularly for populations with mobility constraints. However, adoption should be encouraged based on user needs and digital readiness.
- Recognize the limits of digital substitution. While digital tools enable flexibility and convenience, real-life human networks remain critical for quality of life, mental health, social equity, and disaster resilience. Urban policies should continue to invest in social infrastructure that fosters community cohesion.
- Pursue the development of sustainable compact, well-designed, and inclusive urban forms, where digital services are embedded into daily life, but where walkable neighborhoods, public spaces, and physical connectivity are preserved and enhanced. A sustainable, compact, well-designed smart city model can promote sustainability while supporting social diversity and digital inclusion.

These recommendations can help urban planners navigate the tradeoffs of digital transformation and ensure that smart city development remains equitable, resilient, and centered on human well-being.

3.9.3. Limitations and future research prospects

In this thesis, the author did not include variables such as income, occupation type, or education due to the relatively low variance in these attributes in Japan. This might limit the generalizability of our findings and could be considered a limitation of the study. Future research can expand the study target area to other countries and can incorporate these variables in more diverse socio-economic contexts or cross-country comparative studies to better understand their influence on digital service substitution and residential decision-making. In addition, although we distributed a questionnaire survey that was segmented by age, gender, and place of residence and could obtain enough responses (n = 6,210), there might have been some potential bias with the self-reporting survey. However, a combination of stated preference and revealed preference studies can enhance this study.

Furthermore, another study should be conducted to develop a quantitative tradeoff model between physical and digital service usage to balance digital service substitution while considering the impacts of digital service substitution on sustainable urban structures, social environments, and the overall QOL of individuals. Additionally, a study is required to delve deeper into the role of social networks and the barriers to relocation, especially regarding residential location choices concerning digital service substitution, and explore the longitudinal impacts of digital service substitution on the urban form to investigate the temporal changes in the residential location choices, land use patterns, and transportation demand. Moreover, the development of a comprehensive model that evaluates the impact of digital service substitution within a multi-layer network is crucial for understanding its broader implications on an urban structure while considering the different socio-demographic characteristics of individuals. Incorporating the findings of this chapter (digital substitutability and social network) into SDS models (Sugiki et al., 2021; Mutahari et al., 2025a) would provide an innovative and powerful tool for urban planners and decision-makers.

The subsequent chapter, Chapter 4, considers the recommendation of this chapter and improves the SDS model by incorporating digital accessibility and social networking into it. Additionally, considering the academic gap in incorporating digital accessibility into the QOL evaluation model and the significant social impacts of the substitution of physical access with digital access, the findings of this chapter recommend including digital accessibility into the QOL evaluation model, which will be presented in Chapter 5 of this thesis. This approach can guide sustainable urban development strategies that align with the United Nations' SDGs, ensuring sustainable and inclusive urban environments with a higher QOL for everyone.

Chapter 4

Social Dynamics Simulation Using a Multi-layer Network

This chapter modifies an existing Social Dynamics Simulation (SDS) (Sugiki et al., 2021) by incorporating social networks under life event models and incorporating a service choice model and digital accessibility models. The chapter defines social interaction within the microsimulation model, and based on individual attributes and social interactions, the chapter develops a service choice model and a new accessibility model (physical and digital accessibility index), and incorporates it into the SDS model. A virtual city is constructed to verify the model's ability to replicate population distribution, service usage, and network traffic conditions. This chapter demonstrates how changes in digital service availability or transportation conditions affect long-term urban dynamics, providing a tool for urban planners and policy makers to assess different urban development scenarios. Our paper (Mutahari et al., 2025c) creates the basis of this chapter.

4.1. Introduction

Several existing studies have been conducted to develop models that can express, analyze, and evaluate social and urban structures. Various urban models, particularly land use and transportation models, have been developed to evaluate urban policies by considering the integral relationship and interaction between land use and transportation. Wegener (2003; 2005) systematically summarized the characteristics and development history of such models, and in recent years, urban models using micro-simulation have been actively developed to describe temporal changes in land use and transportation. Representative examples include UrbanSim, TLUMIP, PECAS, ILUTE, ILUMASS, PUMA, and SelfSim.

In parallel, network analysis has been widely applied to the analysis of complex social structures. Relationships between people, organizations, and communities have been modeled using social network analysis (SNA) and examined from the perspectives of graph topology and network science. A social network is defined as a group of individuals in a society or organization, and SNA enables the visual and mathematical quantification of human relationships. Previous studies have applied SNA to web-based interactions, social media platforms, stakeholder networks, and large-scale social interaction systems, demonstrating its effectiveness in representing interaction structures and information propagation.

Network-based approaches have also been applied in the field of transportation, where road networks have been analyzed from the viewpoint of network theory. Studies have examined network vulnerability, eigenvector centrality, and long-term road maintenance impacts, showing that network indicators can effectively represent connectivity and resilience. In addition, social cooperation during disasters, life safety, accessibility to daily life facilities, and urban structure have been analyzed using social networking techniques. By using basic statistics such as degree distribution, clustering coefficient, and eigenvector centrality, network characteristics can be analyzed with relatively small computational load.

These existing research results indicate that complex and large-scale urban structures can be effectively expressed and evaluated from a network theory perspective by describing interrelationships between entities in urban space as networks. Furthermore, by positioning temporal changes in urban structure as network dynamics and combining network theory with urban micro-simulation models, it becomes possible to express social dynamics and evaluate urban policies for sustainable city development.

Sugiki et al. (2021) developed a Social Dynamics Simulation (SDS) model and applied it 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.

Understanding sensitive input parameters is important for model development and application, as it reduces uncertainty and improves estimation accuracy. Sensitivity analysis has been widely used to assess the influence of input parameters on model outputs and to evaluate model efficiency and stability. Previous studies have demonstrated that sensitivity analysis is useful for model validation and uncertainty reduction, highlighting the importance of examining model behavior under different parameter settings.

Based on this background, the sensitivity and stability of the SDS model used in this chapter were tested in a previous study (Mutahari et al., 2025c), which serves as a base for this chapter. That study examined the behavior of the simulation model with respect to demographic changes, land use, and transportation systems by varying key parameters related to birth events, residential location choice, and accessibility. 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, as shown in Figure 4.1. Furthermore, the correlation between birth rate, future population, land price, and transportation cost with urban structure in each future year was investigated. The sensitivity analysis results of the study disclosed that these types of SDS models are stable towards different parameter settings. Accordingly, the paper confirms the applicability and efficiency of SDS models for the evaluation of different urban policies, and they can predict the future situation of a city concerning different scenarios.

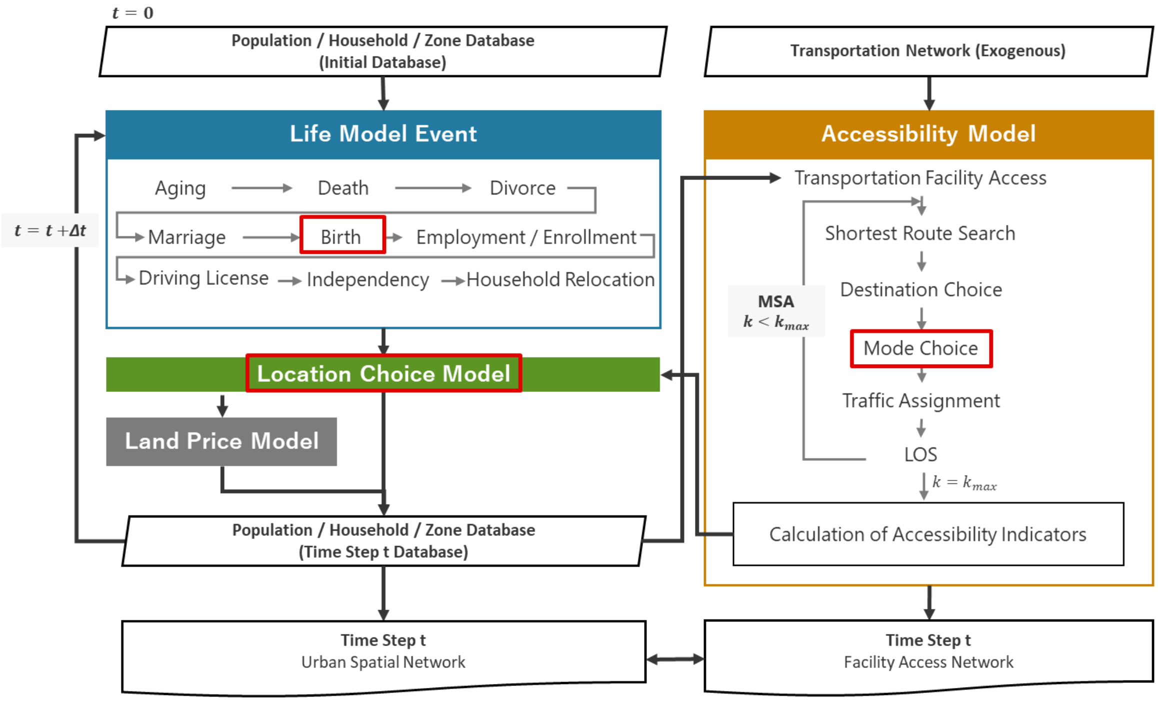


Figure 4.1. Sensitivity analysis of the SDS model. (Mutahari et al., 2025c)

However, the SDS model has been developed only considering the physical accessibility, as shown in Figure 4.1, whereas digital accessibility has not been considered within it for urban policy evaluation. Incorporating digital accessibility, as discussed previously, can greatly enhance the applicability of such SDS models. Furthermore, the impacts of social interactions of human beings on urban structure, which is an integral part of society, have not been studied widely within the existing studies. Incorporating social networks into SDS models alongside a newly defined integrated accessibility index can greatly improve the applicability of SDS models. Furthermore, in the current era of rapid technological developments, individuals have different choices of using services either in physical space or virtual space, as was discussed in the earlier chapters of this thesis. This chapter integrates the service choice behavior of individuals into the microsimulation model.

This chapter develops an integrated accessibility model, which is a combination of digital accessibility and physical accessibility, and incorporates it in the SDS model. Additionally, the chapter based on the investigation results in Chapter 3 of this thesis develops a service choice model that shows the probability of choosing services either in real space or in virtual space, and incorporates it into the microsimulation model. The real space in all chapters of this thesis refers to the physical space where individuals, facilities, and services are connected through real networks (transportation network). The virtual space refers to the cyberspace where individuals and services are connected through virtual networks (ICT networks). Services offered in real and virtual spaces are called physical and digital services, respectively. Physical accessibility refers to the accessibility of individuals to the physical services through a real network. Digital accessibility, also called virtual accessibility, refers to the accessibility of individuals to virtual services through virtual networks. An ICT network refers to the network where individuals use smart terminal devices such as smartphones, PCs, and Virtual Reality (VR) devices, to reach virtual services through the internet.

4.2. Materials and Methods

4.2.1. Representation of urban space by a multi-layer network

A new descriptive image of urban space by a multilayer network has been shown in Figure 4.2, where a layer-breaking K-partite network (Kivelä et al., 2014) has been used. The individuals, their families, and the spaces 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.

As can be seen in Figure 4.2, the author has added a new virtual space layer and social network layer to an existing multi-layer network model to describe urban space. Additionally, the thesis develops a model that integrates the three layers of physical space, virtual space, and social network. Figure 4.2 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 thesis 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 chapter.

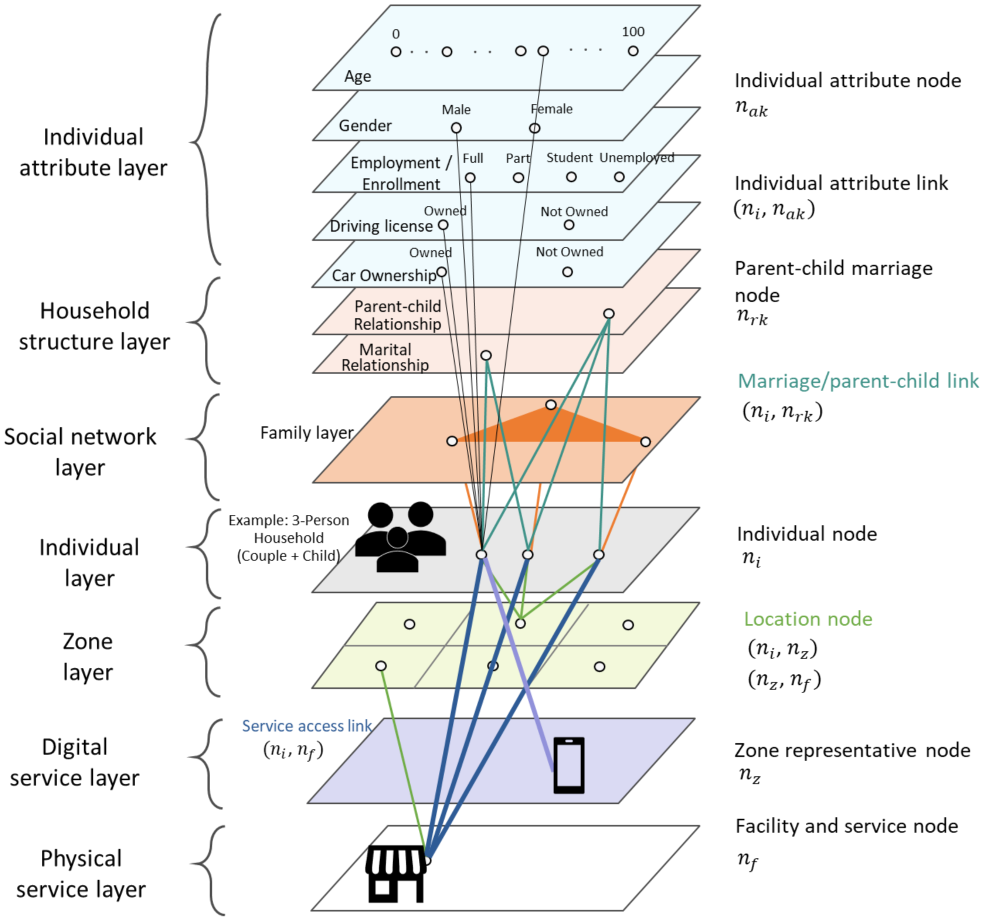


Figure 4.2. Description of urban space by a multi-layer network.

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 physical space and virtual space, and influences the probabilistic decisions made about service choices.

4.2.2. Social dynamics simulation model

This chapter modifies the framework of the existing SDS model (Mutahari et al., 2025a) 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 4.3. 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.

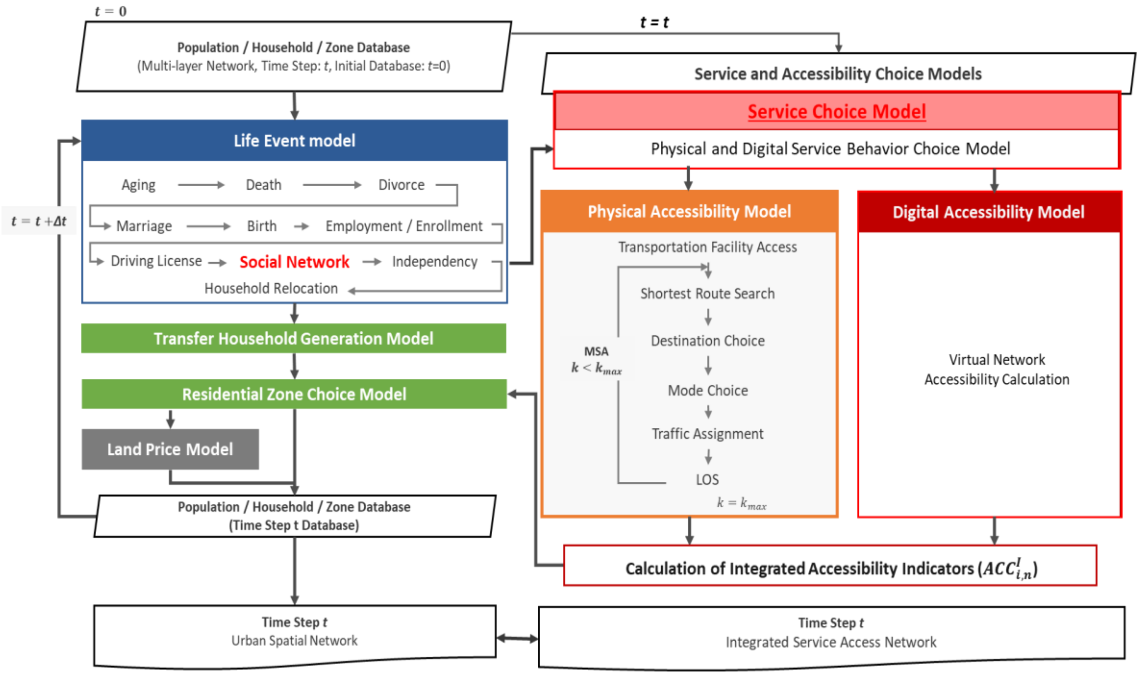


Figure 4.3. Basic structure of the SDS model.

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 the virtual space based on factors such as individual attributes (e.g., age, gender) and values (importance) regarding virtual networks. These 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, 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.

4.2.3. 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:

$$P_n^R = w_n^R = \frac{1}{1 + \exp\left(V_n^D - V_n^R\right)} = \frac{1}{1 + \exp\left(-V_n^R\right)} \tag{4.1}$$

$$V_n^R = \sum_i \alpha_k X_{kn} + \beta_0 \tag{4.2}$$

$$w_n^D = 1 - w_n^R \tag{4.3}$$

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 personal 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 virtual space is defined by 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:

$$V_n^D = \beta_0 + \alpha_1 \cdot Age + \alpha_2 \cdot Male + \alpha_3 \cdot Married + \alpha_4 \cdot Employed + \alpha_5 \cdot IMP_{work} + \alpha_6 \cdot IMP_{internet} \tag{4.4}$$

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*), IMP_{work} is the importance of workplace relationships (1-7), and $IMP_{internet}$ is the importance of internet relationships (1-7).

4.2.4. Physical accessibility model

To calculate accessibility indices in real space, the author formulates a transportation network user equilibrium allocation model using a logit model for user mode choice. 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 chapter 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 (4.5).

$$gc_{ij,n}^{m} = \sum_{a} \delta_a^{ij}\, c_{a,n}^{m} + \zeta_n^m \tag{4.5}$$

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.

$$c_{a,n}^{Auto} = \tau_n\, t_a^{Auto} + cf\ d_a \tag{4.6}$$

$$c_{a,n}^{RS} = \tau_n\, t_a^{Auto} + cf\ d_a \tag{4.7}$$

$$c_{r_l,n}^{PT} = \tau_n \left(t_{r_l}^{PT} + cc_{r_l} + \frac{1}{2f_l} \right) + ca_{r_l} + ct_{r_l} + cd_{r_l}\ ,\ (r_l \in a) \tag{4.8}$$

$$c_{a,n}^{Walk} = \tau_n\, t_a^{Walk} \tag{4.9}$$

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 chapter 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 (4.15), as follows:

$$ACC_{ij,n} = \frac{1}{\mu}\ln\left(\sum_{m\in M_n} av_n^m \exp\left(\mu V_{ij,n}^m\right)\right) \tag{4.10}$$

$$V_{ij,n,k} = ps_{n,k}\, S_{j,k} + pa_n\, ACC_{ij,n} \tag{4.11}$$

$$P_{ij,n,k} = \frac{\exp(V_{ij,n,k})}{\sum_{j'\in J_n} \exp(V_{ij',n,k})} \tag{4.12}$$

Where,

μ : Scale (dispersion) parameter of the stochastic error term

av_n^m : Personal 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, $P_{ij,n,k}$.

$$T_{ij,n,k} = T_{i,n,k} \cdot P_{ij,n,k} \tag{4.13}$$

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

$$V_{ij,n}^{m} = pgc_n \, gc_{ij,n}^{m} \tag{4.14}$$

$$P_{ij,n}^{m} = \frac{av_n^m \exp(V_{ij,n}^{m})}{\sum_{m' \in M_n} av_n^m \exp(V_{ij,n}^{m'})} \tag{4.15}$$

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.

$$av_n^m = av\_m_n^m \times av\_w_n^m \times av\_c_n^m \tag{4.16}$$

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.

$$T_{ij,k}^{m} = \sum_{n} P_{ij,n}^{m} T_{ij,n,k} \tag{4.17}$$

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

$$x_a^m = \sum_{k} \sum_{i} \sum_{j} \delta_a^{ij} \, T_{ij,k}^{m} \tag{4.18}$$

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.

$$t_a^{Auto} = t_{a,0}^{Auto} \left(1 + \alpha \left(\frac{x_a^{Auto}}{K_a} \right)^{\beta} \right) \tag{4.19}$$

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.

$$f_l = \min \left(\max \left(\frac{\max\{x_{r_l}^{PT}\}}{K_l}, \min f_l \right), \max f_l \right) \tag{4.20}$$

Where,

$x_{r_l}^{PT}$: Traffic volume of the public transport link r_l

K_l : Public Transit System Capacity

$minf_l$: 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.

$$cc_{r_l} = \gamma \left(\frac{x_{r_l}^{PT}}{SK_l} \right)^{\eta} \tag{4.21}$$

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.

$$x_a^{m,p+1} = \frac{p}{p+1} x_a^{m,p} + \frac{1}{p+1} x_a^{m,p'} \tag{4.22}$$

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 (4.9) 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.

$$ACC_{ij,n}^{R} = \frac{ACC_{ij,n} - ACC_{ij,n,min}}{ACC_{ij,n,max} - ACC_{ij,n,min}} \tag{4.23}$$

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 $ACC_{ij,n}$

4.2.5. 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 (4.24).

$$ACC_n^D = \alpha V_n^D \cdot e^{-\beta \emptyset_{ns}} \tag{4.24}$$

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

4.2.6. Definition of integrated accessibility index

The integrated accessibility index ($ACC_{i,n}^I$) proposed approach in this chapter quantifies the overall attractiveness of a residential zone when an individual considers the service choices between real 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 4.25 quantifies the integrated accessibility index as follows.

$$ACC_{ij,n}^I = P_n^R \cdot ACC_{ij,n}^R + P_n^D \cdot ACC_n^D \tag{4.25}$$

Where,

$ACC_{i,n}^I$: Integrated accessibility of individual category *n* in zone *i*
ACC_n^D : Digital accessibility of individual category *n* in zone *i*
P_n^R : Probability of choosing real space for individual category *n*
P_n^D : Probability of choosing the virtual space for individual category *n*

Although digital services may partially replace certain activities, the proposed framework in this thesis 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.

4.2.7. 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 (Sugiki et al., 2021). Location changes due to household relocations are represented using a residential zone choice model. Sub-models of the life event model are described below.

Aging

Aging events occur deterministically for individual nodes. If the simulation time step is Δt, then Δt is added to the individual's age. Aging is represented by reassigning the personal attribute links between the personal attribute (age) layer and the individual layer. Subsequent life events occur probabilistically according to the occurrence probability based on age.

Death

Death events occur probabilistically for all individual nodes. The probability of death by gender and age is defined using survival time analysis, assuming a Weibull distribution for the cumulative survival function. The cumulative survival function S(t) of the Weibull distribution is as follows:

$$S(t) = \exp\left\{-\left(\frac{t}{\beta}\right)^{\alpha}\right\} \quad (t \geq 0) \tag{4.26}$$

Here, t is age (survival time), and α and β are parameters. Equation (4.26) can be estimated based on statistical data from life tables. The probability of death is defined as

1-S(t), and death is determined probabilistically. An individual node determined to be dead disappears, and all connected links are deleted from the microsimulation model.

Divorce

Divorce events occur probabilistically for married individual nodes with marriage links. Divorce is determined based on the divorce probability defined by statistical data using the male's age as the reference. Marriage links and marriage nodes connected to an individual node determined to be divorced are deleted. When a marriage link is deleted, either the male or female leaves home and moves out, resulting in a change in the connection relationship of the location link. Furthermore, if a parent-child link exists, for simplicity, the parent-child relationship on the mother's side is maintained, and the link on the father's side is deleted.

Marriage

Marriage events occur probabilistically for unmarried individual nodes (men aged 18 and over, women aged 16 and over) without marriage links. Marriage is determined based on the marriage probability by gender and age, defined by statistical data. Matching between men and women is done based on the distribution of the age difference between married couples by age, as defined by statistical data. Priority is given to matching between men and women within the region, but only if there is no suitable match within the region will a spouse of the same age be allowed to move in from outside the region. For individual nodes determined to be married, a marriage relationship link is generated that connects them to a common marriage node. For household merging and separation, three patterns are considered: 1) merging with the husband's household, 2) merging with the wife's household, and 3) not living with either parent. In cases 1 and 2, the location link connection is changed to be the same as that of the household being merged. In case 3, the location link is changed, just like in the case of relocation, which will be described later.

Birth

Birth events occur probabilistically for individual nodes of married women (aged 16–49) with marital links. Birth is determined based on the birth probability for each mother's age and birth order, as defined by statistical data. The birth probability is defined using the generalized log-gamma distribution shown below.

$$g_n(x) = \frac{C_n|\lambda|}{b_n\Gamma(\lambda_n^{-2})}(\lambda_n^{-2})^{\lambda_n^{-2}}\exp\left[\lambda_n^{-1}(\frac{x-u_n}{b_n}) - \lambda_n^{-2}\exp\left\{\lambda_n\left(\frac{x-u_n}{b_n}\right)\right\}\right] \tag{4.27}$$

Here, $g_n(x)$ is the birth probability of the *nth* child of a woman aged x, Γ is the gamma distribution, and C_n, u_n, b_n, λ_n are parameters. Equation (4.27) can be estimated based on statistical data from the national census and vital statistics. When a birth is determined, a new individual node aged 0 is added, and a parent-child relationship link and a location link are assigned.

Updating employment or school enrollment

Updating employment and school enrollment occurs probabilistically for individual nodes. Based on the educational progression rate and employment rate defined from statistical data, updates to employment and school enrollment are represented by replacing the personal attribute link between the individual attribute (employment/enrollment) layer and the individual layer. Additionally, leaving home (independence) is determined when continuing education or starting work. If the individual leaves home, the location link is replaced, similar to household relocation, which will be described in this section.

Updating license status

Updating license status occurs probabilistically for individual nodes aged 18 or older. Driver's license acquisition and cancellation rates are calculated by sliding the driver's license ownership rates by gender and age, defined from statistical data, by one year. An increase in acquisition rates within a certain age group is defined as the acquisition rate, and a decrease is defined as the cancellation rate. Based on the driver's license acquisition and cancellation rates, updates to license ownership status are expressed by replacing the individual attribute links between the individual attribute (license ownership) layer and the individual layer.

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, the author added two new functions to define 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 chapter 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.

Independency (leaving home)

Independence (leaving home) events occur probabilistically for individual nodes. Separate from leaving home due to divorce, employment, or further education, gender and age-specific leaving rates are defined, and individuals are determined to have left home based on these rates. Individual nodes determined to have left home have their location links replaced.

Household relocation

Relocation events occur probabilistically for individual nodes belonging to the same household. Household relocation is determined based on relocation rates for the household head's age and household size. Individuals determined to have moved have their location links replaced within the same household. Connections to zone nodes via new location links represent the household's choice of location zone, and the destination is determined by the household residential selection model described below.

4.2.8. Transfer household generation model

Households migrating into the target area from external regions are generated based on exogenously specified inflow totals, including the number of incoming households by household size and the number of incoming individuals by age group. Within the target area, populations by gender and age group, as well as the number of households by household size, are aggregated. The population and household totals for the target area at simulation time step $t+\Delta t$ are provided as exogenous control totals. By computing the differences between these aggregate values and the corresponding exogenous totals, the required population by gender and age group, and the number of households are derived.

Using these marginal distributions, consistency with the exogenously given number of incoming households by household size is ensured, and the inflowing population, households, and their attributes are generated using the same procedure as the initial household microdata generation method (Matsuda and Konno, 2010). The residential zones of incoming households are determined jointly with relocating households within the target area through the residential location choice model described later. In addition, attributes related to school attendance, employment status, and driver's license ownership are assigned to the incoming population.

4.2.9. Residential location choice model

In the existing SDS model, the physical accessibility index (ACC_{ih}^{R}) is used to measure the attractiveness of a residential area. However, this thesis 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 for household *h* is *Z_h*, the multinomial logit model and utility function for the probability of selecting zone *i* are as follows:

$$V_{ih} = \sum_{k} \alpha_k X_{ik} + \beta ACC_{ih}^{I} + \gamma LP_i + c \tag{4.28}$$

$$P_{ih} = \frac{e^{V_{ih}}}{\sum_{i' \in Z_h} e^{V_{i'n}}} \text{ , } (i \in Z_h) \tag{4.29}$$

Where,

α_k, β, γ: Parameters

X_{ik} : Zone conditions (distance from city center, distance to nearest station, etc.)

ACC_{ih}^{I} : 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:

$$ACC_{ih}^{I} = \frac{1}{HS_h} \sum_{a_h=1}^{HS_h} ACC_{iah}^{I} \tag{4.30}$$

$$ACC_{iah}^{I} = ACC_{in}^{I} \text{ , } Cat(a_h) = n \tag{4.31}$$

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*

4.2.10. 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.

$$LP_i = \sum_k \gamma_k X_{ki} + \delta D_i + c \tag{4.32}$$

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.

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

4.3.1. Target activity behavior

This chapter utilizes the analysis results from Chapter 3 of this thesis about the substitutability of physical service access with digital alternatives, which was extracted from a web-based questionnaire survey conducted in November 2023, with 6,210 valid samples. As shown repeatedly in Figure 4.4, considering a higher substitution of physical shopping with online shopping, this chapter 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 into the microsimulation model, the chapter investigates the service choice behavior of individuals. In the shopping behavior, the significant relationship type parameters were relationships in the workplace and on the internet. Therefore, this chapter introduces these two types of relationships to the social relationship (interaction) type of microsimulation model.

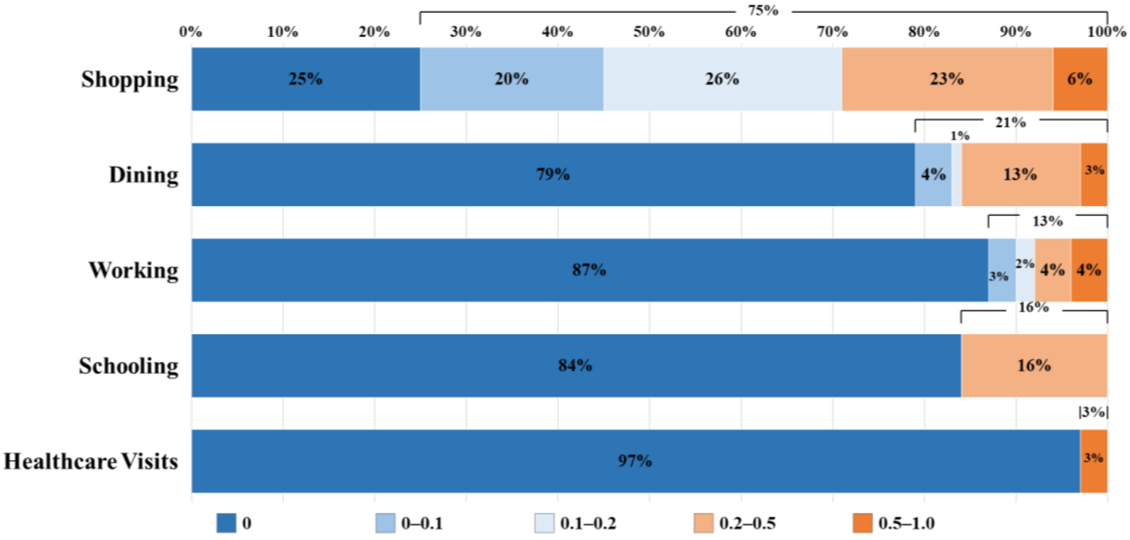


Figure 4.4. Distribution of substitution ratio by activities (Mutahari et al., 2025a)

4.3.2. Virtual city configuration

The constructed multi-layer network model is applied to a virtual city. The shape of the virtual city is shown in Figure 4.5. 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.

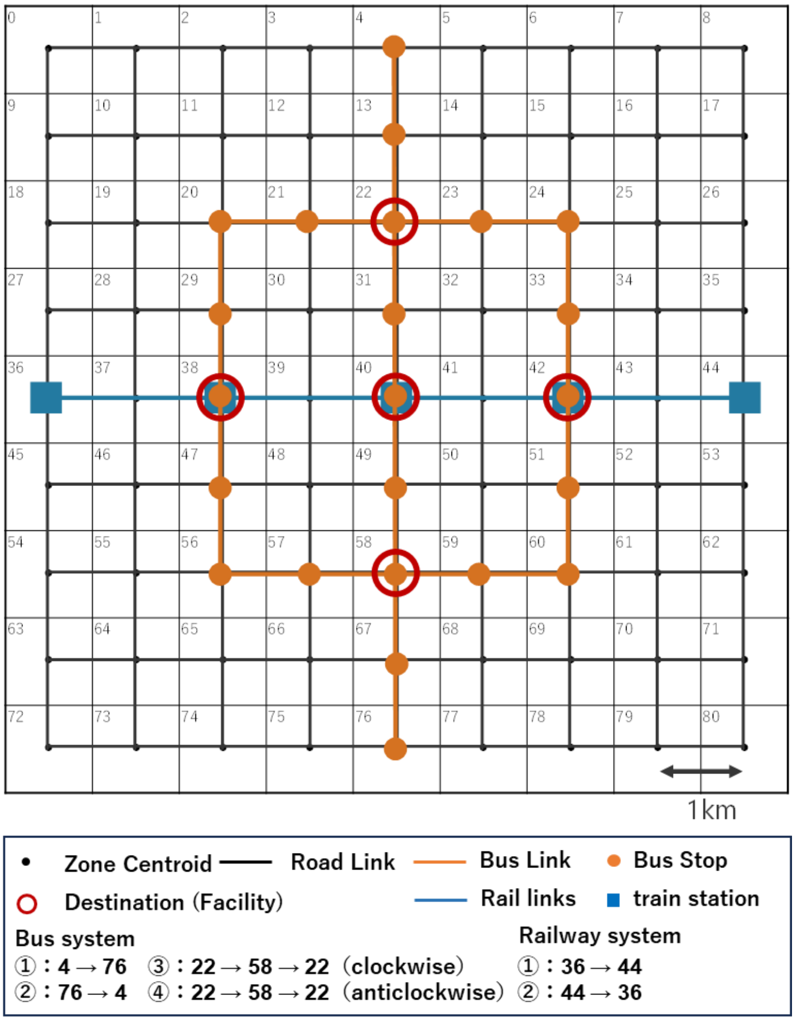


Figure 4.5. Setting of a virtual city (Mutahari et al., 2025c)

4.3.3. Parameter setting

Parameter estimation of service choice model

As described in Chapter 3, this chapter incorporates the results of Chapter 3 for parameter estimation of the service choice model. Parameter estimation for the physical and digital service choice model was performed using the web-based questionnaire survey data described in Chapter 3 of this thesis. In addition to individual and household attributes, the importance of interpersonal relationships was incorporated as an explanatory variable. The chapter 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 4.1 shows the parameter estimation for the service choice model, which is incorporated into the SDS model.

Table 4.1. Parameter estimation results of the service choice model.

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. Log-likelihood=-2737.11. Pseudo R^2=0.007.

Transportation network conditions and model parameters

This chapter utilizes the values defined by Sugiki et al. (2021) 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 shown in Table 4.2 – 4.6.

Table 4.2. Traffic network conditions. (Sugiki et al., 2021)

Transport Mode	System $\boldsymbol{l}$	Capacity $\boldsymbol{K_l}$ (/Mode)	Seat Capacity $\boldsymbol{SK}$ (P/Mode)	Minimum Frequency $\boldsymbol{minf_l}$ (Mode/Time)	Maximum Frequency $\boldsymbol{maxf_l}$ (Mode/Time)	Terminal Charges $\boldsymbol{ct_{r_l}}$(Yen/Times)	Distance Cost $\boldsymbol{ct_{r_l}}$(Yen/km)
Train	East-West (Left and Right)	200	100	2	10	100	20
Bus	North-South (Top and Bottom)	200	100	2	10	100	30
Bus	Circulated	60	30	2	10	100	30

Table 4.3. Residential location choice model parameters. (Sugiki et al., 2021)

Variables	**Parameter**
Land Price（10,000 Yen）	−0.2
City Center（Zone Centroid）Distance（km）* Common Logarithm	−0.3
Nearest Station Distance（km）＊Common Logarithm	−0.6
Household Synthetic ACC	0.5

Table 4.4. Land price model parameters. (Sugiki et al., 2021)

Variables	**Parameter**
City Center（Central Mesh）Distance（km）* Common Logarithm	−8.0
Nearest Station Distance（km）* Common Logarithm	−4.0
Population density＝Population/Zone Area（Person/ha）	0.1
Constant	20

Table 4.5. Facility (destination) unit indicator. (Sugiki et al., 2021)

Facility Zone	**Unit Indicator**	**Facility Zone**	**Unit Indicator**
22	500	42	500
38	500	58	500
40 (Central Zone)	1500		

Table 4.6. Generalized cost threshold. (Sugiki et al., 2021)

Transportation m	**Threshold** $gc\_thr_n^m$ **（Yen）**
Private Vehicle	1000
Car Riding	1000
Public Transport	3300

4.3.4. Virtual city simulation

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 ($ACC_{i,n}^I$) by zone and attribute, and the distribution of population and household locations in response to changes in residential location selection probability.

Simulation setting under integrated accessibility and social network

The integrated accessibility index ($ACC_{i,n}^I$) developed in this thesis 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.

4.4. Results and Discussion

This section presents the results of applying the proposed modified SDS model to a virtual city. The objective is to verify whether the model can plausibly reproduce population distribution, service access behavior, and mobility implications when the integrated accessibility index and social networks are explicitly considered.

4.4.1. Digital service usage

Figure 4.6 illustrates the digital service adoption rates across different age groups throughout the 30-year simulation period. The results reveal a distinct age-based stratification in digital service preference that remains remarkably stable over time. The youngest age group (0–20 years) exhibits the highest digital service share at approximately 25%, followed by the 21–40 age group at around 21%. Middle-aged residents (41–60 years) show moderate digital adoption at approximately 17.5%, while elderly groups demonstrate progressively lower rates: 15% for the 61–80 cohort and approximately 13–14% for those aged 80 and above.

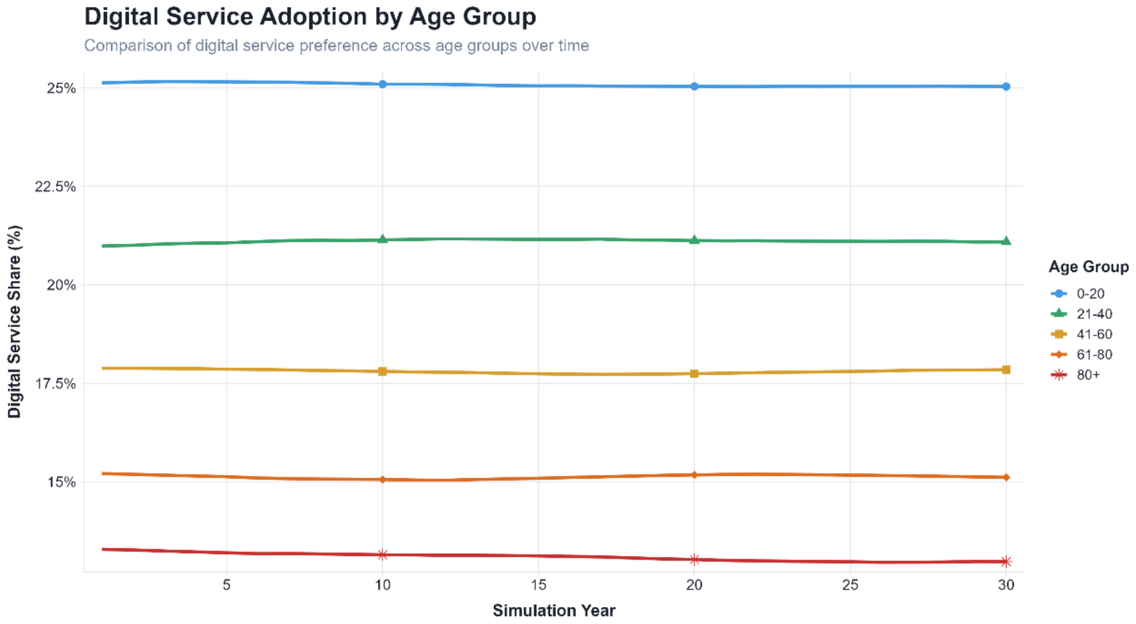


Figure 4.6. Digital service usage by age over 30 TS.

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 from Chapter 3, where age was found to have a significant negative effect on physical service utility ($\alpha_1 = -0.010$, $p<0.001$), 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.

4.4.2. Population distribution

Figure 4.5 illustrates the spatial configuration of the virtual city, including residential zones, service locations, and transportation infrastructure. This configuration provides the baseline for interpreting population redistribution under the SDS model. Figures 4.7 and 4.8 present the spatial distribution of population at the end of the simulation (T31) and the net population change over the 30-year period, respectively. The final population distribution (Figure 4.7) reveals a pronounced concentration pattern, with the highest population densities located at zones 36 and 44, where the train station is located. Secondary concentration areas appear around zones 38 and 42, where trains and buses are running. However, low population concentration is seen at the city center. This can be due to high land prices in the city center.

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.

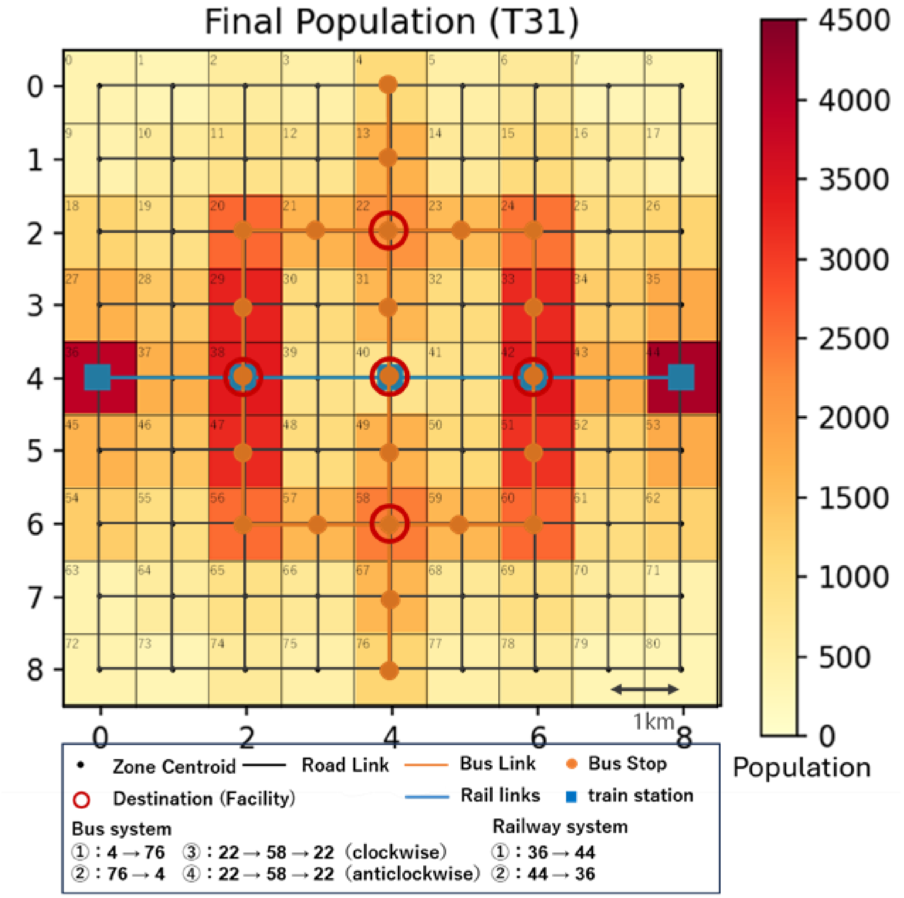


Figure 4.7. Population distribution in 31 TS.

The population change map, as shown in Figure 4.8, provides deeper insights into the dynamics underlying this distribution. The results demonstrate a clear pattern of spatial polarization: zones at 36 and 44 experienced population growth exceeding 3,000 residents, while peripheral zones, particularly in zones 0 and 72, experienced substantial population decline of up to 1,500 residents. This pattern reflects the residential location choice model's response to the integrated accessibility index, wherein households preferentially relocate to zones offering superior combined physical and digital accessibility.

The concentration at edge zones 36 and 44 can be attributed to their strategic position as transportation hubs that provide high physical accessibility while maintaining connectivity to digital services and lower land prices. This finding demonstrates how the model captures the interplay between traditional location factors (transportation accessibility, land price) and emerging factors (digital service availability, social network effects) in shaping residential preferences.

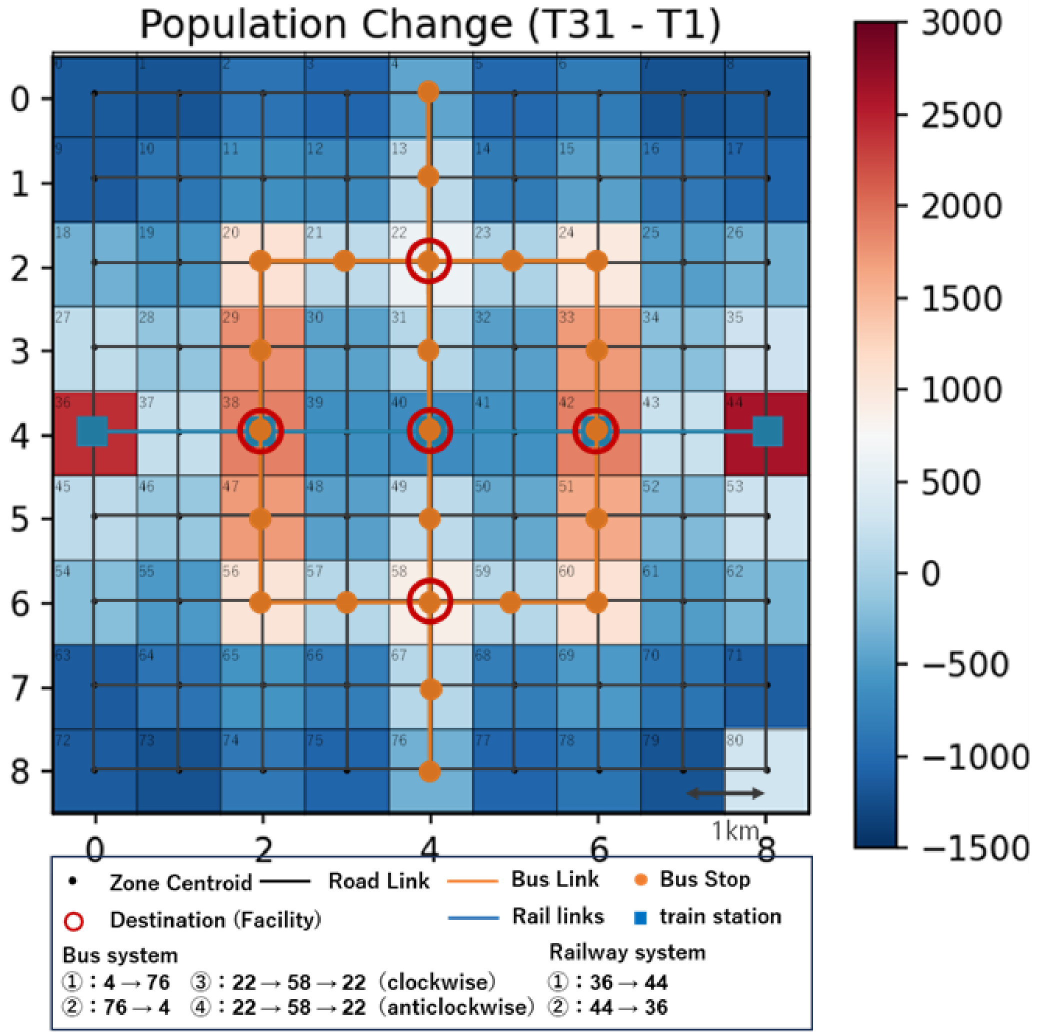
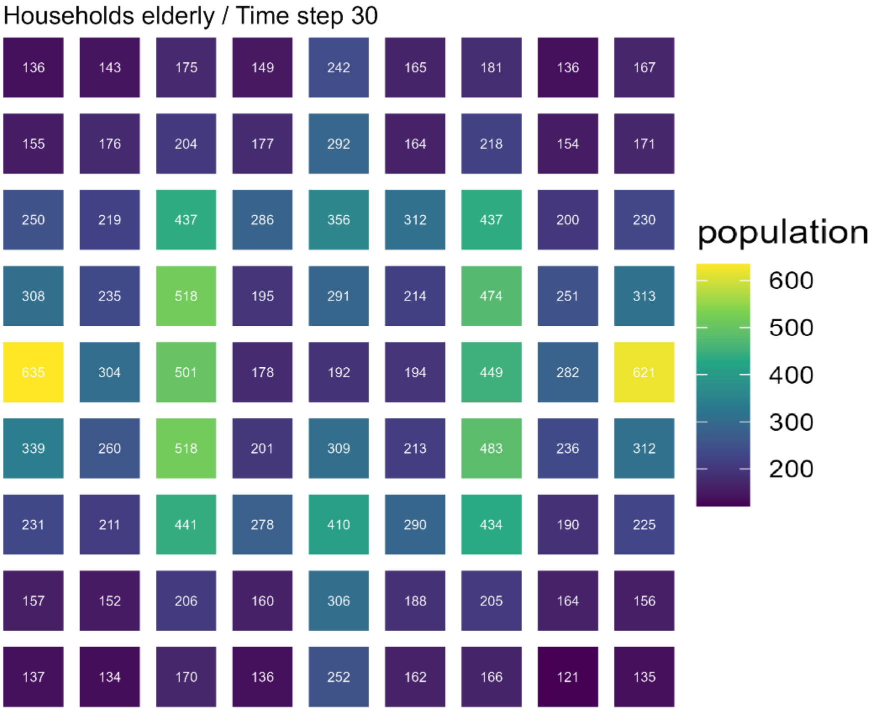


Figure 4.8. Population change distribution.

4.4.3. Household distribution

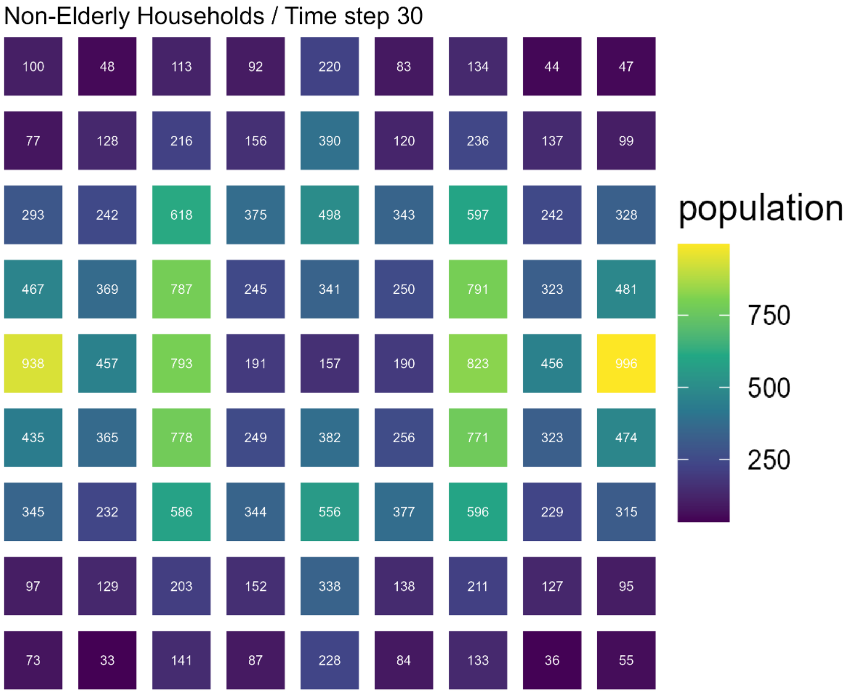
Figures 4.9 and 4.10 illustrate household distribution patterns differentiated by age group at the end of the simulation period (T30). Figure 4.9 shows the distribution of elderly households, revealing the highest concentrations at zones 36 and 44, respectively. A secondary concentration band appears at zones 29 and 47. Figure 4.10 displays the distribution of non-elderly households, which exhibits an even more pronounced concentration pattern. The peak values 36 and 44 substantially exceed those of elderly households, indicating that working-age households are more responsive to accessibility differentials in their location choices. The non-elderly distribution also shows strong clustering at zones 38 and 42.



Households elderly / Time step 30

136	143	175	149	242	165	181	136	167
155	176	204	177	292	164	218	154	171
250	219	437	286	356	312	437	200	230
308	235	518	195	291	214	474	251	313
635	304	501	178	192	194	449	282	621
339	260	518	201	309	213	483	236	312
231	211	441	278	410	290	434	190	225
157	152	206	160	306	188	205	164	156
137	134	170	136	252	162	166	121	135

Figure 4.9. Elderly households in 30 TS.



Non-Elderly Households / Time step 30

100	48	113	92	220	83	134	44	47
77	128	216	156	390	120	236	137	99
293	242	618	375	498	343	597	242	328
467	369	787	245	341	250	791	323	481
938	457	793	191	157	190	823	456	996
435	365	778	249	382	256	771	323	474
345	232	586	344	556	377	596	229	315
97	129	203	152	338	138	211	127	95
73	33	141	87	228	84	133	36	55

Figure 4.10. Non elderly households in 30 TS.

4.4.4. Traffic condition

Figures 4.11 and 4.12 compare road network traffic conditions between Year 0 and Year 30 of the simulation. At Year 0, as shown in Figure 4.11, 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 4.12, 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.

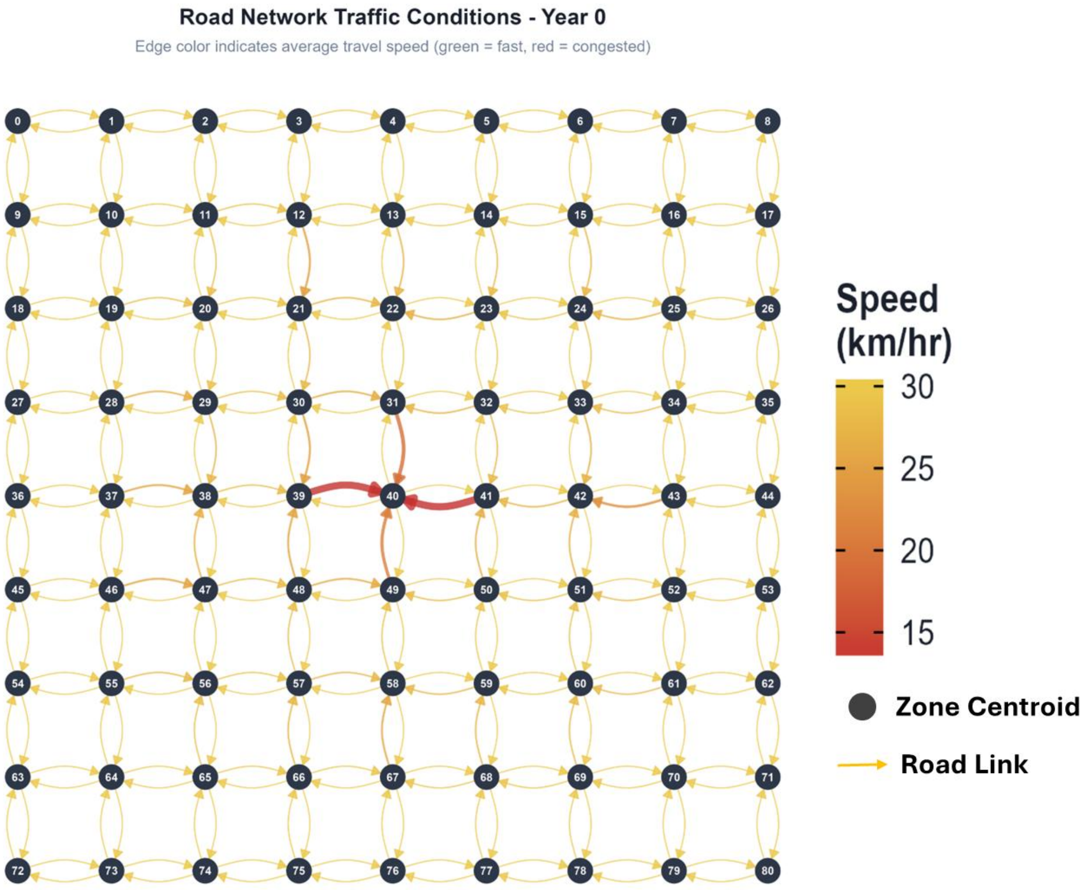


Figure 4.11. Road network traffic condition in 0 TS.

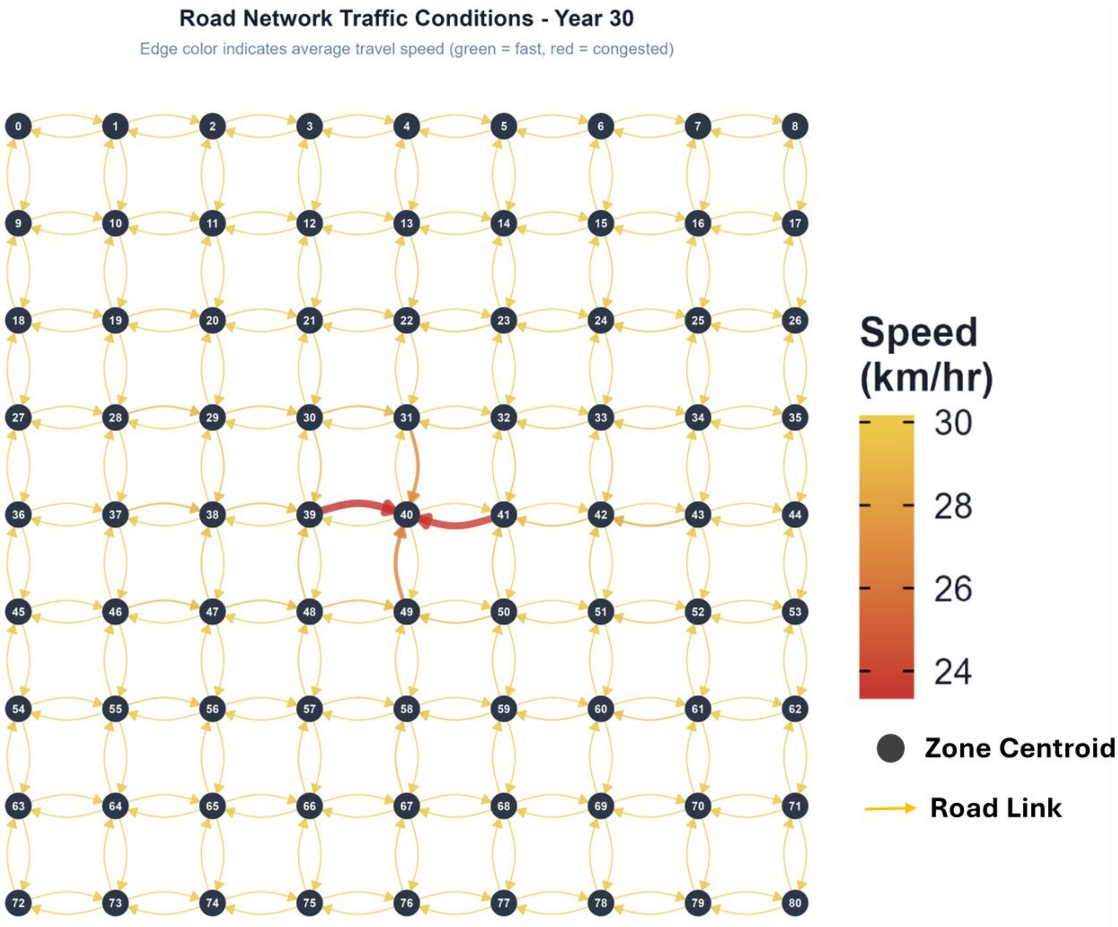


Figure 4.12. Road network traffic condition in 30 TS.

4.4.5. Transportation modes

Figures 4.13 and 4.14 illustrate the change of public transportation frequency and modal choice patterns throughout the 30-year simulation time steps. Figure 4.13 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.

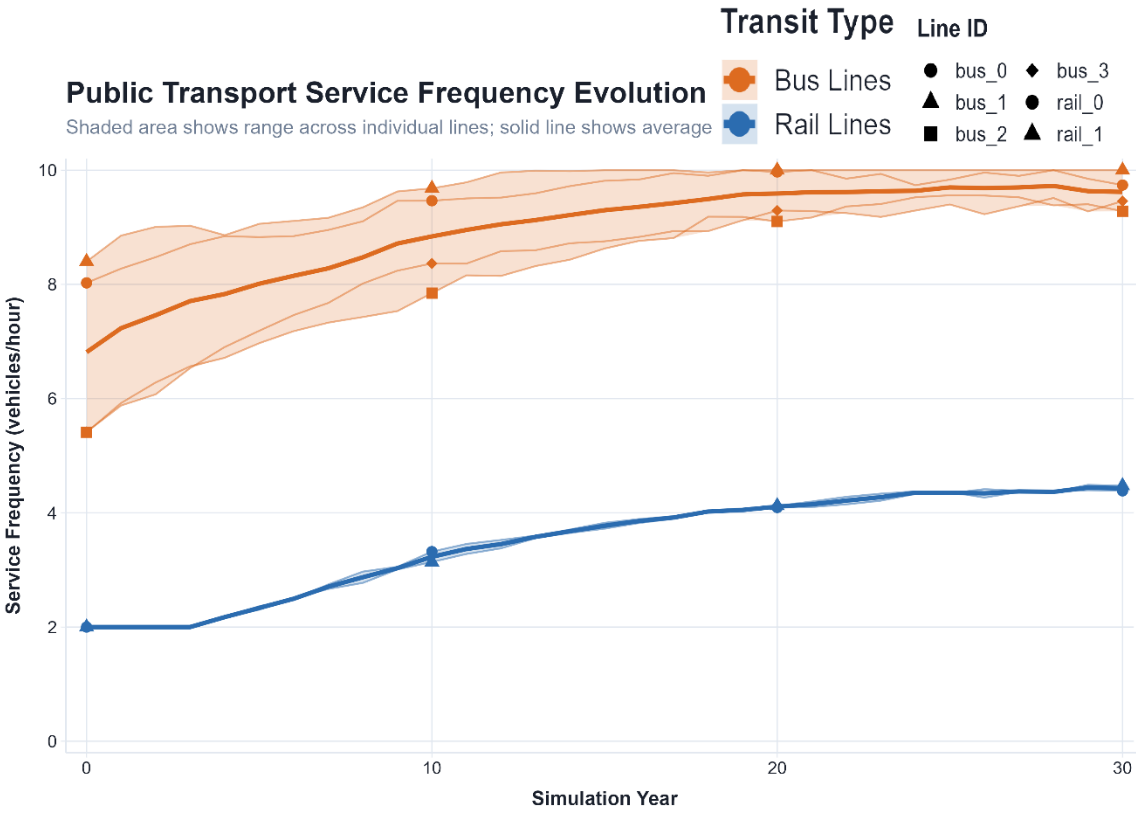


Figure 4.13. Public transport service frequency in different TS.

Figure 4.14 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.

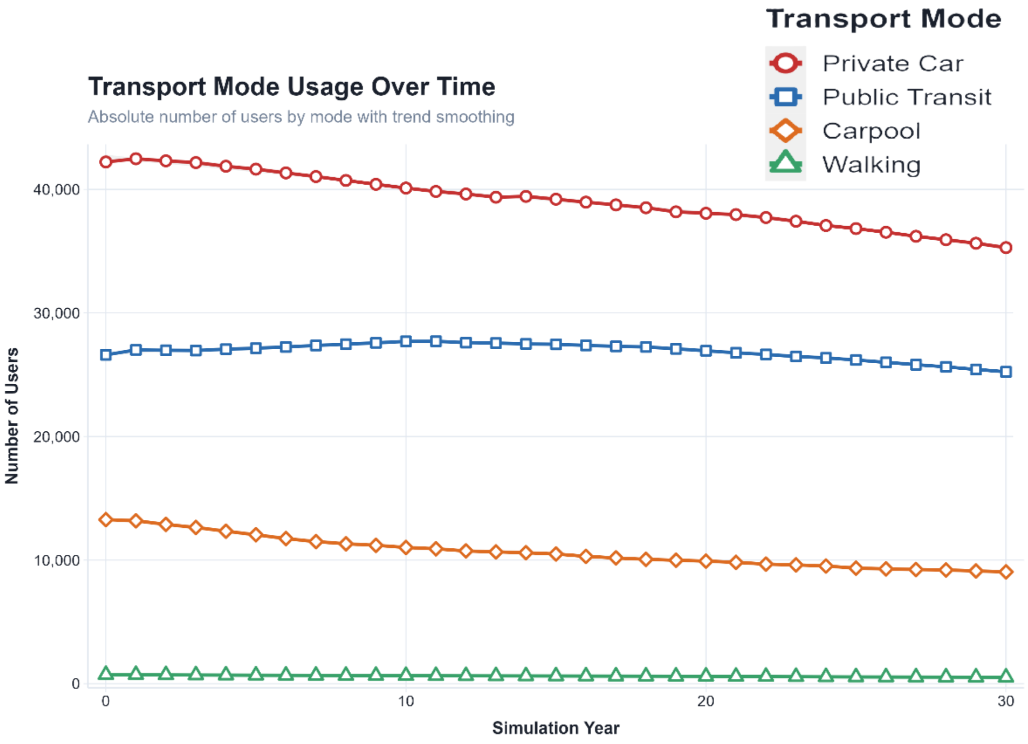


Figure 4.14. Transport mode usage in different TS.

4.4.6. Accessibility

Figures 4.15, 4.16, and 4.17 illustrate individual-level eigenvector centrality (EC), a network-based accessibility index, across different population segments and time periods. Figure 4.15 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 4.16 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.

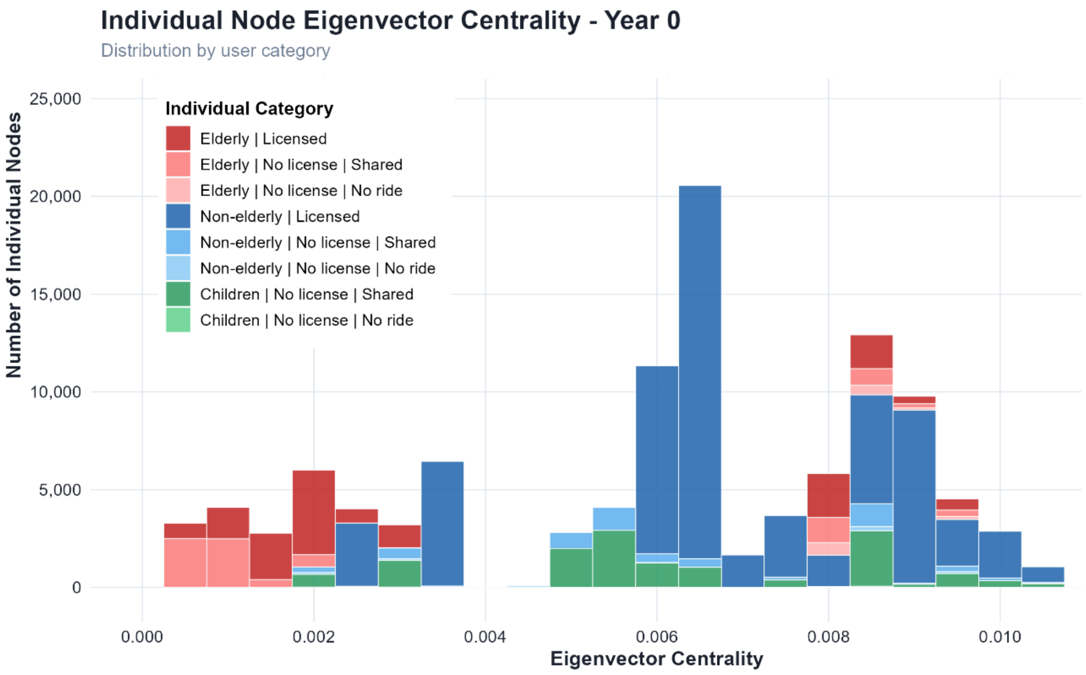


Figure 4.15. Individual node EC in 0 TS.

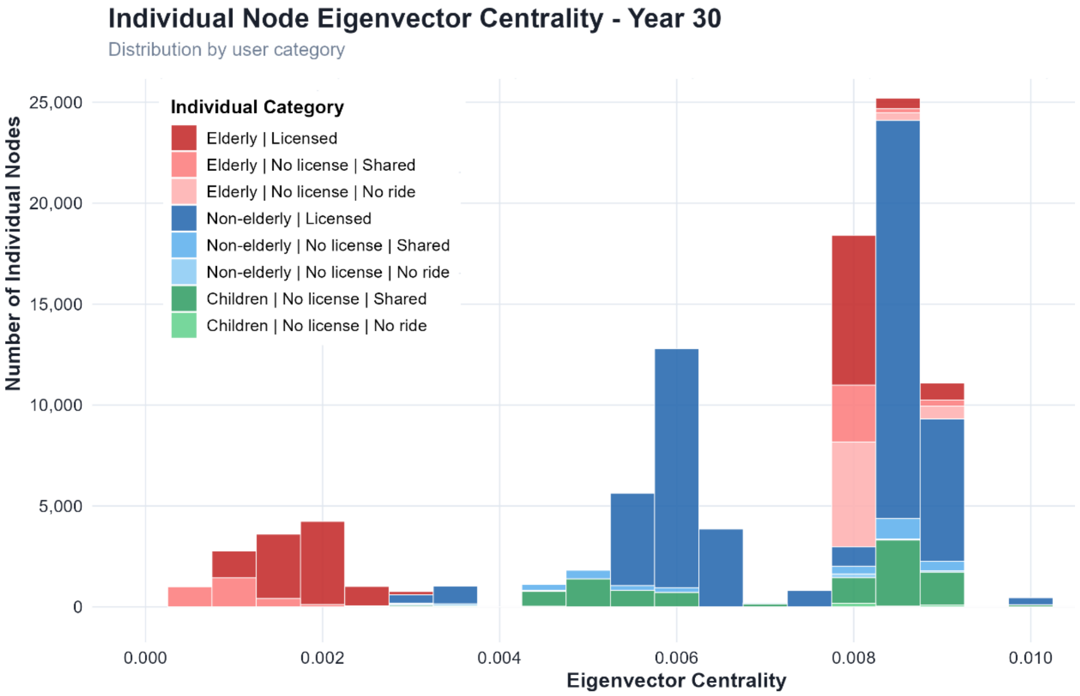


Figure 4.16. Individual node EC in 30 TS.

Figure 4.17 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.

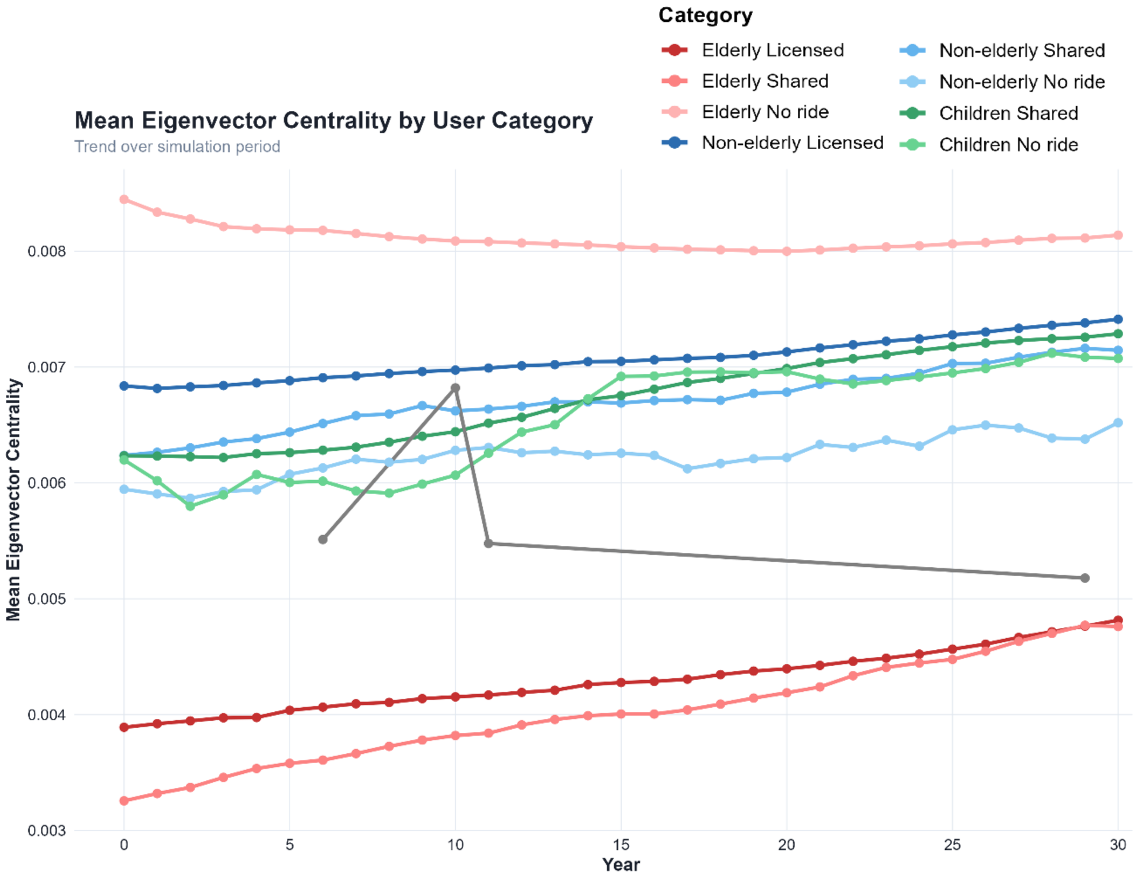


Figure 4.17. Mean EC by user category in different TS.

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 residential location decisions across diverse population groups while incorporating the social network, service choice model, and integrated accessibility model.

4.5. Conclusion

In this chapter, the author modified a multi-layer network SDS model by incorporating the social network, service choice model, and integrated accessibility model into it to predict the urban structure and dynamic changes in a virtual city setting environment. Specifically, by introducing a social network layer that captures individuals' attributes and social interactions and the integrated accessibility model into the existing microsimulation model, the author developed a comprehensive social dynamics simulation system, capable of representing the complex interactions between real space, virtual space, and social networks within an urban environment. To construct the digital service choice model, the author estimated the parameters from a survey, using a binomial logit model to probabilistically determine whether individuals choose services in real space or alternative digital services in virtual space. Taking the results of Chapter 3, the author considered the shopping service as a focal service and proceeded with service choice model parameter estimations, and incorporated it into the microsimulation model alongside the integrated accessibility model to predict household and population distribution alongside other urban dynamics through zone choice analysis.

Subsequently, the SDS model was applied to a virtual city in order to examine the internal consistency and behavioral plausibility of integrating physical accessibility, digital accessibility, and social networks within a unified modeling framework. Rather than aiming to replicate a specific real-world city, the virtual city application served as a controlled environment for verifying model mechanisms and interactions. The results demonstrated that residential location, service access mode choice, mobility demand, and social network structure emerge endogenously from individual-level behavior and accessibility conditions. Digital accessibility was shown to partially relax dependence on physical accessibility, enabling greater spatial flexibility in residential choice while preserving the central role of transport-accessible zones. Service access outcomes varied systematically by activity type, confirming that digital services primarily complement, rather than fully substitute for, physical services.

The evolution of social networks observed in this chapter reflects differences in accessibility and mobility conditions across population groups. A comparison of individual-level eigenvector centrality at Year 0 and Year 30 shows that non-elderly licensed individuals increasingly occupy higher centrality positions, while elderly and mobility-constrained individuals remain concentrated at lower centrality levels. Zone-level interaction distributions at Year 30 further support this pattern, with elderly interactions spatially concentrated and non-elderly interactions more widely distributed across the virtual city. These results indicate that social network structure and urban space evolve jointly within the model through accessibility-dependent interaction mechanisms.

Overall, the virtual city application confirms that the proposed SDS framework can coherently capture the co-evolution of population distribution, service choice behavior, mobility, and social interaction. By explicitly modeling the interactions between physical, digital, and social layers, this chapter provides a robust foundation for evaluating broader well-being and opportunity outcomes. The validated model is therefore well-suited for the integrated Quality of Life (QOL) and Quality of Opportunity (QOB) analyses conducted in the subsequent chapters. However, this thesis does not project QOL and QOB using the SDS model. It is recommended as a future research prospect.

As this study was limited to shopping behavior, future work will require modeling of other purposeful behaviors, such as commuting, eating out, and entertainment, including both real-space behavior and alternative behavior in virtual space. Additionally, this chapter recommends the application of the newly developed SDS model to a real city to examine the practicality of the analytical method and to further analyze the impact of individuals' preferences for physical service access and digital service access on urban structure.

Chapter 5

Developing Quality of Life (QOL) and Quality of Business (QOB) Evaluation Model Using an Integrated Accessibility Index

This chapter presents the total concept and methodological foundation of the second topic of this thesis by developing an integrated accessibility-based evaluation framework for both QOL and QOB solely for the air-front smart city. Based on insights from Chapters 3 and 4, the chapter defines accessibility indices that consider both physical and virtual service accessibility as described in Chapter 4. The QOL and QOB models are developed to evaluate urban living and business environments, respectively, for different stakeholders of business in a specific region based on the definition of an air-front smart city. The chapter showcases indicator definitions and scenario settings (Aichi startups, Baguio agriculture, and Phuket tourism), which illustrate how the framework can be applied to diverse contexts. The chapter establishes the core evaluation methodology for Air-front Smart Cities. Some parts of this chapter are published in the Journal of the Eastern Asia Society for Transportation Studies (Mutahari et al., 2025d).

5.1. Introduction

Air-front smart city concept, which addresses the stagnation of industries in developed countries and stimulate economic growth in developing countries while maintaining a higher QOL for people and contributing to decarbonization (De-CO2) efforts by leveraging advanced technologies, suggests to connect airport developments with urban and industrial innovation, tailored to the unique characteristics of each region, focusing on the impacts not only within the city but also on hinterland areas, on a regional level. Considering the concept of air-front smart cities and sustainable urban developments, it is crucial to evaluate not only the QOL of individuals considering their accessibility to different services, but also urban business environments for the economic growth assessment.

Several existing studies have developed methodologies to evaluate smart cities, including QOL-accessibility evaluation, which can be applied for smart city policy evaluation. QOL-based evaluation of urban policies gives a holistic insight into human-centric urban development, rather than just cost and benefit analysis. Specifically, the individual QOL evaluation methods can provide disaggregated information in individual categories from the perspective of the human. The QOL-accessibility evaluation approach can be subjective and objective, which enhances its applicability and effectiveness. However, the QOL-accessibility evaluation model in the current studies focuses on physical accessibility rather than combining it with digital accessibility. Hence, there is a gap in lacking QOL evaluation model that considers both physical and digital accessibility. This chapter utilizes the results from Chapter 3 and incorporates the integrated accessibility index as introduced in Chapter 4 into an existing QOL-accessibility-based evaluation model. The chapter modifies the model (Hayashi, 2023) to evaluate urban living environments through individuals' perceived accessibility through both real and virtual networks. The definition of physical and digital accessibility, physical and digital services, and real and virtual networks is similar to the previous definition in this thesis.

Additionally, considering the definition of an air-front smart city, this chapter develops a Quality of Business (QOB)-accessibility based evaluation method alongside QOL evaluation for an air-front smart city. The QOB evaluation model evaluates urban business environments for different stakeholders of a business, considering the accessibility of the business to different products and services. The idea of developing the QOB evaluation model in this chapter has emerged from the deep QOL literature surveys and the air-front smart city concept. The author argues that there is a tight relationship between QOL and QOB, as one affects another which will be discussed in the Materials and Methods section of this chapter. Connecting QOB to the QOL framework is essential to ensure the holistic development of urban systems that cater to both resident well-being and economic growth. Therefore, the objective of this chapter is to construct an integrated accessibility-based evaluation model for assessing QOL and QOB in air-front smart cities, and assessing how integrated digital and physical accessibility can inform urban policy and support sustainable development through improved QOL and QOB.

Furthermore, the chapter selects three cities (Aichi, Phuket, and Baguio) with different economic development stages and three industries, such as startup, tourism, and agriculture (see Chapter 2). The author set scenarios for each city to explain how the evaluation framework can be applied, and further present the QOL and QOB component indicators selection for each case. Although Aichi is a prefecture in Japan holding several cities within it, our evaluation methodology rarely cares about municipality boundaries. So, the author considers Aichi as a region for QOL and QOB evaluation.

5.2. Materials and Methods

As was described in Chapter 2 and illustrated in Figure 2.3, the air-front smart city environment is said to be evaluated from three perspectives: human well-being or GRH, economic growth, and De-CO2. The following section of this chapter develops a QOL and QOB evaluation model to tackle the well-being perspective of an air-front smart city, in addition to assessing urban business environments within it, and QOL and QOB will be used as input for the regional evaluation model, as was described in Chapter 2. Following, the chapter will explain why the author has integrated QOB evaluation into the air-front smart city evaluation, and what kind of interactions can exist between QOL and QOB.

Considering the fact that airport function improvements, which can enhance both physical and digital connectivity, can improve access to essential services such as healthcare, education, markets, and logistics. This increased accessibility supports higher QOL by reducing travel time and improving service accessibility, while also boosting QOB by enabling efficient goods movement, workforce mobility, and access to broader customer bases. Collectively, these factors reinforce well-being and economic growth. The author believes these mechanisms are fundamental to the air-front smart city concept, where airports serve as gateways for both regional development and digital transformation.

To develop a comprehensive evaluation methodology for air-front smart cities based on QOL and QOB evaluations, the chapter investigated the relationship and interactions between QOL, QOB, and De-CO2 through literature surveys. The chapter suggests that there is a tight relationship between QOB and QOL, as some outcomes of QOL or QOB will be used as indicators of the other, as shown in Figure 5.1. For instance, places offering a higher QOL will attract people and human resources, and the availability of human resources improves QOB. Additionally, an existing study by Love and Crompton (1999) also confirms that places with higher QOL will encourage businesses to relocate within them.

On the other hand, a higher QOB will result in higher income and job opportunities, which will enhance the QOL of individuals (Takano et al., 2023). Similarly, QOL, QOB, and De-CO2 are affected by accessibility. Higher accessibility will improve the QOL and QOB; however, accessibility affects De-CO2 through individuals and business activities. For instance, accessibility type (physical or digital), either through a real (transportation) network or virtual (ICT) network (Qing et al., 2023), or transportation mode of individuals (Yuan et al., 2018) and businesses (Zhang et al., 2023) to reach or deliver services, will affect De-CO2, considering the CO2 emission. Additionally, existing studies (Chatti, 2021; Baffour Gyau, 2024) confirm that access through ICT networks emits considerably less amount of CO2 compared to access through transportation networks. Enhancing accessibility to different urban services through virtual networks can contribute to De-CO2 efforts. However, to reduce confusion, the author emphasizes again that the De-CO2 concept is out of scope of this thesis. This interactional diagram was constructed to provide a clear picture for the air-front smart city bodies who work in this field.

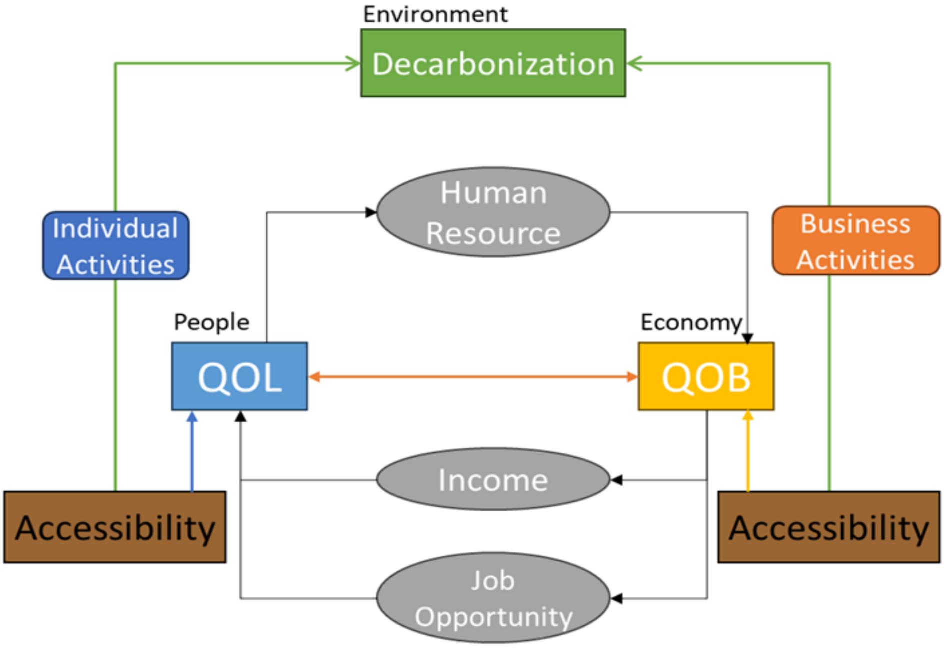


Figure 5.1. Interaction between QOL, QOB, and De-CO2. (Mutahari et al., 2025d)

5.3. Model Developments

5.3.1. Evaluation framework

This section presents a step-by-step development of the proposed evaluation framework for the air-front smart city. The methodology is structured around three key components: 1) defining a conceptual evaluation model linking QOL and QOB to the gross regional happiness (GRH), economic growth (EG), and De-CO2, 2) identification of component indicators for individuals and businesses, and 3) formulating equations to estimate QOL and QOB based on integrated accessibility, service value, and weight of component indicators. The framework is designed to assess how smart city policies, categorized into rules and regulations, infrastructure, and digital technologies, influence urban living and urban business environments in the context of air-front smart cities. These dimensions majorly affect the accessibility of businesses and individuals to essential services and, as a result, influence the QOB and QOL. Ultimately, they contribute to broader outcomes such as EG, GRH, and efforts toward De-CO2. By clearly distinguishing the inputs, dimensions, and evaluation indicators for different case applications (startups in Aichi, tourism in Phuket, and post-harvest agriculture in Baguio), the methodology enables a focused and adaptable assessment approach. The air-front smart city evaluation model framework is shown in Figure 5.2.

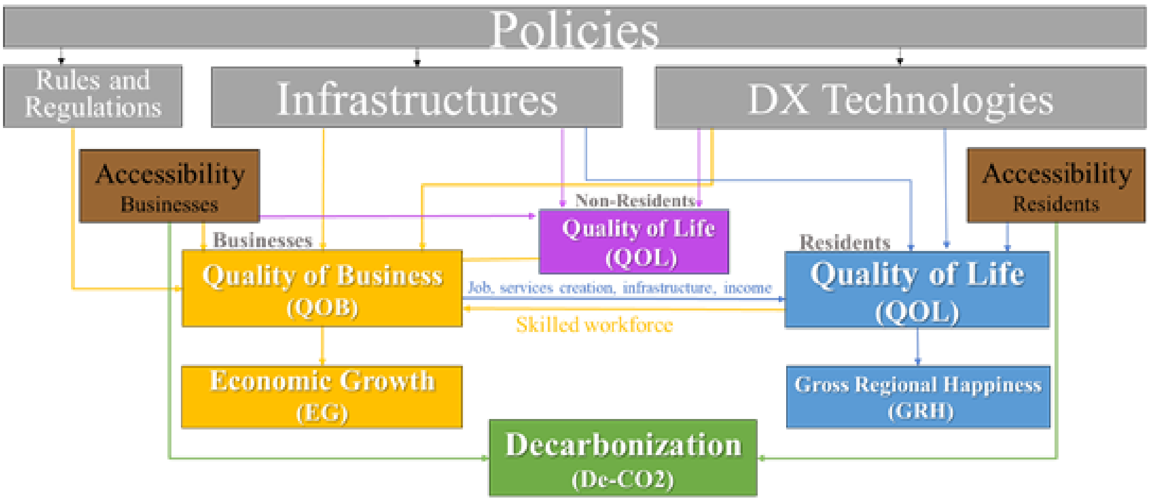


Figure 5.2. Air-front smart city evaluation framework. (Mutahari et al., 2025d)

To comprehensively evaluate the living and business environments, this chapter develops the evaluation framework to not only consider the QOL of the residents but also the QOL of business stakeholders to be assumed as non-residents, such as business partners in case of startups, tourists in case of tourism, and consumers in case of agriculture. For example, when assessing the QOB for startups, tourism, and post-harvest agriculture, the QOL of business partners, tourists, and consumers, respectively, becomes critical, particularly within the context of the air-front smart city concept, as stakeholders of businesses. A higher QOL for business stakeholders (non-residents) who interact with the city can significantly enhance the QOB of specific business categories. The QOL and QOB equation models are described in the following sections of this chapter. The novelty of this chapter is developing the QOL and QOB model, which can consider physical and digital accessibility of individuals and businesses, respectively, to the services and products, and showcases the indicator definition of QOL and QOB for each industry type.

5.3.2. Integrated accessibility index

As was defined in Chapter 4, the integrated accessibility is a linear combination of physical accessibility and digital accessibility, weighted by the probability of choosing each space. Repeatedly, Equation 5.1 calculates the integrated accessibility index as follows.

$$ACC_{ij,n}^{I} = P_n^R \cdot ACC_{ij,n}^{R} + P_n^D \cdot ACC_n^D \tag{5.1}$$

Where,

$ACC_{i,n}^{I}$: Integrated accessibility of individual category *n* in zone *i*
ACC_n^R : Physical accessibility of individual category *n* in zone *i*
ACC_n^D : Digital accessibility of individual category *n* in zone *i*
P_n^R : Probability of choosing real space for individual category *n*
P_n^D : Probability of choosing the virtual space for individual category *n*

5.3.3. Integrated accessibility based QOL evaluation model framework

The integrated accessibility index is used to modify an existing QOL-accessibility-based evaluation model (Hayashi, 2023) to evaluate QOL of individuals by assessing their accessibility through real and virtual networks. The integrated accessibility index considers both transportation and ICT networks to develop a methodology to assess the accessibility of different individual categories to the urban services; as a result, the QOL of individuals will be estimated.

The evaluation framework explicitly considers accessibility of individuals to different urban services through real and virtual networks, as illustrated in Figure 5.3. Individual attributes, travel modes, and digital access modes are directly incorporated into the evaluation model. For the QOL assessment, individuals are classified into two groups: residents and non-residents. Residents are defined as individuals living within zone i, whereas non-residents are individuals located outside zone i who consume services provided by businesses within that zone. This distinction enables the model to capture the QOL of business stakeholders and is consistent with the functional definition of an air-front smart city.

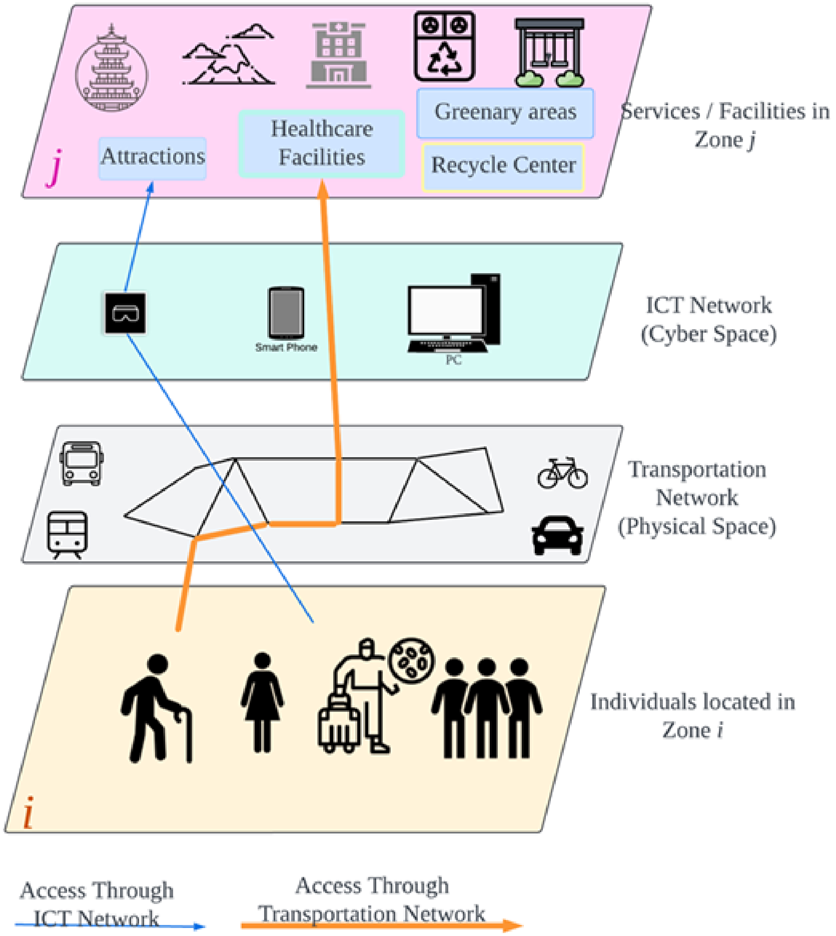


Figure 5.3. QOL evaluation model framework. (Mutahari et al., 2025d)

5.3.4. QOL equation model structure

Figure 5.4 represents the QOL evaluation model structure, where we can see services are categorized into accessibility and non-accessibility-related services. The accessibility-related services include services such as shopping, medical care, etc, whereas non-accessibility-related services include services such as air quality, greenery coverage, etc. Subsequently, accessibility-related services are categorized into real (transportation) network and virtual (ICT) network-based services. The QOL evaluation procedures include component indicator selection, accessibility cost estimation, service weight calculation, and QOL value calculation, as shown in Figure 5.4. Each step of QOL evaluation is explained in the following section.

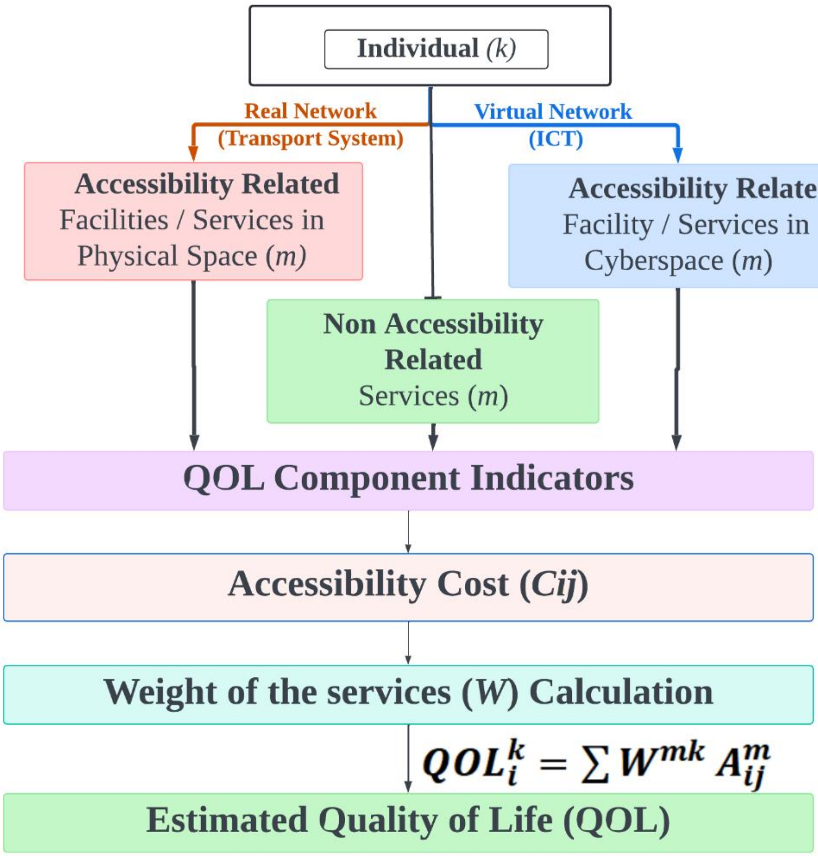


Figure 5.4. QOL evaluation model structure. (Mutahari et al., 2025d)

QOL component indicator selection

Using web-based questionnaire surveys and interviews with the main stakeholders, the necessary QOL component indicators can be selected to ensure they capture the multifaceted nature of QOL. The focus of this chapter is to emphasize the QOL component indicators related to not only services available in physical space but also virtual space.

Integrated accessibility cost estimation

Accessibility-related services, either in physical space or virtual space, need accessibility costs for individuals to reach these services. However, accessibility costs to cyberspace due to relying on ICT networks rather than transportation networks do not require travel costs, but they are influenced by individuals' attributes (e.g., age, gender, social status), internet coverage, terminal devices, and digital literacy (ability and knowledge). Depending on the data availability, these factors can be quantified and incorporated into the QOL evaluation model. Additionally, the value of services offered in each network (real and virtual) is different, and it is weighted by the preference of individuals. For instance, online shopping and in-store shopping have different values for each individual, which can be weighted by stated preference of individuals using questionnaire surveys. The weights of these services can be used to estimate the physical and digital accessibility index. The integrated accessibility index in equation (5.1) will be used to estimate the accessibility cost for QOL evaluation.

Service weight estimation

The value of each service, whether provided in physical or digital spaces, varies based on the attributes of individuals. To estimate this value, a survey can be conducted, followed by mathematical analysis. One of the most effective approaches for determining the weight of services is pairwise conjoint analysis, which allows for the calculation of the monetary value assigned to each service. This thesis will use the conjoint analysis on a questionnaire survey to estimate the monetary value of service weights of QOL and QOB for a startup ecosystem in Chapter 6.

QOL estimation

QOL of individuals is estimated using equation (5.2), considering the accessible values of services and the weight of services. The accessible value of service *m* is calculated using equation (5.3).

$$QOL_i^{mk} = \sum W^{mk} \cdot A_{ij}^{m} \tag{5.2}$$

Where,

QOL_i^{mk} : Perceived value of service *m* for individual *k* located in zone *i*.

W^{mk} : Weight of service *m* for individual *k*.

A_{ij}^{m} : Accessible value of service m located in zone *j*.

$$A_{ij}^{m} = V_j^{m} \cdot e^{-ACC_{ij,n}^{I}} \tag{5.3}$$

Where,

V_j^{m} : Existing value of service *m* in zone *j*.

5.3.5. Integrated accessibility based QOB evaluation model framework

This section introduces the QOB concept and integrates it into the air-front smart city evaluation system, as an evaluation method aimed at assessing the urban business environment by evaluating the accessibility of essential services for businesses, particularly within, but not limited to, the air-front smart city context. The QOB model serves as a mathematical tool to assess how effectively businesses can access critical infrastructure, services, and technologies needed for economic growth. The focus is on evaluating the accessibility of different business categories to the services, as shown in Figure 5.5. By considering these factors, QOB helps identify how well cities can create an environment conducive to economic competitiveness and higher QOL. This framework ensures that air-front smart cities not only support thriving businesses but also contribute to overall urban development, balancing economic success with the well-being of people.

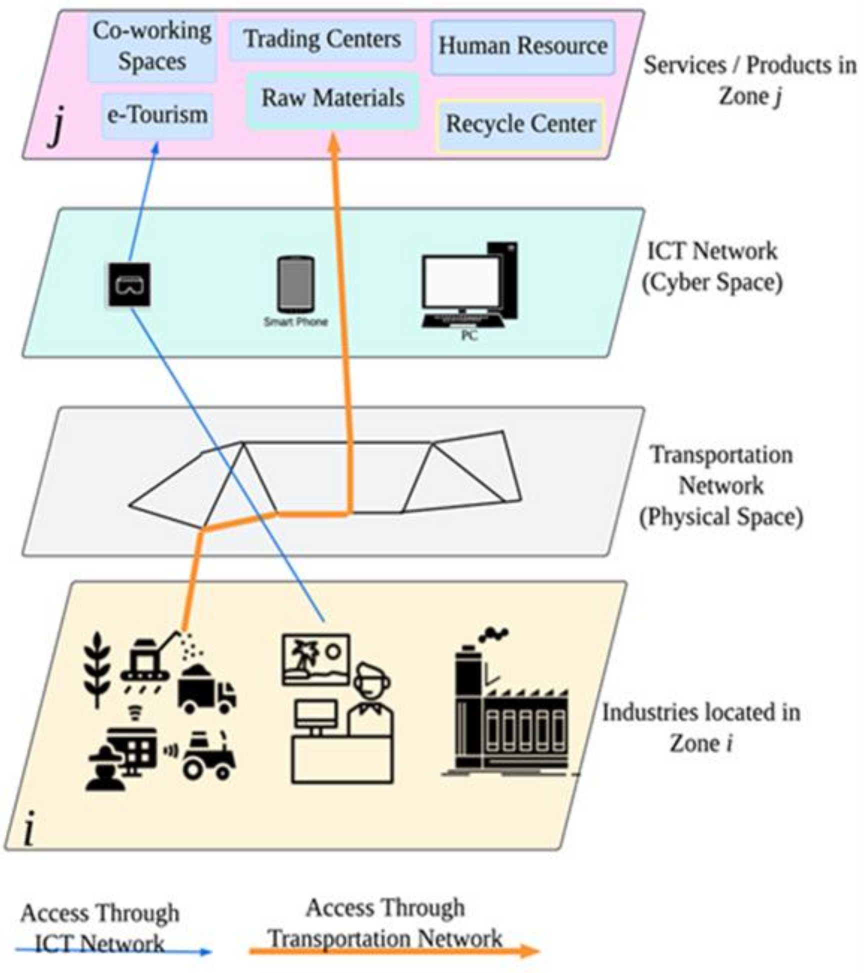


Figure 5.5. QOB evaluation model framework. (Mutahari et al., 2025d)

5.3.6. QOB equation model structure

The QOB evaluation model is based on the integrated accessibility approach evaluation methodology, similar to the QOL evaluation model. The model evaluates the QOB of *k*-type businesses or industries, and as a result, Economic Growth (EG) can be estimated through the Input-Output (IO) model. Additionally, the model can assess the value of urban business services in three stages: existing service value, accessible service value, and perceived service value.

Services (*m*) affecting QOB are categorized into accessibility and non-accessibility related services, where both types of access, access through transportation and ICT networks, are considered in the equation model. The remaining process of QOB estimation, as shown in Figure 5.6, includes QOB component indicators selection, estimating accessibility cost, calculating the weight of the services (*W*), and finally, the QOB can be calculated.

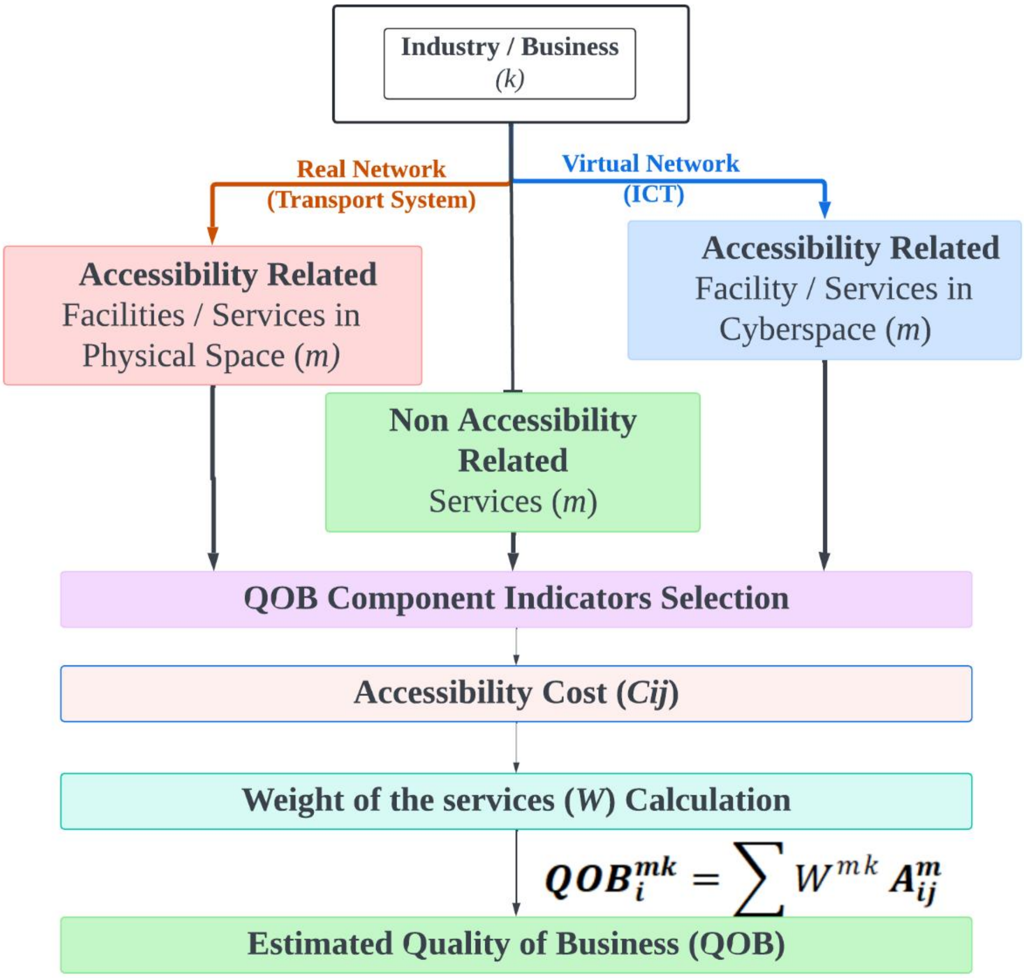


Figure 5.6. QOB evaluation model structure. (Mutahari et al., 2025d)

QOB component indicator selection

Using a questionnaire survey and interviews with the main stakeholders of the businesses, the most important services for the different business categories can be identified, and QOB component indicators to precisely reflect the needs are selected. Services offered in both physical space and virtual space are selected for this purpose.

Integrated accessibility cost estimation

Accessibility-related services, either in physical space or virtual, incur accessibility costs for businesses to access these services. However, accessibility costs to cyberspace due to relying on ICT networks rather than transportation do not need travel costs, but it is dependent on business type, network coverage, and the ability to use digital devices. However, the value of services offered in each space is different, which will be considered while estimating the weight of each service. The integrated accessibility cost is estimated based on equation (5.1). The integrated accessibility costs include the physical accessibility cost and the digital accessibility cost.

Service weight estimation

The value of each service, either offered in physical space or virtual space, is different depending on the business type. The service value can be estimated by conducting a survey and performing a mathematical analysis. The best method to find the weight of the services is pairwise conjoint analysis, which can give the monetary value of each service.

QOB estimation

QOB of k type of business is estimated considering the accessible values of urban business services and the weight of the service according to equation (5.4). The accessible value of the service is estimated using existing values and accessibility cost, according to equation (5.5).

$$QOB_i^{mk} = \sum W^{mk} \cdot A_{ij}^{m} \tag{5.4}$$

Where,

QOB_i^{mk} : Perceived value of service *m* for business *k* located in region *i*.

W^{mk} : Weight of business service *m* for business *k*.

A_{ij}^{m} : Accessible value of service m located in zone j.

$$A_{ij}^{m} = V_{j}^{m} \cdot e^{-ACC_{ij,n}^{I}} \tag{5.5}$$

Where,

V_j^m : Existing value of service m in zone j.

5.4. QOL and QOB Component Indicator Definitions

5.4.1. Scenario settings

To showcase the definition of the QOL and QOB evaluation model, various scenario settings are utilized across three regional contexts. Three cities at distinct stages of economic development, Aichi, Phuket, and Baguio, are selected for this purpose. Aichi's economy is at a regeneration stage and is undergoing the phase of industrial regeneration, and is seeking innovative solutions to revitalize traditional industries. The model evaluates rules and regulations, infrastructure developments, and DX technologies within living and business environments for startup ecosystems. Phuket, whose economy is at the maturity stage, and the main contributing industry to its economy is tourism. On the other hand, Phuket is facing overtourism challenges. For Baguio, whose economy is at a developing stage, the model evaluates urban policies within living and business environments for post-harvest agriculture. This involves leveraging transportation and ICT networks to enhance agricultural supply chains, particularly in the face of geographical challenges and natural disasters such as flooding.

The selection of these three cities with different economic stages and business types can help to understand the development a comprehensive QOL and QOB evaluation framework across diverse urban contexts, and they provide valuable settings to showcase how such a framework can be applied and adapted. The objective is to showcase how the QOL and QOB component indicators are selected for these three cities, considering the three business types. These three cities may not necessarily be smart, but the author has selected these cities because of their distinct characteristics to apply the framework and introduce the air-front smart city concept. These industries were selected to demonstrate the application of the QOL and QOB evaluation methodology, with particular emphasis on identifying component indicators for the air-front smart city policy evaluation framework. Table 5.1 shows the scenarios and policy use cases for each country's application.

Table 5.1. Scenario settings.

City	**Objective**	**Evaluation Model**	**Description**	**Target Industries**	**Target Individuals**
Aichi	Promote startups	A model to evaluate policies regarding startup promotions	Assessing policies, infrastructure, and technologies to promote startup companies	Startups	Business partners, residents
Phuket	Reduce over-tourism	A model to evaluate policies regarding over-tourism, developing new cities near airports to reduce congestion and CO2 emissions	Assessing policies, infrastructure, and technologies to disperse tourists by suggesting alternative attraction points	Tourism	Tourists, residents
Baguio	Improving post-harvest agriculture	A model to evaluate policies regarding improving post-harvest agriculture production and distribution	Assessing policies, infrastructure, technologies, etc., to improve production and distribution by utilizing technologies, sensors, and transportation networks.	Post-Harvest Agriculture	Consumer, residents

5.4.2. Startups, Aichi

Figure 5.7 illustrates the application of the integrated QOL and QOB evaluation methodology in the context of startups. In accordance with the objective of this chapter, this framework demonstrates how air-front smart city policies, categorized into rules and regulations, infrastructure, and DX technologies, shape both business environments and living environments through changes in accessibility and ecosystem performance. Startups are highly sensitive to institutional flexibility, knowledge spillovers, connectivity, and digital infrastructure, making them a suitable case for illustrating how air-front development can foster innovation-oriented urban growth. The evaluation framework assesses QOB for startup companies, QOL for business partners (non-resident stakeholders), and QOL for residents, thereby capturing both economic competitiveness and social sustainability within startup-driven air-front smart city development.

Within this framework, rules and regulations represent policy instruments such as taxation, business registration, intellectual property protection, and airport-related policies that influence startup formation and investment attractiveness. Infrastructure captures physical accessibility to logistics hubs, startup facilities, utilities, and special economic zones that support innovation activities. DX technologies represent access to advanced digital services, such as AI, IoT, cloud computing, and cybersecurity, that enable data-driven innovation and global business connectivity.

Through the structured classification of QOB and QOL components into rules and regulations, infrastructure, and DX technologies, the startup-driven air-front smart city case demonstrates how the integrated evaluation framework operationalizes accessibility-oriented policies to foster innovation, enhance stakeholder experience, and improve resident quality of life.

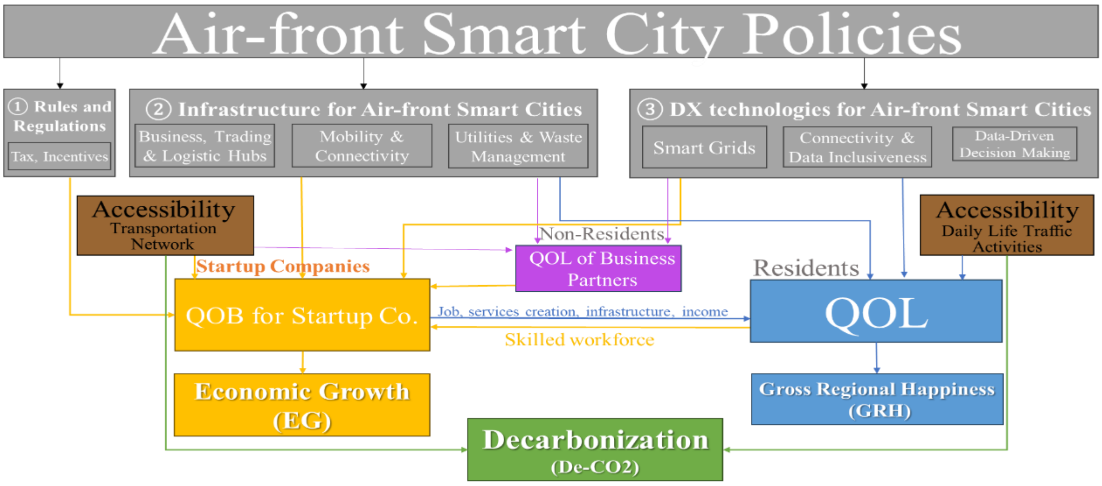


Figure 5.7. Startup-driven air-front smart city evaluation framework.
(Mutahari et al., 2025d)

QOB component indicators for startups

Table 5.2 presents example QOB component indicators for startup companies under the three policy dimensions. These indicators are selected to illustrate how air-front smart city policies influence startup ecosystems.

Under rules and regulations, indicators such as ease of business registration (RR1) capture administrative barriers to startup formation, while tax incentives for startups (RR2) reflect fiscal support mechanisms that reduce early-stage financial burdens. Intellectual property protection (RR3) represents institutional safeguards essential for innovative-driven firms. Startup funding policies (RR4) are reflected through venture capital investment per capita, indicating the strength of the financial ecosystem. Air transport connectivity policy (RR5) captures the role of airport functions in enabling global market access and investor mobility.

The infrastructure dimension focuses on physical and spatial conditions supporting startup activities. Logistics and supply chain connectivity (IF1) measures accessibility to major logistics hubs, which is particularly important for hardware and manufacturing startups. Physical infrastructure for startups (IF2) and access to co-working spaces (IF3) capture the availability of shared innovation environments that facilitate collaboration and knowledge exchange. Access to special economic zones (IF4) reflects spatial policy instruments that concentrate innovation activities near airports. Access to reliable energy and utilities (IF5) ensures operational stability for technology-intensive firms.

The DX technologies dimension captures the degree of digital maturity within the startup ecosystem. IoT integration for business operations (DX1) and AI and machine learning in business analytics (DX2) reflect the adoption of advanced technologies that enhance operational efficiency and strategic decision-making. High-speed internet and 5G (DX3) provide foundational digital connectivity, while cloud computing services (DX4) enable scalable business operations. Cybersecurity frameworks (DX5) capture institutional readiness to protect digital assets and ensure trust in digital transactions. Together, these indicators evaluate QOB as the capacity of the urban business environment to attract, support, and retain startups within an air-front smart city.

Table 5.2. Example of QOB component indicators for startups. (Mutahari et al., 2025d)

Dimensions	QOB component	Indicators
Rules & Regulations	Ease of business registration	RR1: No. of days to register a business (No.)
	Tax incentives for startups	RR2: Tax reduction (%)
	Intellectual Property Protection	RR3: Japan Intellectual Property Rights (IPR) Index score
	Startup Funding Policies	RR4: VC investment per capita (JPY)
	Air Transport Connectivity Policy	RR5: No. of flights per day (No)
Infrastructure	Logistics and Supply Chain Connectivity	IF1: Proximity to major logistic hubs (min)
	Physical Infrastructure for Startups	IF2: Number of startup facilities per 100 businesses (No.)
	Access to Co-working Spaces	IF3: Number of co-working spaces per 10,000 businesses (No.)
	Access to Special Economic Zones	IF4: Airport proximity to economic zones (min)
	Access to Reliable Energy and Utilities	IF5: Percentage of businesses connected to stable energy grids (%)
DX Technologies	IoT Integration for Business Operations	DX1: Percentage of businesses adopting IoT for monitoring and automation (%)
	AI and Machine Learning in Business Analytics	DX2: Percentage of startups using AI-driven business analytics platforms (%)
	High-speed Internet and 5G	DX3: Average internet speed (Mbps)
	Cloud Computing Services	DX4: Number of cloud service providers (No.)
	Cybersecurity Frameworks	DX5: National Cybersecurity Index (NCSI) score

QOL component indicators for business partners

Table 5.3 presents example QOL component indicators for business partners, who are considered non-resident primary stakeholders within the startup-driven air-front smart city framework. As was mentioned before, QOL is evaluated not only for residents but also for key external factors, such as business partners, whose accessibility and experience influence business ecosystem performance.

Under rules and regulations, indicators such as ease of business registration (RR1) and business visa facilitation (RR2) reflect institutional accessibility for international partners. Tax policies for foreign investors (RR3) and cross-border trade facilitation (RR4) capture regulatory conditions affecting international collaboration and investment. Airport function (RR5) represents the availability of air transport services, which directly influences mobility and face-to-face interaction in global business networks.

The infrastructure dimension focuses on physical accessibility and service quality experienced by business partners. Efficient transport connectivity (IF1) measures travel time to business districts, while physical infrastructure for startups and prototyping (IF2) reflects access to innovation facilities. World-class business hotels (IF3) capture accommodation quality for visiting partners, and special economic zones (IF4) represent spatial clusters that facilitate business interaction.

Table 5.3. Example of QOL component indicators for business partners. (Mutahari et al., 2025d)

Dimensions	QOL Component	Indicators
Rules & Regulations	Ease of Business Registration	RR1: No. of days to register a business (No.)
	Business Visa Facilitation	RR2: Average processing time for business visas (days)
	Tax Policies for Foreign Investors	RR3: Corporate tax rate for foreign investors (%)
	Cross-border Trade Facilitation	RR4: WB ease of cross-border trade score
	Airport Function	RR5: No. of flights per day (No)
Infrastructure	Efficient Transport Connectivity	IF1: Travel time to business districts (mins)
	Physical Infrastructure for Startup and Prototyping	IF2: Number of startup facilities per 100 businesses (No.)
	World-class Business Hotels	IF3: Number of 4-star and 5-star hotels (No.)
	Special Economic Zones (SEZs)	IF4: Number of SEZs (No.)
DX Technologies	IoT in Supply Chain Management	DX1: Percentage of logistics companies using IoT in operations (%)
	AI and Machine Learning for Trade and Analytics	DX2: Percentage of businesses using AI for trade facilitation or analytics (%)
	Blockchain for International Trade	DX3: Percentage of cross-border transactions using blockchain technology (%)
	Digital Business Communication	DX4: Percentage of businesses offering virtual meeting solutions (%)
	AI-Powered Business Analytics for Visitors	DX5: Availability of AI-driven market insights (dummy)

The DX technologies dimension emphasizes digital tools that support cross-border collaboration and business efficiency. IoT in supply chain management (DX1) and AI and machine learning for trade and analytics (DX2) reflect advanced digital capabilities supporting business operations. Blockchain for international trade (DX3) captures secure transaction technologies, while digital business communication (DX4) reflects the availability of virtual collaboration tools. AI-powered business analytics for visitors (DX5) represents access to market intelligence supporting informed decision-making. These indicators collectively assess QOL for business partners as the ease, efficiency, and reliability of engaging with the startup ecosystem within an air-front smart city.

QOL component indicators for residents

Table 5.4 presents example QOL component indicators for residents, focusing on how startup-driven air-front development affects daily living conditions, accessibility, and digital inclusion. Considering the concept of air-front smart city, the intention is not to capture all aspects of resident QOL, but rather to evaluate QOL impacts that are directly linked to startup-oriented air-front smart city development.

Table 5.4. Example of QOL component indicators for Residents.
(Mutahari et al., 2025d)

Dimensions	QOL Component	Indicators
Rules & Regulations	Affordable Housing Policies	RR1: Percentage of affordable housing by total housing stock (%)
	Healthcare Access	RR2: Healthcare cost by GDP (%)
	Environmental Sustainability Laws	RR3: Emissions reduction per capita (%)
Infrastructure	Public Transportation	IF1: Access to the nearest public transport station (mins)
	Green Spaces and Recreational Facilities	IF2: Access to recreational facilities (mins)
	Smart Utilities (Energy, Water)	IF3: Smart meter penetration rate (%)
DX Technologies	Smart Home IoT Integration	DX1: Percentage of homes with IoT systems (%)
	AI-powered Public Services	DX2: Percentage of public services utilizing AI (%)
	E-Government Services	DX3: E-Government Services (No.)

Within rules and regulations, affordable housing policies (RR1) address housing pressure arising from innovation-led growth. Healthcare access (RR2) reflects social welfare considerations, while environmental sustainability laws (RR3) capture regulatory efforts to mitigate environmental externalities associated with urban expansion. The infrastructure dimension focuses on everyday accessibility. Public transportation (IF1) captures mobility efficiency, green spaces and recreational facilities (IF2) reflect environmental and social well-being, and smart utilities (IF3) represent infrastructure modernization enabled by smart city investments. The DX technologies dimension evaluates residents’ access to digital services and smart living environments. Smart home IoT integration (DX1) reflects household-level digital adoption, while AI-powered public services (DX2) and e-government services (DX3) capture administrative efficiency and service accessibility. Together, these indicators evaluate resident QOL as the extent to which startup-driven air-front smart city development enhances accessibility, livability, and digital inclusion without compromising social sustainability.

5.4.3. Post-Harvest agriculture, Baguio

Figure 5.8 illustrates the application of the integrated QOL and QOB evaluation methodology in the context of post-harvest agriculture. This framework enables the assessment of living and business environments across three key dimensions: rules and regulations, infrastructure, and digital transformation (DX) technologies aimed at improving post-harvest agricultural production and distribution. These dimensions are evaluated for their impact on residents, consumers, and farmers, providing a comprehensive perspective on the factors influencing post-harvest agriculture efficiency and a higher resident's QOL.

The post-harvest agriculture sector is highly sensitive to logistics performance, regulatory compliance, and information flows, especially for perishable goods. Therefore, the evaluation framework is structured to assess how policy interventions affect QOB for farmers, QOL for consumers, and QOL for residents, while accounting for the role of air-front accessibility and logistics connectivity in supporting agricultural production and distribution. The framework also reflects Chapter 5's emphasis on integrated accessibility, capturing both physical access to markets and infrastructure, and digital access to information, platforms, and services.

Within this framework, rules and regulations represent institutional conditions such as land access, food safety standards, environmental protection, and pricing policies that directly shape agricultural viability and social welfare. Infrastructure captures physical accessibility to logistics hubs, roads, utilities, and public services, which is critical for reducing post-harvest losses and improving distribution efficiency. DX technologies represent the application of AI, IoT, and digital platforms that enhance decision-making, logistics coordination, and market access across the agricultural value chain.

As shown in Figure 5.8, the evaluation framework integrates these dimensions to assess QOB and QOL outcomes within an agriculture-driven air-front smart city. The following subsections present example QOB and QOL component indicators that are suitable for evaluating post-harvest agriculture in Baguio. As discussed earlier in this chapter, a well-structured representation of QOL and QOB in this context requires questionnaire surveys and interviews with key stakeholders, including farmers, consumers, and residents.

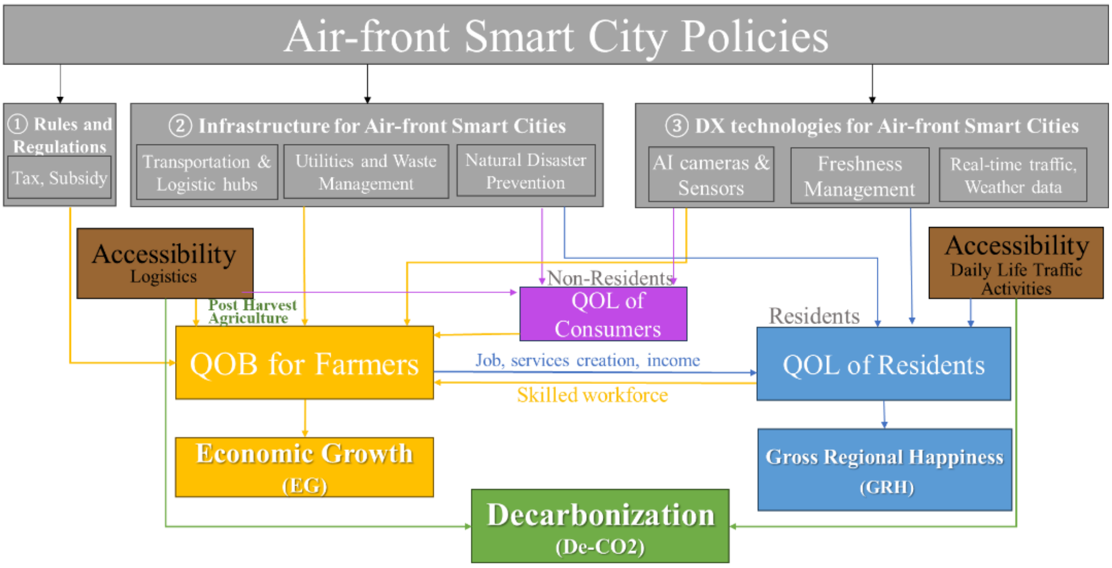


Figure 5.8. Agriculture-driven air-front smart city evaluation framework. (Mutahari et al., 2025d)

QOB Component Indicators for Post-Harvest Agriculture

Table 5.5 presents example QOB component indicators for evaluating the efficiency and sustainability of post-harvest agriculture in Baguio. These indicators are selected to reflect how rules and regulations, infrastructure, and DX interventions influence farmers' productivity, cost structures, and market accessibility, which are central to the Chapter 5 objective of linking accessibility improvements to business outcomes.

Under rules and regulations, indicators such as ease of access to farmland (RR1) capture institutional barriers to agricultural participation, while national food safety compliance (RR2) and reduction of hazardous chemicals (RR3) ensure alignment with food safety standards and environmental sustainability goals, including the UN Sustainable Development Goals. Input cost management (RR4) reflects the economic viability of farming activities, and compliance with packaging standards (RR5) captures regulatory requirements critical for post-harvest handling and market acceptance.

The infrastructure dimension emphasizes logistics efficiency and physical accessibility. Proximity to logistics hubs (IF1) and road accessibility efficiency (IF2) directly influence transportation costs, delivery time, and spoilage risk. Spoilage-free delivery rate (IF3) serves as an outcome-oriented indicator capturing the effectiveness of post-harvest handling and transport infrastructure in preserving product quality.

The DX technologies dimension captures the role of advanced digital tools in improving post-harvest operations. Indicators such as AI-based inventory turnover and forecasting (DX1) and intelligent logistics systems (DX4) reflect data-driven optimization of supply chains. Digital infrastructure for rural areas (DX2) provides the enabling conditions for DX adoption, while e-commerce access (DX3) enhances farmers' market reach. AI-based freshness classification systems (DX5) directly address quality control challenges for perishable products.

Table 5.5. Example of QOB component indicators for post-harvest agricultural. (Mutahari et al., 2025d)

Dimensions	QOB component	Indicators
Rules & Regulations	Ease of Access to Farmland	RR1: Average days and cost required to own farmland (days, PHP)
	National Food Safety Compliance	RR2: National food safety compliance score (scale)
	Reduction of Hazardous Chemicals in Farming	RR3: Average concentration of hazardous chemicals in agricultural products (ppm)
	Input Cost Management	RR4: Median input costs for farmers relative to yield profitability (ratio: currency/yield)
	Compliance with Packaging Standards	RR5: Compliance rate with packaging safety standards (%)
Infrastructure	Proximity to Logistic Hub (BAPTC)	IF1: Average proximity to local agricultural distribution center (km)
	Road Accessibility Efficiency	IF2: Percentage of farms within a 5 km radius of a well-maintained road(%)
	Spoilage-Free Delivery Rate	IF3: Percentage quantity of goods reaching the market without spoilage (%)
DX Technologies	Perishable Inventory Turnover Rate	DX1: Percentage of agricultural businesses using AI in revenue forecasting and inventory optimization (%)
	Digital Infrastructure for Rural Areas	DX2: Percentage of rural areas with stable internet and mobile connectivity (%)
	Access to E-Commerce in Agriculture	DX3: Percentage of agricultural sales conducted via e-commerce platforms (%)
	Intelligent Logistics Systems	DX4: Adoption rate of intelligent transport systems for logistics (%)
	Freshness Classification System	DX5: Adoption rate of AI-based freshness classification systems (%)

QOL Component Indicators for Consumers

Table 5.6 presents QOL component indicators for consumers, focusing on accessibility to safe, affordable, and high-quality agricultural products, which is a key social outcome considered in Chapter 5. The indicators emphasize how post-harvest efficiency and policy interventions translate into consumer welfare. Within rules and regulations, consumer confidence in food safety (RR1) and hazardous chemical-free products (RR2) captures institutional safeguards that protect consumer health. Product freshness standards (RR3) directly reflect the effectiveness of post-harvest handling, while fair price regulation

(RR4) addresses affordability and price stability, particularly important for low-income households.

The infrastructure dimension focuses on physical access and delivery efficiency. Logistics for timely delivery (IF1) measures the speed of product movement from distribution centers to markets, while access to fresh products in local markets (IF2) captures spatial accessibility. Accessibility for differently-abled consumers (IF3) reflects inclusiveness in market infrastructure design. The DX technologies dimension highlights digital channels that improve convenience and transparency. E-commerce platform usage (DX1) reflects consumers' ability to access agricultural products digitally, while access to smart and sustainable farm products (DX2) captures informed consumption supported by certification and digital traceability systems.

Table 5.6. Example of QOL component indicators for consumers.
(Mutahari et al., 2025d)

Dimensions	QOB component	Indicators
Rules & Regulations	Consumer Confidence in Food Safety	RR1: Food safety compliance index (score)
	Hazardous Chemicals-Free Products	RR2: Average concentration of hazardous chemicals in agricultural products (ppm)
	Product Freshness Standards	RR3: Average freshness rating of products (scale)
	Fair Price Regulation	RR4: Median price of agricultural goods relative to income (ratio: currency/income)
Infrastructure	Logistics for Timely Delivery	IF1: Average time from distribution center to markets (hours)
	Access to Fresh Products in Local Markets	IF2: Distance of markets from residential areas (km)
	Accessibility for Differently-Abled Consumers	IF3: Number of accessible markets with persons with disabilities pathways
DX Technologies	E-Commerce Platforms for Consumer Convenience	DX1: Percentage of consumers using e-commerce platforms for agricultural products (%)
	Consumer Access to Smart and Sustainable Farm Products	DX2: Percentage of agricultural products purchased from certified smart and sustainable farms (%)

QOL Component Indicators for Residents

Table 5.7 focuses on assessing the broader QOL impacts of post-harvest agriculture on residents, consistent with Chapter 5's objective of evaluating how economic activities influence living environments within air-front smart cities. Under rules and regulations, indicators such as affordable housing policies (RR1) and agricultural trade policies (RR2) reflect economic stability and cost-of-living considerations. Environmental safety laws (RR3) and waste management laws (RR5) capture environmental risks and sanitation conditions associated with agricultural activities, while traffic laws (RR4) address the impact of logistics-related traffic on rural mobility.

The infrastructure dimension evaluates residents' daily accessibility and resilience.

Public transportation connectivity (IF1) and healthcare and social services access (IF2) reflect access to essential services. Weather monitoring systems (IF3) are particularly relevant in agricultural regions vulnerable to climate risks, while access to clean water and utilities (IF4) captures basic living conditions. The DX technologies dimension focuses on digital inclusion and market participation. Digital infrastructure for rural areas (DX1) provides the foundation for accessing services and information, while e-commerce and digital market access (DX2) reflects residents' ability to engage with agricultural markets and services digitally.

Table 5.7. Example of QOL component indicators for residents.
(Mutahari et al., 2025d)

Dimensions	QOL Component	Indicators
Rules & Regulations	Affordable Housing Policies	RR1: Percentage of affordable housing by total housing stock (%)
	Agricultural Trade Policies	RR2: Agricultural product pricing fairness index (scale)
	Environmental Safety Laws	RR3: Percentage of natural disasters affecting operations per year (%)
	Traffic Laws	RR4: Percentage of traffic incidents affecting rural transportation routes per year (%)
	Waste Management Laws	RR5: Waste collection efficiency in rural areas (%)
Infrastructure	Public Transportation Connectivity	IF1: Average travel time from residence to the nearest market hub (mins)
	Healthcare & Social Services	IF2: Access to healthcare and public facilities (mins)
	Weather Monitoring	IF3: Percentage of weather monitoring stations providing real-time data to locals (%).
	Access to Clean Water & Utilities	IF4: Percentage of rural households with access to clean water (%)
DX Technologies	Digital Infrastructure for Rural Areas	DX1: Percentage of rural areas with stable internet and mobile connectivity (%)
	E-Commerce & Digital Market Access	DX2: Percentage of agricultural transactions conducted via digital marketplaces (%)

5.4.4. Tourism, Phuket

Assuming that the model focuses on urban policies addressing over-tourism, airport-oriented urban expansion, and the reduction of congestion and CO_2 emissions in Phuket, this subsection applies the proposed QOL–QOB evaluation framework to a tourism-driven air-front smart city context. Given Phuket's strong dependence on international and domestic tourism, the QOB model is used to evaluate how combinations of rules and regulations, infrastructure provision, and DX technologies influence the business performance of tourism firms while simultaneously affecting the QOL of tourists and local residents.

As illustrated in Figure 5.9, the tourism-driven air-front smart city evaluation framework captures the interactions between business accessibility and individual accessibility across three stakeholder groups: tourism firms, tourists, and residents. The framework explicitly accounts for both physical accessibility (e.g., transport infrastructure and spatial distribution of activities) and digital accessibility (e.g., online services and smart systems), enabling an integrated assessment of economic efficiency, user convenience, and social sustainability. Through the structured definition of QOB and QOL components across rules and regulations, infrastructure, and DX technologies, the tourism-driven air-front smart city framework enables integrated evaluation of economic performance, tourists' experience, and resident well-being under over-tourism and sustainability-oriented urban policies. The following subsections define the QOB and QOL components and indicators suitable for evaluating tourism-oriented air-front smart city policies in Phuket.

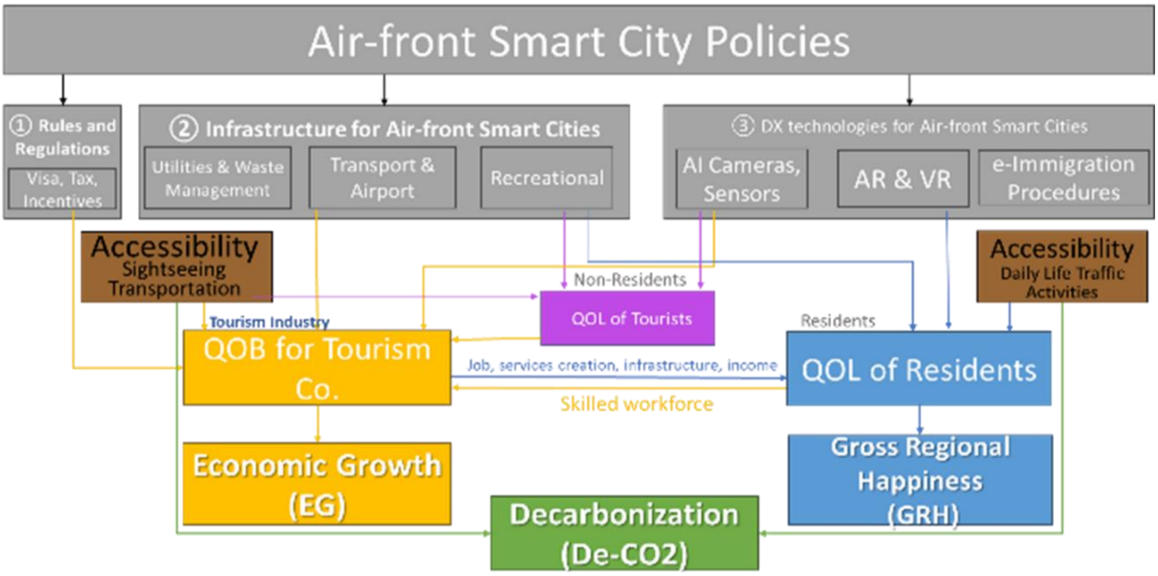


Figure 5.9. Tourism-driven air-front smart city evaluation framework.

QOB for tourism firms

The QOB components for tourism firms in Phuket are listed to showcase how regulatory interventions, infrastructure provision, and DX technologies influence the operational performance, competitiveness, and resilience of tourism-related businesses within an air-front smart city context. Considering Phuket’s strong dependence on tourism and its vulnerability to seasonal demand fluctuations and congestion, the selected indicators emphasize market accessibility, operational efficiency, and regulatory adaptability.

As shown in Table 5.8, under rules and regulations, the indicators reflect the institutional environment shaping tourism business operations. Market entry and business flexibility (RR1) measures the administrative burden associated with establishing tourism firms, which directly affects entrepreneurial activity and market responsiveness. Tourism demand management (RR2) captures the intensity of seasonal or capacity-based operational restrictions introduced to mitigate over-tourism. Digital business regulation (RR3) evaluates the ease of cross-border digital transactions, which is particularly relevant for internationally oriented tourism firms. Environmental and sustainability compliance (RR4) reflects mandatory certification requirements that influence both cost structures and environmental performance. In addition, airport connectivity (RR5) represents an airport function, regulatory, and operational condition that directly affects market access and customer inflows.

The infrastructure dimension focuses on physical accessibility and congestion effects that influence business efficiency. Tourism facility accessibility (IF1) measures travel time to major attractions, reflecting the spatial efficiency of tourism activities. Urban transport infrastructure (IF2) captures congestion conditions that affect service delivery, logistics, and customer satisfaction. Spatial distribution of tourism (IF3) evaluates accessibility to secondary attraction areas, which is critical for dispersing tourist flows and reducing pressure on core tourism zones near the airport.

Table 5.8. Example of QOB component indicators for tourism firms.

Dimensions	QOB component	Indicators
Rules & Regulations	Market Entry & Business Flexibility	RR1: Average days and cost required to start tourism business (days, THB)
	Tourism Demand Management	RR2: Seasonal operation restriction intensity (scale)
	Digital Business Regulation	RR3: Ease of cross-border digital transactions (scale)
	Environmental & Sustainability Compliance	RR4: Mandatory sustainability certification (dummy)
	Airport Connectivity	RR5: Number of flights per day (No./day)
Infrastructure	Tourism Facility Accessibility	IF1: Average access time to attraction spots (time)
	Urban Transport Infrastructure	IF2: Congestion rate (km/h)
	Spatial Distribution of Tourism	IF3: Average time to secondary attraction spots (mins)
DX Technologies	Digital Market Access	DX1: Digital customer acquisition ratio (%)
	Smart Operations	DX2: Percentage of Automation level in service delivery (%)
	Data-Driven Business Decision	DX3: Percentage of Dynamic pricing adoption (%)
	Hybrid Tourism Products	DX4: Adoption rate of virtual/augmented tourism services (%)
	High Speed Internet Coverage	DX5: Internet speed (Mbps)

The DX technologies dimension represents the role of DX technology in enhancing business performance and resilience. Digital market access (DX1) measures the extent to which firms rely on digital channels for customer acquisition. Smart operations (DX2) reflect the degree of automation in service delivery, contributing to labor efficiency and cost reduction. Data-driven business decision-making (DX3) captures the adoption of dynamic pricing strategies, enabling firms to respond flexibly to demand fluctuations. Hybrid tourism products (DX4) represent the integration of virtual or augmented tourism services that complement physical visits and alleviate congestion. Finally, high-speed internet coverage (DX5) provides the foundational digital infrastructure enabling all DX-related activities.

QOL for tourists

The QOL components for tourists are defined to evaluate how accessibility, service quality, safety, and digital convenience shape the overall tourism experience in Phuket under air-front smart city policies. The indicators explicitly reflect both physical and digital accessibility, acknowledging the hybrid nature of contemporary tourism consumption.

As shown in Table 5.9, within the rules and regulations category, the selected indicators focus on entry conditions, safety, and price fairness. Entry and mobility regulation (RR1) captures the ease of visa procedures, which directly affect international tourist accessibility. Safety and security regulation (RR2) is represented by emergency response time, reflecting institutional preparedness for health and safety incidents. Airport connectivity (RR3) indicates the availability of flights, which influences travel convenience and destination attractiveness. Fair price regulation (RR4) measures service price fluctuation, reflecting regulatory effectiveness in preventing excessive price volatility during peak tourism periods.

The infrastructure dimension emphasizes the quality of physical facilities and mobility systems experienced by tourists. Airport–destination accessibility (IF1) captures the convenience of airport transfers, a critical first impression for visitors. Tourism transport system performance (IF2) evaluates accessibility to attractions via public transport, reflecting ease of intra-island movement. Health and emergency infrastructure (IF3) measures access time to hospitals, which is essential for perceived safety. Accommodation and facility quality (IF4) reflects the availability and quality of lodging, directly influencing comfort and satisfaction.

The DX technologies dimension focuses on digital convenience and connectivity. Digital convenience (DX1) measures the usage of integrated tourism applications that support navigation, booking, and information access. High-speed internet coverage (DX2) provides the digital backbone enabling real-time information access, digital payments, and smart tourism services, thereby enhancing overall tourist QOL.0

Table 5.9. Example of QOL component indicators for tourists.

Dimensions	QOB component	Indicators
Rules & Regulations	Entry & Mobility Regulation	RR1: Visa Ease Index
	Safety & Security Regulation	RR2: Emergency response time (mins)
	Airport Connectivity	RR3: Number of flights per day (No./day)
	Fair Price Regulation	RR4: Service price fluctuation (%)
Infrastructure	Airport–Destination Accessibility	IF1: Airport transfer quality (convenience level, %)
	Tourism Transport System	IF2: Public transport accessibility to attractions (mins)
	Health & Emergency Infrastructure	IF3: Access to hospitals (mins)
	Accommodation & Facility Quality	IF4: Hotel density and quality index
DX Technologies	Digital Convenience	DX1: Integrated tourism apps usage (%)
	High Speed Internet Coverage	DX2: Internet speed (Mbps)

QOL for residents

The QOL components for residents are designed to assess how tourism-driven air-front smart city development affects residents' daily life, environmental quality, mobility, and social equity. Unlike tourists, residents experience tourism impacts continuously, making regulation, infrastructure, and digital governance particularly critical.

As shown in Table 5.10, under the rules and regulations category, the indicators capture governance mechanisms for mitigating over-tourism and protecting community well-being. Tourism management policy (RR1) measures the effectiveness of tourist flow regulation in reducing congestion and environmental pressure. Safety rules (RR2) represent community protection measures aimed at safeguarding residents from tourism-related risks. Environmental regulation (RR3) captures noise and emission controls near the airport, addressing a key negative externality of air-front development. Traffic laws (RR4) reflect the impact of tourism-related traffic on rural transportation routes, while land-use and zoning control (RR5) evaluates the balance between tourism and residential land uses.

The infrastructure category focuses on residents' daily accessibility and environmental resilience. Daily life accessibility (IF1) measures travel time to essential services, reflecting the efficiency of urban structure. Transport system performance (IF2) captures congestion levels in public transport, which often worsens under intense tourism activity. Environmental infrastructure (IF3) measures disaster resilience facilities, which are particularly important in island contexts. Public space quality (IF4) evaluates access to parks and community spaces, contributing to physical and mental well-being. Cultural exchange facilities (IF5) reflect infrastructure that supports positive interaction between residents and tourists.

The DX technologies dimension captures the role of digital tools in governance, inclusion, and mobility. Digital service accessibility (DX1) measures the use of e-government services, indicating administrative convenience for residents. Tourism impact monitoring systems (DX2) reflect transparency and public access to tourism-related data, enabling informed community participation. High-speed internet coverage (DX3) underpins digital inclusion and access to services. Digital inclusion (DX4) measures digital literacy, ensuring that DX benefits are equitably distributed. Smart mobility services (DX5) capture the availability of demand-responsive transport, which can mitigate congestion while improving accessibility for residents.

Table 5.10. Example of QOL component indicators for residents.

Dimensions	QOL Component	Indicators
Rules & Regulations	Tourism Management Policy	RR1: Tourist flow regulation effectiveness (%)
	Safety Rules	RR2: Community protection measures (dummy)
	Environmental Regulation	RR3: Noise and emission regulation near airport (dB, Kg)
	Traffic Laws	RR4: Percentage of traffic incidents affecting rural transportation routes per year (%)
	Land-Use & Zoning Control	RR5: Tourism–residential land-use balance (%)
Infrastructure	Daily Life Accessibility	IF1: Average travel time to essential services (mins)
	Transport System Performance	IF2: Public transport congestion level (%)
	Environmental Infrastructure	IF3: Number of flood and disaster resilience facilities (No.)
	Public Space Quality	IF4: Access to parks and community spaces (mins)
	Cultural Exchange Facility	IF5: No of culture exchange facilities for residents and tourists (no.)
DX Technologies	Digital Service Accessibility	DX1: Percentage of e-government service usage (%)
	Tourism Impact Monitoring System	DX2: Percentage of public access to tourism data (%)
	High Speed Internet Coverage	DX3: Internet speed (Mbps)
	Digital Inclusion	DX4: Digital literacy level (%)
	Smart Mobility Services	DX5: Demand-responsive transport availability (dummy)

5.5. Evaluation Method of Potential QOL and QOB Impacts

In addition to the QOL and QOB models developed in this chapter, which evaluate the perceived impacts of air-front smart city policies on living and business environments, this study also uses a scenario-based assessment of potential QOL and QOB impacts. The purpose of this assessment is to quantify the maximum policy leverage embedded in individual indicators and to support ex-ante policy comparison before implementation.

The potential impact assessment isolates the effect of a policy intervention by modifying a single policy-relevant indicator while holding all other indicators constant at their baseline values. Unlike the realized QOL and QOB scores, which incorporate normalization and integrated accessibility effects reflecting current urban constraints, the potential impact represents a rent-equivalent, unconstrained valuation derived directly from the monetary weights estimated through the conjoint analysis. The potential change in QOL or QOB resulting from a policy intervention on indicator m is expressed in equation (5.6):

$$\varDelta QOLB_{potential}^{m} = W^{m} \times \varDelta V^{m} \tag{5.6}$$

$$\varDelta V^{m} = V_{0}^{m} - V_{1}^{m} \tag{5.6}$$

Where $W^{m}$is the monetary weight of indicator m (JPY/tsubo/month per unit), and ΔV^{m} represents the magnitude of the policy-induced change in indicator (m). V_{0}^{m} is the original value of the indicator m, whereas V_{1}^{m} is the induced value of indicator m. This formulation yields a monetary-equivalent value that captures the perceived importance of the policy independent of spatial accessibility or interactions with other indicators. In contrast, the perceived QOL and QOB impacts are computed by re-estimating the composite indices after updating the relevant indicator values, thereby accounting for normalization effects, integrated accessibility constraints, and the fixed contributions of non-targeted indicators. As a result, the potential impact should be interpreted as an upper-bound measure of policy effectiveness, while the realized impact reflects the practical and context-dependent outcome within the existing urban system.

Although this method is not considered a novelty of this thesis, introducing and applying it for air-front smart city policy evaluation, in addition to the developed QOL and QOB model, will be novel. By comparing potential and perceived impacts across scenarios, this framework enables a structured evaluation of (i) the intrinsic attractiveness of individual policy instruments, (ii) the degree to which current urban conditions limit policy effectiveness, and (iii) the relative efficiency of alternative policy interventions in enhancing QOL and QOB. This dual assessment provides decision-makers with a transparent basis for prioritizing air-front smart city policies under budgetary and institutional constraints.

5.6. Results and Discussion

The chapter developed an integrated QOL and QOB evaluation methodology to assess the accessibility of essential services for various individual and business categories through both physical and virtual networks, enabling a comprehensive assessment of how well cities support the economic competitiveness and well-being of people. The development of the QOB model represents a significant step forward in assessing the urban business environment within air-front smart cities. However, the QOB model's versatility allows for its application beyond just air-front smart cities, covering diverse urban settings where economic activity is influenced by transportation infrastructure, DX technology, and other key factors. This broader approach ensures the QOB framework is versatile enough to be applied to various urban development models, accommodating the needs of both established and emerging business environments.

A well-integrated QOB and QOL framework ensures that while business accessibility is improving, the well-being of the people who sustain these businesses is also prioritized. By incorporating dimensions such as rules and regulations, infrastructure, and DX technologies, the QOB model captures the multifaceted nature of business accessibility in air-front smart cities. These components are critical in evaluating the potential for business growth and industrial innovation, ensuring that smart cities are not only technologically advanced but also conducive to sustainable and economic development.

The QOL and QOB models in this chapter use an integrated accessibility-based evaluation approach to assess how businesses interact with services through real (transportation) and virtual (ICT) networks. Integrated accessibility costs and the perceived value of services are incorporated into the model to provide a realistic measure of QOL and QOB. This allows for the evaluation of economic performance across different industries, as discussed in the scenario settings of startup, tourism, and post-harvest agriculture sectors in Japan, Thailand, and the Philippines, respectively. These future case studies can illustrate how specific rules and regulations, infrastructure developments, and DX adoption affect the QOB and, by extension, the overall economic growth in each region.

While QOL and QOB presented in this study are conceptually linked through shared dependencies on accessibility and urban services, their interactions are not always mutually reinforcing and may involve feedback loops and trade-offs. For example, enhanced QOL in a region may attract businesses and skilled labor, which in turn raises economic activity and improves job availability (QOB). However, this growth may lead to increased demand for housing and services, potentially driving up living costs and creating affordability issues, thus negatively impacting QOL, especially for vulnerable populations. Similarly, rapid business expansion may strain infrastructure or exacerbate traffic congestion and emissions, unless balanced by appropriate policy interventions. These dynamics highlight the importance of integrated evaluation and planning, and future studies are recommended to develop models to incorporate these feedback effects to support more resilient urban policy design. By applying the QOB framework to these diverse economic contexts, the study aims to provide a comprehensive evaluation methodology that is adaptable to cities at different stages of development, thus contributing to more targeted and effective urban policy planning.

5.7. Conclusion

This chapter has developed an integrated accessibility-based approach of QOL and QOB evaluation for the novel concept of air-front smart city. A key insight is that both QOL and QOB are not only interrelated but also jointly influenced by digital and physical accessibility. The application of the framework to startup ecosystems in Aichi, Tourism in Phuket, and post-harvest agriculture in Baguio demonstrates its flexibility and relevance across diverse industries and development stages. These conceptual contributions advance current air-front smart city evaluation practices by linking policies with measurable outcomes related to livability and economic productivity.

As a limitation of this chapter, the proposed QOL and QOB evaluation framework has only been developed conceptually and has not yet been validated with real-world data, which will be addressed in the subsequent chapter of this thesis. The integrated QOL and QOB models need to be developed and validated by applying them to a real case using actual data. Chapter 6 of this thesis conducts questionnaire surveys and interviews with startup companies to identify and weigh the QOL and QOB component indicators. The gathered data will help to develop a comprehensive model and implement it across different cities, as demonstrated in the case studies outlined in this chapter. The research specifically focuses on enhancing the QOL and QOB model's applicability by incorporating real-world insights from the startup ecosystem. Additionally, while the current study developed an evaluation system and framework, future research can evaluate urban living and business policies and forecast QOL and QOB, considering the temporal changes using the SDS model developed in Chapter 4. However, this thesis does not incorporate the QOL and QOB evaluation into the SDS model.

Chapter 6

Application and Policy Evaluation

This chapter applies the developed QOL and QOB evaluation methodology to an air-front smart city policy evaluation in the case of startup ecosystems. The chapter first uses survey data to estimate QOL and QOB component indicators' monetary value, and then calculates integrated accessibility indices. Using open-access regional data, the monetary value of QOL and QOB component indicators, and the accessibility index, the chapter applies the parameters to Aichi in Japan to assess the QOL and QOB within the city. Furthermore, the chapter sets some scenarios to assess the impacts of different urban policies within the framework of a startup-driven air-front smart city in Aichi, including startups, business partners, and residents. Additionally, the chapter compares the startup ecosystems in Aichi, Singapore, and Munich.

6.1. Introduction

In recent years, attracting and nurturing startups has become an increasingly important policy objective for regional economic revitalization. Startups tend to be highly sensitive to both business-related conditions and living environments when selecting their locations. Therefore, evaluating urban environments from an integrated perspective that incorporates QOL and QOB is essential for formulating effective startup attraction policies.

The promotion of startup ecosystems has become a central pillar of urban and regional development policy (Fritsch, 2013), particularly in advanced economies facing structural economic transformation, demographic decline, and intensified global competition for talent and innovation. Startups are widely recognized as key drivers of technological innovation, productivity growth, and regional economic resilience. Fritsch (2013) provides a comprehensive synthesis of empirical evidence showing that startups contribute to regional development not only directly through job creation but also indirectly through competition, knowledge spillovers, and long-term evolutionary processes within regional economies. Importantly, these effects are highly spatially heterogeneous and depend on regional characteristics such as human capital, infrastructure, and institutional context. However, unlike traditional firms, startups exhibit high sensitivity to their surrounding urban environments, as their survival and growth depend not only on market opportunities and financial access but also on human capital availability, institutional support, and everyday living conditions for founders and employees.

Recent empirical studies provide robust evidence that airport investment contributes to urban economic development. Using global nighttime light data as a proxy for economic activity, Uchida et al. (2024) demonstrate that the opening of new airports leads to statistically significant increases in urban economic intensity across diverse regional contexts. Their findings confirm that airport infrastructure functions as a catalyst for spatial economic growth by enhancing regional accessibility and connectivity. Within this context, air-front urban areas, cities located in proximity to international airports, can emerge as strategic spaces for startup-oriented development. These areas offer unique advantages, including superior international accessibility, concentration of global business interactions, and potential integration of physical and digital infrastructures. Consequently, many governments and local authorities have positioned cities with higher transportation connectivity as innovation hubs intended to attract globally oriented startups. Despite these policy ambitions, systematic methods for evaluating the effectiveness of air-front smart city environments in supporting startup development remain limited.

Existing studies and policy evaluations tend to focus predominantly on economic and business-related indicators, such as market size, industrial agglomeration, and investment volume. While these factors are undoubtedly critical, they provide only a partial explanation of startup location behavior. Increasingly, empirical evidence suggests that QOL, including housing conditions, accessibility to services, environmental quality, safety, and overall urban livability, plays a decisive role in attracting entrepreneurial talent, particularly in knowledge-intensive and internationally mobile sectors. As a result, startup competitiveness cannot be adequately assessed without simultaneously considering QOB and QOL as interdependent dimensions of the urban environment.

Building on this premise, this chapter advances an integrated QOL–QOB evaluation framework that captures both the economic-functional and socio-spatial characteristics of cities. In earlier chapters, the framework was conceptually developed, whereas this chapter extends this framework by applying it explicitly to startup development policy evaluation, with a particular focus on air-front smart cities.

The purpose of this chapter is to operationalize the integrated QOL–QOB framework for evaluating startup attraction potential and to demonstrate its applicability through a case study of Aichi Prefecture, Japan. Aichi represents a compelling empirical setting due to its strong manufacturing base, growing startup support initiatives, and strategic emphasis on airport-oriented development centered around Chubu Centrair International Airport. By incorporating insights directly obtained from startup founders, this study bridges the gap between top-down policy objectives and bottom-up perceptions of urban environments, thereby enhancing the policy relevance of the evaluation. Specifically, this section translates qualitative knowledge derived from group interviews with startups into a structured set of measurable indicators reflecting both QOB and QOL dimensions. These indicators are designed to enable cross-city comparison, support scenario-based policy evaluation, and identify structural strengths and weaknesses of air-front smart city strategies. Through this application, the study contributes not only to the empirical assessment of startup ecosystems but also to the broader discourse on smart city policy design, demonstrating how integrated evaluation approaches can support evidence-based urban and regional planning.

Furthermore, this chapter extends the empirical applicability of the proposed framework by transferring the parameters estimated from the Japanese startup case to international contexts. Specifically, the parameters derived from the startup ecosystem evaluation in Japan are applied to comparative case studies in Singapore and Munich. These cities were selected due to their differing institutional settings, levels of global connectivity, and maturity of startup ecosystems, which together provide a robust basis for testing the external validity and transferability of the QOL–QOB-based evaluation framework. By applying a common set of parameters across heterogeneous urban contexts, the analysis enables systematic cross-city comparison and assesses whether the relative importance of QOL and QOB factors identified in Japan can explain startup ecosystem performance in other leading global cities. This comparative exercise contributes to policy evaluation by clarifying the extent to which startup-oriented air-front smart city strategies can be generalized beyond the Japanese context.

6.2. QOL and QOB-Based Air-Front Smart City Evaluation for Startup Development: A Case Study in Aichi, Japan

In Japan, the Cabinet Office has promoted the initiative “Formation of Startup Ecosystem Hub Cities Competitive on a Global Scale,” designating four Global Hub Cities and a further four Promotion Hub Cities. Through these designated startup ecosystem hub cities, various programs have been implemented to support ecosystem formation and accelerate growth in each city. However, without an accurate understanding of local conditions and bottom-up processes, it is difficult to construct sustainable and regionally appropriate startup ecosystems. Aichi Prefecture, one of the Global Hub Cities, has also strengthened its efforts to foster a startup ecosystem in line with this national policy direction. As regional industrial economies face a historic turning point, identifying new business opportunities and enabling entry into new business domains, structural transformation, and business innovation require leveraging existing industrial assets and urban environmental resources to create pathways for regionally rooted, innovation-driven economic development. This section applies the developed framework in this thesis, assessing urban policies affecting the startup ecosystem in Japan. The result of this section would be filling up the academic gap and providing policymakers with a mathematical tool to quantitatively evaluate startup-related urban development policies, as showcased in this chapter.

6.2.1. Survey and data

To operationalize the QOL and QOB-based evaluation framework for air-front smart city development, this chapter first uses the results of a series of structured group interviews with startup founders to identify the urban business, service, and living environment conditions that facilitate startup establishment and growth, as well as those that act as barriers. These qualitative investigations were designed to capture startups' revealed preferences regarding both QOB, such as market access, talent availability, institutional support, and operational costs, and QOL, including living convenience, safety, and overall urban comfort, which increasingly influence location decisions in knowledge-intensive and innovation-driven firms.

The preliminary questionnaire survey could produce a list of QOL and QOB component indicators, where, with a web-based questionnaire survey, the author could get the perceived value of each component indicator, and could estimate the monetary value of the parameters. The component indicator selection and the monetary value of these indicators are described in the following section of this chapter. The web-based questionnaire survey was conducted between January and June 2025. Survey invitations were primarily distributed to firms located in startup hubs within Aichi Prefecture, including partner hubs. A total of 35 valid responses were obtained.

6.2.2. QOL and QOB component indicator selections

With the cooperation of the Aichi Prefecture Startup Promotion Division, interview requests were extended to startups located within officially designated startup hubs and partner hubs across the prefecture, as well as to firms participating in public startup support programs. A total of 18 startups agreed to participate. To efficiently collect diverse perspectives within a limited timeframe, the interviews were conducted in a group format. The result of the preliminary questionnaire survey enabled the identification of both shared and stage-specific urban needs among startups, resulting in the listing of 30 component indicators as shown in Table 6.1.

Building on this qualitative foundation, a set of evaluation indicators for startup attraction potential was established. The indicators were further restructured into three air-front policy evaluation categories: rules and regulations, infrastructure, and DX technology. The indicator selection process followed three guiding principles. First, each component was represented by approximately three indicators to ensure analytical balance while avoiding excessive complexity. Second, indicators were defined to enable comparative evaluation across different urban hierarchies, including global cities, metropolitan cores, and cities within metropolitan regions, an essential requirement for air-front smart city policy assessment. Third, all indicators were constrained by data availability at the regional or municipal scale, ensuring empirical applicability and reproducibility in policy evaluation contexts.

Through this process, qualitative perceptions of startup founders collected through the survey were translated into a standardized, data-driven evaluation system capable of quantifying startup attraction potential from both QOL and QOB perspectives. This indicator framework forms the empirical foundation for subsequent component weighting, aggregation, and comparative analysis, enabling the assessment of how air-front smart city policies and spatial configurations in Aichi Prefecture contribute to startup development within a broader air-front smart city strategy.

Table 6.1. QOL and QOB component indicators for the startup ecosystem.

No	Components indicators	Description
1	Population (Person)	Total population within the city
2	GRP (JPY)	The Gross Regional Product (GRP) of a city is divided by its total population, indicating the average economic output per person in that city
3	Economic Growth (%)	The rate of increase in the economic output of a city or region in recent years
4	Venture per Capita (VCs) (No.)	The number of venture capital firms based in the city
5	Related Industries (No.)	Number of significant companies in fields related to your business that are based in the city
6	Startup Support Budget (JPY)	Annual startup support budgets of the city
7	Young Population (%)	Percentage of young population (15-34 years) in the city's labor force
8	Number of Major Universities (No.)	Number of major universities in the city (Universities capable of accepting joint research funds from companies, etc.)
9	English Proficiency (%)	Percentage of individuals in the city with an English proficiency index (EF EPI) score of 500 or above, indicative of the ability to participate in professional field-specific English meetings
10	High-Class Hotels (No.)	Number of 5-star class hotels in the city
11	International Conferences (No.)	Number of international conferences held per year in the city
12	World Heritage Sites (No.)	Number of World Heritage Sites accessible within about 2 hours from the city
13	Corporate Tax Rate (%)	Effective corporate tax rate in the city
14	Business Registration (days)	Minimum days required to open a new office and start a business (includes visa process if outside the country)
15	International Flights Destinations (No.)	Number of destinations served by direct international flights from the nearest airport.
16	High-Speed Rail (No.)	Number of high-speed rail stations within 2 hours, including those reachable by taking the nearest high-speed train
17	Traffic Congestion Rate (Km/h)	Average travel speeds on roads within the city
18	Internet Speed (Mbps)	Average Internet speed on mobile devices
19	Digital Administrative Services (%)	Percentage of administrative procedures, such as tax payments, bidding, permit applications, and applications for municipally sponsored training and events, that are available online
20	Digital Lifestyle Services (%)	Percentage of services available online for shopping, medical care, transportation, and other daily living services
21	Time medical Facilities (mins)	Travel time to the nearest general hospital
22	Time retail and Dining Facilities (mins)	Travel time to the nearest large retail store (>1,000 sq. m. of retail space)
23	Time to childcare facilities (mins)	Travel time to the nearest kindergarten or preschool.
24	Floor Area (sq. m)	Size of living space per person in housing
25	Greenery (%)	The percentage of land covered by greenery and water in the city
26	Air quality	PM2.5 concentration in the atmosphere in the city
27	Criminal Offenses (No.)	Annual number of criminal offenses in the city (per 1,000 population)
28	Traffic Accident (No.)	Annual fatalities due to traffic accidents in the city (per 100,000 population)
29	Flood Risk (%)	The percentage of land (inhabitable land) expected to be inundated in the event of the largest possible heavy rainfall.
30	Office Rent (JPY)	Monthly office rent

6.2.3. Estimation of indicator weights using questionnaire surveys

To estimate indicator weights, a pairwise comparison–based conjoint analysis was adopted. In this approach, respondents are repeatedly asked to choose the more preferable option from two alternative profiles, each consisting of different attribute levels across multiple indicators. Based on the observed choice outcomes, a binary logit model, as shown in Equation (6.1), was constructed, and the weight parameters were estimated using the maximum likelihood estimation method.

$$P(i) = \exp(\beta_k . x_{k,i}) / \sum_j \exp(\beta_k . x_{k,i}) \tag{6.1}$$

Where $P(i)$denotes the probability of selecting an alternative i, $\beta_k$represents the weight parameter of the evaluation indicator k, and $x_{k,i}$is the value of the evaluation indicator k for alternative i. By taking the ratio of the weight parameter of each indicator to that of office rent, it is possible to derive a monetary equivalent value. The monetary equivalent value w_k for each indicator is made using the weight parameter for office rent, β_{rent}, as shown in Equation (6.2).

$$W_k = \beta_k / \beta_{rent} \tag{6.2}$$

This monetary equivalent value represents the extent to which a unit improvement in a given indicator corresponds to a reduction in office rent, thereby enabling diverse indicators to be compared on a unified monetary scale in terms of their contribution to startup attraction and growth. The questionnaire items used for estimating the weight parameters were designed by first providing respondents with explanations of each indicator, followed by presenting profiles of two hypothetical cities and asking respondents to select the more preferable one. Each profile consisted of four attributes: three evaluation indicators and office rent. The attribute levels for each indicator were shown in Table 6.2. Although respondents were required to answer repeated choice tasks across different profile combinations, respondent burden was reduced by limiting the number of tasks. Specifically, for each component, four randomly selected profile combinations were presented, and choice responses were collected accordingly.

Table 6.2. Component indicators and attribute levels used in conjoint analysis.

No	Indicators	Level 1	Level 2	Level 3
1	Population (Person)	0.5 M	2 M	10 M
2	GRP (JPY)	JPY 5 M	JPY 10 M	–
3	Economic Growth (%)	0%	5%	–
4	Venture per Capita (VCs) (No.)	100	200	300
5	Related Industries (No.)	200	1,000	–
6	Startup Support Budget (JPY)	JPY 3 B	JPY 30 B	–
7	Young Population (%)	20%	30%	–
8	Number of Major Universities (No.)	2	10	–
9	English Proficiency (%)	10%	70%	–
10	High-Class Hotels (No.)	1	60	–
11	International Conferences (No.)	20	100	–
12	World Heritage Sites (No.)	0	1	–
13	Corporate Tax Rate (%)	15%	20%	25%
14	Business Registration (days)	1 day	10 days	–
15	International Flights (No.)	20 cities	200 cities	–
16	High-Speed Rail (No.)	20	40	–
17	Traffic Congestion Rate (Km/h)	20 km/h	40 km/h	–
18	Internet Speed (Mbps)	25 Mbps	50 Mbps	100 Mbps
19	Digital Administrative Services (%)	20%	80%	–
20	Digital Lifestyle Services (%)	20%	80%	–
21	Time medical Facilities (mins)	5 min	15 min	–
22	Time retail and Dining Facilities (mins)	5 min	15 min	–
23	Time to childcare facilities (mins)	5 min	15 min	–
24	Floor Area (sq. m)	25 m^2	40 m^2	–
25	Greenery (%)	5%	40%	–
26	Air quality ($\mu g/m^3$)	10 $\mu g/m^3$	20 $\mu g/m^3$	–
27	Criminal Offenses (cases per 1,000 persons)	3 /1,000	15 /1,000	–
28	Traffic Accident (persons per 100,000)	3 /100,000	30/100,000	–
29	Flood Risk (%)	20%	80%	–
30	Office Rent (JPY)	JPY 5,000	JPY 10,000	JPY 20,000

Table 6.3 presents the parameter estimation results of the conjoint analysis, indicating the direction, statistical significance, and economic magnitude of each indicator affecting startup location preferences. Overall, most variables exhibit statistically significant coefficients with expected signs, suggesting that the model robustly captures startups' urban evaluation behavior.

Population size has a positive and statistically significant effect, suggesting that larger cities are perceived as more attractive due to broader market opportunities. Economic growth rate also shows a strong positive and significant coefficient, indicating that startups place considerable value on dynamic and future-oriented economic environments. In contrast, per-capita GRP does not yield a statistically significant estimate, implying that aggregate economic affluence alone does not strongly influence startup location decisions.

The number of venture capital firms and the number of related large industries are not statistically significant, indicating that the mere presence of financial institutions or large firms does not directly drive startup preferences. Conversely, the size of the startup support budget provided by local governments has a positive and highly significant effect, highlighting the importance of tangible and accessible public support.

A higher proportion of the young population significantly increases urban attractiveness, reflecting startups' preference for locations with a robust labor supply. The number of major universities and the share of English-proficient talent are also positive and significant, underscoring the value of human capital availability and international communication capacity. The number of high-class hotels and international conferences both show positive and significant coefficients, suggesting that business hospitality and opportunities for global interaction contribute to location appeal. The number of World Heritage Sites, however, does not exhibit a significant effect, indicating that cultural prestige alone is not a decisive factor.

The corporate tax rate has the largest negative and most statistically significant coefficient in the model, demonstrating that taxation exerts a substantial deterrent effect on startup location choice. Its monetary-equivalent value is the highest among all indicators, indicating that tax reductions generate the strongest incentive for startup attraction. Business registration time is not statistically significant, suggesting that procedural speed alone may be less influential than ongoing cost burdens. Office rent shows a significant negative effect, confirming that higher fixed operating costs reduce urban attractiveness.

The number of international flight destinations and high-speed rail stations within two hours both have positive and significant effects, indicating that domestic and international accessibility is a critical consideration. Higher average road travel speed is also positively associated with startup preference, reflecting the importance of efficient daily mobility.

Average internet speed and the diffusion of digital administrative services and digital lifestyle services are all positive and statistically significant, demonstrating that both business-related and daily digital infrastructures materially enhance urban attractiveness for startups. Longer travel times to retail, dining, and childcare facilities have significant negative effects, indicating that everyday accessibility constraints reduce location desirability. Residential floor area per capita is not statistically significant, suggesting that housing size alone is not a primary concern. Poor air quality, higher crime rates, increased traffic fatalities, and greater flood risk all show significant negative coefficients, indicating that safety and environmental risks directly and adversely affect startups’ urban preferences. Indicators that are not statistically significant are not included in our analysis.

Table 6.3. Parameter estimation results.

No	Indicators	β	z	p	M. value (JPY)
1	Population (100 Persons)	0.079	2.547	0.011	2,319
2	GRP (JPY)	–	–	–	–
3	Economic Growth (%)	0.142	3.25	0.001	4,182
4	Venture per Capita (VCs) (No./10 firms)	-	-	-	-
5	Related Industries (No.)	-	-	-	-
6	Startup Support Budget (JPY)	0.041	4.601	0.000	1,200
7	Young Population (%)	0.061	2.695	0.007	1,806
8	Number of Major Universities (No.)	0.022	3.668	0.000	637
9	English Proficiency (%)	0.018	3.085	0.002	544
10	High-Class Hotels (No.)	0.007	2.532	0.011	212
11	International Conferences (No.)	0.085	3.118	0.002	2,521
12	World Heritage Sites (No.)	–	–	–	–
13	Corporate Tax Rate (%)	−0.275	−6.193	0.000	8,095
14	Business Registration (days)	–	–	–	–
15	International Flights (No.)	0.012	4.436	0.000	347
16	High-Speed Rail (No.)	0.065	3.982	0.000	1,931
17	Traffic Congestion Rate (Km/h)	0.034	2.432	0.015	1,012
18	Internet Speed (Mbps)	0.022	3.878	0.000	637
19	Digital Administrative Services (%)	0.015	3.39	0.001	455
20	Digital Lifestyle Services (%)	0.014	3.272	0.001	416
21	Time medical Facilities (mins)	–	–	–	–
22	Time retail and Dining Facilities (mins)	−0.055	−2.486	0.013	1,616
23	Time to childcare facilities (mins)	−0.055	−2.486	0.013	1,616
24	Floor Area (sq. m)	0.018	1.293	0.196	539
25	Greenery (%)	–	–	–	–
26	Air quality (μg/m³)	−0.063	−2.970	0.003	1,868
27	Criminal Offenses (cases per 1,000 persons)	−0.112	−4.723	0.000	3,291
28	Traffic Accident (persons per 100,000)	−0.028	−2.742	0.006	819
29	Flood Risk (%)	−0.017	−3.411	0.001	488
30	Office Rent (JPY)	−0.034	−4.745	0.000	1,000

Figure 6.1. presents the office rent equivalent monetary value of indicators, and it is expressed in JPY/tsubo/month. Tsubo is a traditional Japanese unit of area, and 1 tsubo is almost equal to 3.3058 Sq. m. The corporate tax rate exhibits the largest monetary impact (approximately 8,100 JPY/tsubo/month per 1% change), followed by economic growth, criminal offenses, international conferences, and so on. Where the lowest are high-class hotels, international flights, and digital life services.

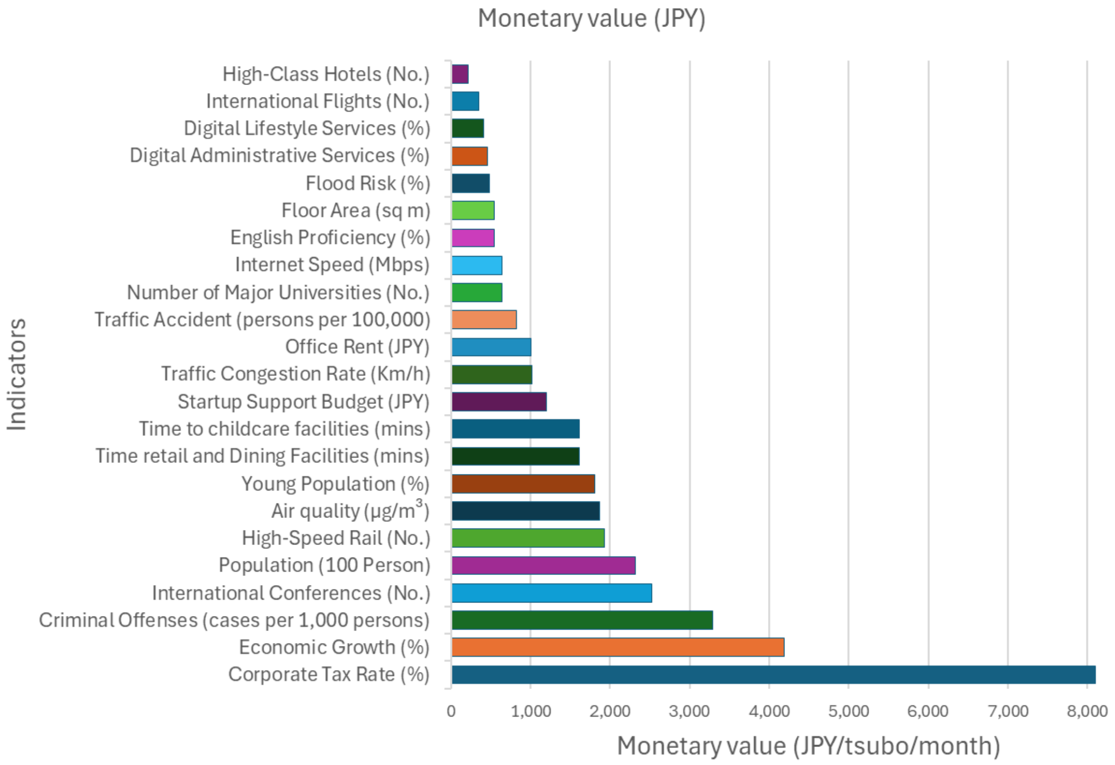


Figure 6.1. Equivalent monetary value of indicators (JPY/tsubo/month).

6.2.4. Integrated accessibility index

The integrated accessibility index is calculated as a combination of the physical accessibility index multiplied by the probability of choosing physical service and the digital accessibility index multiplied by the probability of choosing digital service, as it was explained in Chapters 4 and 5 of this thesis (see equation 5.1). However, due to data limitations, the chapter considers road congestion as a physical accessibility index and internet speed as a digital accessibility index. For the weight (probability) calculation of physical (P_m^R) and digital (P_m^D) service choice. The author incorporates the results from Chapter 3 of this thesis into this chapter. The integrated accessibility cost is applied to the accessibility related indicators that rely on both real and virtual networks, such as access to shopping and access to education centers. Using equation (6.3), the chapter estimates integrated accessibility cost for real and virtual networks.

$$ACC_{ij}^{I} = P_m^R \cdot \frac{1}{C_{ij}^R} + P_m^D \cdot \frac{1}{C^D} \tag{6.3}$$

Where,

P_m^R : Probability of choosing a service m in real space (physical service)
C_{ij}^R : Real space access cost from zone i to zone j (Road congestion, Km/h)
P_{m}^D : Probability of choosing a service m in virtual space (digital service)
C^D : Virtual access cost (Internet speed, Mbps)
ACC_{ij}^I : Integrated accessibility from zone *i* to zone *j*

Table 6.4 shows the recategorized QOL and QOB indicators, and the tick mark shows if it is related to any accessibility related indicators. Additionally, the city data, which is gathered from the internet and open sources, is also listed in Table 6.4.

Table 6.4. Indicators and city data.

Category	Indicator	Unit	ACC^R	ACC^D	City data
Rules & Regulations	Corporate Tax Rate	%			24.86
	Startup Support Budget	B JPY			0.2
	Crime Risk	reports/1000			6.670
	Intl. Flight Destinations	No.			27
	Economic Growth Rate	%			4.98
	Intl. Conferences Held	No. (10×)			8
	Air Quality PM2.5	µg/m³			15
	Traffic Accident Risk	deaths/100000			3.99
	Office Rents	1000 JPY/tsubo			13.45
Infrastructures	High-Speed Rail Stations	No.	✓		21
	Major Universities	No.	✓	✓	53
	Flood Risk	%			20
	English Proficiency	%			11
	City Population (100 P)	100 people			74800
	Young Population	%			23.7
	Time to Childcare Facilities	min	✓		14
	High-Class Hotels	No.	✓		17
	Time to Shopping Facilities	min	✓	✓	8.41
DX Technology	Road Congestion (speed)	km/h			30.1
	Internet Speed	Mbps			55.99
	Online Admin Services	%		✓	30.5
	Online Living Services	%		✓	52.6

6.2.5. QOL and QOB estimations

Startup's QOB

Table 6.5 presents the estimated QOB for startups, calculated by aggregating the perceived values of the business services within the startup ecosystem. Twelve indicators, which are categorized into three categories, are selected for the QOB evaluation for startups. Monetary-equivalent values of indicators estimated from the conjoint analysis of the survey, perceived accessible values of the services are calculated using equations (5.4 and 5.5) in Chapter 5. The monetary equivalent value of each indicator relative to its coefficient sign shows that an increase or reduction of a unit of the indicator corresponds to that equivalent monetary value expressed in JPY/tsubo/month of office rent for startup businesses. The gross startup's QOB score is estimated to be equivalent to 10,489, representing the comprehensive business attractiveness of the case city from the startup perspective.

From a category-level viewpoint, rules and regulations account for the largest share of QOB. Indicators such as the economic growth rate, startup support budget, and corporate tax rate exhibit high monetary-equivalent weights derived from the estimated parameter coefficients, resulting in substantial QOB contributions. This indicates that startups are particularly sensitive to institutional and macroeconomic conditions that directly affect long-term profitability, growth expectations, and investment risk. The relatively high estimated weights (coefficients) for these indicators imply that policy interventions in regulatory and fiscal domains yield disproportionately large impacts on startup attractiveness, especially considering the corporate tax rate, which has the highest parameter coefficient.

Table 6.5. Startup's QOB estimation results.

Category	Indicator (unit)	W^m (JPY)	Normalized V_i^m	ACC_{ij}^l	QOB_i^m
Rules & Regulations	RR1: Corporate Tax Rate (%)	8097	0.014	-	113
	RR2: Startup Support Budget (B JPY)	1196	0.629	-	753
	RR3: Intl. Flight Destinations (No.)	346	0.038	-	13
	RR3: Economic Growth Rate (%)	4176	0.996	-	4159
	RR4: Intl. Conferences Held No. x10)	2483	0.75	-	1862
Infrastructures	IF1: Office Rents (1000 JPY/tsubo)	1000	0.436	-	436
	IF2: High-Speed Rail Stations (No.)	1926	0.05	0.03	93
	IF3: Major Universities (No.)	635	0.879	0.03	541
	IF4: English Proficiency (%)	542	0.016	-	9
	IF5: City Population (100 P)	2324	0.734	-	1707
	IF6: Young Population (%)	1801	0.37	-	666
	IF7: High-Class Hotels (No.)	214	0.271	0.03	56
DX Technology	DX1: Online Admin Services (%)	454	0.175	0.017	78
				Startup's QOB	10489

Infrastructure-related indicators form the second-largest contribution to QOB. High values for city population size, young population ratio, and office rents reflect the importance of labor-market scale, demographic structure, and operational cost conditions. Indicators related to physical connectivity and business support facilities, such as high-speed rail stations, major universities, and high-class hotels, exhibit moderate weights but contribute meaningfully when combined with favorable accessibility conditions. For these indicators, QOB contributions are partially mediated by the ACC^I, indicating that their effectiveness depends not only on the existing value of the services but also on their spatial and functional accessibility through real and virtual networks.

DX technology–related indicators, represented by online administrative services, show a positive but relatively smaller contribution to QOB of startups in Aichi. Although the monetary-equivalent weight of this indicator is lower than that of fiscal or economic indicators, its contribution is enhanced through the ACC^I, reflecting the role of digital accessibility in reducing transaction costs and administrative burdens. This suggests that DX policies function as efficiency enhancers that strengthen the overall business environment rather than acting as primary attraction drivers on their own.

Business partner's QOL

Table 6.6 presents the estimated Quality of Life (QOL) for business partners, calculated using the perceived monetary value of indicators, normalized city-level conditions, and the Integrated Accessibility Index (ACCI) for accessibility-related indicators. The total business partner's QOL is estimated at 6,967, representing the rent-equivalent value of Aichi's living and business environment for business partners under existing conditions.

The Rules and Regulations category contributes approximately 4,460, accounting for about 64% of the total business partner's QOL. This category clearly dominates the evaluation, driven primarily by indicators related to international business interaction, environmental quality, traffic safety, and public support measures. The Infrastructure category contributes approximately 2,410, representing about 35% of the total QOL. The majority of this contribution comes from indicators associated with urban scale and knowledge infrastructure, while accessibility-dependent infrastructure elements show reduced perceived values due to integrated accessibility constraints. The DX Technologies category contributes approximately 78, accounting for about 1% of the total Business Partner's QOL. Although quantitatively small, this value captures the realized benefit of digital administrative services under existing digital accessibility conditions.

These results indicate that, from a startup-driven air-front smart city perspective, institutional and regulatory policies currently account for nearly two-thirds of business partner QOL in Aichi. Similarly, infrastructure policies provide a substantial supporting role for the QOL of business partners, whereas DX-oriented policies yield a smaller role. Some of the perceived accessibility related indicators get reduced due to the integrated accessibility constraints incorporated into the evaluation model.

Table 6.6. Business Partner’s QOL estimation results.

Category	Indicator (unit)	$\boldsymbol{W^m}$ (JPY)	Normalized $\boldsymbol{V_i^m}$	$\boldsymbol{ACC_{ij}^l}$	$\boldsymbol{QOL_i^m}$
Rules & Regulations	RR1: Corporate Tax Rate (%)	8097	0.014	-	113.35
	RR2: Startup Support Budget (B JPY)	1196	0.629	-	753.03
	RR3: Intl. Flight Destinations (No.)	346	0.038	-	13.45
	RR4: Intl. Conferences Held No. x10)	2483	0.75	-	1862.25
	RR5: Air Quality PM2.5 (µg/m³)	1863	0.50	-	931.5
	RR6: Traffic Accident Risk (deaths/100,000)	817	0.96	-	787.04
Infrastructure	IF1: High-Speed Rail Stations (No.)	1926	0.05	0.033	93.15
	IF2: Major Universities (No.)	635	0.879	0.03	541.44
	IF3: English Proficiency (%)	542	0.016	-	9.03
	IF4: City Population (100 P)	2324	0.734	-	1707.52
	IF5: High-Class Hotels (No.)	214	0.271	0.033	56.13
DX Technology	DX1: Online Admin Services (%)	454	0.175	0.017	78.04
			Business Partner’s QOB		6967

Resident’s QOL

Table 6.7 presents the estimated resident’s QOL, calculated using perceived monetary values of indicators, normalized city conditions, and integrated accessibility constraints for accessibility-related indicators. The total Residents’ QOL is estimated at 12,483.

Comparative Policy Impact on Startup QOB and Stakeholder QOL

To clarify the relative importance of air-front smart city policy categories for business-related stakeholders, this part examines the contribution of each policy category to startups’ QOB, business partners’ QOL, and residents’ QOL. Figure 6.2 illustrates the proportional shares of rules and regulations, infrastructure, and DX technologies in shaping QOB and QOL across these stakeholder groups.

Table 6.7. Resident's QOL estimation result.

Category	Indicator	W^m (JPY)	Normalized V_i^m	ACC_{ij}^l	QOL_i^m
Rules and Regulations	RR1: Crime Risk	3282	0.694	-	2278
	RR2: Economic Growth Rate	4176	0.996	-	4159
	RR3: Air Quality PM2.5	1863	0.5	-	931
	RR4: Traffic Accident Risk	817	0.963	-	787
Infrastructures	IF1: High-Speed Rail Stations	1926	0.05	0.033	93
	IF2: Major Universities	635	0.87	0.030	541
	IF3: Flood Risk	486	1	-	486
	IF4: City Population (100 P)	2324	0.734	-	1707
	IF5: Time to Childcare Facilities	1618	0.1	0.033	156
	IF6: Time to Shopping Facilities	1618	0.659	0.021	1043
DX Technologies	DX1: Online Admin Services	454	0.175	0.017	78
	DX2: Online Living Services	415	0.543	0.017	221
				Resident's QOL	12483

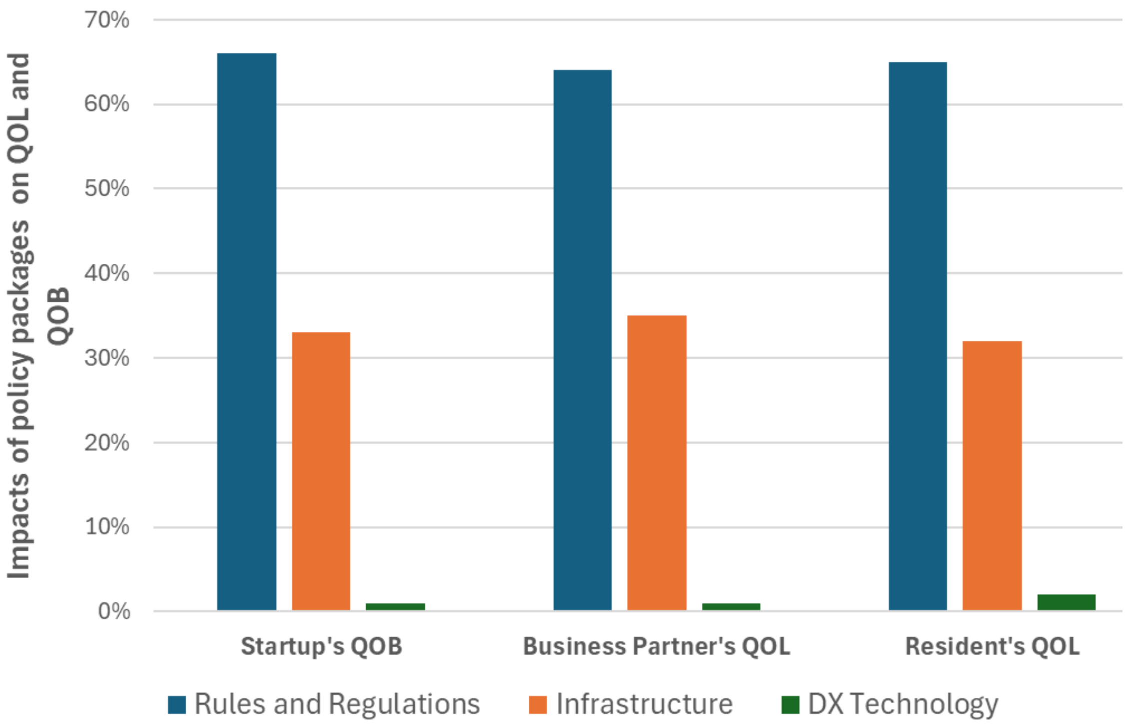


Figure 6.2. Share of policy categories in Aichi's startup ecosystem.

Rules and Regulations

As shown in Figure 6.2, policies classified under Rules and Regulations contribute to approximately 66% of the total Startup QOB. The largest contributions arise from economic growth rate and international conferences, indicating that macroeconomic performance and international business exposure dominate startup business value under current conditions. Other regulatory instruments, including startup support budgets and corporate tax rates, contribute to smaller but measurable values. The Rules and Regulations category contributes to 64% of the total Business Partner's QOL. This category clearly dominates the evaluation, driven primarily by indicators related to international business interaction, environmental quality, traffic safety, and public support measures. Similarly, policies classified under Rules and Regulations contribute to 65% of the total Residents' QOL. The largest contribution is generated by the economic growth rate, followed by crime risk. Air quality and traffic accident risk also provide substantial contributions. These results indicate that residents' QOL is strongly shaped by macroeconomic conditions and safety-related regulatory outcomes. As was witnessed, the major contributor to QOL and QOB is rules and regulations related to policies.

Infrastructure

The Infrastructure category contributes 33% of the total Startup QOB. Within this category, city population size and young population share provide the largest contributions, followed by major universities and office rent. Infrastructure indicators subject to integrated accessibility constraints, such as high-speed rail stations and high-class hotels, show reduced perceived value. The infrastructure category contributes 35% of the total business partner's QOL. Most of this contribution comes from indicators associated with urban scale and knowledge infrastructure, while accessibility-dependent infrastructure elements show reduced realized values due to integrated accessibility constraints. Similarly, the infrastructure category contributes to 32% of the total Residents' QOL. Within this category, city population size provides the largest contribution, followed by time to shopping facilities and major universities. Indicators directly affected by physical accessibility, such as high-speed rail stations and time to childcare facilities, show reduced perceived contributions due to the application of the integrated accessibility index.

DX Technology

The DX Technologies category contributes less than 1% of the total Startup QOB. This value represents the perceived contribution of online administrative services after accounting for digital accessibility constraints. The DX technology category contributes about 1% of the total business partner's QOL. Although quantitatively small, this value captures the realized benefit of digital administrative services under existing digital accessibility conditions. The DX technology category contributes about 2% of the total Residents' QOL. This contribution is composed of online living services and online administrative services, reflecting the realized benefits of digital services under existing digital accessibility conditions.

6.3. Policy Evaluation

This section evaluates air-front smart city policies using the developed QOL and QOB evaluation framework. Policy impacts are examined under two analytical settings. Setting 1 assesses the effects of individual policy interventions on startups' QOB and on the QOL of relevant stakeholders, while Setting 2 evaluates the combined effects of multiple air-front smart city policies on startups' QOB and stakeholders' QOL.

Indicators are selected for this purpose based on direct policy controllability (if authorities can realistically change these indicators within a policy cycle), air-front smart city specificity (if the indicators are specific to the air-front smart city concept), strong impact (if the indicators have a higher monetary weight or large marginal impact on QOL and QOB), and clear interpretability (if policy impact can be clearly explained without ambiguity). For the policy evaluation purpose, 6 key indicators (corporate tax rate, number of international flights, air quality, number of high-speed rails, online administrative service coverage, and number of international flight destinations) are selected.

The primary objective of this section is to examine how different air-front smart city policies contribute to the enhancement of business and living environments and to verify the effectiveness of the proposed QOL and QOB models. In addition to estimating perceived QOL and QOB scores, this section also analyzes changes in existing QOL conditions under each policy intervention.

6.3.1. Scenario setting 1

This scenario examines the effects of a single air-front smart city policy on living and business environments, using the startup ecosystem in Aichi as a case study. For this purpose, one representative indicator is selected from each policy category: the corporate tax rate for Rules and Regulations, the number of high-speed rail stations for Infrastructure, and the level of online administrative services for DX Technologies.

Scenario A: 50% Reduction in the corporate tax rate

In this scenario, the corporate tax rate is reduced from 24.86% to 12.43%. Such a reduction is expected to substantially improve the urban business environment for startup firms. Given the relatively large estimated coefficient for the corporate tax rate, the results indicate that a 50% reduction leads to a 95% increase in startups' QOB, nearly doubling their perceived business value. In parallel, business partners' QOL increases by 115%, reflecting strong spillover effects on the broader business ecosystem. By contrast, this policy intervention has no direct impact on residents' QOL, as the corporate tax rate does not enter the residential QOL evaluation model.

Using equations (5.6 and 5.7) in Chapter 5, and taking V_0^{ct}=24.86%, V_1^{ct}=12.43%, $W^{ct} = 8{,}097$ JPY/tsubo/month, the chapter estimates $\Delta QOLB_{potential}^{\mathrm{m}}$ equivalent to 100,650 JPY/tsubo/month. This can be interpreted as reducing the corporate tax rate to 12.43 %, generating an increase in potential startup QOB of approximately 100,650 JPY/tsubo/month. This value represents a rent-equivalent business benefit, indicating that regulatory tax relief produces an economic effect comparable to a substantial reduction in office rent. The result confirms that corporate tax policy is one of the most powerful levers for enhancing startup business value within air-front smart city development.

Scenario B: Adding 9 train stations

In this scenario, the number of high-speed rail stations accessible within two hours is increased from 21 to 30. This policy intervention is expected to enhance both living and business environments by improving regional and intercity accessibility within the startup ecosystem. The estimation results indicate that this improvement leads to an 8% increase in startups' QOB, a 12% increase in business partners' QOL, and a 6.7% increase in residents' QOL. These results highlight a key feature of the air-front smart city concept: infrastructure investments aimed at strengthening regional connectivity can simultaneously support economic activities and improve quality of life for multiple stakeholder groups, rather than benefiting only businesses. This emphasizes the novelty of the air-front smart city concept, which connects economic growth with residents' QOL, considering the strength and uniqueness of the city.

Furthermore, this scenario demonstrates the capability of the proposed QOL and QOB model to quantitatively capture the spillover effects of transport infrastructure policies across different stakeholders. In monetary terms, the addition of nine high-speed rail stations generates an estimated 17,334 JPY/tsubo/month in aggregate business value within the startup ecosystem in Aichi, indicating a substantial rent-equivalent gain attributable to improved accessibility. The result can confirm that enhancing high-speed rail accessibility within a two-hour range represents a highly effective air-front smart city strategy, as it generates measurable business value for startups while simultaneously improving quality of life for business partners and residents through integrated regional connectivity.

Scenario C: 100% increase in online administrative service percentage

In this scenario, the proportion of administrative services delivered online is increased from 30% to 60%. Using the proposed QOL and QOB evaluation framework, the impacts on urban living environments and the business environment are assessed. The results indicate improvements of 2% in startups' QOB, 3% in business partners' QOL, and 1.7% in residents' QOL. Furthermore, the analysis reveals that a 100% increase in online administrative service utilization generates an additional equivalent office rent value of 13,393 JPY per tsubo per month for the startup ecosystem in Aichi. Figure 6.3 illustrates the impacts of scenario setting 1 on QOL and QOB.

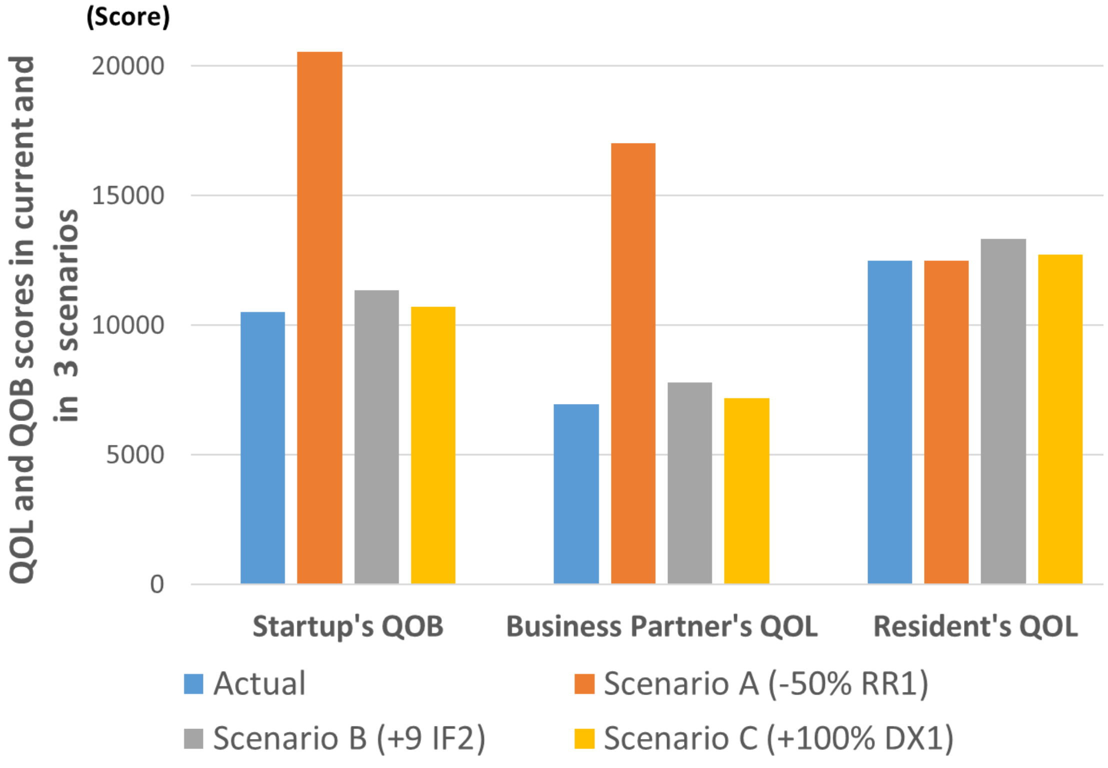


Figure 6.3. Impacts of scenarios on QOL and QOB.

6.3.2. Scenario setting 2

In this scenario setting, multiple air-front smart city policies are simultaneously implemented to evaluate their combined effects on startup-driven air-front smart cities. Specifically, six key policy indicators are selected: corporate tax rate, number of international conferences, number of high-speed rail stations, coverage of digital administrative services, number of international flight destinations, and air quality. Each indicator is adjusted by ±10 percent relative to the baseline condition.

To systematically examine different policy orientations, the policy indicators in Scenario Setting 2 are organized into two distinct policy sets in order to reflect different strategic orientations of air-front smart city development and to explicitly examine how policy bundles with different functional roles influence startup QOB and stakeholders' QOL. The primary criterion for constructing the policy sets is the mechanism through which each policy affects urban value creation within a startup-driven air-front smart city. Specifically, the indicators are classified based on whether they primarily influence internal operational efficiency and institutional conditions, or whether they enhance the city's external connectivity and international attractiveness.

Policy Set 1, comprising corporate tax rate, number of high-speed rail stations, and coverage of online administrative services, represents foundational competitiveness policies as shown in Table 6.8. These indicators directly affect a startup's day-to-day business costs, administrative efficiency, and domestic accessibility. Their impacts are largely realized through improvements in regulatory efficiency, infrastructure availability, and digital service provision, making them essential baseline conditions for startup activity regardless of global positioning. Whereas, policy Set 2, including the number of international conferences, the number of international flight destinations, and air quality, represents global orientation and place-attractiveness policies. These indicators primarily influence a city's visibility, connectivity, and reputation within international bodies and innovation networks. Their effects are strongly mediated by air-front characteristics, such as airport connectivity and international mobility, and are therefore particularly relevant to the air-front smart city concept.

Separating policies into these two sets allows the analysis to (i) isolate the relative effectiveness of internal efficiency–oriented versus external connectivity-oriented policy packages, and (ii) evaluate potential synergies and trade-offs between improving baseline business conditions and enhancing global competitiveness. This distinction reflects real-world policy-making practices, in which air-front smart city strategies typically combine regulatory reforms with investments aimed at strengthening international linkages.

Table 6.8. Mapping of policy sets to air-front smart city policy categories.

Policy Set	Indicators	Policy Category	Role in Air-Front Smart City
Set 1: Foundational Competitiveness Policies	Corporate tax rate	Rules & Regulations	Directly reduces startup business costs and improves regulatory attractiveness.
	High-speed rail stations (within 2 h)	Infrastructure	Enhances domestic and interregional accessibility for firms, employees, and residents
	Online administrative services coverage	DX Technologies	Improves administrative efficiency and reduces transaction costs
Set 2: Global Orientation and Attractiveness Policies	International conferences	Rules & Regulations	Strengthens international business interaction and global visibility
	International flight destinations	Rules & Regulations	Expands global connectivity through airport functions
	Air quality (PM2.5)	Rules & Regulations	Enhances environmental quality for businesses and individuals

Policy Set 1 scenario assessment results

Policy Set 1 comprises the corporate tax rate, the number of high-speed rail stations, and the coverage of online administrative services. Two scenarios are evaluated. Scenario A applies a 10% increase to the existing values of the indicators in this package, while Scenario B applies a 20% increase. The resulting impacts on startups' QOB and stakeholders' QOL are examined. Figure 6.4 presents the results of the scenario analysis for Policy Set 1, where S1-A and S1-B denote Scenario A and Scenario B, respectively. As shown in the figure, a 10% improvement in the selected indicators leads to a 21% increase in startups' QOB, a 32% increase in business partners' QOL, and a 1.7% increase in residents' QOL.

When the magnitude of policy intervention is doubled to 20%, the impacts scale proportionally. Specifically, startups' QOB increases by 42%, business partners' QOL by 64%, and residents' QOL by 3.4%. These results indicate a near-linear response of economic and quality-of-life outcomes to improvements in foundational regulatory, infrastructure, and DX-oriented policies, with particularly strong effects observed for startups and business partners.

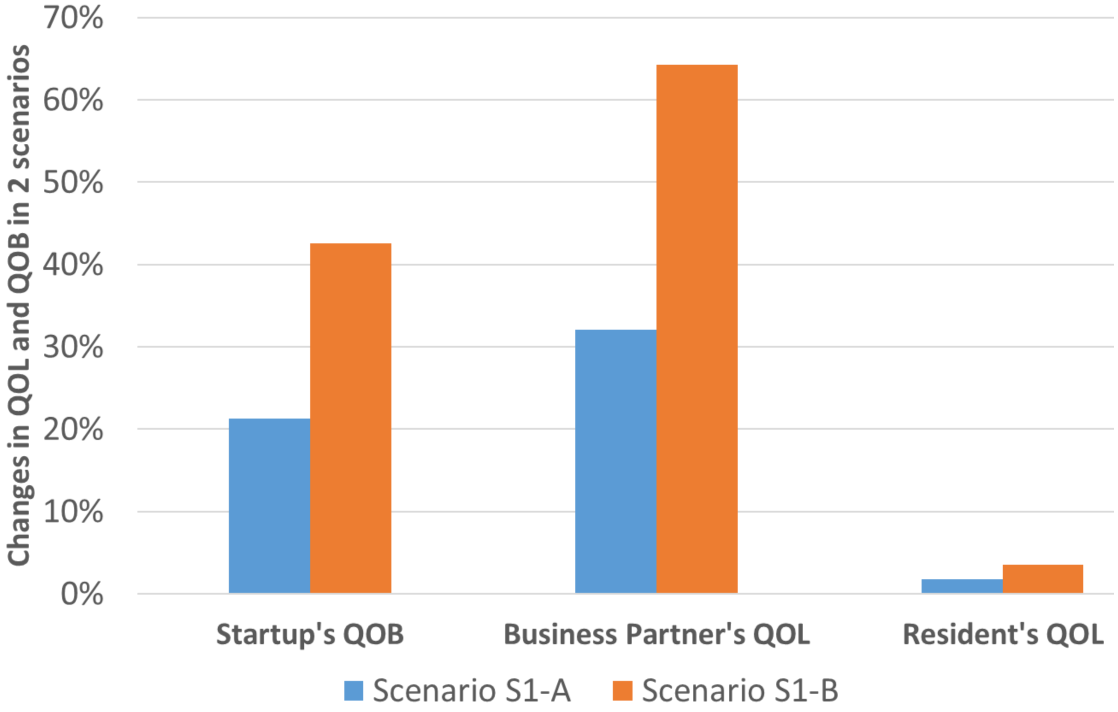


Figure 6.4. Impacts of Policy Set 1 scenarios on QOL and QOB.

Policy set 2 scenario assessment results

Policy Set 2 includes the number of international conferences held, the number of international flight destinations, and the air quality. Two scenarios are evaluated. Scenario A applies a 10% increase to the existing values of the indicators in this package, while Scenario B applies a 20% increase, similar to policy set 2 scenario assessment. The resulting impacts on startups' QOB and stakeholders' QOL are investigated. Figure 6.5 presents the results of the scenario analysis for Policy Set 2, where S2-A and S2-B denote Scenario A and Scenario B, respectively. As shown in the figure, a 10% improvement in the selected indicators leads to a 2.2% increase in startups' QOB, a 7.6% increase in business partners' QOL, and a 2.2% increase in residents' QOL.

When the magnitude of policy intervention is doubled to 20%, the impact scales proportionally. Specifically, startups' QOB increases by 4.8%, business partners' QOL by 15.3%, and residents' QOL by 4.4%. Compared with Policy Set 1, these results indicate that policies enhancing international connectivity and urban attractiveness yield more moderate direct gains for startups' business value, while generating relatively greater improvements in stakeholders' quality of life, particularly for business partners and residents.

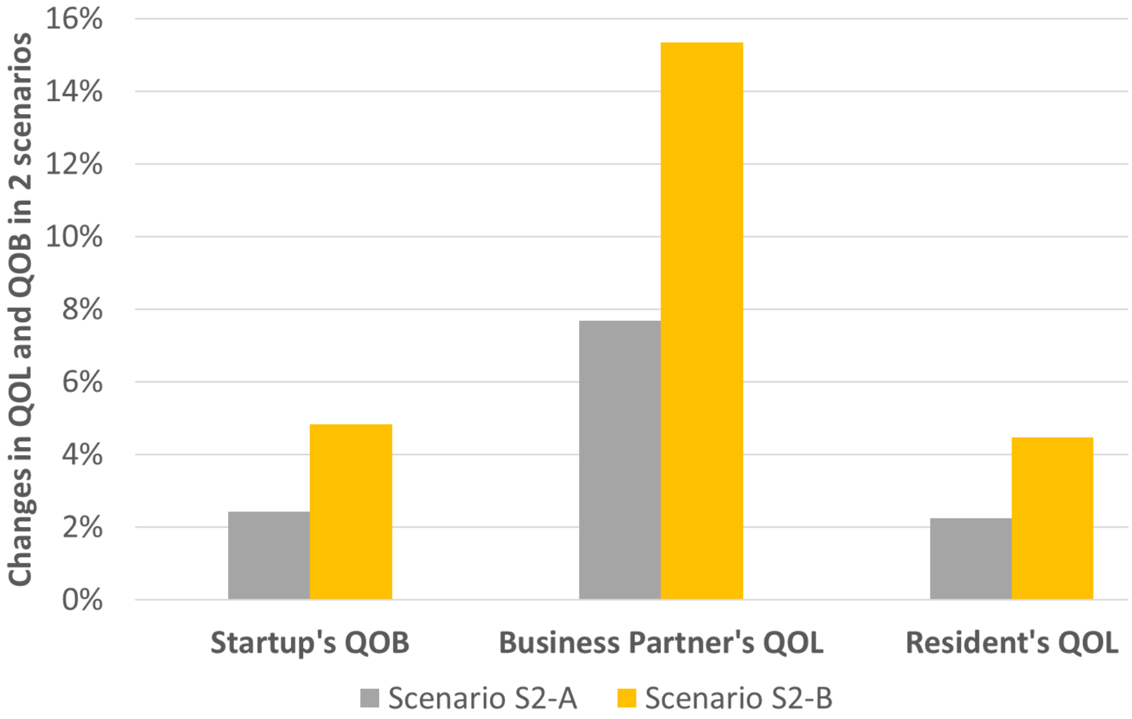


Figure 6.5. Impacts of Policy Set 2 scenarios on QOL and QOB.

6.4. Startup Ecosystem Comparison in Different Cities

This section applies the startup attraction parameters estimated for Aichi to two international cities, Singapore and Munich, and compares their urban business and living environments from the perspective of air-front smart city development. By transferring the parameter values, the analysis ensures a consistent evaluative framework, allowing differences in QOL and QOB outcomes to be attributed to variations in city characteristics rather than to changes in preference structures.

The objective of this section is twofold. First, it provides comparative insights into startup-driven air-front smart city development across three international cities, highlighting similarities and contrasts in their policy environments and stakeholder outcomes. Second, it examines the applicability and robustness of the proposed integrated accessibility–based QOL and QOB evaluation framework in a broader international context. Through this comparative analysis, the section demonstrates the generalizability of the model and its potential usefulness for evaluating air-front smart city strategies beyond the case of Aichi.

6.4.1. Singapore

Singapore, with a population of approximately 6 million, is a global city-state in Southeast Asia that functions as a major international hub for finance, trade, logistics, and innovation. Owing to its strategic geographic location, world-class airport (Changi Airport), and highly integrated transport and digital infrastructure, Singapore has developed strong air-front characteristics that support global business connectivity. The city-state is also known for its stable regulatory environment, pro-business policies, and advanced digital government services, which have contributed to the rapid growth of its startup ecosystem, particularly in sectors such as fintech, deep tech, and urban solutions. These features make Singapore a representative benchmark city for evaluating startup-driven air-front smart city development in an international context.

The chapter has used parameters estimated for a startup-driven air-front smart city in Aichi, and data available on the internet to estimate QOB and QOL in Singapore. Table 6.9 shows the three cities' attributes side by side. As can be seen in the table, Singapore exhibits strong air-front smart city characteristics compared with Aichi and Munich, particularly in the domains of institutional support for startups. Under Rules and Regulations, Singapore benefits from a relatively low corporate tax rate and an exceptionally large startup support budget, alongside a very high number of international flight destinations compared to Aichi, reflecting its role as a global aviation and business hub. Although its economic growth rate is moderate, low traffic accident risk and a stable regulatory environment that supports business environments.

In terms of Infrastructure, Singapore stands out for its high English proficiency, large young population share, dense urban population, and extensive supply of high-class hotels, all of which are advantageous for international startups and business partners. While Singapore does not have high-speed rail stations in the conventional sense, its compact urban structure and efficient transport system compensate for this limitation. Office rents are relatively competitive compared with Munich, supporting business location attractiveness. For DX Technology, Singapore clearly outperforms the other cities, with extremely high coverage of online administrative and living services. Considering Singapore`s relatively higher internet speed, the indicators directly enhance integrated accessibility and enhance the living and business environments.

Table 6.9. Three cities' attributes.

Category	Indicator	Cities' attributes		
		Aichi	Singapore	Munich
Rules & Regulations	Corporate Tax Rate (%)	24.86	17	33
	Startup Support Budget (1B JPY)	0.2	8.18	3.54
	Crime Risk (Report / 1000)	6.670	12.5	16.15
	No. Intl. Flight Destinations (No.)	27	161	184
	Economic Growth Rate (%)	4.98	2.4	1.1
	No. Intl. Conferences Held (10)	8	8	8
	Air Quality PM 2.5 (µg/m³)	15	19	12
Infrastructures	Traffic Accident Risk (death/100,000)	3.99	2.35	0.56
	Office Rents (1k JPY/Sqm)	13.45	4.79	20.6
	No. High-Speed Rail Stations (No.)	21	0	7
	No. of Major Universities (No.)	53	34	22
	Flood Risk (%)	20	30	15
	High English Proficiency (%)	11	74	50
	City Population (100 people)	74800	60000	15900
	Young Population (%)	23.7	30	33
	Time to Childcare Facilities (mins)	14	14	14
	High-Class Hotels (No.)	17	70	14
	Time to Shopping Facilities (mins)	8.41	7	10
	Road Congestion (km/h)	30.1	28.9	20
DX Technology	Internet Speed (Mbps)	55.99	372	130
	Online Administrative Services (%)	30.5	70	54
	Online Living Services (%)	52.6	82	80

Startup's QOB in Singapore

Table 6.10 presents the estimated Startup's QOB for Singapore using the Aichi-calibrated monetary weights, city-specific indicator values, and the integrated accessibility index (ACCI). The total startup QOB score for Singapore is 50,553, indicating a very strong business environment for startups under the air-front smart city framework.

Under the rules and regulations category, Singapore shows large contributions to the startup QOB. The startup support budget is the dominant factor, generating 36,101 scores, which alone accounts for more than two-thirds of the total QOB. This reflects Singapore's substantial public financial commitment to startup development. The corporate tax rate also contributes strongly (6,477 scores), as Singapore's relatively low tax rate translates into a high normalized value. Economic growth and international conferences contribute 2,004 and 1,862 scores, respectively, confirming the importance of macroeconomic stability and international business exposure within a startup-driven air-front smart city. In contrast, the contribution of international flight destinations is comparatively small (271 scores), but it is larger in the case of Aichi.

Office rents contribute positively (1,013 scores), city population (1,345 scores), and young population share (1,801 scores) significantly enhance startup QOB. Under DX Technology, online administrative services contribute a 377 score, indicating that Singapore's advanced digital government environment positively supports startup operations, although its marginal contribution is smaller than regulatory and financial factors. Singapore has a higher internet speed and lower traffic congestion compared to Aichi; this attribute, as an accessibility index, enhances accessibility to the services. Overall, the table shows that Singapore's startup QOB is overwhelmingly driven by regulatory and financial support mechanisms, complemented by a young, skilled population and strong digital governance.

Table 6.10. Startup's QOB in Singapore.

Category	Indicator (unit)	W^m (JPY)	Normalized V_i^m	ACC_{ij}^I	QOB_i^m
Rules & Regulations	RR1: Corporate Tax Rate (%)	8097	0.8	-	6477
	RR2: Startup Support Budget (B JPY)	1196	30.18	-	36101
	RR3: Intl. Flight Destinations (No.)	346	0.78	-	271
	RR3: Economic Growth Rate (%)	4176	0.48	-	2004
	RR4: Intl. Conferences Held No. x10)	2483	0.75	-	1862
Infrastructures	IF1: Office Rents (1000 JPY/tsubo)	1000	1.013	-	1013
	IF2: High-Speed Rail Stations (No.)	1926	-1	0.034	-1860
	IF3: Major Universities (No.)	635	0.55	0.029	340
	IF4: English Proficiency (%)	542	1.06	-	578
	IF5: City Population (100 P)	2324	0.57	-	1345
	IF6: Young Population (%)	1801	1	-	1801
	IF7: High-Class Hotels (No.)	214	1.169	0.034	241
DX Technology	DX1: Online Admin Services (%)	454	0.83	0.0026	377
				Startup's QOB	50553

Business partner`s QOL

Table 6.11 presents the Business Partner's QOL score in Singapore, which is 46,757, and is substantially higher than the corresponding score for Aichi (6,967). The largest contribution to Singapore's Business Partners' QOL is from startup support budgets, which account for 36,101 points, dominating the overall score. In comparison, the same indicator contributes only 753 points in Aichi, indicating that fiscal support policies are far more influential in Singapore's startup ecosystem.

The corporate tax rate is the second most influential factor in Singapore, contributing 6,477 points, whereas its contribution in Aichi is limited to 113 points. This contrast demonstrates that tax competitiveness plays a much stronger role in shaping business partner perceptions in Singapore. International flight destinations contribute 271 points in Singapore but only 13 points in Aichi, reflecting Singapore's stronger air-front connectivity.

In the infrastructure domain, Singapore exhibits a negative contribution from high-speed rail accessibility (−1,860 points) due to the absence of high-speed rail, while Aichi shows a positive contribution (93 points). This contrast highlights that rail-based accessibility is a critical air-front component for regional cities like Aichi, but not for compact city-states such as Singapore. Conversely, English proficiency contributes 578 points in Singapore but only 9 points in Aichi, emphasizing the importance of human-capital-related infrastructure in internationally oriented startup ecosystems.

The contribution of DX technology policies, represented by online administrative services, is 377 points in Singapore compared with 78 points in Aichi. While positive in both cases, DX-related impacts are relatively less dominant in Singapore due to the overwhelming influence of regulatory and fiscal policies.

Table 6.11. Business partner's QOL in Singapore.

Category	Indicator (unit)	W^m (JPY)	Normalized V_i^m	ACC_{ij}^l	QOL_i^m
Rules & Regulations	RR1: Corporate Tax Rate (%)	8097	0.8	-	6477
	RR2: Startup Support Budget (B JPY)	1196	30.18	-	36101
	RR3: Intl. Flight Destinations (No.)	346	0.783	-	271
	RR4: Intl. Conferences Held No. x10)	2483	0.75	-	1862
	RR5: Air Quality PM2.5 (μg/m³)	1863	0.1	-	186
	RR6: Traffic Accident Risk (deaths/100,000)	817	1.024	-	836
Infrastructure	IF1: High-Speed Rail Stations (No.)	1926	-1	0.034	-1860
	IF2: Major Universities (No.)	635	0.55	0.029	340
	IF3: English Proficiency (%)	542	1.06	-	578
	IF4: City Population (100 P)	2324	0.57	-	1345
	IF5: High-Class Hotels (No.)	214	1.16	0.034	241
DX Technology	DX1: Online Admin Services (%)	454	0.83	0.002	377
			Business Partner's QOB		46757

Resident's QOL in Singapore

Table 6.12 presents the Residents' QOL score in Singapore, which is estimated to be 6,183, half of Aichi's score (12,483).

Table 6.12. Resident’s QOL in Singapore.

Category	Indicator	W^m (JPY)	Normalized V_i^m	ACC_{ij}^l	QOL_i^m
Rules and Regulations	RR1: Crime Risk	3282	0.20	-	683
	RR2: Economic Growth Rate	4176	0.48	-	2004
	RR3: Air Quality PM2.5	1863	0.1	-	186
	RR4: Traffic Accident Risk	817	1.02	-	836
Infrastructures	IF1: High-Speed Rail Stations	1926	-1	0.034	-1860
	IF2: Major Universities	635	0.55	0.029	340
	IF3: Flood Risk	486	0.83	-	405
	IF4: City Population (100 P)	2324	0.57	-	1345
	IF5: Time to Childcare Facilities	1618	0.1	0.034	156
	IF6: Time to Shopping Facilities	1618	0.8	0.010	1280
DX Technologies	DX1: Online Admin Services	454	0.83	0.002	377
	DX2: Online Living Services	415	1.03	0.002	427
				Resident’s QOL	6183

6.4.2. Munich

Munich is one of the main economic hubs of southern Germany and is known for combining strong industry, modern technology, and a rich cultural background. The city has about 1.59 million residents and covers an area of 308 square kilometers. It plays an important role in Germany’s economy and innovation activities. In 2024, Munich’s city budget is about 7.91 billion GBP, showing its strong financial capacity to support urban development and public services. Although the city accounts for only around 1.9% of Germany’s total population, it has a high GDP per capita of 36,664 GBP. Population growth continues, but at a slow and stable rate of about 0.2%.

As can be seen in Table 6.9, Munich exhibits a strong but cost-intensive air-front smart city profile. Under Rules and Regulations, Munich has the highest corporate tax rate among the three cities at 33%, compared with 24.86% in Aichi and 17% in Singapore. The other strength of Munich is having a larger international flight destination, with 184 international flight destinations, exceeding both Aichi (27) and Singapore (161). However, its economic growth rate is only 1.1%, indicating a mature and stable economy. In terms of Infrastructure, Munich has higher office costs. Office rents are the highest among the three cities at 20.6 thousand JPY/tsubo/month compared with 13.45 in Aichi and 4.79 in Singapore. The young population share is 33%, higher than both Aichi (23.7%) and Singapore (30%), supporting startup activity. Munich also benefits from 7 high-speed rail stations, reinforcing regional accessibility, while flood risk remains relatively low at 15%.

Regarding DX Technologies, Munich performs at an intermediate level. Coverage of online administrative services is 54%, and online living services reach 80%, indicating advanced but not fully optimized digital governance compared with Singapore. The average internet speed is 130 Mbps, higher than Aichi (55.99 Mbps) but significantly lower than Singapore (372 Mbps). Also, road congestion is high compared to other cities, which reduces the QOL and QOB scores.

Startup's QOB in Munich

Table 6.13 shows that Munich's Startup QOB score is 14,414, which is substantially lower than Singapore's (50,553) but higher than Aichi under baseline conditions. The results indicate a mixed policy environment for startup business value. Under rules and regulations, Munich is penalized by a high corporate tax rate (−6,477), in sharp contrast to Singapore's strong positive contribution from low taxation and large startup support budgets. While Munich benefits from a moderate startup support budget (15,548) and a stable international conference environment (1,862), its low economic growth rate (918) limits overall business attractiveness compared to Aichi.

Table 6.13. Startup's QOB in Munich.

Category	Indicator (unit)	W^m (JPY)	Normalized V_i^m	ACC_{ij}^I	QOB_i^m
Rules & Regulations	RR1: Corporate Tax Rate (%)	8097	-0.8	-	-6477
	RR2: Startup Support Budget (B JPY)	1196	13	-	15548
	RR3: Intl. Flight Destinations (No.)	346	0.91	-	315
	RR3: Economic Growth Rate (%)	4176	0.22	-	918
	RR4: Intl. Conferences Held No. x10)	2483	0.75	-	1862
Infrastructures	IF1: Office Rents (1000 JPY/tsubo)	1000	-0.04	-	-40
	IF2: High-Speed Rail Stations (No.)	1926	-0.65	0.05	-1190
	IF3: Major Universities (No.)	635	0.34	0.04	209
	IF4: English Proficiency (%)	542	0.66	-	361
	IF5: City Population (100 P)	2324	0.11	-	266
	IF6: Young Population (%)	1801	1.3	-	2341
	IF7: High-Class Hotels (No.)	214	0.22	0.05	44
DX Technology	DX1: Online Admin Services (%)	454	0.56	0.007	255
				Startup's QOB	14414

From an infrastructure perspective, Munich's negative high-speed rail accessibility (−1,190) significantly reduces QOB, similar to Singapore but unlike Aichi, where rail accessibility is a major strength. Positive contributions from the young population (2,341) and major universities (209) partially offset these losses but remain insufficient to drive high startup value. DX technology contributes modestly (255), remaining weaker than

Singapore’s digital advantage and only marginally improving overall QOB.

Business partner’s QOL

Table 6.14 presents that Munich’s Business Partner QOL score is 13,576, which is substantially lower than Singapore (46,757) and lower than Aichi, reflecting structural constraints from an air-front smart city perspective. Under rules and regulations, Munich shows a strong positive contribution from startup support budgets (15,548), weaker than Singapore. However, this is largely offset by a strongly negative impact of the high corporate tax rate (−6,477), which contrasts sharply with Singapore and also underperforms Aichi. Contributions from international conferences (1,862), air quality (1,490), and traffic safety (890) provide positive scores but do not dominate the overall QOL outcome.

Table 6.14. Business Partner’s QOL in Munich.

Category	**Indicator (unit)**	W^m **(JPY)**	**Normalized** V_i^m	ACC_{ij}^I	QOL_i^m
Rules & Regulations	RR1: Corporate Tax Rate (%)	8097	-0.8	-	-6477
	RR2: Startup Support Budget (B JPY)	1196	13	-	15548
	RR3: Intl. Flight Destinations (No.)	346	0.91	-	315
	RR4: Intl. Conferences Held No. x10)	2483	0.75	-	1862
	RR5: Air Quality PM2.5 (μg/m³)	1863	0.8	-	1490
	RR6: Traffic Accident Risk (deaths/100,000)	817	1.09	-	890
Infrastructure	IF1: High-Speed Rail Stations (No.)	1926	-0.65	0.05	-1190
	IF2: Major Universities (No.)	635	0.34	0.043	209
	IF3: English Proficiency (%)	542	0.66	-	361
	IF4: City Population (100 P)	2324	0.11	-	266
	IF5: High-Class Hotels (No.)	214	0.22	0.05	44
DX Technology	DX1: Online Admin Services (%)	454	0.56	0.007	255
			Business Partner’s QOB		13576

Resident’s QOL

Table 6.15 shows that Munich’s residents’ QOL score is 4,412, which is substantially lower than both Aichi and Singapore, indicating that Munich’s air-front smart city advantages translate less effectively into everyday living conditions. Within rules and regulations, air quality (1,490) and traffic safety (890) provide the largest positive contributions, reflecting Munich’s strong environmental and safety standards. Economic growth (918) also contributes positively, but lags behind Singapore and Aichi. However, crime risk shows a small negative effect (−314), which contrasts with Singapore’s stronger safety-related performance and slightly weakens overall resident QOL.

Table 6.15. Resident's QOL in Munich.

Category	Indicator	W^m (JPY)	Normalized V_i^m	ACC_{ij}^l	QOL_i^m
Rules and Regulations	RR1: Crime Risk	3282	-0.09	-	-314
	RR2: Economic Growth Rate	4176	0.22	-	918
	RR3: Air Quality PM2.5	1863	0.8	-	1490
	RR4: Traffic Accident Risk	817	1.09	-	890
Infrastructures	IF1: High-Speed Rail Stations	1926	-0.65	0.05	-1190
	IF2: Major Universities	635	0.34	0.041	209
	IF3: Flood Risk	486	1.08	-	526
	IF4: City Population (100 P)	2324	0.11	-	266
	IF5: Time to Childcare Facilities	1618	0.1	0.05	153
	IF6: Time to Shopping Facilities	1618	0.5	0.01	794
DX Technologies	DX1: Online Admin Services	454	0.56	0.007	255
	DX2: Online Living Services	415	1	0.007	411
				Resident's QOL	4412

6.4.3. Comparative results

Figure 6.6 presents the estimated QOB and QOL values for Aichi, Singapore, and Munich. As illustrated in the figure, Singapore exhibits substantially higher startup QOB and the business partner's QOL than both Aichi and Munich, while the resident's QOL remains comparatively low. Munich shows a higher startup's QOB and business partner's QOL than Aichi, reflecting stronger business-oriented conditions; however, its residents' QOL is lower than that of Aichi. In contrast, Aichi demonstrates a more balanced profile, with moderate business performance and the highest residents' QOL among the three cities.

The corporate tax rate, as a main indicator of a startup-driven air-front smart city, largely contributes to the enhancement of business environments. Additionally, considering lower traffic congestion (physical accessibility) and higher internet speed (virtual accessibility), captured by the integrated accessibility index, significantly contribute to simultaneous gains in QOL and QOB. This highlights the effectiveness of air-front smart city policies that jointly integrate regulatory measures, infrastructure, and digital services to amplify both urban business performance and living environments.

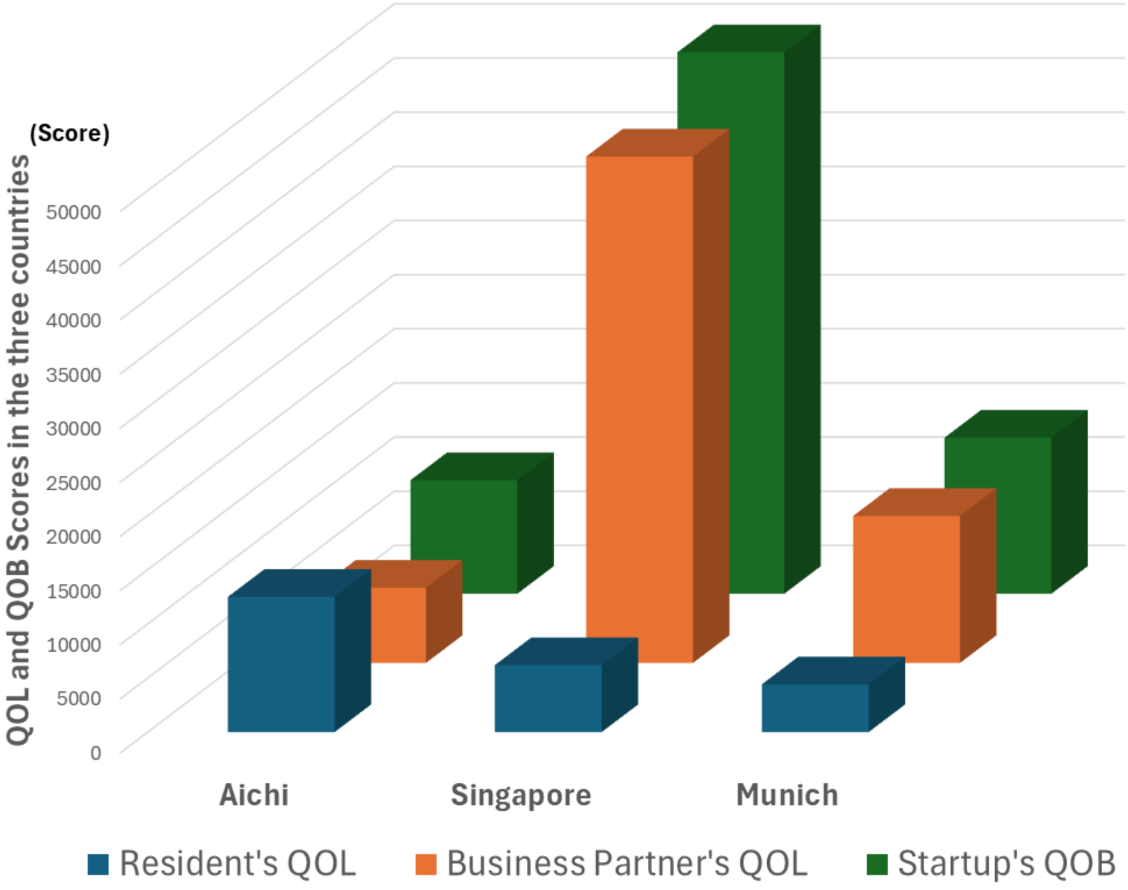


Figure 6.6. QOL and QOB in Aichi, Singapore, and Munich.

Figure 6.7 illustrates how Aichi, Singapore, and Munich generate QOB and QOL through different configurations of air-front smart city policies that extend beyond the immediate site to include broader urban and regional systems. Considering the air-front smart city concept, hinterland regions are not treated as separate or competing spaces but as functionally integrated areas that enhance the overall accessibility, attractiveness, and competitiveness of the air-front. In this respect, Aichi, Singapore, and Munich`s performance reflects, in addition to business-related regulations, the strength of linking air-front functions with regional accessibility and service coverage, rather than focusing solely on airport-adjacent development.

As can be seen in the figure, Singapore’s QOB is strongly driven by regulatory and global connectivity advantages. Its low corporate tax rate generates a large positive contribution to startup QOB (6,478), while its exceptionally high startup support budget (36,101) dominates the business value structure. Strong performance in international flight destinations (271), English proficiency (578), and digital administrative services

(377) reflect Singapore’s highly concentrated air-front smart city model, where global accessibility is primarily achieved through air networks and advanced digital services. However, weaker environmental indicators, such as air quality (186), and limited integration with surrounding regions constrain the spillover of business value into residents’ QOL.

Aichi demonstrates how an air-front smart city can leverage regional connectivity and distribute urban assets to enhance both QOB and QOL. High contributions from high-speed rail accessibility (93), major universities (541), and population scale (1,708) indicate that startups and residents benefit from access to a wide range of services, talent, and markets beyond the immediate air-front. These elements strengthen perceived accessibility through both physical and virtual networks, reinforcing economic growth while maintaining relatively balanced living conditions. This illustrates that the effectiveness of air-front smart city policies depends on how well airport functions are embedded within the wider metropolitan and regional system.

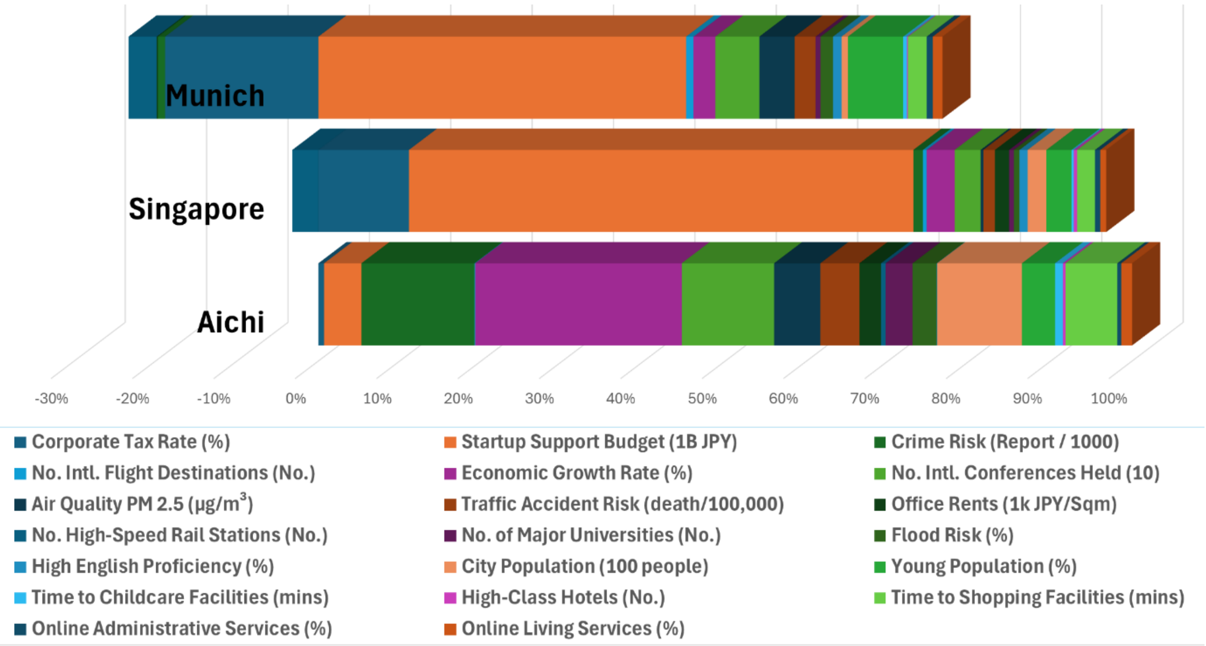


Figure 6.7. QOL and QOB Components in Aichi, Singapore, and Munich.

Munich represents a case where strong environmental quality (1,490) and demographic advantages, such as a high share of young population (2,341), contribute positively to QOL and QOB. However, a high corporate tax burden results in a substantial negative contribution to startup QOB (–6,478), limiting the city’s competitiveness in attracting startups despite favorable living conditions. While Munich benefits from strong startup support budget (15548), international flight destination (315), and lower traffic accidents (890), weaker crime rates (-314), office rent (-40), and high-speed rail stations (-1190) reduce the overall QOB and QOL.

6.5. Conclusion

This chapter applied the developed QOL and QOB evaluation methodology from Chapter 5 to assess urban business and living environments within a startup-driven air-front smart city concept in Aichi. The chapter used preliminary interview survey data for selecting indicators for startup ecosystem evaluation, then used conjoint analysis data to estimate indicator weight parameters. Indicators' weight parameters are the values of indicators. Taking advantage of conjoint analysis, the chapter estimated the monetary value of each indicator with respect to office rent (JPY/tsubo/month). The chapter took traffic congestion (km/h) and internet speed (Mbps) as physical and digital accessibility indices, respectively, for integrated accessibility index calculation. The integrated accessibility calculation, which is a novelty of this thesis, was used to estimate the perceived accessible values of each component indicator.

The model was applied to three cities: Aichi, Singapore, and Munich, by calibrating parameters estimated within Aichi’s startup ecosystem for the other two cities. All three cities are investing in promoting startups to boost their economic growth. However, within the concept of an air-front smart city, economic growth is not the only focus, but the residents' and business stakeholders' QOL as well. Therefore, this chapter estimated the QOB score for startups and the QOL scores for business partners of startups, and the residents in the three cities.

The chapter could positively test different urban policy scenarios in different settings, by which the author could verify the effectiveness and applicability of the model for assessing air-front smart city policies. Incorporating the integrated accessibility in the model could give us a clear picture of scenarios for startup developments within the concept of an air-front smart city.

The result of this chapter disclosed that corporate tax rates have a higher weight compared to other air-front smart city policies, which are followed by economic growth, criminal offenses, international conferences, and so on. Whereas the lower rank indicators are high-class hotels, international flight destinations, digital life services, and so on. Using these parameter weights, living and business environments for startup developments were evaluated within the context of an air-front smart city. The result disclosed that Singapore has a higher Startup's QOB score compared to Munich and Aichi, which is followed by Munich and Aichi. This is because of a lower corporate tax rate, higher startup support budget, lower office rent, moderate economic growth, and higher internet speed and moderate traffic congestion as access cost, in Singapore. Similarly, the business partner`s QOL was estimated to be higher in Singapore than in the other two cities due to the lower corporate tax rate, a higher number of international flight destinations than Aichi, a higher number of five-star hotels, and higher English proficiency, compared to Aichi and Munich. Resident's QOL was estimated to be higher in Aichi than in Singapore and Munich due to low crime rate, higher economic growth, and moderate air quality.

The result of this chapter emphasized reducing corporate tax rates and startup support budgets, which substantially improve business environments. Whereas policies related to the improvements of airport function, physical and digital accessibility, crime rate, and air quality enhance both living and business environments. Therefore, policymakers are advised to look for policy packages that can enhance opportunities for both residents and businesses. Such a way of policy assessment, while considering the uniqueness and strength of the region, and integrating airport functions and DX technologies, aligns with the air-front smart city policy implementations.

As a future research prospect, this chapter suggests incorporating QOL and QOB evaluation into regional evaluation models and regenerative economic models. A decarbonization estimation model can be developed to assess the three-fold air-front smart city (happiness for people, happiness for businesses, and happiness for the environment).

Chapter 7

Conclusion

This chapter summarizes the major contributions, discusses future research opportunities, and closes the thesis with final remarks.

7.1. Summary of Contributions

This thesis investigated the integrated evaluation of real and virtual networks within the context of air-front smart cities. The central contribution of the research lies in developing and verifying a comprehensive analytical framework that captures the interactions between physical accessibility, digital accessibility, social networks, and urban behavior. Through Chapters 2 to 6, the thesis systematically identified academic gaps, developed new methodologies, and applied them to evaluate urban living and business environments under air-front smart city conditions. The major findings of each chapter are summarized below.

Chapter 2: Literature review and research positioning

Chapter 2 reviewed relevant literature on air-front smart cities, real and virtual networks, social dynamics simulation, and QOL evaluation methods, focusing on accessibility, digital substitution, social networks, and urban simulation. The chapter identified clear gaps in the integration of these elements within a unified analytical framework: (a) smart city research prioritizes technology over human-centric development; (b) airport economic impacts are studied separately from smart city policies; (c) no joint evaluation of physical and digital accessibility exists; (d) social dynamics simulation models lack virtual network integration; and (e) QOL evaluation methods ignore digital accessibility. In response to these gaps, the chapter proposed a research design combining empirical behavioral analysis with methodology development, establishing a theoretical foundation for subsequent chapters.

Chapter 3: Substitutability and complementarity of physical services with digital alternatives

Chapter 3 empirically examined the substitutability and complementarity between physical services and digital alternatives using nationwide survey data from Japan (n =

6,210). The results revealed substantial heterogeneity across activity types, demographic groups, mobility conditions, social networks, and residential contexts. Digital substitution was highest for shopping and schooling, moderate for dining and working, and minimal for healthcare-related activities, indicating continued dependence on physical access for socially intensive services. Younger individuals and males exhibited higher substitution tendencies, while older individuals relied more on physical networks. Importantly, license holders were more likely to engage in online shopping than non-license holders, suggesting that digital services often complement rather than replace physical mobility. Social network structures further shaped digital adoption, with online-oriented individuals favoring digital alternatives and community-oriented individuals maintaining physical activity patterns. Digital accessibility significantly influenced residential relocation in urban areas but had a limited impact in rural contexts. Overall, the findings confirm that digital services primarily complement physical urban systems and provide a robust empirical foundation for the integrated modeling framework developed in subsequent chapters.

Chapter 4: Social dynamics simulation using a multi-layer network

Chapter 4 developed and verified a Social Dynamics Simulation (SDS) model that integrates physical accessibility, digital accessibility, and endogenous social networks within a multi-layer network, building directly on the empirical findings of Chapter 3. The chapter introduced a service choice model, estimated from survey data, to represent individual decisions between physical and digital service access, and an integrated accessibility index that combines physical and digital accessibility weighted by service choice probabilities. Social networks were incorporated as an endogenous layer influencing service choice. Application of the model to a virtual city over a 30-year simulation demonstrated that digital service usage patterns remain relatively stable across age groups, population concentration persists around transport-accessible zones despite improved traffic conditions, and digital accessibility partially relaxes, but does not replace, dependence on physical accessibility in residential choice. The results further showed that social network structure and urban space co-evolve through accessibility-dependent interaction mechanisms, with mobility-advantaged individuals becoming increasingly central within social networks. Overall, the chapter verified the behavioral plausibility and internal consistency of the SDS model, establishing a robust foundation for subsequent evaluations of well-being and business opportunity.

Chapter 5: Developing Quality of Life (QOL) and Quality of Business (QOB) Evaluation Model Using an Integrated Accessibility Index

Chapter 5 developed an integrated evaluation framework for assessing Quality of Life (QOL) and Quality of Business (QOB) by extending the empirical and simulation results of Chapters 3 and 4. The chapter introduced an integrated evaluation method for air-front smart cities policy evaluation, encompassing rules and regulations, infrastructure, and digital transformation technologies, and explicitly accounting for heterogeneous stakeholders of businesses, such as residents, business partners, tourists, and consumers. The QOL and QOB models were constructed using integrated accessibility measures, enabling simultaneous evaluation of living and business environments and their linkages to economic performance. The framework was applied to diverse contexts, startups in Aichi, post-harvest agriculture in Baguio, and tourism in Phuket, each with comprehensive indicator sets tailored to local conditions. A scenario-based potential impact assessment method was also proposed to support ex-ante comparison of policy and investment alternatives. The results highlight that QOL and QOB are interdependent and jointly shaped by physical and digital accessibility, establishing a novel and comprehensive evaluation methodology for air-front smart cities.

Chapter 6: Application and policy evaluation

Chapter 6 applied the proposed QOL and QOB evaluation models to a policy-oriented case study of startup-driven air-front smart cities. Using preliminary interviews with 18 startups and a conjoint-based web survey with 35 valid responses, the chapter estimated stakeholder-specific indicator weights for evaluating living and business environments. The results showed that corporate tax rate exerts the strongest influence on startup location attractiveness, followed by economic growth, crime risk, and international conferences, while indicators such as high-class hotels, international flights, and digital services have comparatively smaller marginal effects. Baseline evaluation for Aichi revealed that both QOL and QOB are predominantly driven by rules and regulations, with infrastructure playing a secondary role and DX technologies contributing marginally. Scenario analysis demonstrated that substantial reductions in corporate tax rates generate the largest gains in startup QOB and business partner QOL, whereas infrastructure investments, such as high-speed rail expansion, produce more balanced improvements across stakeholders. Cross-city comparison indicated that Singapore achieves the highest startup competitiveness due to favorable taxation and support budgets, Munich's performance is constrained by high corporate taxes, and Aichi exhibits a more balanced trade-off between business competitiveness and resident well-being through regional connectivity. Overall, the results highlight that regulatory and fiscal policies primarily shape business environments, while accessibility, safety, and environmental-related policies simultaneously enhance both living and business conditions.

7.2. Future Research Prospects

While this thesis has advanced the methodological integration of real and virtual networks, social dynamics simulation, and QOL–QOB evaluation within the context of air-front smart cities, it also revealed several conceptual and methodological challenges that warrant further investigation. These challenges primarily relate to model validation, behavioral generalization, dynamic integration, and environmental sustainability. Addressing them would not only strengthen the robustness and transferability of the proposed methods but also expand their applicability to broader urban and regional contexts. Based on these considerations, five priority directions for future research are identified below.

1. Real-city calibration and validation of the SDS model

The most critical next step is to apply and calibrate the proposed SDS model to real-world cities. While the virtual city application verified internal consistency and behavioral plausibility, real city implementation would allow external validation against observed residential patterns, mobility demand, and social interaction structures. This extension is essential for testing model robustness, transferability, and practical applicability.

2. Integration of QOL and QOB into dynamic simulation

Future research should directly embed the QOL and QOB evaluation models within the SDS model to enable dynamic, time-evolving assessment of well-being and business performance. Such integration would allow feedback effects between accessibility, social interaction, residential choice, and economic outcomes to be explicitly modeled, enabling long-term forecasting rather than static scenario comparison.

3. Multi-activity and longitudinal behavioral modeling

This thesis focused primarily on shopping behavior and relied on cross-sectional survey data. Future work should extend the behavioral framework to multiple activity types, such as commuting, healthcare, education, and entertainment, and incorporate longitudinal data to capture temporal changes in digital substitution, land-use patterns, and social networks. This would significantly enhance the realism of behavioral representation in urban simulation.

4. Cross-country behavioral and parameter validation

Given that key parameters were estimated primarily from Japanese data, future studies should conduct original behavioral surveys and parameter estimation in diverse socio-economic and cultural contexts. Cross-country validation would improve generalizability, identify region-specific digital substitution mechanisms, and strengthen the global relevance of the air-front smart city evaluation framework.

5. Environmental sustainability and climate integration

Future research should explicitly integrate environmental performance into the framework by developing decarbonization and climate-resilience modules. This includes modeling CO_2 emissions associated with both physical mobility and digital infrastructure, as well as incorporating climate adaptation and disaster resilience indicators. Such integration would enable a comprehensive evaluation of air-front smart cities across social, economic, and environmental dimensions.

7.3. Concluding Remarks

This thesis established a comprehensive empirical and methodological framework for air-front smart city policy evaluation by integrating the physical and digital accessibility index into the QOL and QOB evaluation models. Additionally, the thesis integrated digital service substitutability and social networks in the SDS model to enhance the applicability of the SDS model for urban policy evaluation. Subsequently, by systematically linking behavioral evidence, model development, and applied evaluation, the thesis advances understanding of how digital services, mobility systems, and social interactions jointly shape urban structure and performance.

The results consistently demonstrate that sustainable air-front smart city or urban development depends on a balanced interaction between physical and digital systems, in which digital services primarily complement rather than replace physical accessibility. The findings highlight the importance of coordinated approaches that simultaneously consider digital transformation, human mobility, social interaction, and spatial organization. Such integration is essential for achieving resilient, inclusive, and environmentally sustainable urban environments, particularly in areas influenced by airport-related functions and global connectivity.

By providing an integrated modeling and evaluation framework, this thesis offers a transferable foundation for researchers and practitioners to assess urban living and business environments while accounting for regional characteristics and long-term dynamics. The future research directions outlined in this chapter indicate clear pathways for extending the framework toward real-city applications, dynamic forecasting, cross-country validation, and environmental integration. As digital technologies and mobility patterns continue to evolve, the approach developed in this thesis contributes a robust analytical basis for guiding air-front smart city development toward more sustainable, equitable, and human-centered outcomes.

References

Abraham, J.E.; Garry, G.R.; Hunt, J.D. The Sacramento PECAS model. In *Proceedings of the Transportation Research Board Annual Meeting*; Transportation Research Board: Washington, DC, USA, pp. 1–20, 2005.

Abu-Rayash, A.; Dincer, I. Analysis of mobility trends during the COVID-19 coronavirus pandemic: Exploring the impacts on global aviation and travel in selected cities. *Energy Research & Social Science*, Vol. 68, 101693, 2020.

Addie, J.D. Flying high (in the competitive sky): Conceptualizing the role of airports in global city-regions through “aero-regionalism”. Geoforum, Vol. 55, pp. 87–99, 2014.

Air-front smart city: A business-life regenerative innovation gateway hub as transformer of economic-system for the region towards 2050. e-ASIA Joint Research Program. Available online: https://www.the-easia.org/jrp/projects/project_95.html (accessed on 11 December 2025).

Alam, K.M.; Li, X.; Baig, S.; Ghanem, O.; Hanif, S. Causality between transportation infrastructure and economic development in Pakistan: An ARDL analysis. *Research in Transportation Economics*, Vol. 88, 100974, 2020.

Alfano, V.; Mariotti, I.; Marra, M.; Vecchione, G. I want to break free: The influence of the COVID-19 pandemic on work–life balance satisfaction. *Regional Studies, Regional Science*, Vol. 10, pp. 70–88, 2023.

Alfaro-Navarro, J.L.; López-Ruiz, V.R.; Huete-Alcocer, N.; Nevado-Peña, D. Quality of Life in the Urban Context, within the Paradigm of Digital Human Capital. *Cities*, Vol. 153, 105284, 2024.

Alhassan, M.D.; Adam, I.O. The effects of digital inclusion and ICT access on the quality of life: A global perspective. *Technology in Society*, Vol. 64, 101511, 2021.

Almahmoud, E.; Doloi, H.K. Assessment of social sustainability in construction projects using social network analysis. *Facilities*, Vol. 33, No. 3–4, pp. 152–176, 2015.

An, X.; Yang, Y.; Zhang, X.; Zeng, X. Smarter and cleaner? The carbon reduction effect of smart cities: A perspective on green technology progress. *Sustainability*, Vol. 16, 8048, 2024.

Ando, H.; Kurauchi, F. Evaluation of road network investment using a network topology method. *Journal of Japan Society of Civil Engineers*, Vol. 75, pp. I_445–I_454, 2020.

Ando, H.; Michael, B.; Kurauchi, F.; Wong, K.I.; Cheung, K.F. Connectivity evaluation of large road networks by capacity-weighted eigenvector centrality analysis. *Transportmetrica A: Transport Science*, Vol. 17, pp. 648–674, 2021.

Aroca, P.; Gonzalez, P.A.; Valdebenito, R. The heterogeneous level of life quality across Chilean regions. *Habitat International*, Vol. 68, pp. 84–98, 2017.

Baffour Gyau, E.; Li, Y.; Adu, D. Investigating the impact of ICT on transport-based CO_2 emissions: Empirical evidence from a quantile cointegration regression analysis. *Environmental Science and Pollution Research*, Vol. 31, pp. 4606–4629, 2024.

Basu, B.; Murphy, E.; Molter, A.; Sarkar Basu, A.; Sannigrahi, S.; Belmonte, M.; Pilla, F. Investigating changes in noise pollution due to the COVID-19 lockdown: The case of Dublin, Ireland. *Sustainable Cities and Society*, Vol. 65, 102597, 2021.

Bavelas, A. A mathematical model for group structures. *Applied Anthropology*, Vol. 7, pp. 16–30, 1949.

Beria, P.; Lunkar, V. Presence and mobility of the population during the first wave of the COVID-19 outbreak and lockdown in Italy. *Sustainable Cities and Society*, Vol. 65, 102616, 2021.

Bilotkach, V. Are airports engines of economic development? A dynamic panel data approach. *Urban Studies*, Vol. 52, pp. 1577–1593, 2015.

Birenbaum, M.; Nasser-Abu Alhija, F.; Shilton, H.; Kimron, H.; Rosanski, R. Perceived quality of life, well-being, and curiosity of older adults. *Societies*, Vol. 15, 224, 2025.

Brazier, J.; Roberts, J.; Deverill, M. The estimation of a preference-based measure of health from the SF-36. *Journal of Health Economics*, Vol. 21, pp. 271–292, 2002.

Bucsky, P. Modal share changes due to COVID-19: The case of Budapest. *Transportation Research Interdisciplinary Perspectives*, Vol. 8, 100141, 2020.

Cahill, D.; Ho, C.Y.C.; Yang, J.W. The COVID-19 pandemic: How important is face-to-face interaction for information dissemination? *Global Finance Journal*, Vol. 54, 100674, 2022.

Calder, J.D. Presidents and crime control: Kennedy, Johnson and Nixon and the influences of ideology. *Presidential Studies Quarterly*, Vol. 12, pp. 574–589, 1982.

Camarasa, C.; Heiberger, R.; Hennes, L.; Jakob, M.; Ostermeyer, Y.; Rosado, L. Key decision-makers and persuaders in the selection of energy-efficient technologies in EU residential buildings. *Buildings*, Vol. 10, 70, 2020.

Chang, S.; Smith, M.K. Residents' Quality of Life in Smart Cities: A Systematic Literature Review. *Land*, Vol. 12, 876, 2023.

Chatti, W. Moving towards environmental sustainability: Information and communication technology (ICT), freight transport, and CO_2 emissions. *Heliyon*, Vol. 7, e08190, 2021.

Chen, Z.; Gan, W.; Wu, J.; Lin, H.; Chen, C.M. Metaverse for smart cities: A survey. *Internet of Things and Cyber-Physical Systems*, Vol. 4, pp. 203–216, 2024.

Chengxiang, Z.; Chunfu, S.; Jian, G.; Chunjiao, D.; Hui, Z. Agent-based joint model of residential location choice and real estate price for land-use and transport modeling. *Computers, Environment and Urban Systems*, Vol. 57, pp. 93–105, 2016.

Cohen, B. The three generations of smart cities: Inside the development of the technology-driven city. *FastCompany CoExist*, Vol. 25, 2015.

Dai, Y.; Hasanefendic, S.; Bossink, B. A systematic literature review of the smart city transformation process: The role and interaction of stakeholders and technology. *Sustainable Cities and Society*, Vol. 101, 105112, 2024.

Daimon, H. Fundamental study on the influence of urban smartness on residential choice—Assuming the promotion of telework, internet shopping, and automated driving. *Journal of Urban Planning*, Vol. 57, pp. 98–105, 2022. (In Japanese)

Das, D. Urban quality of life: A case study of Guwahati. *Social Indicators Research*, Vol. 88, pp. 297–310, 2008.

De Vos, J. The effect of COVID-19 and subsequent social distancing on travel behavior. *Transportation Research Interdisciplinary Perspectives*, Vol. 5, 100121, 2020.

Diener, E.; Suh, E. Measuring quality of life: Economic, social, and subjective indicators. *Social Indicators Research*, Vol. 40, pp. 189–216, 1997.

Ejaz, W.; Anpalagan, A. Internet of Things for smart cities: Overview and key challenges. In *Internet of Things for Smart Cities*; SpringerBriefs in Electrical and Computer Engineering; Springer: Cham, Switzerland, pp. 1–15, 2019.

El-Fadel, M.; Shazbak, S.; Baaj, H.; Saliby, E. Parametric sensitivity analysis of noise impact of multi-highways in urban areas. *Environmental Impact Assessment Review*, Vol. 22, pp. 145–162, 2002.

Ettema, D.; de Jong, K.; Timmermans, H.; Bakema, A. PUMA: Multi-agent modelling of urban systems. In *Modelling Land-Use Change*; Koomen, E., Stillwell, J., Bakema, A., Scholten, H., Eds.; Springer: Berlin/Heidelberg, Germany, pp. 237–258, 2007.

EuroQol Group. EuroQol—A new facility for the measurement of health-related quality of life. *Health Policy*, Vol. 16, pp. 199–208, 1990

Feeny, D.; Furlong, W.; Boyle, M.; Torrance, G.W. Multi-attribute health status classification systems: Health utilities index. *Pharmacoeconomics*, Vol. 7, pp. 490–502, 1995.

Flak, L.S.; Hofmann, S. The impact of smart city initiatives on human rights. In EGOV-CeDEM-ePart, 2020.

Fritsch, M. New business formation and regional development: A survey and assessment of the evidence. *Foundations and Trends in Entrepreneurship*, Vol. 9, pp. 249–364, 2013.

Furtado, L.S.; Coelho da Silva, T.L.; Ferreira, M.G.F.; Fernandes de Macedo, J.A.; Cavalcanti Moreira, J.K.M.L. A framework for digital transformation towards smart governance: Using big data tools to target SDGs in Ceará, Brazil. *Journal of Urban Management*, Vol. 12, pp. 74–87, 2023.

Gautam, S. COVID-19: Air pollution remains low as people stay at home. *Air Quality, Atmosphere & Health*, Vol. 13, pp. 853–857, 2020.

Gomyo, M. Study of remote island networks by analogy with graph theory. *Journal of Japan Society of Civil Engineers B3*, Vol. 69, pp. I_604–I_609, 2013.

Gu, F.; Hayashi, Y.; Shi, F.; Zhang, H.; Kato, H. Measuring and mapping the spatial distribution of quality of life in a city: A case study in Nanjing. *International Journal of Urban Sciences*, Vol. 20, pp. 107–128, 2016.

Guancen, W.; Jing, L.; Dan, C.; Xing, N. Analysis on the housing price relationship network of large and medium-sized cities in China based on gravity model. *Sustainability*, Vol. 13, 4071, 2021.

Hämäläinen, M. A framework for a smart city design: Digital transformation in the Helsinki smart city. In Entrepreneurship and the Community; Ratten, V., Ed.; Springer: Cham, Switzerland, 2020.

Hamby, D.M. A review of techniques for parameter sensitivity analysis of environmental models. *Environmental Monitoring and Assessment*, Vol. 32, pp. 135–154, 1994.

Hartley, K. Public perceptions about smart cities: Governance and quality-of-life in Hong Kong. *Social Indicators Research*, Vol. 166, pp. 731–753, 2023.

Hayashi, Y. Introduction to the Quality of Life Accessibility Method. In Quality of Life Assessment in Urban Development and Transport Policymaking; Hayashi, Y., Ed.; Asian Development Bank: Tokyo, Japan; Part 1, pp. 1–5, 2023.

He, S.; Mei, L.; Wang, L. The dynamic influence of high-speed rail on the spatial structure of economic networks and the underlying mechanisms in northeastern

China. *ISPRS International Journal of Geo-Information*, Vol. 10, 776, 2021.

Hensher, D.A.; Beck, M.J.; Balbontin, C. What does the quantum of working from home do to the value of commuting time used in transport appraisal? *Transportation Research Part A: Policy and Practice*, Vol. 153, pp. 35–51, 2021.

Hsiaoping, Y. The effects of successful ICT-based smart city services: From citizens' perspectives. *Government Information Quarterly*, Vol. 34, pp. 556–565, 2017.

Hu, M.; Roberts, J.D.; Azevedo, G.P.; Milner, D. The role of built and social environmental factors in COVID-19 transmission: A look at America's capital city. *Sustainable Cities and Society*, Vol. 65, 102580, 2020.

Hui, Z.; Tingting, X. A key to urban economic growth or an unnecessary burden? Opening airports in small and medium-sized cities. *Cities*, Vol. 133, 104105, 2023.

Hunt, J.D.; Abraham, J.E. PECAS for spatial economic modelling: Theoretical formulation. Technical Memorandum 1 (Working Draft), 2009. Available online: https://www.hbaspecto.com/resources/PECASTheoreticalFormulation.pdf (accessed on 2 December 2021).

Hunt, J.D.; Donnelly, R.; Abraham, J.E.; Batten, C.; Freedman, J.; Hicks, J.; Costinett, P.J.; Upton, W.J. Design of a statewide land-use transport interaction model for Oregon. In Proceedings of the 9th World Conference on Transport Research; Seoul, 2001.

Jain, A.K. Data clustering: 50 years beyond K-means. *Pattern Recognition Letters*, Vol. 31, No. 8, pp. 651–666, 2010.

Jamali, M.; Abolhassani, H. Different aspects of social network analysis. In Proceedings of the IEEE/WIC/ACM International Conference on Web Intelligence (WI 2006); Hong Kong, China, 18–22 December 2006.

Janaina, M.; Rodrigo, M.C.; João, A.R.S.; Kelin, A.S. Smart city and quality of life: Citizens' perception in a Brazilian case study. *Journal of Cleaner Production*, Vol. 182, pp. 717–726, 2018.

Jiao, L.; Li, D.; Zhang, Y.; Zhu, Y.; Huo, X.; Wu, Y. Identification of the key influencing factors of urban rail transit station resilience against disasters caused by rainstorms. *Land*, Vol. 10, 1298, 2021.

John, J.; Amar Raj, D.; Karimi, M.; Nazari, R.; Yanamala, R.M.R.; Pallakonda, A. Artificial intelligence for smart cities: A comprehensive review across six pillars and global case studies. *Urban Science*, Vol. 9, 249, 2025.

Jonek-Kowalska, I.; Wolny, M. Age sustainability in smart cities: Seniors as urban stakeholders in the light of literature studies. *Sustainability*, Vol. 17, 6333, 2025.

Ke, M.; Baker, D.; Collis, C. Impact of airports on landside industrial development: A case study of Brisbane Airport. *Land*, Vol. 12, 1327, 2023.

Kenyon, S.; Rafferty, J.; Lyons, G. Social exclusion and transport in the UK: A role for virtual accessibility in the alleviation of mobility-related social exclusion? *Journal of Social Policy*, Vol. 32, pp. 317–338, 2003.

Kim, E.-J.; Lim, J.-Y.; Kim, G.-M.; Kim, S.-K. Nursing students' subjective happiness: A social network analysis. *International Journal of Environmental Research and Public Health*, Vol. 18, 11612, 2021.

Kim, S. Effects of perceived accessibility to living infrastructure on positive feelings among older adults. *Behavioral Sciences*, Vol. 14, 1025, 2024.

Kim, S.; Suh, E.; Jun, Y. Building a knowledge brokering system using social network analysis: A case study of the Korean financial industry. *Expert Systems with Applications*, Vol. 38, pp. 14633–14649, 2011.

Kivelä, M.; Arenas, A.; Barthelemy, M.; Gleeson, J.P.; Moreno, Y.; Porter, M.A. Multilayer networks. *Journal of Complex Networks*, Vol. 2, pp. 203–271, 2014.

Kruhlov, V.; Dvorak, J. Social inclusivity in smart city governance: Overcoming the digital divide. *Sustainability*, Vol. 17, 5735, 2025.

Kuse, H. Lifestyle changes caused by the new coronavirus and issues in urban logistics planning. *Journal of Logistics Research*, Vol. 69, pp. 20–23, 2020. (In Japanese)

Kuwano, M. Study on the comparison of social network characteristics by population size. *Journal of the City Planning Institute of Japan*, Vol. 49, pp. 999–1004, 2014.

Kuwano, M.; Fukuyama, K. An analysis of accessibility of life-related facilities considering social networks. *Journal of Japan Society of Civil Engineers D3*, Vol. 71, pp. 293–303, 2015.

Kuwano, M.; Fukuyama, K.; Inoue, W. Relationship between human ties and individuals' security feelings based on social network analysis. *Journal of Japan Society of Civil Engineers D3*, Vol. 72, pp. 415–422, 2016.

Larrinaga, F.; Pérez, A.; Aldalur, I.; Hernández, J.L.; Izkara, J.L.; Sáez de Viteri, P. A holistic and interoperable approach toward the implementation of services for the digital transformation of smart cities: The case of Vitoria-Gasteiz (Spain). *Sensors*, Vol. 21, 8061, 2021.

Le Quéré, C.; Jackson, R.B.; Jones, M.W.; Smith, A.J.P.; Abernethy, S.; Andrew, R.M.; De-Gol, A.J.; Willis, D.R.; Shan, Y.; Canadell, J.G.; Friedlingstein, P.; Creutzig, F.; Peters, G.P. Temporary reduction in daily global CO_2 emissions during the COVID-19 forced confinement. *Nature Climate Change*, Vol. 10, pp. 647–653, 2020.

Lenhart, T.; Eckhardt, K.; Fohrer, N.; Frede, H.-G. Comparison of two different approaches of sensitivity analysis. *Physics and Chemistry of the Earth, Parts A/B/C*, Vol. 27, pp. 645–654, 2002.

Lever, J.P. The development of an instrument to measure quality of life in Mexico City. *Social Indicators Research*, Vol. 50, pp. 187–208, 2000.

Li, B.; Yang, X.; Wu, X. Role of net-zero renewable-based transportation systems in smart cities toward enhancing cultural diversity: A realistic model using a digital twin. *Sustainable Energy Technologies and Assessments*, Vol. 65, 103715, 2024.

Lingli, L.; Li, D.; Zhou, S.; Huang, H.; Huang, G.; Yu, L. Unveiling age-friendliness in smart cities: A heterogeneity analysis based on the IAHP–CRITIC–IFCE approach. *Habitat International*, Vol. 151, 103153, 2024.

Loosemore, M. Social network analysis: Using a quantitative tool within an interpretative context to explore the management of construction crises. *Engineering, Construction and Architectural Management*, Vol. 5, pp. 315–326, 1998.

Lu, H.; Stratton, C.W.; Tang, Y.-W. Outbreak of pneumonia of unknown etiology in Wuhan, China: The mystery and the miracle. *Journal of Medical Virology*, Vol. 92, pp. 401–402, 2020.

Madakam, S.; Ramaswamy, R.; Date, H. Quality of life @ Palava smart city: A case study. *Glob. Bus. Rev.* 2019, *20*, 708–742.

Makieła, Z.J.; Stuss, M.M.; Mucha-Kuś, K.; Kinelski, G.; Budziński, M.; Michałek, J. Smart City 4.0: Sustainable urban development in the Metropolis GZM. *Sustainability*, Vol. 14, 3516, 2022.

Marchesani, F.; Masciarelli, F.; Bikfalvi, A. Smart city as a hub for talent and innovative companies: Exploring the (dis)advantages of digital technology implementation in cities. *Technological Forecasting and Social Change*, Vol. 193, 122636, 2023.

Martín, J.C.; Mendoza, C. A DEA approach to measure the quality of life in the municipalities of the Canary Islands. *Social Indicators Research*, Vol. 113, pp. 335–353, 2013.

Maskil-Leitan, R.; Gurevich, U.; Reychav, I. BIM management measure for an effective green building project. *Buildings*, Vol. 10, 147, 2020.

Masuda, N.; Konno, N. Complex Networks: From Fundamentals to Applications; Kindai Kagaku-sha: Tokyo, Japan, 2010.

Matous, P. Complementarity and substitution between physical and virtual travel for instrumental information sharing in remote rural regions: A social network approach. *Transportation Research Part A: Policy and Practice*, Vol. 99, pp. 61–79, 2017.

Matthew, R.A.; McDonald, B. Cities under siege: Urban planning and the threat of infectious disease. *Journal of the American Planning Association*, Vol. 72, pp. 109–117, 2006.

Mehmet, F.; Hakan, A.; Hakan, K.; Köksal, B. Determining open education-related social media usage trends in Turkey using a holistic social network analysis. *Educational Sciences: Theory and Practice*, Vol. 17, pp. 1361–1382, 2017.

Merchant, R.M.; Lurie, N. Social media and emergency preparedness in response to novel coronavirus. *JAMA*, Vol. 323, pp. 2011–2012, 2020.

Mittal, S.; Chadchan, J.; Mishra, S.K. Evaluation of quality of life in cities of diverse neighbourhood typologies: A scientific study of New Delhi. *International Journal of Urban Sustainable Development*, Vol. 13, pp. 400–419, 2021.

Moeckel, R.; Spiekermann, K.; Wegener, M. Creating a synthetic population. In Proceedings of the 8th International Conference on Computers in Urban Planning and Urban Management (CUPUM); Sendai, Japan, 27–29 May 2003.

Mora, H.; Gilart-Iglesias, V.; Pérez-del Hoyo, R.; Andújar-Montoya, M.D. A comprehensive system for monitoring urban accessibility in smart cities. *Sensors*, Vol. 17, 1834, 2017.

Mouratidis, K. Commute satisfaction, neighborhood satisfaction, and housing satisfaction as predictors of subjective well-being and indicators of urban livability. *Travel Behaviour and Society*, Vol. 21, pp. 265–278, 2020.

Muhammad, S.; Long, X.; Salman, M. COVID-19 pandemic and environmental pollution: A blessing in disguise? *Science of the Total Environment*, Vol. 728, 138820, 2020.

Murgaš, F.; Klobučník, M. Municipalities and regions as good places to live: Index of quality of life in the Czech Republic. *Applied Research in Quality of Life*, Vol. 11, pp. 553–570, 2016.

Mutahari, M.; Sugiki, N.; Kurauchi, F.; Matsuo, K. Parameter setting examination of social dynamic simulation using a multi-layer network. *Transportation Research Procedia*, Vol. 82, pp. 3960–3979, 2025c.

Mutahari, M.; Sugiki, N.; Mababangloob, G.R.; Concepcion II, R.; Maniquiz-Redillas, M.; Hayashi, Y.; Matsuo, K. A holistic evaluation framework for air-front smart cities: Integrating quality of life and quality of business via accessibility modeling. *Journal of the Eastern Asia Society for Transportation Studies*, 2025d. (accepted for publication)

Mutahari, M.; Sugiki, N.; Suzuki, D.; Hayashi, Y.; Matsuo, K. A computational framework for evaluating quality of life in sustainable urban environments: Integrating physical and digital service accessibility. *Sustainability*, Vol. 17, 9660, 2025b.

Mutahari, M.; Suzuki, D.; Sugiki, N.; Matsuo, K. Digital service substitution and social networks: Implications for sustainable urban development. *Sustainability*, Vol. 17, 5185, 2025a.

Nakaminami, T.; Nakayama, S.; Kobayashi, S.; Yamaguchi, H. Vulnerability assessment of emergency transportation road networks based on eigenvalue analysis. *Journal of Japan Society of Civil Engineers D3*, Vol. 74, pp. I_1141–I_1148, 2018.

Nakamura, K.; Fujita, M.; Kato, H.; Hayashi, Y. Evaluation for quality improvement of transport systems for Asian developing megacities. *Journal of Infrastructure Planning and Management*, Vol. 75, pp. 453–462, 2014.

Newman, M.E.J. Networks: An Introduction; Oxford University Press: Oxford, UK, 2010.

Nicola, M.; Alsafi, Z.; Sohrabi, C.; Kerwan, A.; Al-Jabir, A.; Iosifidis, C.; Agha, M.; Agha, R. The socio-economic implications of the coronavirus pandemic (COVID-19): A review. *International Journal of Surgery*, Vol. 78, pp. 185–193, 2020.

Noda, T.; Sugiki, N.; Mutahari, M.; Matsuo, K. Large-scale disaster evacuation choice behavior modelling under compound risk of natural disasters amid the COVID-19 pandemic in Japan. *Journal of the Eastern Asia Society for Transportation Studies*, Vol. 15, pp. 102–121, 2024.

Nussbaum, M.; Sen, A. The Quality of Life; Clarendon Press: Oxford, UK, 1993.

OECD. How's Life?: Measuring Well-Being; OECD Publishing: Paris, France, 2011.

Ohata, T.; Ujihara, T. A study on the actual condition of changes in the use of internet shopping during the COVID-19 epidemic. *Journal of Urban Planning*, Vol. 53, pp. 151–156, 2022. (In Japanese)

Oliveira, Á. de; Campolargo, M. From smart cities to human smart cities. In Proceedings of the 48th Hawaii International Conference on System Sciences; Kauai, HI, USA, pp. 2336–2344, 2015.

Omori, N. Changes in transportation behavior due to information and communication usage: Evidence from group interview surveys. *Journal of Civil Engineering Planning*, Vol. 27, CD-ROM, 2003. (In Japanese)

Osman, A.M.S.; Elragal, A.A.; Ståhlbröst, A. Data-driven decisions in smart cities: A digital transformation case study. *Applied Sciences*, Vol. 12, 1732, 2022.

Pacione, M. Urban environmental quality and human wellbeing: A social geographical perspective. *Landscape and Urban Planning*, Vol. 65, pp. 19–30, 2003.

Pandey, V.; Mohan, R.; Kumar, A.; Gangadevi, P.; Kurien, N. The impact of the COVID-19 outbreak on lifestyle-related behavior among the general population. *Cureus*, Vol. 15, e45756, 2023.

Politis, I.; Georgiadis, G.; Papadopoulos, E.; Fyrogenis, I.; Nikolaidou, A.; Kopsacheilis, A.; Sdoukopoulos, A.; Verani, E. COVID-19 lockdown measures and travel behavior: The case of Thessaloniki, Greece. *Transportation Research Interdisciplinary Perspectives*, Vol. 10, 100345, 2021.

Porta, S.; Crucitti, P.; Latora, V. Multiple centrality assessment in Parma: A network analysis of paths and open spaces. *Urban Design International*, Vol. 13, pp. 41–50, 2008.

Qing, Z.; Dan, M.; Xin, H. Digital transformation and firms' pollution emissions. *Technological Forecasting and Social Change*, Vol. 197, 122910, 2023.

Rashid, Z.; Melià-Seguí, J.; Pous, R.; Peig, E. Using augmented reality and the Internet of Things to improve accessibility for people with motor disabilities in smart cities. *Future Generation Computer Systems*, Vol. 76, pp. 248–261, 2017.

Rumpler, R.; Venkataraman, S.; Göransson, P. An observation of the impact of COVID-19 recommendation measures monitored through urban noise levels in central Stockholm, Sweden. *Sustainable Cities and Society*, Vol. 63, 102469, 2020.

Salvini, P.; Miller, E.J. ILUTE: An operational prototype of a comprehensive microsimulation model of urban systems. *Networks and Spatial Economics*, Vol. 5, pp. 217–234, 2005.

Segev-Jacubovski, O. Perceived Accessibility of Living Environment and Services Questionnaire: Validity and reliability. *OTJR: Occupation, Participation and Health*, Vol. 45, 15394492251322494, 2025.

Senaratne, S.; Rodrigo, M.N.N.; Jin, X.; Perera, S. Current trends and future directions in knowledge management in construction research using social network analysis. *Buildings*, Vol. 11, 599, 2021.

Shakibaei, S.; de Jong, G.C.; Alpkökin, P.; Rashidi, T.H. Impact of the COVID-19 pandemic on travel behavior in Istanbul: A panel data analysis. *Sustainable Cities and Society*, Vol. 65, 102619, 2021.

Shao, J.; Yang, H.; Xing, X.; Yang, L. E-commerce and traffic congestion: An economic and policy analysis. *Transportation Research Part B: Methodological*, Vol. 83, pp. 91–103, 2016.

Sharifi, A.; Beris, A.T.; Javidi, A.S.; Nouri, M.; Lonbar, A.G.; Ahmadi, M. Application of artificial intelligence in digital twin models for stormwater infrastructure systems in smart cities. *Advanced Engineering Informatics*, Vol. 61, 102485, 2024.

Sharifi, A.; Khavarian-Garmsir, A.R. The COVID-19 pandemic: Impacts on cities and major lessons for urban planning, design, and management. *Science of the Total Environment*, Vol. 749, 142391, 2020.

Sheng, H.; Zhang, Y.; Wang, W.; Shan, Z.; Fang, Y.; Lyu, W.; Xiong, Z. High-confidence evaluation for smart city services. *Frontiers in Environmental Science*, Vol. 10, 950055, 2022.

Siikavirta, H.; Punakivi, M.; Kärkkäinen, M.; Linnanen, L. Effects of e-commerce on greenhouse gas emissions: A case study of grocery home delivery in Finland. *Journal of Industrial Ecology*, Vol. 6, pp. 83–97, 2002.

Silva, P.L.; Du, Q.; Banister, D. Using virtual accessibility and physical accessibility as joint predictors of activity–travel behavior. *Transportation Research Part A: Policy and Practice*, Vol. 118, pp. 527–544, 2018.

Smart City Expo Poland. Generations of smart cities: 1.0, 2.0, 3.0 and 5.0. Available online: Smart City Expo Poland (accessed on 13 December 2025).

Soyata, T.; Habibzadeh, H.; Ekenna, C.; Nussbaum, B.; Lozano, J. Smart city in crisis: Technology and policy concerns. *Sustainable Cities and Society*, Vol. 50, 101566, 2019.

Strauch, D.; Moeckel, R.; Wegener, M.; Gräfe, J.; Mühlhans, H.; Rindsfüser, G.; Beckmann, K.J. Linking transport and land-use planning: The microscopic dynamic simulation model ILUMASS. In *Geodynamics*; CRC Press: Boca Raton, FL, USA, pp. 295–311, 2005.

Sugiki, N.; Nagao, S.; Kurauchi, F.; Mutahari, M.; Matsuo, K. Social dynamics simulation using a multi-layer network. *Sustainability*, Vol. 13, 13744, 2021.

Sun, C.; Zhai, Z. The efficacy of social distance and ventilation effectiveness in preventing COVID-19 transmission. *Sustainable Cities and Society*, Vol. 62, 102390, 2020.

Svitek, M.; Kozhevnikov, S. Smart City 5.0 as a digital ecosystem of smart services: Basic concept. In *Smart Cities and Digital Transformation: Empowering Communities, Limitless Innovation, Sustainable Development and the Next Generation*; Lytras, M.D.; Housawi, A.A.; Alsaywid, B.S., Eds.; 2023.

Syakur, M.A.; Khotimah, B.K.; Rochman, E.M.S.; Satoto, B.D. Integration of K-means clustering method and elbow method for identification of the best customer profile cluster. *IOP Conference Series: Materials Science and Engineering*, Vol. 336, 012017, 2018.

Takano, T.; Morita, H.; Nakamura, S.; Togawa, T.; Kachi, N.; Kato, H.; Hayashi, Y. Evaluating the quality of life for sustainable urban development. *Cities*, Vol. 142, 104561, 2023.

Tamura, S.; Namerikawa, S.; Murakami, K.; Yamanaka, H.; Sawada, T.; Hanaoka, F. A study on monitoring methods of participatory process networks using social network analysis. *Proceedings of Infrastructure Planning*, Vol. 32, pp. 158_1–158_4, 2005.

Tang, K.; Wang, H.J.; Wang, N. The relationship between the airport economy and regional development in China. *Emerging Markets Finance and Trade*, Vol. 58, No. 3, pp. 812–822, 2021.

Tang, Q.; Zhang, K.; Li, Y. The important role of social media during the COVID-19 epidemic. *Disaster Medicine and Public Health Preparedness*, Vol. 15, 4, 2021.

Tozzi, J.J. OIRA's formative years: The historical record of centralized review preceding OIRA's founding. 2011.

Tsugawa, S.; Ohsaki, H. Community structure and interaction locality in social networks. *Journal of Information Processing*, Vol. 23, pp. 402–410, 2015.

Uchida, K.; Kato, H.; Murakami, J.; Takeuchi, W. Does new airport investment promote urban economic development? Global evidence from nighttime light data. *Transportation Research Part A: Policy and Practice*, Vol. 180, 103948, 2024.

Uchida, M.; Shirayama, S. Analysis of network structure and model estimation for SNS. *Journal of Information Processing*, Vol. 47, pp. 2840–2849, 2006.

Ülengin, B.; Ülengin, F.; Güvenç, Ü. A multidimensional approach to urban quality of life: The case of Istanbul. *European Journal of Operational Research*, Vol. 130, pp. 361–374, 2001.

UNDP. *Human Development Report 1990*; United Nations Development Programme: New York, NY, USA, 1990.

UN-Habitat. *Measurement of City Prosperity: Methodology and Metadata*. 2016. Available online: UN-Habitat (accessed on 13 December 2025).

Vodak, J.; Šulyová, D.; Kubina, M. Advanced technologies and their use in smart city management. *Sustainability*, Vol. 13, No. 10, 5746, 2021.

Vojković, G.; Milenković, M. Legal relationship between smart airport and smart city. In *Proceedings of the 47th MIPRO ICT and Electronics Convention (MIPRO)*; Opatija, Croatia, pp. 1464–1468, 2024.

Waddell, P. UrbanSim: Modeling urban development for land use, transportation, and environmental planning. *Journal of the American Planning Association*, Vol. 68, pp. 297–314, 2002.

Wang, H.; Zhang, X.; Lu, W. Improving social sustainability in construction: A conceptual framework based on social network analysis. *Journal of Management in Engineering*, Vol. 34, 05018012, 2018.

Wang, J.; Hao, S. Analysis of the carbon reduction effect of smart city construction. *Procedia Computer Science*, Vol. 221, pp. 94–99, 2023.

Wang, P.; Chen, K.; Zhu, S.; Wang, P.; Zhang, H. Severe air pollution events not avoided by reduced anthropogenic activities during the COVID-19 outbreak. *Resources, Conservation and Recycling*, Vol. 158, 104814, 2020.

Wasserman, S.; Faust, K. *Social Network Analysis: Methods and Applications*; Cambridge University Press: Cambridge, UK, 1994.

Wegener, M. Integrated land-use transport modelling: Progress around the globe. In *Proceedings of the Fourth Oregon Symposium on Integrated Land-Use Transport Models*; Oregon, USA, 2005.
(duplicate entry removed and consolidated)

Wegener, M. Overview of land-use transport models. In *Proceedings of the Conference on Computers in Urban Planning and Urban Management (CUPUM)*; Sendai, Japan, 2003.

WHO Kobe Centre; World Health Organization. *The Urban Health Index: A Handbook for Its Calculation and Use*; World Health Organization: Geneva, Switzerland, 2014.

World Health Organization. *Constitution of the World Health Organization*. 1948.

World Health Organization. Statement on the second meeting of the International Health Regulations (2005) Emergency Committee regarding the outbreak of novel coronavirus (2019-nCoV). Available online: World Health Organization (accessed on 8 November 2025).

World Health Organization. *WHOQOL: Measuring Quality of Life*. 2012. Available online: World Health Organization (accessed on 13 December 2025).

Wu, D.; Xie, Y.; Lyu, S. Disentangling the complex impacts of urban digital transformation and environmental pollution: Evidence from smart city pilots in China. *Sustainable Cities and Society*, Vol. 88, 104266, 2023.

Xue-Ming, Y.; Joyce, M.W.; Low, L.C.T. Roles of the airport and logistics services on the economic outcomes of an air cargo supply chain. *International Journal of Production Economics*, Vol. 127, No. 2, pp. 215–225, 2010.

Yie, K.-Y.; Chien, T.-W.; Yeh, Y.-T.; Chou, W.; Su, S.-B. Using social network analysis to identify spatiotemporal spread patterns of COVID-19 worldwide: Online dashboard development. *International Journal of Environmental Research and Public Health*, Vol. 18, 2461, 2021.

Young, M.; Soza-Parra, J.; Circella, G. The increase in online shopping during COVID-19: Who is responsible, will it last, and what does it mean for cities? *Regional Science Policy and Practice*, Vol. 14, pp. 162–179, 2022.

Yuan, Y.; Can, W.; Wenling, L.; Peng, Z. Understanding the determinants of travel mode choice of residents and its carbon mitigation potential. *Energy Policy*, Vol. 115, pp. 486–493, 2018.

Zhan, D.; et al. Assessment and determinants of satisfaction with urban livability in China. *Cities*, Vol. 79, pp. 92–101, 2018.

Zhang, Y.; Peng, T.; Yuan, C.; Ping, Y. Assessment of carbon emissions at the logistics and transportation stage of prefabricated buildings. *Applied Sciences*, Vol. 13, 552, 2023.

Zhao, F.; Fashola, O.I.; Olarewaju, T.I.; Onwumere, I. Smart city research: A holistic and state-of-the-art literature review. *Cities*, Vol. 119, 103406, 2021.

Zhu, Q.; Ma, D.; He, X. Digital transformation and firms' pollution emissions. *Technological Forecasting and Social Change*, Vol. 197, 122910, 2023.

Publications

Peer-Reviewed Journal Papers

Mustafa Mutahari, Daiki Suzuki, Nao Sugiki, Kojiro Matsuo, Digital Service Substitution and Social Networks: Implications for Sustainable Urban Development, *Sustainability*, Vol. 17, No. 11, 5185, 2025.

Mustafa Mutahari, Nao Sugiki, Fumitaka Kurauchi, Kojiro Matsuo, Parameter Setting Examination of Social Dynamic Simulation Using a Multi-layer Network, *Transportation Research Procedia*, Vol. 82, pp.3960-3979, 2025.

Mustafa Mutahari, Nao Sugiki, Daiki Suzuki, Yoshitsugu Hayashi, Kojiro Matsuo, A Computational Framework for Evaluating Quality of Life in Sustainable Urban Environments: Integrating Physical and Digital Service Accessibility, *Sustainability*, Vol. 17, No. 21, 9660, 2025.

Mustafa Mutahari, Nao Sugiki, Giolo Rei Mababangloob, Ronnie Concepcion II, Marla Maniquiz-Redillas, Yoshitsugu Hayashi, Kojiro Matsuo, A Holistic Evaluation Framework for Air-Front Smart Cities: Integrating Quality of Life and Quality of Business via Accessibility Modeling, *Journal of the Eastern Asia Society for Transportation Studies*, 2025. [Accepted, November 2025]

International Conference Papers with Referees' Review

Mustafa Mutahari, Nao Sugiki, Yoshitsugu Hayashi, Tsuyoshi Takano, Hiroyoshi Morita, and Kojiro Matsuo, Developing Quality of Business (QOB) Evaluation Model for Air-front Smart Cities, the 14th International Symposium on City Planning and Environmental Management in Asian Countries (AURG) Proceedings, pp.605-612, 2025.

Mustafa Mutahari, Daiki Suzuki, Nao Sugiki, Kojiro Matsuo, Integrated Evaluation of Real and Virtual Networks, European Transport Conference (ETC), Antwerp, 2024.

Presentation at International Conference

Mustafa Mutahari, Nao Sugiki, Giolo Rei Mababangloob, Ronnie Concepcion II, Marla Maniquiz-Redillas, Yoshitsugu Hayashi, Kojiro Matsuo, QOL and QOB Accessibility-Based Evaluation Method for Air-front Smart Cities Application: Startup and Post-Harvest Agriculture Cases, 16th International Conference of Eastern Asia Society for Transportation Studies (EASTS) Conference, Surakarta, 2025.