Leveraging urban informatics on human mobility for enhancing geographies of health

博 士 学 位 論 文

Doctoral Dissertation

Leveraging urban informatics on human mobility

for enhancing geographies of health

（健康地理学研究の発展のための

人のモビリティに関する都市情報学の応用）

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Doctoral Dissertation

Leveraging urban informatics on human mobility for enhancing geographies of health

健康地理学研究の発展のための

人のモビリティに関する都市情報学の応用

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Abstract

Human mobility is an important theme while planning public health measures. In the case of infectious disease control, the scale of the outbreak can be mitigated by appropriately reducing the movement of people, while in chronic disease prevention, increased active mobilities of daily life such as walking and cycling can be effective in preventing obesity and non-communicable diseases. Therefore, suitable human mobility to prevent diseases, and promote people's health and well-being, should be considered an important area of public health.

Studies regarding the geographies of health, which analyze the causality between disease and geographical factors, have provided a wealth of research on the relationship among health, human mobility, and environmental factors. It has been pointed out by deductive mathematical modeling studies that local travel in daily life plays an important role in the spread of infectious diseases leading to epidemics. In addition, audit survey studies have found that perceptual environmental factors of pedestrians are related to the amount of walking. However, there have been spatial and temporal limitations, due to the maintenance area and update frequency of data used in previous studies, such as static GIS data, statistical survey-based data, and questionnaire survey-based data. Therefore, it has been difficult to observe local human mobility and micro-scale environmental elements that impact health based on actual data. In addition, most quantitative studies in this field have been limited to macro and static perspectives. The development of "urban informatics," which is a novel interdisciplinary field that attempts to undertake a

quantitative analysis of complex urban phenomena by using scientific tools such as big data, machine learning, and statistical methods, can be expected to promote the accurate observation of such local mobility and micro-environmental factors. However, technical challenges have prevented the widespread use of big data in geographies of health. The present thesis aimed to contribute to the development of geographies of health by providing the methods that enable the dynamic micro-observation of human mobility and its related contexts using urban informatics approaches.

First, to implement the quantitative observation of micro-scale environment factors related to human mobility, this thesis took a novel approach toward automatic neighborhood assessment by using the streetscape imagery platform. Although the pedestrian-friendly qualities of streetscapes promote walking, it is difficult to quantitatively evaluate them in a wide area, owing to the limitations of conventional field investigation and questionnaire surveys. This study attempted to build a statistical model for streetscape walkability (SW) evaluation based on quantified streetscape elements, by using Google Street View imagery with a semantic segmentation method. It was found that the predicted SW was related to active leisure walking by older females. This approach will contribute toward implementing a unified evaluation of the leisure-walking-friendly streetscape in a wide area.

Second, as a practice of a dynamic mobility observation, this thesis analyzed the changes in mobility during the COVID-19 pandemic in Japan. The effect of human mobility on the mitigation of the infection has been well documented; however, few studies have investigated the “place” where the relationship can be remarkably confirmed. By using mobile phone network data, this study examined the relationship between the changes in mobility in working, nightlife, and residential places and the number of infected people in the metropolitan areas of Japan (Tokyo, Osaka, and Nagoya). The results indicated that the mobility in nightlife places was especially related to the COVID-19 outbreak. The present approach will help observe the mobility associated with a high risk of infection and implement infection control at appropriate places in the future.

Third, this thesis attempted to examine the geographic and social contexts of the changes in mobility by combining mobile device-based data with social surveys. It has been pointed out in several studies that the amount of physical activity has declined throughout the world owing to the COVID-19 pandemic; however, the individual background of decreased physical inactivity during the pandemic in Japan has not been clearly understood. Based on online surveys and healthcare app data installed on smartphones, this study explored the relationships among physical inactivity—specifically decreased walking and increased sedentary behaviors—during the pandemic, individual geographic and socioeconomic background, changes in work situation, and the perception of anxiety related to infection. The results indicated decreased walking behavior in younger individuals and those living in high-density neighborhoods. In addition, increased sedentary behavior was recorded in the female population. Furthermore, while individuals with higher socioeconomic status (SES) were more likely to become inactive owing to work-from-home/standby-at-home protocols, individuals with lower SES tended to become inactive owing to the decreased amount of work. Decreased walking behavior and increased sedentary behavior were associated with a perception of high levels of anxiety related to the pandemic. The present approach can support the understanding of individual and geographical contexts behind changes in human mobility during emergencies and the implementation of optimal public health measures.

Although further research is needed to achieve more detailed mobility and environmental observations, the approaches proposed by the present thesis by applying urban informatics can enable the dynamical analysis of the relationship among health, human mobility, and environment and social contexts with multiple spatio-temporal scales. Furthermore, the approaches have the potential to contribute to the development of smart public health systems in the future by incorporated into a systematic health impact assessment. However, there are technical, data-related, and ethical challenges that need further discussion. To develop urban informatics approaches in the area of geographies of health, it would be necessary to establish an interdisciplinary research system and to validate big data using existing public statistical data or survey data. In addition, it is pertinent to further explore the social and geographical contexts behind the phenomenon for avoiding overgeneralization or over-abstraction of space. Lastly, an appropriate balance needs to be achieved between privacy protection versus the wider availability of data.

要旨

人々の移動は、感染症流行の要因となる一方で、歩行やサイクリングといった日常生活でのアクティブな移動が慢性疾患の予防に寄与するなど、公衆衛生対策にとって重要な要素である。そのため健康地理学の分野では、健康とモビリティおよびモビリティに関連する環境について継続的な研究がなされており、演繹的なモデル研究によって日常生活の中でのローカルな移動が感染症流行に重要な役割を果たしていることや、現地調査やアンケート調査に基づく研究によって歩行者の知覚に関連する要素が歩行量に影響を及ぼすことが指摘されてきた。しかし、静的な GIS データや統計調査、アンケート調査に基づくデータなど、先行研究で用いられてきたデータには、集計単位や集計頻度による制約があり、健康への関与が指摘されてきたローカルな流動や微細な環境要素を実際のデータから広範囲で観察することが困難であった。そのため、この分野における定量的な研究の多くはマクロで静的な視点に限られた。近年、情報技術の進展を受け、ビッグデータや機械学習によって都市の諸現象の定量的理解を試みる都市情報学（Urban informatics）と呼ばれる分野が発達し、分析可能な時空間スケールが拡大しつつある。これにより、ミクロスケールな環境や動的なモビリティ変化など、従来の健康地理学研究では広域での観察が困難であった要素の定量的な理解の促進が期待されるが、現時点では、技術的な課題からビッグデータの広範囲での活用には至っていない。本博士論文は、都市情報学的アプローチを健康地理学的テーマに応用し、ミクロかつ動的な分析手法を提供することで、健康地理学研究の発展に貢献することを目的とした。

本論文では、まず、人々のモビリティに関連するミクロな環境要素の定量的な観察を実現するために、街路景観画像プラットフォームを用いた新しい近隣環境評価手法を提案した。街路景観は、人々の歩行に関連する要素であり、適度な身体活動を日常生活の中で実施するために重要である。しかし従来、街路景観を評価するためには現地調査やアンケート調査が必要であり、広い範囲での評価が困難であった。本研究は、Google Street View とセマンティックセグメンテーション手法によって街路景観を定量化し、街路景観ウォーカビリティ（Streetscape Walkability: SW）を評価する統計モデルを構築した。構築したモデルによって評価された SW は、高齢女性の余暇歩行と有意に関連し、本研究のアプローチが、余暇歩行に適した街路景観を統一的な基準に基づいて広範囲にわたり評価する上で有用であることが示された。

次に、動的なモビリティ観察の実践として、新型コロナウイルス感染症（COVID-19）流行下のモビリティ変化と感染者数推移の関係を分析した。COVID-19 流行対策として、モビリティ削減の効果が多くの先行研究によって示されてきたが、どの場所でのモビリティが特に流行推移と関連するのかについては検証が不十分であった。本研究では、携帯電話の基地局ネットワークに基づく流動人口データを活用し、日本の三都市圏（東京、大阪、名古屋）における職場、夜の街、居住地でのモビリティ変化と感染者数推移の関係を分析

した。その結果、夜の街のモビリティは他の場所と比べて感染者数推移との関連が強いことが明らかになった。本研究のアプローチは、感染リスクが高い場所でのモビリティをモニタリングし、効率的な感染対策を実施する上で有用である。

さらに本論文では、人々のモビリティ変化の背後にあるミクロな地理的・社会的要素の観察も試みた。COVID-19 流行対策としてのモビリティ削減は、人々の身体活動の低下を引き起こしていることが指摘されている。しかし、日本における身体活動低下の地理的・社会的コンテキストの検証は乏しい。そこで本論文では、スマートフォンによって取得されたデータと社会調査の結果に基づき、COVID-19 流行下での歩行や座位行動の変化と、地理的・社会的属性、仕事の変化、流行に関連する不安の関係を検討した。その結果、若年層および高密度な地域に居住する人の歩数の減少および女性の座位行動の増加が明確に見て取れた。さらに、社会経済的に恵まれた人は、在宅ワークや自宅待機によって非アクティブになる一方で、社会経済的に貧しい人は仕事の減少によって非アクティブになる傾向が確認された。さらに歩数の減少や座位行動の増加と COVID-19 流行に関する強い不安感との間には有意な関係が存在した。本研究のアプローチは、緊急時におけるモビリティ変化の背後にある社会的・地理的要素を理解し、的確な公衆衛生対策を実施する上で有用である。

本論文が提示した都市情報学的アプローチの健康地理学研究への応用によって、健康とモビリティの関係や、その背後にある環境要素や社会的要素を様々な時空間スケールかつ動的に検証することが可能となることが示された。さらに、本論文のアプローチを体系的な健康影響評価手法へと発展させることで、スマートな公衆衛生対策への活用が期待できる。ただし、本研究をさらに発展させていくためには、学際的な研究体制の構築や、既存の統計調査データを用いたビッグデータの質の検証、現象や空間の過剰な一般化や抽象化を避けるための地理的背景のさらなる探索、データの利用可能性とプライバシー保護の適度なバランスの議論など、検討すべき課題が多く存在することを指摘した。

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List of Related Publications

The following chapters are based on published articles.

Chapter 2

Nagata, S., Nakaya, T., Hanibuchi, T., Amagasa, S., Kikuchi, H., & Inoue, S., 2020. Objective scoring of streetscape walkability related to leisure walking: statistical modeling approach with semantic segmentation of Google Street View images. *Health & Place* 66, 102428. https://doi.org/10.1016/j.healthplace.2020.102428

Chapter 3

Nagata, S., Nakaya, T., Adachi, Y., Inamori, T., Nakamura, K., Arima, D., Nishiura, H., 2021. Mobility change and COVID-19 in Japan: Mobile data analysis of locations of infection. *Journal of Epidemiology* 31, 387-391. https://doi.org/10.2188/jea.JE20200625

Chapter 4

Nagata, S., Adachi, H. M., Hanibuchi, T., Amagasa, S., Inoue, S., Nakaya, T., 2021. Relationships among changes in walking and sedentary behaviors, individual attributes, changes in work situation, and anxiety during the COVID-19 pandemic in Japan. *Preventive Medicine Reports* 24, 101640. https://doi.org/10.1016/j.pmedr.2021.101640

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1. Introduction

Health is not geographically equal. The spread of emerging infectious diseases is heterogeneous and erratic in space owing to transportation networks (Colizza et al., 2006), and the high mortality of residents is related to the increased poverty level of areas (Haan et al., 1987). Therefore, to protect and promote the health of the population, geographic approaches based on the theorization of the relationship among places, people, and health are important (Curtis et al., 2009). The history of the geographic approach to health dates back to the time of Hippocrates in 400 B.C. (Meade and Earickson, 2000), and its analytical approaches have continued to develop to the present day. In the 19th century, the disease mapping technique was developed to explore the cause of diseases (Barrett, 1998), and in the 20th century, the development of computer technology led to the formulation of geographic theories and methods related to health (Krieger, 2003; Mayer, 2009). The recent development of big data technology has provided new opportunities in many fields (Benjelloun et al., 2015). For a deeper understanding of the relationship among health, spatial location, and people, this study attempts to apply a novel information technology-backed approach to the study of geographies of health (also called “health geography”).

1.1 Rise of spatial big data era

The rapid growth of information technology in recent years has made it possible for researchers to access large data sets and observe phenomena with superior algorithms (Agarwal and Dhar, 2014). It has been pointed out that the current progress of science based on abundant digital data is the fourth paradigm, following empirical science, based on the description of natural phenomena, which has evolved for thousands of years; theoretical science, represented by Newtonian mechanics and Maxwell's equations, which has prevailed for hundreds of years; and computational science, based on the simulation of complex phenomena, which has been developed for decades (Hey et al., 2009; Miller and Goodchild, 2015).

Geographic information is also experiencing an exponential growth phase fueled by an increase in location data owing to location-aware and geosensing technologies, open geospatial data, development of smart cities, and the internet of things (IoT) technology (Miller, 2017a). In studies pertaining to social sciences and humanities where qualitative survey-based data or statistical survey-based data are usually employed (Kitchin, 2013), there are spatial and temporal limitations due to the location, time, and frequency of surveys. However, in the ongoing spatial big data era, it is expected that new geographic information obtained by ubiquitous and continuous mechanisms enables capturing spatial phenomena and conditions dynamically at an unprecedentedly detailed spatio-temporal scale (Kitchin, 2013; Miller and Goodchild, 2015).

1.2 Progress of quantitative analysis of urban systems

Amid the abundance of massive geographic information, there has been a growing movement called "urban informatics" or "urban science" to unravel and quantify the complex urban systems formed by the interaction between human activities and the urban environment using spatial big data during the last decade. Although the interpretation of the relationship between urban informatics and urban science varies (Kitchin, 2020), according to a description from Shi et al. (2021), urban informatics is an interdisciplinary approach to understanding, managing, and designing cities through systematic theories and methods based on new information technologies, and urban science is a component of urban informatics for understanding the relationships among human activities, places, and flows within cities. Namely, urban informatics aims for the application of computer technology to urban functions based on the quantitative analyses of urban science using big data, machine learning, and statistical analysis methods (Batty, 2021, 2013; Kitchin, 2020).

The attempt to quantitatively measure the relationships between human activities and space or place began with the "quantitative revolution," a movement toward positivistic geography in the 1950s and 1960s (Burton, 1963; Kitchin, 2006). The background of the movement was a backlash against traditional human geography studies based on the descriptive, regional, and environmentally deterministic approach, which ignored causality (Hubbard et al., 2002). The shift to positivism in human geography was supported by the development of computing technology, evolving into "spatial science," which built theories on spatial phenomena based on statistical approaches (Hubbard et al., 2002). Spatial science has contributed to the progress of spatial theories supporting present spatial and urban analyses, such as: mathematical modeling of classical location theories (Garner, 1967; Hamilton, 1967); development of the spatial interaction model, which generalized population movement, based on population size and distance (Fotheringham and O'Kelly, 1989); and development of the spatial autoregressive model, which integrates spatial dependency into a statistical model (Anselin, 1988). Furthermore, based on the criticism that spatial phenomena are not uniformly experienced and understood by all individuals, behavioral geography, which attempted to quantitatively understand the relationship between human perception and space by using the psychological approach and mental mapping technique, has been developed (Hubbard et al., 2002). In addition, the growth of geographic information system (GIS) technology in the 1980s with the so-called "GIS revolution" (Yano, 2000), enables geographers to visualize and analyze spatial data easily. With the development of the GIS, the disciplines associated with the urban space have expanded to include not only geography, but also public health (Cromley et al., 2011), sociology (Ballas et al., 2017), and computer science (Tao, 2013). Even now, geographic information science and urban informatics/science continue to develop in an interdisciplinary manner.

Despite the continued development of positivistic and quantitative geography, there are still many issues in the field. In particular, the spatial scientific approaches to modeling urban or regional systems have been criticized for lack of consideration for humanity (Miller, 2017b). Although behavioral geographers have attempted to ascertain the relationship between people's perception of space and behavior based on psychological concepts, they were criticized by humanistic geographers regarding their oversimplification of phenomena through scientific explanation, and by structuralists regarding their lack of consideration of the material context in which human action takes place owing to their over-consciousness of the minutiae of individuals' lives (Hubbard et al., 2002). In addition, there were limitations of data and technology in quantitative research at the time (Miller, 2017b). In other words, limited data made it difficult to quantitatively examine the interaction between people and the material context based on observations of individual-level behavior and the urban environment at high spatio-temporal resolution.

However, in the current situation, sensing the urban environment and human behavior with the help of big data will supplement the quantitative analysis of human perception or experience in minute physical and social contexts, enabling more realistic modeling of the interactions in an urban space. For instance, it is possible to analyze the kind of emotions people had in a specific place from geotagged social networking service (SNS) posts (Nguyen et al., 2016), to observe the streetscape elements, that pedestrians see, from images captured by vehicles (Zünd and Bettencourt, 2021), or to determine the detailed lifestyle and socioeconomic background of residents or visitors in the neighborhood from the massive credit card information or GPS data (di Clemente et al., 2018). As the above examples, progress of urban science can facilitate the observation of the micro-scale human behaviors and urban environments, which were excluded in the usual spatial scientific approach, and has the potential to address some of the criticisms of quantitative spatial analysis.

1.3 Application of spatial big data for understanding human mobility

Human mobility is one of the topics gathering attention in the urban informatics studies (Shi et al., 2021). Numerous issues such as greenhouse gas emissions, air pollution, and traffic congestion are caused by increased human mobility owing to growing urbanization throughout the world (Raubal et al., 2021). This has resulted in an increased need for the construction of an appropriate mobility system based on big data analysis. This section will provide an overview of the urban informatics approach to understanding human mobility.

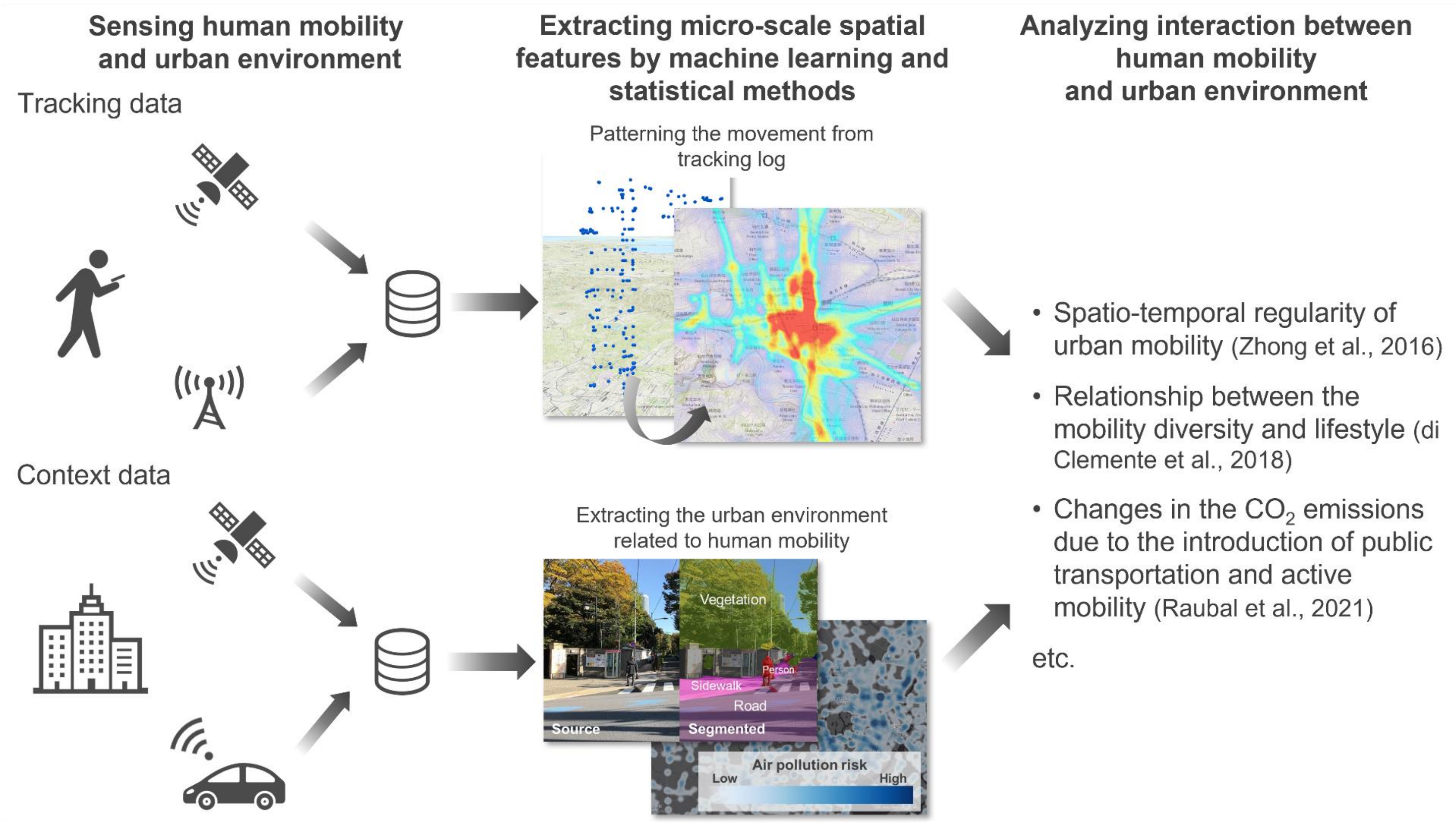


Fig. 1.1. Mobility analysis with big data

Fig. 1.1 shows a brief overview of mobility analysis by using spatial big data. Two types of data can be used to understand human mobility: tracking data representing human movement, and context data representing the environment related to human mobility (Raubal et al., 2021). Although traditionally, the collection of tracking data has required questionnaires or telephone surveys, recently, various data sources such as GPS (Zheng et al., 2008), Wi-Fi access points (Sapiezynski et al., 2015), smart cards for public transportation (Zhong et al., 2016), mobile phone networks (Deville et al., 2014), and credit card information (di Clemente et al., 2018) have been employed to observe human movement dynamically.

The context data was available from sources with coarse spatio-temporal resolution before the digitization of cities (Raubal et al., 2021), and the range of the coverage was also limited. However, it is now possible to quantitively and longitudinally observe the condition of urban infrastructures pedestrians see or the degree of air pollution people are exposed to while walking using high-resolution satellite imagery (e.g. USGS EarthExplorer published by the United States Geological Survey), 3D models of cities (e.g. PLATEAU published by Ministry of Land, Infrastructure, Transport and Tourism in Japan), Google Street View (GSV) images (Alipour and Harris, 2020), and sensors mounted on vehicles (Apte et al., 2017). In addition, expanding volunteered geographic information (VGI) communities has enabled access to basic context data related to human mobility such as road networks or points-of-interest (POI) throughout the world (Kloog et al., 2018; Smirnov and Kudinov, 2021). With the ongoing development of sensing technologies such as drones and IoT, tracking and context data will continue to expand.

Although spatial big data are essential for sensing human mobility, in general, most of the raw data are unstructured (Batty, 2021). Therefore, machine learning or statistical analysis techniques are an essential part of urban informatics along with big data. For example, a streetscape image by itself is just an array of pixel values; however, semantic segmentation, a deep learning technique, can identify the streetscape elements corresponding to each pixel (Zünd and Bettencourt, 2021). The GPS tracking data is also not significant if it only shows an individual's travel route on a given day; however, it is possible to capture the mobility pattern within cities by incorporating the tracking data with statistical methods such as cluster analysis (di Clemente et al., 2018). Therefore, tracking data, context data, and machine learning or statistical analysis techniques that extract "meaning" from these data are necessary to understand human mobility in cities via high spatial resolution.

Based on the spatial features extracted by the techniques described above, previous studies have observed people's movements at an unprecedentedly detailed spatio-temporal scale and provided meaningful insights into efficient public transport services and decarbonization efforts. For instance, the discovery of spatio-temporal regularity of urban mobility (Zhong et al., 2016), observation of purchasing pattern, mobility diversity, and social network diversity within cities by lifestyle (di Clemente et al., 2018), and the assessment of changes in CO_2 emissions due to the introduction of public transportation, car-sharing, and bike-sharing (Raubal et al., 2021) have been conducted.

1.4 Human mobility and health

The study of human mobility in urban informatics is to support the construction of efficient and sustainable mobility systems in cities (Raubal et al., 2021). In addition to reducing energy consumption, air pollution emissions, and social inequities, a sustainable mobility design requires improving people’s health (Banister, 2008; Zheng et al., 2011). However, research on mobility in urban informatics has usually focused on the examination of decarbonization (Nikitas et al., 2017; Raubal et al., 2021) and accessibility change (Papa and Ferreira, 2018) through the mobility shift. Although these studies are indirectly related to health, there is still a lack of research investigating the relationship between health and the complexity of urban structures and dynamics (Krefis et al., 2018).

Human mobility and health are closely related both positively and negatively. For example, expanding international mobility caused the outbreak of smallpox in the “New World” after 1492, the global spread of SARS in 2003, and the pandemic of A(H1N1)pdm09 in 2009 (Gatrell, 2016). Furthermore, as a measure against the ongoing novel coronavirus disease (COVID-19) pandemic, massive lockdowns were implemented in many countries to reduce the contact that causes the infection (Flaxman et al., 2020; Yang et al., 2021). Contrastingly, human mobility also has a beneficial effect on health. For example, increased physical activity related to active mobilities such as walking and cycling contributes to risk reduction of non-communicable diseases (NCDs) (Hu et al., 1999; Riiser et al., 2018; Usui et al., 1998; Williams and Thompson, 2013). Therefore, it is necessary to discuss the sustainable mobility and regions taking into account both the positive and negative impacts on health.

Studies in geographies of health and spatial epidemiology, which analyze the causality between disease and geographical factors, have continuously examined the relationship between human mobility and infectious diseases or physical activity. Prior to the early 1960s, the studies in geographies of health were dominated by disease mapping and disease ecology, both of which explained the background of disease occurrence at specific places and times (Mayer, 2009). However, beginning in the 1960s, quantitative methods and research on disease diffusion/spread have developed (Mayer, 2009). For instance, the Monte Carlo approach–based spatial diffusion model proposed by Hägerstrand has accelerated the analysis of the spatial spread of disease (Hägerstrand, 1965; Mayer, 2009), which was applied to a simulation study on the spread of influenza based on commuting flows (Sugiura, 1975). Furthermore, based on spatial interactions, the spatial extension of mathematical models for disease epidemics has made it possible to predict not only the diffusion process of infectious diseases, but also epidemic waves in multiple regions (Cliff and Haggett, 1993, 1986; Cliff et al., 1981). Nakaya (1994) explained the influenza epidemic in Japan by incorporating spatial interactions based on passenger flows between prefectures into the mathematical model. In recent years, the increased availability of data related to diseases has helped understand the link between the spread of infectious diseases and local movements of people, such as daily commuting flows and travel of children (Gog et al., 2014; Viboud et al., 2006).

In the 1990s, with the mainstream of geographical thought having shifted to issues of social theory, a shift from a biomedical model to a socio-ecological model that emphasizes understanding the social structure of health was demanded in this field (Kearns, 1993; Mayer, 2009; Nakaya, 2011). Since the shift, many studies in the field of geographies of health have focused on the constructed and experiential aspects of “place” rather than the geometric structure of space, and their interest has expanded beyond specific diseases to include aspects of social, physical, and mental well-being (Kearns and Collins, 2009). Regarding the human mobility study in this context, since active mobilities such as walking and cycling can contribute to the prevention of NCDs (Pucher et al., 2010; Shephard, 2008), many studies have evaluated neighborhood environments that promote them (Saelens and Handy, 2008; Winters et al., 2013), including demographic and socioeconomic aspects (Adkins et al., 2017; Jun and Hur, 2015). Both biomedical and socio-ecological studies in the geographies of health have contributed to public health measures by predicting the spatial spread of infectious disease epidemics and providing evaluation criteria of the environment for healthy neighborhood planning.

However, since previous studies have usually employed static data, such as air and rail line passenger counts, existing GIS data (land use, road networks, etc.), and demographic data to quantitatively observe mobilities and environmental contexts, there were spatio-temporal limitations due to data specification (Poorthuis, 2018), as seen in traditional positivistic geography. Therefore, although daily work commute and local travel play an important role in the spread of infectious disease epidemics, according to deductive mathematical modeling studies (Gog et al., 2014; Viboud et al., 2006) and that perceptual environmental factors of pedestrians are related to the amount of walking as found by audit survey studies (Cain et al., 2014), a robust quantitative analysis of such micro-scale mobility and environment based on actual data has been difficult to conduct. Incorporating spatial big data into geographies of health research will enable gaining new insights on the relationship between mobility and health.

1.5 Geographies of health and spatial big data: Application and challenges

Several types of spatial big data are recently being used in the field of geographies of health. One such type of data comes from streetscape imagery platforms such as GSV and Mapillary for micro-scale neighborhood environment evaluation (Rzotkiewicz et al., 2018). Many studies employ virtual assessment that auditors manipulate manually (Rzotkiewicz et al., 2018). By developing systematic observation tools, the efficient assessment of street environments has been enabled, thereby facilitating a comparison of the micro-scale environment in different locations (Bader et al., 2015; Mertens et al., 2017). Only a few studies have attempted an automatic assessment of the environment by using machine learning techniques (Lu, 2018; Villeneuve et al., 2018; Yin and Wang, 2016).

The use of dynamic geographic information has also increased in the observation of active mobility (Katapally et al., 2020). Many of these studies have employed the method requiring survey participants to use wearable devices with GPS and accelerometers (Katapally et al., 2020). They demonstrated that such methods enable the exclusion of recall bias in questionnaire surveys (Brown et al., 2014) and help extensively observe the changes in physical activities of participants during specific events (Cohen et al., 2016).

However, technical challenges in the observation of urban spaces and dynamics on a large scale continue to persist. While the virtual audit of streetscapes enables the efficient assessment of multiple cities by a unified criterion, it is still difficult to observe a large area because of a dependency on the manual method. In addition, automatic streetscapes evaluations based on machine learning methods recognize limited elements such as the sky (Yin and Wang, 2016) or greenness (Lu, 2018; Villeneuve et al., 2018). Complex cityscapes, as seen by pedestrians, are not captured comprehensively. Furthermore, in many studies based on tracking observations, the survey participants were recruited in specific regions and periods; therefore, it is still difficult to capture the human mobility dynamically over a wide range of space and time.

1.6 Objective

The issues pertaining to mobility and health in urban informatics and geographies of health are summarized as follows. First, in urban informatics, despite the development of sustainable human mobility, there is still a lack of research investigating the relationship among mobility, health outcomes, and environmental, social, and individual contexts. Second, in geographies of health, although ample knowledge on the interaction between human mobility and health has been accumulated, it is still difficult to observe the urban environment, human mobility, and health outcomes on a high spatial-temporal scale by using spatial big data owing to technical challenges.

The objective of this thesis is to reduce the spatio-temporal limitations in the observation of health-related human mobility and its environmental context by integrating approaches of urban informatics into the study in geographies of health (Fig. 1.2). Furthermore, to analyze health and well-being in social contexts, this thesis attempts to examine the geographical and social backgrounds of human mobility that are difficult to capture with big data alone. This thesis aims to contribute to the development of geographies of health and urban informatics by recommending the following three methods: extensive quantitative evaluation of micro-scale environmental factors related to mobility by using spatial big data; dynamic mobility observation for public health measures in emergencies using data obtained by ubiquitous and continuous systems; and exploring the social contexts of human mobility by combining information obtained from mobile phones and a social survey. In addition, at the end of the thesis, the benefits, possibilities, and challenges of applying urban informatics in geographies of health will be discussed. It is important to note that the geographic movement of people on a daily basis, and in the short term, will be considered as human mobility in this study. Therefore, long-term migration and social mobility that represents changes in social classes are not within the scope of this thesis.

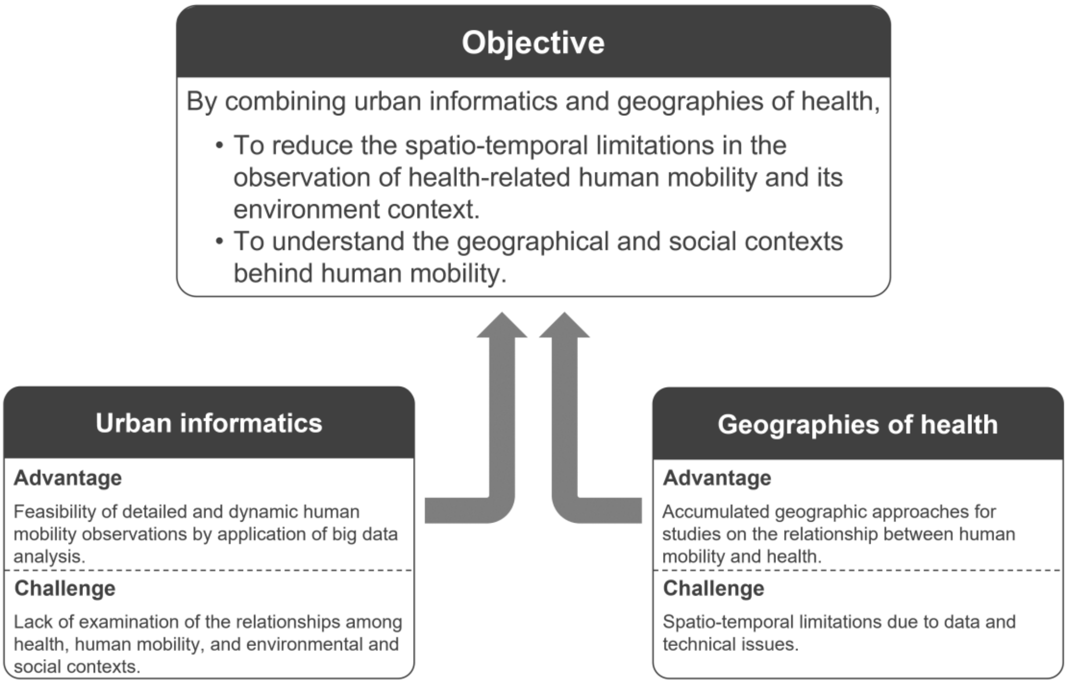


Fig. 1.2. Objective of this study

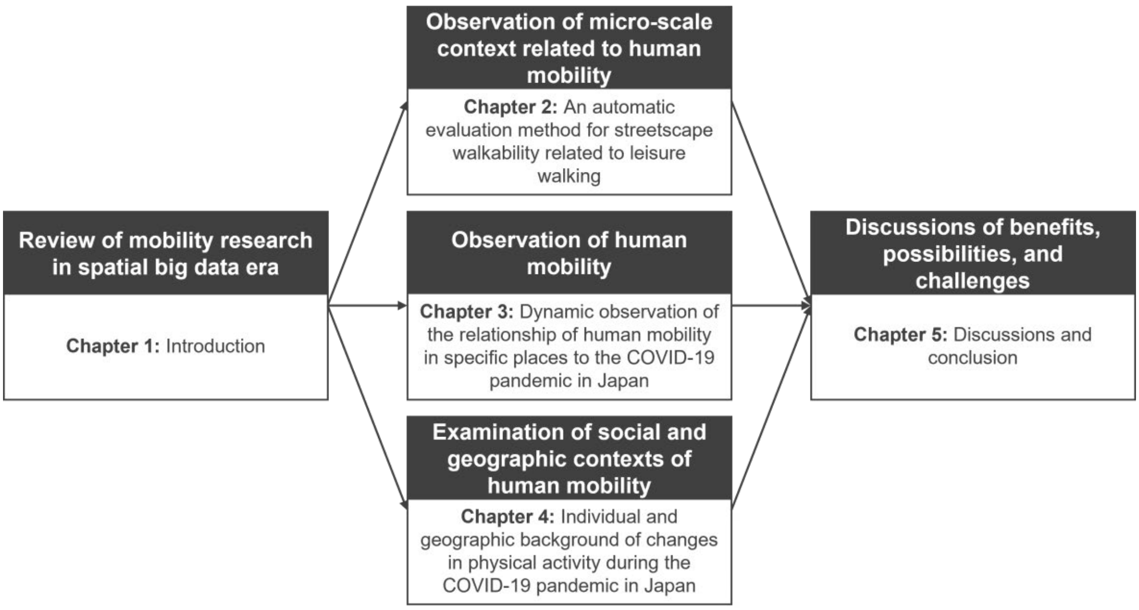


Fig. 1.3. Structure of this thesis

Fig. 1.3 shows the structure of the present thesis. Chapters 2, 3, and 4 will discuss studies that examined human mobility and the built environment, as well as the geographic and socioeconomic contexts related to mobility by using big data, deep learning, and statistical approaches. In Chapters 2 and 3, to implement precise and quantitative mobility evaluation methods for geographies of health, the observation of micro-scale physical context of the healthy mobility and dynamic human mobility at specific places related to the infectious disease spread using spatial big data was attempted.

Chapter 2 demonstrates the method for automatic neighborhood assessment by using the streetscape imagery platform. The frequency of physical activity is related to the neighborhood environment, and “walkability” has attracted attention as the environment promoting walking (Saelens and Handy, 2008). While macro-scale environments such as land use can be extensively assessed using existing GIS data, micro-scale walkability related to people's perceptions such as streetscapes has traditionally been observed through field surveys, making extensive assessment impractical from a cost perspective (Duncan et al., 2018). Chapter 2 explains the method for constructing a model for automatic and comprehensive evaluation of streetscapes facilitating older adults’ walking for leisure based on GSV images, the deep learning model, and the statistical approach.

Chapter 3 demonstrates the observation of dynamic mobility during the COVID-19 pandemic in Japan. The significant relationship between human mobility and the spread of the COVID-19 outbreak has been well documented (Kraemer et al., 2020). However, little attention has been given to the “place” where the relationship is remarkably confirmed. Chapter 3 examines the relationship between dynamic mobility in nightlife places, workplaces, and residential places observed by mobile phone networks and the number of infected people in the metropolitan area of Japan.

Furthermore, to capture the social contexts of the changes in activity related to health due to a specific event, Chapter 4 explores the relationship between social and geographic background and human mobility during the COVID-19 pandemic by combining mobile device-based data with social surveys. The amount of physical activity has declined throughout the world owing to the pandemic (Tison et al., 2020; Yamada et al., 2020). However, individual aspects related to decreased physical activity during the outbreak have not been clearly understood. Chapter 4 examines the relationship between physical inactivity during the pandemic, individual geographic and socioeconomic background, changes in work situation, and the perception of anxiety related to infection, based on an online survey and healthcare app data installed on smartphones.

Finally, Chapter 5 discusses the benefits, future possibilities, and challenges in geographies of health, based on the results discussed in Chapters 2, 3, and 4.

2. An automatic evaluation method for streetscape walkability related to leisure walking

The next three chapters, including the present one, are a series of research results on urban informatics approaches to the geographies of health. First, in the context of physical activity and environment—a topic of recent interest in the geographies of health—this chapter will demonstrate a novel method for assessing human mobility-related micro-scale neighborhood environments using streetscape imagery.

2.1 Introduction

Physical inactivity is a leading risk factor for non-communicable diseases, including coronary heart disease, type 2 diabetes, and breast and colon cancers (Lee et al., 2012; World Health Organization, 2017). Guthold et al. (2018) reported that 27.5% of the total population worldwide are insufficiently active. Walking is a physical activity that most can do relatively easily (Handy et al., 2002) and contributes to risk reduction of chronic disease, including cardiovascular disease (Hu et al., 2001), type 2 diabetes (Hu et al., 1999), and hypertension (Williams and Thompson, 2013). It has been found that the built environment of one's neighborhood, including distances to non-residential destinations, street connectivity, and the condition of pedestrian infrastructure, affects walking behavior (Christiansen et al., 2016; Saelens and Handy, 2008; Sugiyama et al., 2014). Therefore, understanding the construction of walkable or unwalkable places is crucial for urban planners and epidemiologists.

It has been well documented that macro-scale walkability, based on objective measurements of land use mix, street connectivity, and distance to facilities, is related to the choice of walking as a mode of transportation (Owen et al., 2007; Saelens and Handy, 2008) due to the abundance of data and the ready availability of GIS methods. Although it has been proven in many contexts that micro-scale walkability, as determined by pedestrian perception, including the attractiveness of streetscape and the condition of the sidewalks, is effective for promoting walking (Cain et al., 2014; Ewing et al., 2016; Kim et al., 2014), measuring these attributes with traditional methods (audits/systematic social observation) requires time and resources (Duncan et al., 2018). Thus, it is difficult to use traditional methods to assess micro-scale walkability over a large area.

In recent years, several studies have effectively used Google Street View (GSV) to evaluate micro-scale walkability, a method that achieves cost reduction, remote evaluation of neighborhoods over a wide range of global contexts, and automated assessment (Rzotkiewicz et al., 2018). Pliakas et al. (2017) demonstrated that GSV-based audits can provide significant reduction in time costs compared with foot-based audits while maintaining audit quality. In addition, Hanibuchi et al. (2019) developed a simple checklist for virtual audits of streetscape walkability (SW) and proved inter-source (between in-person and virtual audits) and inter-rater (between two trained auditors and between trained auditors and untrained crowd-sourced workers) reliability for GSV-based evaluation. From an urban informatics approach, several studies have extracted elements of streetscapes through assessment of images from GSV and similar services (e.g., Tencent Street View) using machine learning or deep learning methods for automatic observation (Lu, 2018; Villeneuve et al., 2018; Wang et al., 2019a; Yin et al., 2015; Yin and Wang, 2016). These studies analyzed the relationships among each component element to SW, physical activity, or walking behavior. For example, methods of detecting pedestrians from GSV images with deep learning showed acceptable accuracy for automated audits (Yin et al., 2015). In studies that examined the relationship between specific component elements of the streetscape extracted from GSV and SW or walking behavior, Yin and Wang (2016) ascertained a significant correlation between visual enclosure, determined by sky visibility, and WalkScore® or pedestrian volume. Further, Lu (2018) found that neighborhood greenness is significantly related to walking behavior. Cai et al. (2018) published an open-source library called "Treepedia" that allows calculation, using GSV images, of the amount of vegetation cover along a street, and Villeneuve et al. (2018) showed the relationship between promoting summer leisure physical activity and neighborhood greenness calculated by Treepedia.

However, several issues continue to have importance to fulfill automated assessment study based on streetscape images and machine/deep learning approach. Previous studies have proposed protocols, such as imageability, enclosure, human scale, transparency, and complexity, as quantitatively measurable aspects of urban design for walkability (Ewing et al., 2016, 2006; Ewing and Handy, 2009). For instance, "enclosure," measured by the proportion of street wall or sky, indicates an area's room-like quality that can make pedestrians feel comfortable and secure (Ewing, 1996). "Human scale" is evaluated by the proportion of buildings whose first floors have windows, the number of small planters, and other similar factors presenting the size, texture, and articulation of physical elements corresponding to the speed at which humans walk. Although multiple components of streetscapes influence walkability, the number of streetscape components found by automated methods and their relationship to walking behavior are still limited. Wang et al. (2019a) produced an automatic classification of cityscape images including multiple components such as trees and grasses into six types (wealthy, safe, lively, depressing, boring, and beautiful) based on human perception and clarified the relationship between each category of perception and types of associated physical activity. However, how these streetscape components, such as vegetation, affect walkability or walking behavior has not been sufficiently discussed. Moreover, although several studies have indicated that micro-scale walkability, such as sidewalk conditions and the streetscape aesthetics, affects physical activity for leisure (de Bourdeaudhuij et al., 2005; Inoue et al., 2010; Saelens and Handy, 2008; Witten et al., 2012), little attention has been paid to the relationship between SW, as determined from GSV images, and leisure walking.

Lately, a number of semantic segmentation methods and annotated datasets have been developed (Lateef and Ruichek, 2019), making it possible to recognize the multiple objects that a streetscape image contains. The combination of such resources and statistical approach will help us understand the relationship between objects in a streetscape and walking behavior in detail. In this study, the relationships among multiple streetscape components, micro-scale walkability, and older adults' leisure walking using semantic segmentation and a statistical approach to GSV images has been examined. A systematic review describes the positive relationship between a neighborhood's physical environment and older people's physical activity (Yen et al., 2010). Thus, management to ensure pedestrian-friendly neighborhoods is important to promote older people's well-being. The study consists of two phases: building a prediction model for the SW scores based on the evaluation of streetscapes by manual audits and the component elements of the streetscape, and analyzing the relationships between leisure walking by older people and neighborhood SW. In the first phase, we extract component elements of the streetscape from GSV images using a semantic image segmentation method of deep learning. The segmented components are used as independent variables in the prediction model for SW scores. In the second phase, we predict SW scores for each intersection in Bunkyo-ward in central Tokyo and analyze the relationship between the SW score and older people's walking for leisure. This study contributes to the evaluation of the effectiveness of the automated assessment of neighborhood environments by using quantitative methods to examine the relationship between older people's leisure walking and micro-scale walkability based on multiple components of the streetscape.

2.2 Methods

2.2.1 Data collection

SW score using manual audits

To build an SW score prediction model, the results of an SW evaluation by manual audits using GSV were used as the dependent variable. The evaluation was based on a checklist developed by Hanibuchi et al. (2019) and is related to SW as regards physical conditions, safety, and aesthetics. This checklist was developed to be simple and easy to use for practical purposes (i.e., reducing time cost and enabling many untrained auditors to participate over large study areas) and included only 14 items with dichotomous responses. The checklist was reported to have good inter-rater and inter-source reliability (Hanibuchi et al., 2019). The 14 items included the presence or absence of the following features: sidewalk, wide sidewalk, obstructions, steep slopes, street parking, heavy traffic, heavy foot traffic, crosswalk, traffic mirrors, streetlights, street trees, attractive streetscapes, graffiti and litter, and abandoned buildings. These were selected by considering frequency of use in existing audit tools, multiple aspects of micro-scale streetscape, and the Asian and Japanese urban context. Each item is evaluated with a binary value (Yes/No) and converted into a numerical point. In the conversion process, for items assumed pedestrian-friendly (i.e., presence of sidewalk, wide sidewalk, crosswalk, traffic mirrors, streetlights, street trees, and attractive streetscape), "Yes" is valued at 1 point, and "No" at 0. For items assumed to create a pedestrian-unfriendly environment (i.e., presence of obstructions, steep slopes, street parking, heavy traffic, heavy foot traffic, graffiti and litter, and abandoned buildings), "Yes" is valued at 0, and "No" at 1. The SW score at each assessed location is the sum of all items' points, and the maximum score is 14. Using the checklist, from August to October 2018, we assessed the streetscape in Bunkyo-ward, Tokyo, and the surrounding neighborhoods. After initial instruction with brief material provided by Hanibuchi et al. (2019) and repeated consultation, a trained auditor (a freelance research assistant) evaluated 2,842 street segments connected to 854 intersections using "walking through" target streets on GSV. These target intersections were randomly selected, and they amounted to 10% of all intersections in the study area. We calculated the means of the scores for the connecting streets with the intersection as the SW score assessed by the manual audit.

Walking time data

For the walking time source data, we used results of a questionnaire survey conducted to analyze the relationship between the neighborhood environment and the health of older people in three locations in Japan, including Bunkyo-ward. The details of the questionnaire are given in different publications (Amagasa et al., 2019; Inoue et al., 2011; Kikuchi et al., 2018). The questionnaire includes questions on weekly frequency of walking (days/week) and average walking duration each day (min/day) for the purposes of daily errands, leisure, commuting to work, working, etc. The walking measure's validity based on the questionnaire was ascertained by Spearman correlation coefficient between walking time and step counts per day assessed by an accelerometer ($R = 0.3$; $p < 0.001$) (Inoue et al., 2010). Participants were also asked about their lifestyles and health conditions such as living arrangements, physical limitations, and perception of neighborhood environments. In this study, we calculated participants' walking time for leisure from the frequency (days/week) and duration (min/day) of leisure walking. We defined participants as "active leisure walkers" if they walked more than 150 min/week for leisure, referring to a guideline by Nelson et al. (2007). Inoue et al. (2011) described the sampling methods they used in this survey. In 2010, the authors of this study used stratified random sampling, selecting a total of 900 residents in Bunkyo-ward from a residential registry to acquire the baseline data. In 2015, we conducted a follow-up survey of 373 respondents who had participated in the baseline survey in 2010 and agreed to enroll in the follow-up survey in 2015. Of these, 312 residents responded, and their data were used for this study (Table 2.1). We used information provided on age, educational attainment, living arrangements, working status, car driving, and physical limitations, in addition to weekly frequency of walking and average walking duration each day for leisure.

Before the survey in 2015, ethical approval for this study was obtained from the Tokyo Medical University Ethics Committee (No. 2898). Before completing the questionnaire, all participants signed an informed consent form.

Table 2.1. Participant characteristics by gender

		Overall n = 312	Male n = 164	Female n = 148
Walking for leisure				
≥150 min/week	n (%)	98 (31.4%)	61 (37.2%)	37 (25.0%)
<150 min/week	n (%)	214 (68.6%)	103 (62.8%)	111 (75.0%)
min/week	Mean/SD	127.3/188.8	150.2/208.2	101.9/161.7
Living arrangements				
With others	n (%)	252 (80.8%)	143 (87.2%)	109 (73.6%)
Alone	n (%)	59 (18.9%)	20 (12.2%)	39 (26.4%)
Missing	n (%)	1 (0.3%)	1 (0.6%)	0 (0.0%)
Working status				
Working with income	n (%)	111 (35.6%)	76 (46.3%)	35 (23.6%)
Not working	n (%)	201 (64.4%)	88 (53.7%)	113 (76.4%)
Educational attainment				
≥13 years	n (%)	175 (56.1%)	109 (66.5%)	66 (44.6%)
<13 years	n (%)	137 (43.9%)	55 (33.5%)	82 (55.4%)
Car driving				
Routine car driving	n (%)	64 (20.5%)	59 (36.0%)	5 (3.4%)
Not routine	n (%)	243 (77.9%)	101 (61.6%)	142 (95.9%)
Missing	n (%)	5 (1.6%)	4 (2.4%)	1 (0.7%)
Physical limitation				
Limited (somewhat, quite a lot, could not do physical activity)	n (%)	74 (23.7%)	30 (18.3%)	44 (29.7%)
Not limited (not at all, very little)	n (%)	232 (74.4%)	131 (79.9%)	101 (68.2%)
Missing	n (%)	6 (1.9%)	3 (1.8%)	3 (2.0%)
Age	Mean/SD	74.3/2.9	74.3/3.0	74.3/2.8

Streetscape images

This study estimated the SW score based on the streetscape images taken at intersections in Bukyo-ward. Because the SW score assessed by manual audit was summarized at intersections to which streets connect, the estimation of the SW score using GSV images at the intersection can simplify the calculation process. Furthermore, because the distance between intersections is short in the study area (mean distance =

45.6 m), it is possible to evaluate the SW there using GSV images from intersections. We requested GSV images for 5,321 intersections using Street View Static API (Google Inc.) and collected 17,276 images for 5,317 intersections. GSV images were taken from 2009 to 2019 and more than 90% after 2016. These intersections are at the same locations where SW evaluation was completed by manual audits or covered in 1,000 m network buffers from the residence of the participants in the follow-up survey. At each intersection, we obtained street images in each direction toward the intersections to which it connects. The procedure for obtaining the GSV images for each intersection was as follows: obtain latitude and longitude for the intersection; calculate the bearing (heading) from the intersection to the street; set API parameters, including location and the bearing; and download outdoor images. An example of this procedure and its result is shown for the Koishikawakorakuen-iriguchi intersection in Fig. 2.1. The latitude and longitude were set to 35.704824 and 139.747541, and the bearings in the A, B, and C directions were 3.23, 110.89, and 183.55, respectively. Images showing each street from the intersection were obtained as a response to the API request.

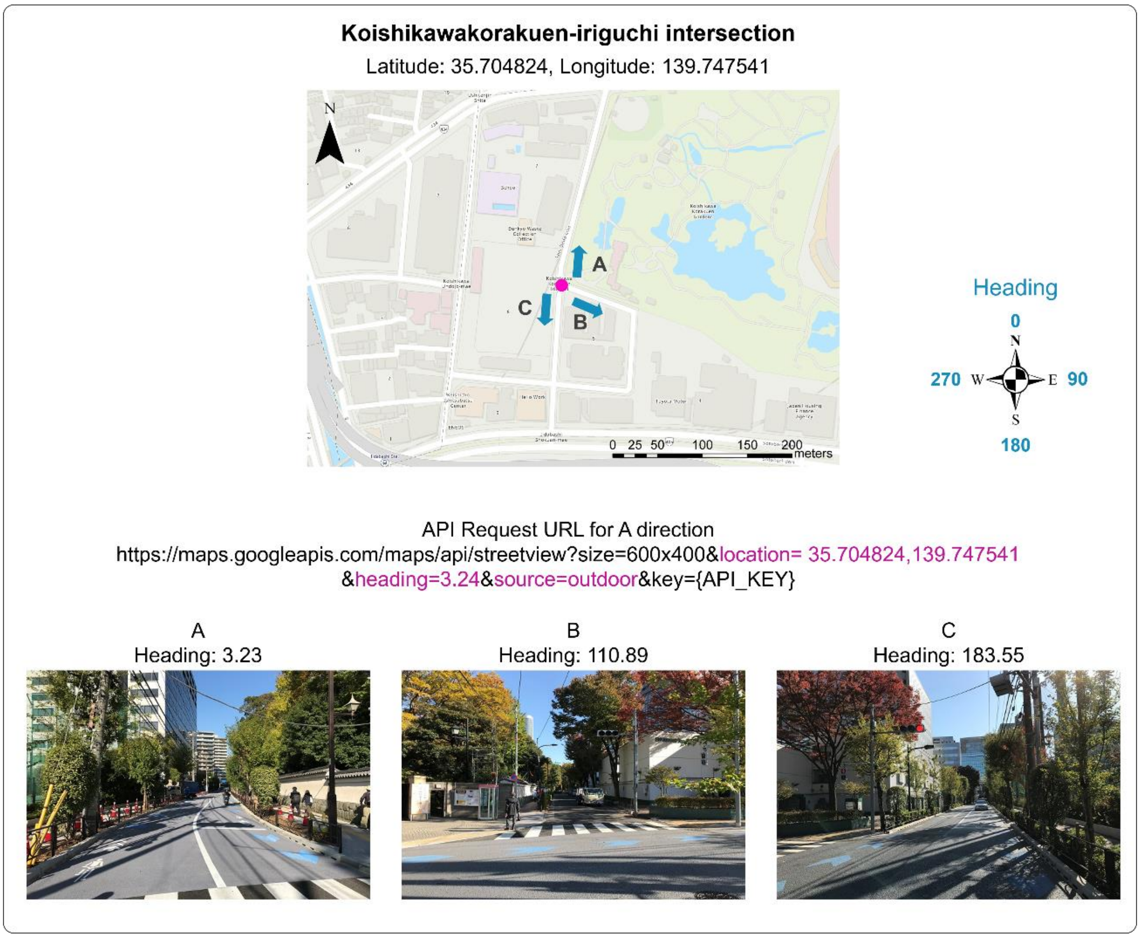


Fig. 2.1. Example of the API request to obtain GSV images

Sources: Map: Esri, HERE, Garmin, FAO, NOAA, USGS, © OpenStreetMap contributors, and the GIS User Community. Photo: Author’s photo

GIS data and software

In this study, published GIS data were used as data sources for road segments and geographic variables to construct the SW score prediction model and analyze the relationships between leisure walking and the SW. For the source of data on the network segments and the locations of the intersection, we used ArcGIS Geo Suite Douromo (road network) (Esri Japan Inc.). The digital elevation model (DEM) (Geospatial Information Authority of Japan) was used to obtain elevation data to calculate slope of the road segments and to build a prediction model for the SW score. Each intersection's slope value was calculated as follows: First, road segments connected from an intersection were split into links at every vertex; second, the elevation value of DEM was given to the vertices; third, the slope was calculated by the elevation value of the vertices and the length of the link between the vertices; fourth, the mean of the slope values was calculated for the road segment, weighted by the length of the links; and fifth, the steps above were repeated for every intersection. The National Land Numerical Information (Ministry of Land, Infrastructure, Transport and Tourism, Japan) and telephone directory data as of June 2017 (Eins Inc.) were used as destination data to calculate objective walkability to analyze the relationship between leisure walking and SW. Moreover, population density, based on the population census of 2015 (Statistics Bureau of Japan) was used for the objective walkability score as well. Objective walkability was defined as the sum of z scores for population density, intersection density, and variety of destinations, all calculated in 1,000 m network buffers from participants' residences, in accordance with a previous study (Kikuchi et al., 2018). We defined the variety of destinations as the sum of z scores for the number of destination facilities (station, post office, elementary school, community center, bank, bookstore, convenience store, restaurant, supermarket, department store, and sports and fitness club) in the 1,000 m network buffer. We used ArcGIS Pro 2.3.2 (Esri Inc.) to conduct all GIS processing.

2.2.2 Streetscape segment detection

To detect the component elements of each intersection's streetscape, we used DeepLab v3+ (Chen et al., 2018), a deep learning model developed for semantic image segmentation. DeepLab v3+ architecture characteristically adopts atrous convolution in encoder–decoder networks (Chen et al., 2018), which are used in semantic image segmentation models such as U-Net (Ronneberger et al., 2015) and SegNet (Badrinarayanan et al., 2017). Typically, pooling and convolution processes included in an encoder module reduce the resolution of feature maps and obtain high semantic information using filters based on an object's feature to be extracted; a decoder module gradually recovers spatial information lost during encoding processes (Chen et al., 2018). While retaining the feature map's resolution calculated by Deep Convolutional Neural Networks (DCNN), atrous convolution can capture multi-scale information by adjusting the filter's field-of-view (Chen et al., 2018). Fig. 2.2 shows the structure of the encoder–decoder networks in DeepLab v3+ (Chen et al., 2018). In the encoder module, Atrous Spatial Pyramid Pooling (ASPP) investigates the convolutional features at multi-scales using atrous convolution with different rates (A) and generates a feature map including abundant semantic information (B). In the decoder module, the feature map (B) is up-sampled four times by bilinear sampling and concatenated with low-level features from the network backbone to recover spatial information (C). The feature map before processing ASPP is reused as a low-level feature to improve spatial information's recovery accuracy. Finally, predicted segmentation results are exported after refinement by convolution processes and four times bilinear up-sampling (D).

In this study, we used DeepLab v3+ trained on streetscapes using Cityscapes Dataset (Cordts et al., 2016). The model is published at "Supervise.ly" (Deep System Inc.). The Cityscapes Dataset is an image dataset with annotation of streetscape segments. Annotation is defined as 30 classes based on groups recognized as streetscape components such as flat, human, vehicle, construction, object, nature, sky, and void. The dataset provides 19 classes for training (Table 2.2), while the other 11 classes are excluded from the dataset due to rare segments in streetscapes (Cordts et al., 2016). Regarding model validation, we calculated the agreement of segmentation recognition between the model and manual process using GSV images in the study area. We employed the kappa coefficient to validate the agreement of object recognition. We also used the intersection-over-union metric (IoU) to validate the agreement of the area recognition of the segments. The definition of the IoU is as follows:

$$IoU = \frac{TP}{TP+FP+FN},$$

where TP, FP, and FN are the number of true positive, false positive, and false negative pixels, respectively, of the segmented images. For kappa coefficient calculation, we randomly selected 100 images and added five random points to an image; two contributors classified the points into one streetscape segment based on Table 2.2. Regarding the IoU calculation, we selected 30 random images, and the model and two contributors ran segmentation for the images, respectively. The irr library, which is the R package, was used to calculate the kappa coefficient, and the mIoU plugin of the Supervise.ly was used to calculate the IoU.

Every pixel of all GSV images was classified into one of 19 segments by DeepLab v3+. We calculated the percentages of segments for each intersection.

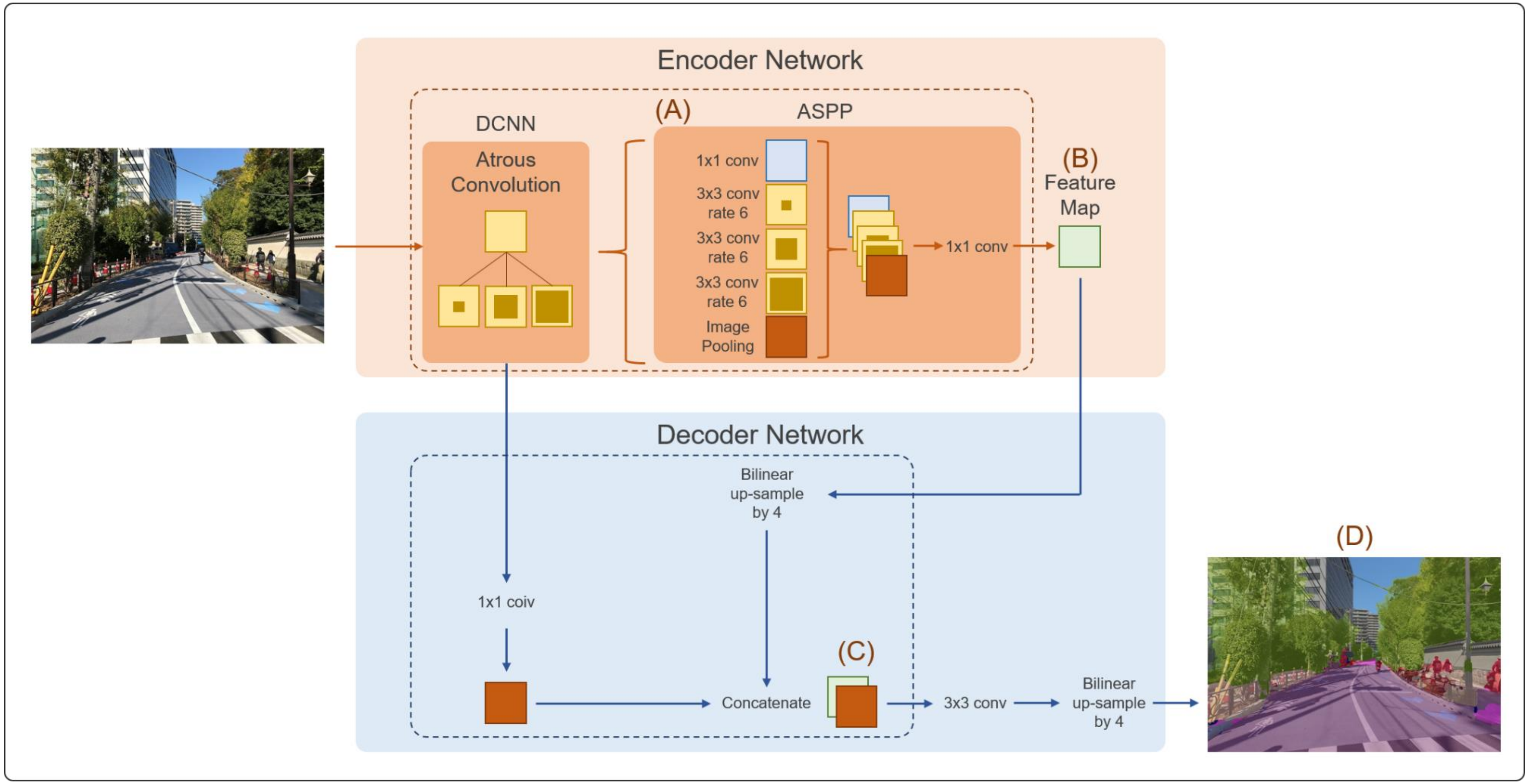


Fig. 2.2. Structure of encoder–decoder networks of DeepLab v3+ (Chen et al., 2018)

Table 2.2. Definition of segment classes provided by Cityscapes Dataset

Group	Class	Description
Flat	Road	Area where cars usually drive, e.g., lanes, directions, and streets. Areas only delimited by markings from the main road are also roads, e.g., bicycle lanes, roundabout lanes, or parking spaces. This label does not include curbs.
	Sidewalk	Area located at the side of a road and delimited from the road by some obstacle for pedestrians or cyclists, e.g., curbs or poles (perhaps small). This label includes a possibly delimiting curb, traffic islands (the walkable part), or pedestrian zones (where usually cars are not allowed during daytime).
Human	Person	A human walking, standing, or sitting on the ground, on a bench, or on a chair. This class includes toddlers and someone pushing a bicycle or standing next to it with both legs on the same side of the bicycle. This class also includes anything carried by the person, e.g., backpack, but not items touching the ground, e.g., trolleys.
	Rider	A human using some device to move, e.g., riders/drivers of bicycles, motorbikes, scooters, skateboards, horses, roller-blades, wheel-chairs, road cleaning cars, cars without a roof. Note that a visible driver of a car with a roof can be seen only through the window. Since holes are not labeled, the human is included in the car label.
Vehicle	Car	Automobile, jeep, SUV, van with continuous body shape, caravan, but no trailers.
	Truck	Truck, box truck, pickup truck, including their trailers. Back part / loading area is physically separated from the driving compartment.
	Bus	Bus for 9+ persons, public transport, or long distance transport.
	Train	Vehicle on rails, e.g., tram, train.
	Motorcycle	Motorbike, moped, scooter without a driver (a rider—see above).
	Bicycle	Bicycle without a driver (a rider—see above).
Construction	Building	Building, skyscraper, house, bus stop building, garage, car port.
	Wall	Individual standing wall. Not part of a building.
	Fence	Fence including any holes.

Object	Pole	Small, mainly vertically oriented pole or having a diameter (in pixels) of at most twice the diameter of the pole, e.g., sign pole, traffic light poles, streetlights.
	Traffic sign	A sign without a pole, showing information of the driver/cyclist/pedestrian in an everyday traffic scene, e.g., traffic signs, parking signs, direction signs. This label counts only the front side of a sign containing information. No ads/commercial signs.
	Traffic light	A traffic light box without its poles.
Nature	Vegetation	Tree, hedge, all kinds of vertical vegetation. Plants attached to buildings are usually not annotated separately and are labeled “building” as well. If growing at the side of a wall or building, it is marked as vegetation if it covers a substantial part of the surface (more than 20%).
	Terrain	Grass, all kinds of horizontal vegetation, soil, or sand. This label includes a possibly delimiting curb.
Sky	Sky	Open sky, without tree leaves. Includes thin electrical wires visible in skyscape.

Note: This table is retrieved from the website of Cityscapes Dataset. More detailed information is available at the website (https://www.cityscapes-dataset.com/).

2.2.3 Building the SW score prediction model

To build the model based on the linear relationship between SW and streetscape components, we used a regression analysis on all the SW scores from manual audits as a dependent variable and the percentage of streetscape segments detected by the deep learning model, slope, and road width as independent variables. All variables were calculated for each intersection. The road width was given in ranges (3–5.5, 5.5–13, and 13 m or more) for each road segment attribute. For the value of the road width, we chose the largest width values for the streets connected to the intersection. For the model selection, first, the stepwise method was applied to select the independent variables;

second, the genetic algorithm (GA) (Holland, 1992) was used to select the model with interaction effects based on the Akaike Information Criterion (AIC) to avoid overfitting; and lastly, the final model was calibrated as a spatial simultaneous autoregressive error (SAR) model (Anselin, 2003). In calibrating the final model, we adopted Gabriel graph neighbors (Matula and Sokal, 1980) to create the adjacency matrix between the intersections. All processes for the regression analysis were completed in R 3.6.1. The glmulti library was used for model selection including the stepwise and GA to select statistically meaningful variables and interaction effects, and the spdep library was used for spatial regression modeling.

2.2.4 Relationship between leisure walking and SW

To ascertain whether any relationship between leisure walking and neighborhood SW exists, we estimated the odds ratios (ORs) and 95% confidence intervals (CIs) of the neighborhood SW using the logistic regression analysis. The dependent variable was defined as "1" if the participant was an active leisure walker or as "0" otherwise. The neighborhood SW was used as the independent variable. As control variables, age, physical limitation, educational attainment, living arrangements, working status, routine car driving, and objective walkability were selected by referring to previous studies (Amagasa et al., 2019; Inoue et al., 2011; Kikuchi et al., 2018). Because several studies have shown that physical activity data features different trends depending on the walker's gender (Amagasa et al., 2017; Caspersen et al., 2000), regression models were estimated for each gender. In calculating the neighborhood SW, first, the SW scores for all intersections within 1,000 m network buffers from the participant residence were predicted with the SW score prediction model; next, we calculated the median values for the predicted SW score in 500 or 1,000 m as values for neighborhood SW in 500 m or 1,000 m. Adjusted p-values were calculated by Bonferroni adjustment (Bland and Altman, 1995) to control Type I Error because we compared the four models (two gender groups × two neighborhood definitions of the SW in 500 m and 1000 m).

2.3 Results

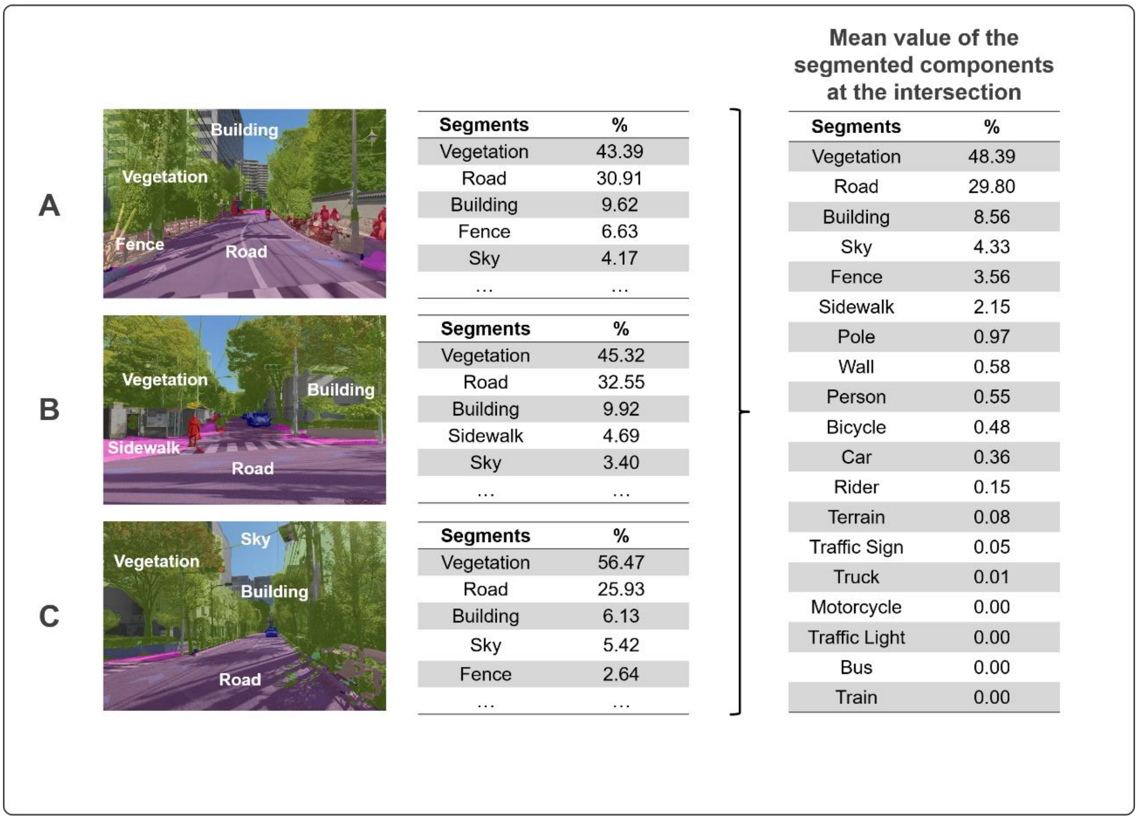
2.3.1 Streetscape segment detection

The deep learning model was applied to all images (n = 17,276), and all of the 19 segments were detected (Table 2.3). The kappa coefficient was 0.76 (agreement = 82%, $p < 0.001$), and IoU was 70%. Then, the percentage of the segments in the GSV images was calculated. Fig. 2.3 shows the results of segmentation at the same intersection as Fig. 2.1. For instance, in the B direction, the largest segment shows vegetation (45.32%), the second is the road segment (32.55%), and the third is the building segment (9.92%). Likewise, for the mean value of the segments at the intersection, the largest segment consists of vegetation (48.39%) (Fig. 2.3). By comparison with the mean values for the segments in all images (Table 2.3), the streetscape at the intersection shows abundant vegetation. We excluded 1,313 unsuitable images from the streetscape evaluation due to massive inclusion of the platform of a subway station, the exterior of a house, or other unsuitable items. The criterion for this exclusion was road segment less than 5%. After this, the mean values for the proportion per segment were calculated at 5,293 intersections.

Table 2.3. Detected segments from all obtained GSV images

Segments	%	Segments	%
Building	45.00	Person	0.74
Road	23.49	Bicycle	0.50
Vegetation	9.94	Traffic sign	0.34
Sky	6.65	Terrain	0.24
Fence	3.02	Train	0.10
Wall	2.83	Bus	0.03
Sidewalk	2.29	Motorcycle	0.03
Car	2.26	Rider	0.03
Truck	1.26	Traffic light	0.01
Pole	1.24		

Note: Kappa coefficient was 0.76 (agreement = 82%, p < 0.001), and IoU was 70%.



Segments	%
Vegetation	43.39
Road	30.91
Building	9.62
Fence	6.63
Sky	4.17
…	…

Segments	%
Vegetation	45.32
Road	32.55
Building	9.92
Sidewalk	4.69
Sky	3.40
…	…

Segments	%
Vegetation	56.47
Road	25.93
Building	6.13
Sky	5.42
Fence	2.64
…	…

Segments	%
Vegetation	48.39
Road	29.80
Building	8.56
Sky	4.33
Fence	3.56
Sidewalk	2.15
Pole	0.97
Wall	0.58
Person	0.55
Bicycle	0.48
Car	0.36
Rider	0.15
Terrain	0.08
Traffic Sign	0.05
Truck	0.01
Motorcycle	0.00
Traffic Light	0.00
Bus	0.00
Train	0.00

Fig. 2.3. Examples of semantic segmentation results

Sources: Author’s photo and Supervise.ly.

2.3.2 Building a prediction model for SW score

Table 2.4 shows the optimal combination of independent variables, including interaction effects, based on stepwise GA–SAR modeling, and we used this as the prediction model for the SW score ($R^2 = 0.51$; MAE = 0.66). Fig. 2.4 shows the spatial distribution of SW scores predicted by the model and the streetscape images with high or low scores. In the study area, the SW score tends to be higher in the southeast. In addition, the high SW sites are distributed in a linear form, while the low SW sites tend to be spatially clustered. Regarding the streetscape features, locations with high SW scores are well-designed and well-maintained streetscapes, and include sophisticated road facilities, such as wide sidewalks or trees lining the street. By contrast, locations with low SW scores consist of pedestrian-unfriendly streetscape components, such as narrow and dark streets, no sidewalks, or steep slopes.

From the model results (Table 2.4), nine types of segments (road, building, sky, terrain, pole, sidewalk, vegetation, traffic light, and rider), including their interaction effects, are associated with SW scores. For a streetscape segment with a positive coefficient, the estimated SW score increases when the percentage of the segment in the GSV image increases. For instance, since a building segment has a positive coefficient ($\beta = 0.047$; 95% CI = 0.022 to 0.071), the existence of the building segment increases the SW. When the building segment occupies 30% of pixels in the GSV images taken at an intersection, the building segment causes an increase in the SW score at the intersection by 1.41 points (30×0.047). In contrast, a streetscape segment with a negative coefficient decreases the estimated SW score. For instance, since a sky segment has a negative coefficient ($\beta = -0.153$; 95% CI = −0.209 to −0.096), the existence of the sky segment relates to a decreased SW. When the sky segment occupies 30% of pixels in the GSV images, the sky segment causes a decreased SW score at the intersection by 4.59 points (30 × −0.153).

The member, as the combination of two streetscape segments shown in Table 2.4, is the interaction effect when these segments in the combination appear in the GSV image. The interaction effect between a road segment and a terrain segment is positively associated with SW (β = 0.006; 95% CI = 0.002 to 0.011). When the road segment occupies 30% of pixels and the terrain segment occupies 5% of pixels of GSV images, the interaction of the two segments increases the SW score at the intersection by 2.85 points (30 × 5 × 0.019). The interaction effect between the road segment and the building segment is negatively associated with SW (β = −0.003; 95% CI = −0.004 to −0.002).

Regarding the variable other than streetscape segments, slope is marginally associated with a decrease in SW score (β = −0.239; 95% CI = −0.478 to 0.000). When the mean value of the slope of the street connected from an intersection is 5%, the SW score decreases by 1.195 points (5 × −0.239). The interaction effects between a building and road width 5.5–13 m or a building and road width 3–5.5 m relate to a decrease in SW score (β = −0.033; 95% CI = −0.045 to −0.021, and β = −0.030; 95% CI = −0.043 to −0.017). When the building segment occupies 30% of pixels of the GSV images taken at an intersection with the road width of 5.5–13 m, the interaction effect of the two variables decreases the SW score at the intersection by 0.99 points (30 × 1 × −0.033). In case of the road width of 3–5.5 m, the SW score decreases by 0.9 points (30 × 1 × −0.03). While the building segment positively relates to the SW, the influence of the building segment on the SW will be small on a narrow street.

Table 2.4. Summary of the SW score prediction model

	β	95% CI	p	
(Intercept)	8.297	7.211 to 9.382	< 0.001	***
Road : Building	−0.003	−0.004 to −0.002	<0.001	***
Road	0.147	0.098 to 0.195	<0.001	***
Building : Road Width 5.5–13 m	−0.033	−0.045 to −0.021	<0.001	***
Sky	−0.153	−0.209 to −0.096	<0.001	***
Road : Vegetation	−0.002	−0.002 to −0.001	<0.001	***
Building : Road Width 3–5.5 m	−0.030	−0.043 to −0.017	<0.001	***
Slope : Traffic light	3.740	2.147 to 5.333	<0.001	***
Terrain : Rider	−1.712	−2.580 to −0.845	<0.001	***
Building	0.047	0.022 to 0.071	<0.001	***
Road : Road Width 5.5–13 m	0.029	0.013 to 0.046	<0.001	***
Pole	−0.864	−1.368 to −0.360	<0.001	***
Pole : Vegetation	0.013	0.005 to 0.022	0.002	**
Slope : Rider	0.584	0.172 to 0.995	0.005	**
Building : Pole	0.011	0.003 to 0.018	0.006	**
Pole : Sky	0.022	0.006 to 0.038	0.008	**
Road : Sidewalk	0.006	0.002 to 0.011	0.008	**
Building : Sky	0.002	0.000 to 0.003	0.008	**
Road : Terrain	0.019	0.002 to 0.035	0.026	*
Road : Rider	−0.061	−0.116 to −0.006	0.029	*
Building : Slope	0.003	0.000 to 0.006	0.039	*
Pole : Rider	0.815	0.032 to 1.597	0.041	*
Sidewalk : Terrain	0.059	0.002 to 0.116	0.043	*
Slope	−0.239	−0.478 to 0.000	0.050	.
Terrain	−0.459	−0.928 to 0.01	0.055	.
Sidewalk : Rider	0.297	−0.033 to 0.627	0.078	.
Sky : Slope	0.009	−0.001 to 0.020	0.091	.
Road : Slope	−0.005	−0.012 to 0.001	0.121	
Pole : Slope	0.026	−0.008 to 0.060	0.128	
Sidewalk	−0.092	−0.220 to 0.035	0.157	
Sidewalk : Road Width 5.5–13 m	0.045	−0.038 to 0.128	0.286	
Sidewalk : Road Width 3–5.5 m	−0.037	−0.123 to 0.049	0.404	
Road : Road Width 3–5.5 m	0.003	−0.017 to 0.024	0.753	
R^2	0.51			
MAE	0.66			
AIC	2198			
Λ	0.14	LR test value: 8.381, p value: 0.004		

Note: CI: confidence interval; MAE: Mean Absolute Error; AIC: Akaike Information Criterion; and λ: Simultaneous autoregressive error coefficient.

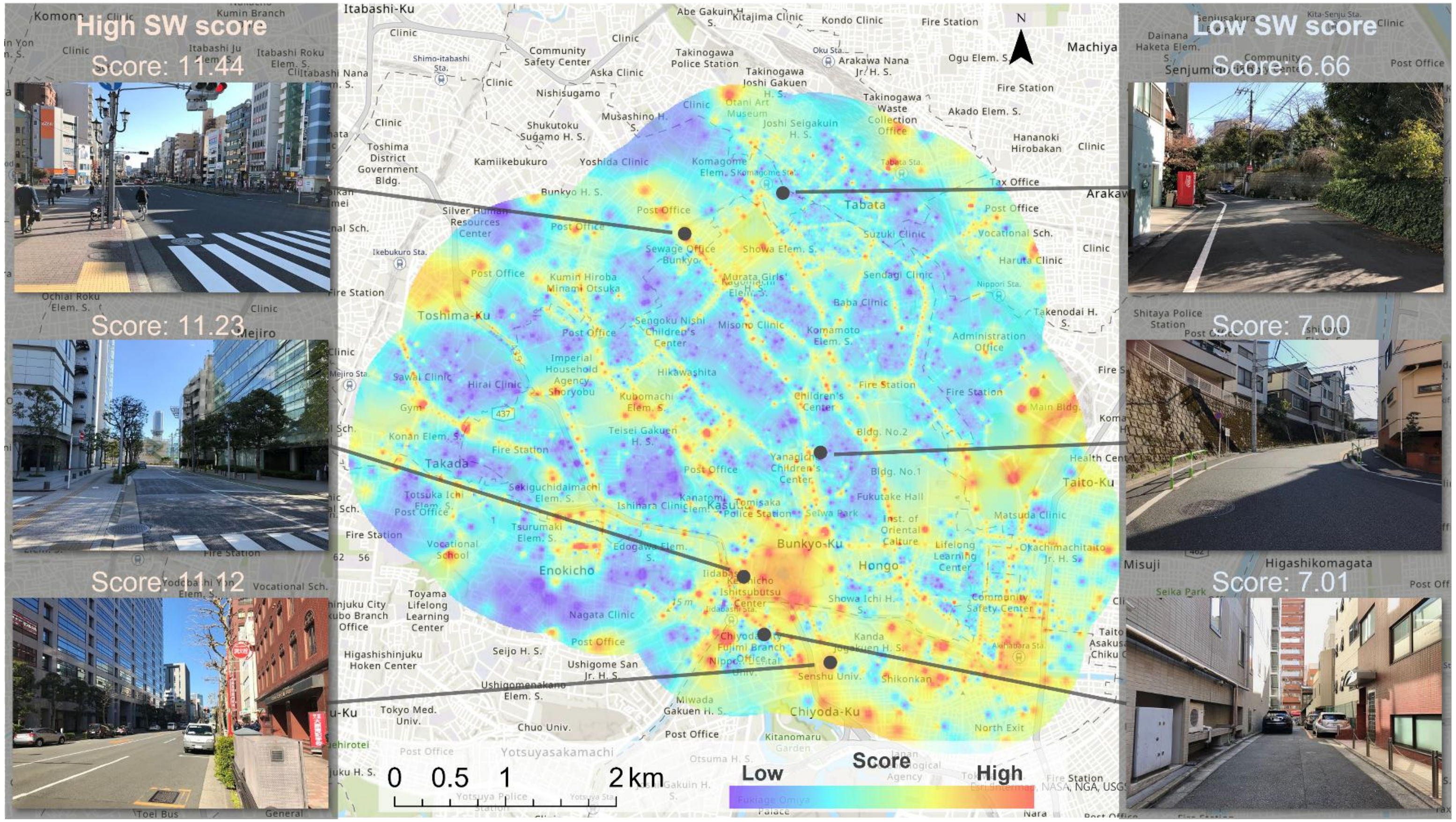


Fig. 2.4. Distribution of predicted SW scores and the streetscape images with high scores or low scores

Sources of Background Map: Esri, HERE, Garmin, FAO, NOAA, USGS, © OpenStreetMap contributors, and the GIS User Community.

Photo: Author's photo

Note: The predicted SW scores for each intersection were interpolated by Inverse Distance Weighted (search radius: 500 meters).

2.3.3 Relationship between walking time and SW

Table 2.5 presents the estimated ORs and 95% CI of the neighborhood SW for active leisure walkers. The neighborhood SW in 500 m is associated with female active leisure walkers, and female participants more actively walked for leisure if the neighborhood SW is high (OR = 3.783; 95% CI = 1.459 to 10.409). When the neighborhood SW in 500 m increases by one point, the odds of older females walking more than 150 min/week for leisure are 3.78 times higher. There is no relationship between the neighborhood SW in 500 m and male active leisure walkers, and the neighborhood SW in 1000 m is not associated with both male and female active leisure walkers.

We applied multilevel logistic regression models with a random intercept to the data using the sampling neighborhood unit (chocho-aza) to consider a possible clustering tendency due to the area stratified sampling design; however, it did not improve the model performance and produced the same estimates of coefficients and their standard errors.

Table 2.5. Estimated odds ratios and 95% confidential intervals of the neighborhood SW for active leisure walkers

		OR	95% CI	p	Adjusted p
Male (N = 156)	SW 500 m	1.534	0.696 to 3.438	0.290	1.000
	SW 1000 m	0.810	0.228 to 2.787	0.739	1.000
Female (N = 144)	SW 500 m	3.783	1.459 to 10.409	0.007**	0.028*
	SW 1000 m	3.373	0.747 to 15.277	0.110	0.440

Notes: OR: odds ratio; CI: confidence interval; and Adjusted covariates are age, educational attainment, living arrangements, working status, routine car driving, physical limitation, and objective walkability. Participants who had at least one missing variable were excluded. Active leisure walker is defined as a participant who walks for leisure more than 150 min/week. Adjusted p-values were calculated by Bonferroni adjustment.

2.4 Discussion

This is the first study to examine the relationship among leisure walking, micro-scale walkability, and multiple components of streetscape using GSV images and a deep learning approach. We built a prediction model for the SW score that can evaluate micro-scale walkability in relation to streetscape images and examined the relationship between older females walking for leisure and predicted neighborhood SW.

Through the construction of the prediction model for SW scores, the relationships that we found between each component of the streetscape and micro-scale walkability support quantitative evaluation for pedestrian-(un)friendly streetscapes. Previous studies attempted extracting features associated with walkable urban design using objective or automated methods quantitively to understand pedestrian-friendly streetscapes (Purciel et al., 2009; Yin, 2017; Yin and Wang, 2016). Purciel et al. (2009) translated urban design variables into GIS measures, but there are still no data for several types of features, such as the proportion of sky and number of small planters. Furthermore, Yin and Wang (2016) demonstrated an automated measurement of proportion of sky using a machine learning approach, and Yin (2017) suggested that GSV and computer vision can assist in the evaluation of urban design. This study supports the assertion that GSV and the computer vision approach can produce usable results, including semantic image segmentation performed by deep learning approach, for walkable urban design.

Supporting the results of Ewing and Handy (2009) and Yin and Wang (2016) on visual enclosure, the results of our regression show that building segments lead to increases in SW, and sky segments are negatively associated with SW. This suggests that locations enclosed by buildings increase pedestrian comfort, unlike streets with low-rise buildings, such as those found in suburban residential area. However, the model also indicates that several interaction effects, including building segment, have negative effects on the SW. For instance, interaction effects between road and building lead to decreases in SW. It is conceivable that locations mostly occupied by road segments and building segments, such as shown in Fig. 2.5, are situated on highly enclosed streets, and such locations could be dark and make pedestrians feel unsafe. A highly enclosed streetscape may have a negative influence on the psychology of pedestrians that would carry over to their sense of the street. Further research is needed to clarify the optimality of quantitative enclosures and to advance the semantic segmentation methods that can help measure the amount of enclosure.

Besides small planters and street trees in urban design variables (Ewing and Handy, 2009; Yin, 2017), our model indicated interaction effects between the road and the terrain segments or between the sidewalk and terrain segments cause increases in the SW. Although the plant factor increases the perception of human scale of the urban design protocol (Ewing and Handy, 2009), it is difficult to obtain the distribution of this factor from objective data sources. The results of semantic segmentation indicate that a small planter or street tree may exist at locations where there is a combination of a terrain segment and a road segment or of a terrain segment and a sidewalk segment (Fig. 2.6). Although further research is needed to improve accuracy, it is certain that GSV and the deep learning approach can objectively extract plant components related to human scale. In case of the vegetation segment, contrast to terrain segment, the interaction effects with the road segment have a negative relationship to SW. However, locations with high proportions of road and vegetation segments include both maintained street plants and dense vegetation in yards and parks (Fig. 2.6). Although greenness is commonly recognized as an effective positive factors promoting physical activity and mental health

(Bell et al., 2008; Lu, 2018; Sugiyama et al., 2008), dense vegetation that creates a blind space could potentially lead to an increase in fear of crime (Bogar and Beyer, 2016) and perceptions of unsafety (Jansson et al., 2013). Clarifying the best arrangement of greenness to increase physical activity by objective methods, such as computer vision, would be needed.

Fig. 2.5. Examples of locations mostly occupied by road and building segments
Source: Author's photo at the same location as the GSV images used for the analysis.

Fig. 2.6. Examples of locations with nature-related segments
Source: Author's photo at the same location as the GSV images used for the analysis.

From the analytical results on the association between leisure walking and the neighborhood SW, improving the neighborhood SW based on the condition of pedestrian infrastructure, safety, and aesthetics facilitates older females' active walking for leisure although there is no association with male leisure walking. The positive relationship between micro-scale walkability and leisure walking has been clarified by previous studies (de Bourdeaudhuij et al., 2005; Inoue et al., 2010; Saelens and Handy, 2008; Witten et al., 2012). Moreover, several studies also proved that street safety and condition encourage females' physical activity (Richardson et al., 2017; Suminski et al., 2005). To the best of our knowledge, however, little work has been done to analyze this relationship based on walkability evaluated by an automatic method. Saelens and Handy (2008) found that measurement of the built environment related to aesthetics varies widely across studies. That is, the quantitative understanding of suitable streetscapes for leisure walking is not yet complete. Therefore, automated method of the SW evaluation that this study demonstrated can help enable the evaluation of the locations that comprise leisure walking-friendly streetscapes with a unified criterion.

In terms of neighborhood distance, for GIS-based objective walkability scores based on destinations' density and accessibility, several studies have found that walkability in the 1,000 m buffer affects physical activity (Arvidsson et al., 2012; de Sa and Ardern, 2014). Furthermore, a longitudinal study has specified that walkability in the 1,000 m network buffer has a greater effect on physical activity than walkability in the 500 m network buffer (Kikuchi et al., 2018). Conversely, this study's results reveal that although a relationship does appear between the neighborhood SW in 500 m and older females walking for leisure, the neighborhood SW in 1,000 m is not related to walking behavior for leisure. In brief, the area in which micro-scale walkability based on pedestrian perceptions affects walking behavior is smaller than objective walkability. This suggests a functional difference between objective walkability and micro-scale walkability. Neighborhoods that have abundant destinations, such as stations, shops, and restaurants, include purposes for walking behavior, and its area is often stipulated using a range of about 1,000 m, which matches the distance that most people are willing to walk (Arvidsson et al., 2012; Lee and Moudon, 2006). On the other hand, neighborhoods including safe streets, well-maintained pedestrian infrastructure, and attractive streetscapes encourage older females to go out. Conditions around one's residence are particularly important.

This study's result was adjusted by objective walkability. Considered together with the foregoing discussion, it is found that older female residents could lose interest in leisure walking when nearby streets are pedestrian-unfriendly, despite an abundance of destinations in the neighborhood. Maintaining a pedestrian-friendly environment and street on a micro-scale (e.g., for each residential unit) is a subject of concern, in addition to enhancing accessibility to destinations on the macro-scale. The results of our study enable us to envisage an automatic detection of streetscapes that should be maintained or repaired in detailed spatial resolution to the level of the intersection.

This study has several limitations. First, GSV images were not taken in the same years or seasons. Although more than 90% of the GSV images we used were taken from 2016 to 2019, some images might not reflect the current streetscapes. How the changes of streetscapes by year or season influence micro-scale walkability should be studied further. Second, the deep learning model used is to segment the general streetscape but not specifically based on pedestrian perceptions. Although the regression model based on the semantic segmentation of the streetscape can predict the SW score, there are other components that encourage or discourage walking behavior, such as the presence of historic buildings, color, graffiti, and noise. Further studies are needed to increase the accuracy of the model based on walkability-specific components. Third, there is bias due to study design. Although active older people might select more walkable neighborhoods for their residences, the cross-sectional study has difficulty explaining whether the walkable neighborhood causes older people to be more active or not. Additionally, since leisure walking time is self-reported, we need to consider recall bias. Future studies should reduce this bias through a longitudinal approach and objective measurement of walking behavior. Fourth, the study area and the ages of the participants that we examined are limited. In relation to the analysis of the relationship between micro-scale walkability and leisure walking behavior, this study found that SW based on automated evaluation is positively related to active leisure walking by older females. It is possible that pedestrian perceptions of streetscapes vary depending on other stipulations, such as age and location. Therefore, extensive tests of multiple aspects, such as age, other sociodemographic characteristics, and other cities, are also needed.

2.5 Conclusion

Micro-scale walkability in relation to pedestrian perceptions is an important factor in walking behavior. This study found that the deep learning approach is a useful tool to quantify streetscapes. Furthermore, we found a relationship between leisure walking by older females and micro-scale walkability based on the quantified streetscape. The proposed automated method allows assessment of the micro-scale aspects of the neighborhood environment with a unified objective criterion and the detection of leisure walking-(un)friendly streetscapes over large areas. This may be of widespread benefit to urban planning and studies on the urban environment and human health.

3. Dynamic observation of the relationship of human mobility in specific places to the COVID-19 pandemic in Japan

The previous chapter discussed the method for the evaluation of the micro-scale environment related to healthy mobility in daily activity. In addition, dynamic observation of the relationship between human mobility and health can help provide efficient public health measures for suitable places in real-time. This chapter will present a method for human mobility observation in specific places, using dynamic mobility data during the COVID-19 pandemic.

3.1 Introduction

With the global spread of the novel coronavirus disease (COVID-19), many countries have implemented non-pharmaceutical interventions, including lockdowns and travel restrictions, to control the pandemic (Chinazzi et al., 2020; Flaxman et al., 2020). In Japan, the government declared a state of emergency (SOE) on April 7, 2020 for seven prefectures, where the confirmed cases had increased markedly (Fig. 3.1), and requested people to adopt self-restraining behaviors, such as cancelling nonessential outings and avoiding the “3Cs” conditions (closed spaces, crowded places, and close-contact settings) (Ministry of Health, Labour and Welfare, 2020a). On April 11, the Prime Minister urged people to work from home (Prime Minister’s Office of Japan, 2020), and governors advised people to refrain from visiting nightlife spots, such as nightclubs and bars. SOE was applied to all 47 prefectures on April 16 (Ministry of Health, Labour and Welfare, 2020a).

To understand contact patterns while such social measures were in place, published studies, including one from Japan, reported that human mobility was associated with the incidence of COVID-19 (Badr et al., 2020; Cartenì et al., 2020; Glaeser et al., 2020; Kraemer et al., 2020; Li et al., 2020; Yabe et al., 2020; Zhou et al., 2020). Despite numerous studies, the effectiveness of reducing contact in focal areas at high risk (e.g., workplaces or nightlife places) is yet to be understood. To efficiently control the infection, it is important to identify the high-risk areas within cities and reduce the mobility in such areas by an appropriate amount. The present study aimed to examine the mobility changes in work, nightlife, and residential places in Japan based on mobile device data and to clarify the association of mobility change at these places with COVID-19 incidences.

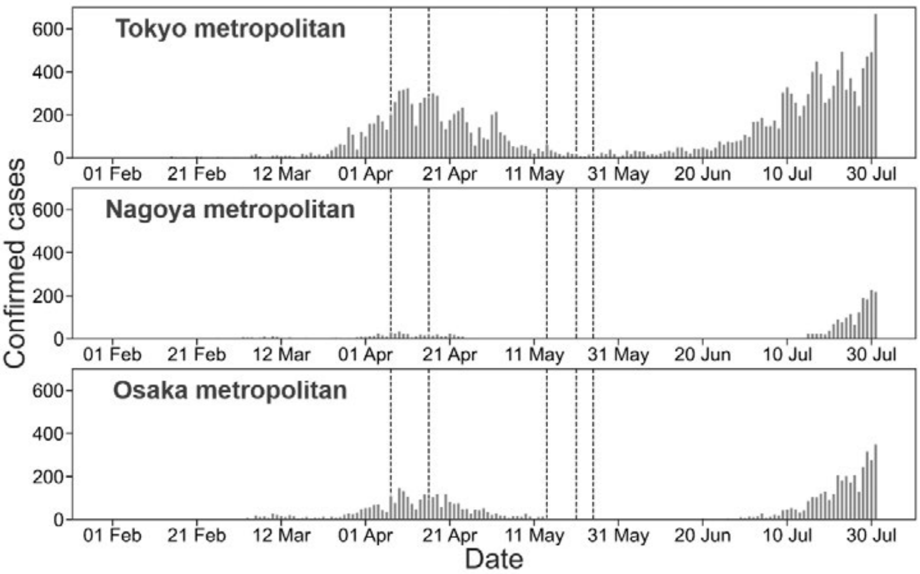


Fig. 3.1. Number of daily confirmed cases in major metropolitan areas. Vertical dash lines represent the start/end date of state of emergency (SOE) declaration. (On April 7, 2020, SOE declaration for Tokyo, Osaka, Kanagawa, Saitama, Chiba, Hyogo, and Fukuoka; on April 16, 2020, SOE declaration for the remaining prefectures; on May 14, 2020, lifting of SOE declaration for prefectures excluding the ones in Hokkaido, Tokyo, and Osaka metropolitan areas; on May 21, 2020, lifting of SOE declaration for Kyoto, Osaka, and Hyogo; on May 25, 2020, lifting of SOE declaration for Hokkaido, Saitama, Chiba, Tokyo, and Kanagawa.)

3.2 Methods

We observed the mobility changes resulting from the outbreak of COVID-19 in three major metropolitan areas — Tokyo, Osaka, and Nagoya — from March 1 to July 31, 2020. Although there are multiple definitions of metropolitan areas in Japan, in this study, Tokyo, Kanagawa, Saitama, and Chiba Prefectures were defined as the Tokyo metropolitan area; Osaka, Kyoto, Hyogo, Shiga, Nara, and Wakayama Prefectures were defined as the Osaka metropolitan area; and Aichi, Gifu, and Mie Prefectures were defined as the Nagoya metropolitan area.

3.2.1 Mobility data and defining the specific places

To observe the mobility change dynamics during the outbreak, "Mobile Spatial Statistics" (DOCOMO InsightMarketing, Inc., Tokyo, Japan), which provide the estimated hourly population in a 500-m-square grid based on mobile device locations (Terada et al., 2013), were employed. We classified the grids into work, nightlife, or residential place based on the median of population at specific times (midnight: 3:00 AM–5:59 AM, daytime: 2:00 PM–4:59 PM, nighttime: 8:00 PM–10:59 PM) of each weekday from January 3 to February 6, 2020. When the median of daytime population was 10,000 or more and twice as large as the median of midnight population, the corresponding grid was designated as a "workplace." When the median of nighttime population was 10,000 or more and twice as large as the median of midnight population, the grid was designated as a "nightlife place." When the median of midnight population was 100 or more and smaller than the median of daytime population, the grid was set as a "residential place."

3.2.2 Mobility change index

For the mobility change index of each place type, we determined the ratio of the daily population to the baseline population in each grid from March to July 2020. Specifically, the mobility change index m of each specific place type p on day t is as follows:

$$m_{p,t} = \frac{Pop_{p,t}}{B_p},$$

where $Pop_{p,t}$ is the total hourly population in p at specific times (workplaces: 2:00 PM–4:59 PM; nightlife places: 8:00 PM–10:59 PM; residential places: 3:00 AM–5:59 AM) on day t. The baseline in each place type (B_p) was defined according to the median of the total hourly population at the corresponding time on a day, from January 3 to February 6, 2020. In the statistical analysis described below, we employed a 7-day moving average to exclude the day-of-the-week effects on the daily mobility change index, m. The moving average M of each specific place type p on the day t is as follows:

$$M_{p,t} = \frac{\sum_{i=t-6}^{t} m_{p,i}}{7}.$$

3.2.3 Epidemiological data

For obtaining the daily counts of positively confirmed cases, we used the open-source epidemiological data provided by J.A.G JAPAN Corp, which summarizes the press releases of confirmed cases published by local governments. We counted the number of daily positive cases, excluding re-positive cases, by each metropolitan area based on the confirmed date (or reported date if confirmed date of the case is unknown).

3.2.4 Statistical analysis

To evaluate the relationship between mobility changes and COVID-19 incidences, we employed the following model (model 1) to predict the cumulative number of confirmed cases in the last 7 days beginning from day t, y_t:

$$y_t = \alpha + \beta_t y_{t-7} + \varepsilon_t,$$

$$\beta_t = \beta_0 + \beta_1 M_{p,t-L} \ ,$$

$$\varepsilon_t = \rho\varepsilon_{t-1} + \omega_t,$$

where α, β_0, β_1, and ρ are parameters to be estimated through generalized least squares. The response variable, y_t, is defined as:

$$y_t = \sum_{i=t-6}^{t} c_i,$$

where c_i is the number of daily confirmed cases on day i. In the model, the coefficient, β_t, is the increasing rate of the 7-day cumulative cases, y_t, compared to the earlier 7 days ($y_{t-7} = \sum_{i=t-13}^{t-7} c_i$). This parameter approximately represents the number of people an infected person infects on day t. We assumed that β_t is dependent on the mobility change index of the specific place p at day t with L day lag, $M_{p,t-L}$. Because the mobility changes may be associated with the incidence after around 2 weeks, due to the time lag between infection and diagnosis or reporting (Badr et al., 2020), we substituted the value from 7 to 20 for the lag period, L, and selected the optimal value of L to estimate β_t based on the Akaike Information Criterion (AIC) by each specific place type and metropolitan area. In addition, with the independent and identically distributed white noise, $\omega_t \sim_{iid} N(0, \sigma^2)$, we used the first-order autoregressive error, ε_t, to adjust the temporal dependency caused by unknown factors, where ρ is the so-called autocorrelation parameter; $E(\varepsilon_t) = 0$, $Var(\varepsilon_t) = \sigma^2/(1-\rho^2)$, and $Cov(\varepsilon_t, \varepsilon_{t-1}) = \rho\, \sigma^2/(1-\rho^2)$.

We also considered the model in which β_t is simultaneously dependent on the mobility change indices of all place types to improve the predictive accuracy of the model (model 2). In this model, β_t is as follows:

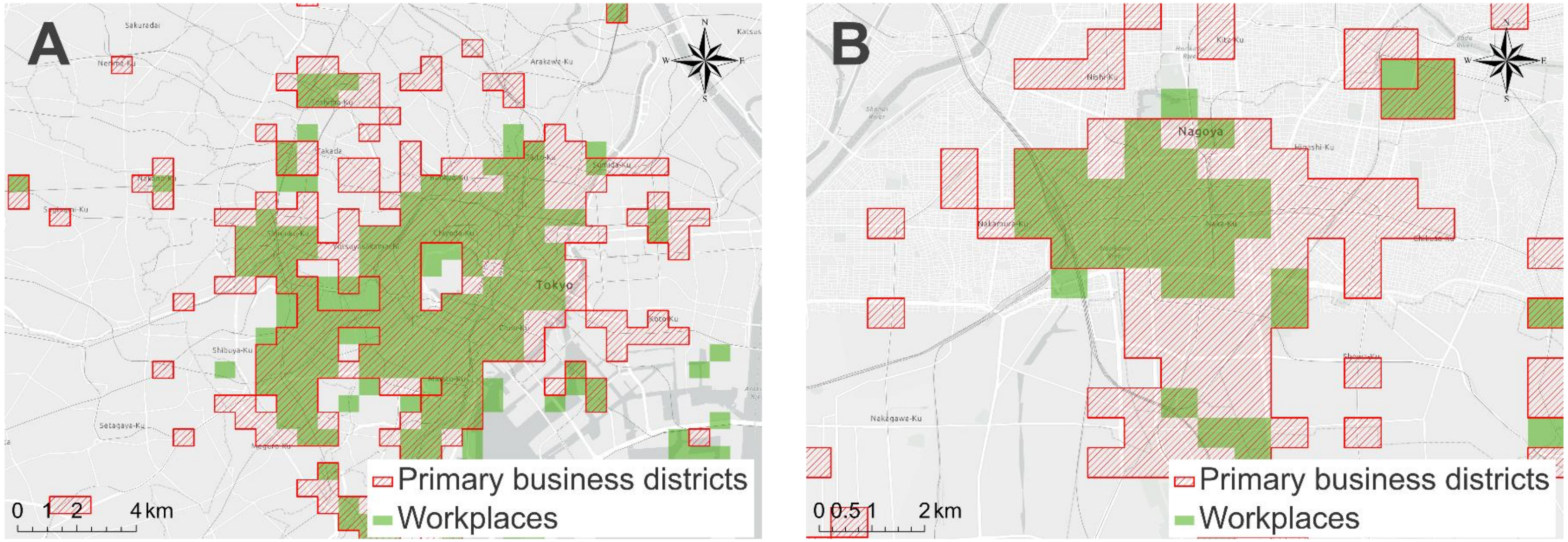
$$\beta_t = \beta_0 + \sum_{p \in \{Work, Nightlife, Residential\}} \beta_p \, M_{p,t-L_p}.$$

Regarding the lag period of each place category, p (L_p), we substituted the optimal value for each place type determined through the results of model 1 in the respective metropolitan areas.

3.3 Results

Regarding the specific place based on the hourly population, Fig. 3.2 and Fig. 3.3 shows the geographical distribution of the workplace and nightlife-place grids we defined, respectively. In addition, to ascertain the validity of the distribution, we also overlaid the primary business districts and nightlife spots on the maps. The primary business districts were identified 500 m square grids where there was a large working population—in central Tokyo, Nagoya City, and Osaka City—based on the 2014 Economic Census. When the number of employees was equal to or larger than its mean plus one standard deviation, the grid was herewith defined as a primary business district. The primary nightlife spots were identified by referring the materials disclosed on the police department websites of Tokyo, Osaka City, and Nagoya City (Aichi Prefectural Police Department, 2018; Metropolitan Police Department, 2018; Osaka Prefectural Police Department, 2006, 2005).

Although the distribution of the primary business districts/nightlife spots and the workplaces/nightlife-places we defined overlap in many parts, there are a few gaps between them. Since we identified these specific places based on the ratio of the daytime/nighttime population to midnight population, the workplaces or nightlife places did not include the business districts or nightlife spots where large populations reside. However, we considered areas with mixed land-use composing both business districts or nightlife spots and residential area as inappropriate for measuring the mobility changes because the increase in residential population and the decrease in visitor population in daytime/nighttime often occur simultaneously in such areas. Therefore, as we defined, the workplaces/nightlife places based on the population differences between midnight and daytime/nighttime should be suitable for analyzing the mobility changes.



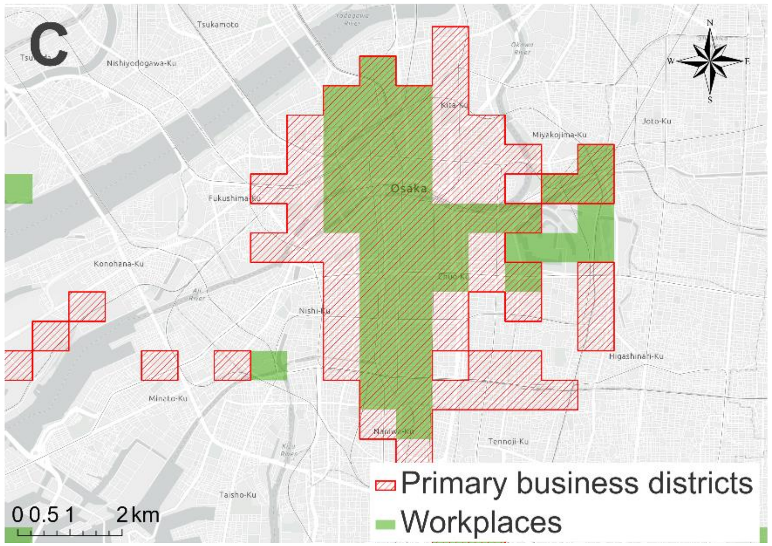


Fig. 3.2. Geographical distribution of the primary business districts and workplaces in Central Tokyo (A), Nagoya City (B), and Osaka City (C). Solid green areas represent the workplaces we defined. Red-hatched areas represent the primary business districts based on the 2014 Economic Census. Map sources: Esri, HERE, Garmin, FAO, NOAA, USGS, (c) OpenStreetMap contributors, and the GIS User Community.

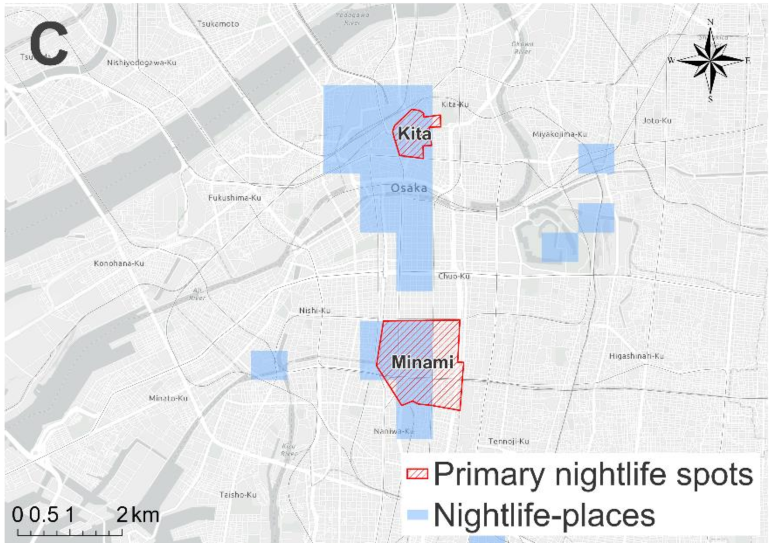


Fig. 3.3. Geographical distribution of the primary nightlife spots and nightlife places in Central Tokyo (A), Nagoya City (B), and Osaka City (C). Solid blue areas represent the nightlife places we defined. Red points or red-hatched areas represent the primary nightlife spots listed by the police department websites. Map sources: Esri, HERE, Garmin, FAO, NOAA, USGS, (c) OpenStreetMap contributors, and the GIS User Community.

In terms of the mobility changes during the pandemic, although the indices in workplaces and nightlife places had already declined slightly as of early March, it showed a drastic downward trend in all regions from late March, before SOE was declared (Fig. 3.4A and Fig. 3.4B). Because mobility reduction in nightlife places was particularly significant during SOE, it can be presumed that the majority of people refrained from visiting nightlife spots, as requested by the government. In contrast, the index in residential places that reflected staying at home showed an upward trend from March to May (Fig. 3.4C).

According to the estimated β_1 and the optimal lag period of the models with the single mobility change index (model 1), the mobility changes in workplaces and nightlife places were positively associated with the incidence after 8 to 16 days in all metropolitan areas, and the residential places' mobility was negatively associated (Table 3.1); that is, the decrease in people visiting workplaces or nightlife places, as well as the increase in stay-at-home population, could have led to reducing the outbreak, although its sensitivity varied by area type. Notably, judging from Nagelkerke's R^2, the mobility changes in the nightlife spots better explained the outbreak of COVID-19 compared to workplaces and residential areas in the respective metropolitan areas. However, the goodness of fit of the models based on the Tokyo metropolitan area's mobility changes was lower than that of the other areas' models.

In addition, while the models with all mobility change variables (model 2) slightly improved the accuracy of predicting the number of new positive cases, their results also indicate that the mobility changes in nightlife places were more significantly associated with the outbreak than those in workplaces and residential places in each metropolitan area (Table 3.2). Model 2 also shows that the relationships of the residential places' mobility changes to the outbreak were statistically significant only in the Nagoya metropolitan area, and the mobility changes in workplaces were no longer significantly associated with the outbreak in all metropolitan areas.

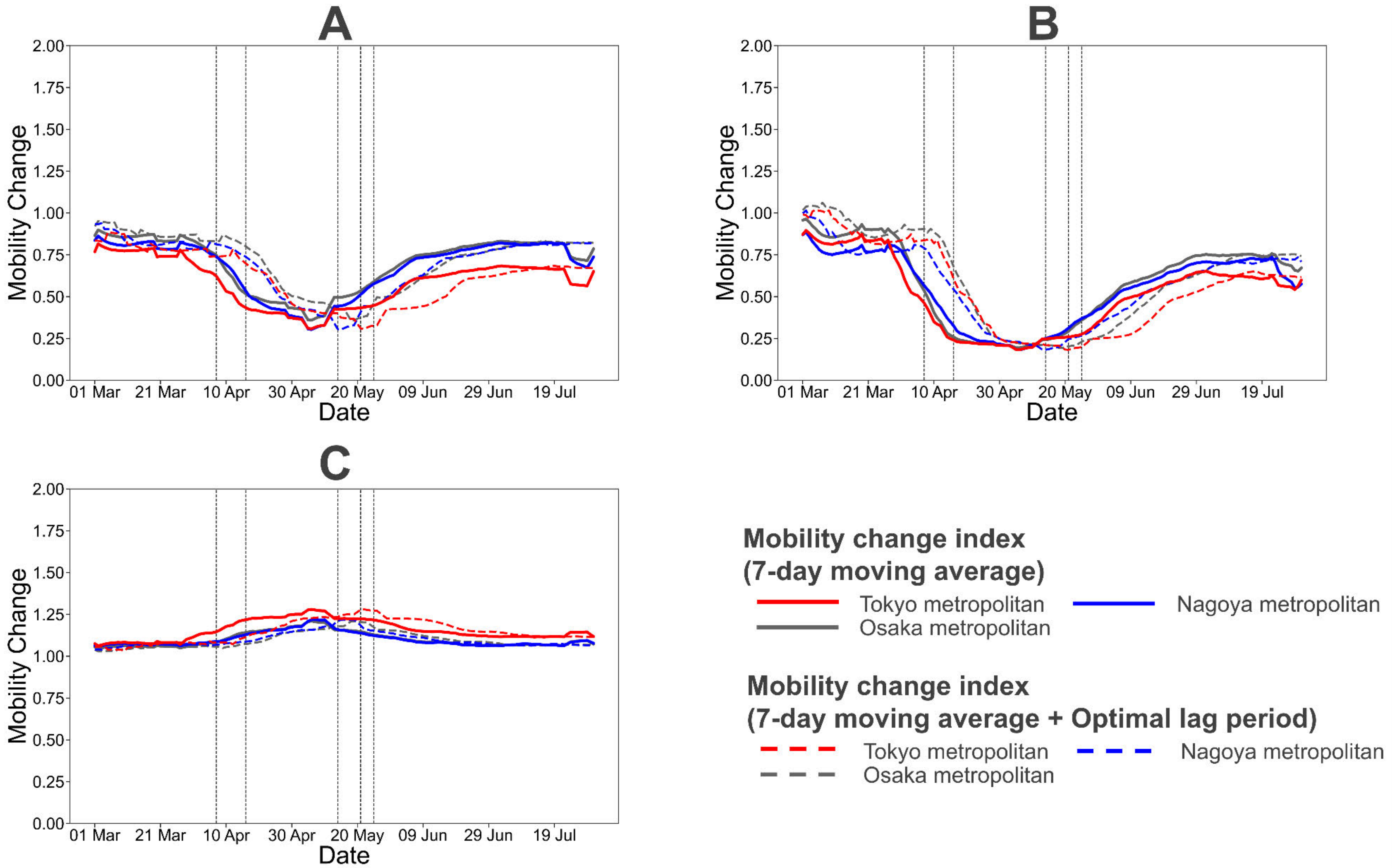

A
B
C
Mobility Change
Date
2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
01 Mar
21 Mar
10 Apr
30 Apr
20 May
09 Jun
29 Jun
19 Jul
Mobility change index
(7-day moving average)
Tokyo metropolitan
Osaka metropolitan
Nagoya metropolitan
Mobility change index
(7-day moving average + Optimal lag period)
Tokyo metropolitan
Osaka metropolitan
Nagoya metropolitan

Fig. 3.4. Daily change of mobility in workplaces (A), nightlife places (B), and residential places (C). The solid and dashed lines represent the 7-day moving average of the mobility change index and the 7-day moving average of the mobility change index delayed by the optimal lag period, respectively. The mobility change index is represented by the ratio of the population of each place at specific times (workplaces: 2:00 PM–4:59 PM, nightlife places: 8:00 PM–10:59 PM, residential places: 3:00 AM–5:59 AM) to the baseline population. The baseline in each place was defined based on the median of population at corresponding time of each day from January 3, 2020 to February 6, 2020. The optimal lag period was determined using AIC. Vertical dash lines represent the start/end date of state of emergency (SOE) declaration. (On April 7, 2020, SOE declaration for Tokyo, Osaka, Kanagawa, Saitama, Chiba, Hyogo, and Fukuoka; on April 16, 2020, SOE declaration for the remaining prefectures; on May 14, 2020, lifting of SOE declaration for prefectures excluding the ones in Hokkaido, Tokyo, and Osaka metropolitan areas; on May 21, 2020, lifting of SOE declaration for Kyoto, Osaka, and Hyogo; on May 25, 2020, lifting of SOE declaration for Hokkaido, Saitama, Chiba, Tokyo, and Kanagawa.)

Table 3.1. Estimated α and βt of Model 1

Area	Place	Lag period	AIC	R^2	α		
					Coef.	95% CI	p
Tokyo metropolitan	Workplace	16	1,706.30	0.25	857.28	-657.63 to 2372.18	0.265
	Nightlife place	15	1,697.88	0.29	701.99	-487.91 to 1891.88	0.246
	Residential place	16	1,705.05	0.25	805.57	-587.56 to 2198.69	0.255
Nagoya metropolitan	Workplace	9	1,253.60	0.72	154.87	-181.81 to 491.54	0.365
	Nightlife place	8	1,238.71	0.75	138.51	-176.25 to 453.28	0.386
	Residential place	9	1,249.40	0.73	157.82	-180.05 to 495.68	0.358
Osaka metropolitan	Workplace	13	1,436.46	0.54	295.18	-266.09 to 856.45	0.300
	Nightlife place	13	1,426.41	0.57	251.57	-223.78 to 726.92	0.297
	Residential place	13	1,435.25	0.54	306.93	-277.43 to 891.28	0.301

(βt is shown on the next page)

Table 3.1 (continued)

Area	Place	Lag period	AIC	R^2	β_0			β_1		
					Coef.	95% CI	p	Coef.	95% CI	p
Tokyo metropolitan	Workplace	16	1,706.30	0.25	-0.91	-1.43 to -0.39	<0.001***	2.06	1.27 to 2.84	<0.001***
	Nightlife place	15	1,697.88	0.29	-0.37	-0.66 to -0.08	0.012*	1.55	1.05 to 2.06	<0.001***
	Residential place	16	1,705.05	0.25	6.31	4.10 to 8.52	<0.001***	-5.20	-7.13 to -3.27	<0.001***
Nagoya metropolitan	Workplace	9	1,253.60	0.72	-2.50	-3.70 to -1.31	<0.001***	5.23	3.72 to 6.75	<0.001***
	Nightlife place	8	1,238.71	0.75	-1.07	-1.74 to -0.41	0.002**	4.11	3.11 to 5.10	<0.001***
	Residential place	9	1,249.40	0.73	26.05	19.35 to 32.75	<0.001***	-22.86	-29.12 to -16.60	<0.001***
Osaka metropolitan	Workplace	13	1,436.46	0.54	-1.01	-1.52 to -0.50	<0.001***	2.41	1.74 to 3.08	<0.001***
	Nightlife place	13	1,426.41	0.57	-0.22	-0.49 to 0.06	0.119	1.70	1.28 to 2.12	<0.001***
	Residential place	13	1,435.25	0.54	10.99	8.19 to 13.78	<0.001***	-9.42	-11.99 to -6.84	<0.001***

Notes: AIC, Akaike Information Criterion; CI, confidence interval. *Coef.: Coefficient, R^2: Nagelkerke's R^2 with the null model assuming zero coefficients of explanatory variables with AR1 error, "***," "**," and "*," denote the statistical significance at 0.1%, 1%, and 5% levels, respectively. The sample size for each model was 153.

Table 3.2. Estimated α and βt of Model 2

Area	AIC	R^2	α		
			Coef.	95% CI	p
Tokyo metropolitan	1,699.55	0.30	719.36	-512.11 to 1950.84	0.250
Nagoya metropolitan	1,238.50	0.76	141.58	-176.40 to 459.56	0.380
Osaka metropolitan	1,427.24	0.58	254.21	-229.55 to 737.97	0.301

(βt is shown on the next page)

Table 3.2 (continued)

Area	AIC	R^2	β_0			Workplaces β_{Work}			Nightlife places $\beta_{Nightlife}$			Residential places $\beta_{Residential}$		
			Coef.	95% CI	p	Coef.	95% CI	p	Coef.	95% CI	p	Coef.	95% CI	p
Tokyo metropolitan	1,699.55	0.30	0.69	-9.78 to 11.17	0.896	0.44	-2.50 to 3.39	0.766	1.15	0.41 to 1.89	0.003**	-1.00	-8.58 to 6.57	0.794
Nagoya metropolitan	1,238.50	0.76	22.70	-1.36 to 46.76	0.064	-3.63	-8.69 to 1.42	0.158	3.65	1.80 to 5.51	<0.001***	-19.28	-38.56 to 0.00	0.050*
Osaka metropolitan	1,427.24	0.58	9.95	-1.54 to 21.44	0.089	-2.37	-5.36 to 0.62	0.119	1.96	0.82 to 3.10	<0.001***	-7.90	-16.89 to 1.09	0.085

Notes: AIC, Akaike Information Criterion; and CI, confidence interval. "***," *Coef.: Coefficient, R^2: Nagelkerke's R^2 with the null model assuming zero coefficients of explanatory variables with AR1 error, "**," and "*," denote the statistical significance at the 0.1%, 1%, and 5% levels, respectively. The sample size for each model was 153.

3.4 Discussion

We demonstrated that the mobility changes in all types of places were associated with COVID-19 incidence in Japan. Although the mobility had been slightly reduced in March, possibly reflecting the increased individual awareness of infection prevention, mobility in nightlife places was clearly reduced from mid-April to mid-May and was more strongly associated with the trends of confirmed cases compared to other potential locations of transmission. In fact, a published study has shown that the proportion of positive cases in the nightlife group was significantly higher than that in the non-nightlife group based on the SARS-CoV-2 PCR test at a clinic in Tokyo from early March to late April (Takaya et al., 2020). Our finding and such published evidence imply that SOE and public warnings to avoid nightlife places were effective in reducing the outbreak.

Regarding the regional differences in the relationship between the mobility change and outbreak, the sensitivity and predictive accuracy of mobility in the Tokyo metropolitan area to new positive cases was the lowest in the results of models with a single mobility change (model 1). Moreover, the models with all mobility change variables (model 2) showed that the mobility changes in residential places were related to the outbreak only in the Nagoya metropolitan area, but those in the Tokyo and Osaka metropolitan areas were not. These findings suggest that there may still be various opportunities having risks of infection (such as a nosocomial infection, infection at jobs where face-to-face interaction is required, or infections at daily life areas near residential places) in largely populated regions, such as the Tokyo and Osaka metropolitan areas, even though mobility was reduced in highly-sensitive places, and the stay-at-home population increased.

The ongoing COVID-19 pandemic has also been the cause of economic damages.

A previous study indicates that if Tokyo were locked down for a month, the economic impacts would spill over to other regions and the total loss of productive activity in Japan would be 5.2% of the annual GDP (Inoue and Todo, 2020). Therefore, it would be important to stimulate economic activities while monitoring the mobility in high-risk locations such as nightlife places. The observation of mobility using mobile phone networks, as shown in this study, can be applied to capture changes in mobility at specific places in near-real-time, thereby facilitating immediate infection control measures. In addition, for a more detailed analysis of the spatial characteristics of the contacts that cause the infection, the observation of GPS-based mobility in nightlife places would be required.

Our study has several limitations. First, we used the confirmed date to compile the incidence data, because several local governments have not disclosed their onset date, but ideally the date of illness onset would more properly reflect the epidemic dynamics. The differences in the optimal lag periods among the metropolitan areas could possibly be explained by regional differences in the period from onset to diagnosis/reporting, due to the testing system. Second, the choice of "place" we analyzed was defined only by the ratio of population during a specific time, and there is a possibility that some places might have been wrongly identified as nightlife places. However, we manually ascertained that the primary business/nightlife districts are correctly included in workplaces/nightlife places that we defined. Third, our study considered only the mobility changes as an environmental factor that was associated with the outbreak of COVID-19. Further studies are needed to ascertain the effect of mobility changes on the outbreak by taking into account other environmental factors, such as improvements in testing and treatment systems, seasonal effects, and increase in individual awareness of infection prevention.

Our study's methods and findings can be used for designing future public health and social measures against COVID-19. The results indicate that mobility reduction, particularly in nightlife places, may contribute to reducing the transmission of infectious diseases. This will help us to accurately observe the mobility associated with a high risk of infection and implement prompt infection control measures at appropriate places in the future.

4. Individual and geographic background of changes in physical activity during the COVID-19 pandemic in Japan

The previous two chapters demonstrated the usefulness of spatial big data for observing mobility and its related environmental context in the geographies of health. In addition, to promote people's health and well-being, the social factors impacting disease and health inequalities should also be considered. This chapter will explore the individual and geographic background of changes in mobility during a specific event by combining mobile phone data and an online survey.

4.1 Introduction

The novel coronavirus disease (COVID-19) pandemic is ongoing as of August 2021. Although vaccinations have been administered in many countries, the World Health Organization reported that as of August 3, 2021, the number of new COVID-19 cases per week worldwide is still increasing (World Health Organization, 2021). Up until August 10, 2021, more than 200 million cases have been confirmed globally, including more than 4.3 million deaths (Johns Hopkins Coronavirus Resource Center, 2021). To reduce the spread of infection, non-pharmaceutical interventions (NPIs), such as social distancing measures and lockdowns, were implemented in many countries (BBC, 2021; Courtemanche et al., 2020; Lau et al., 2020). In Japan, to prevent the health system from collapsing due to rapid increase in new positive cases, the government declared a state of emergency (SoE) four times until August 10, 2021 and requested people to show self-restraining behaviors such as shortening business hours at restaurants, avoiding nonessential outings, and working from home (Office for Novel Coronavirus Disease Control Cabinet Secretariat, Government of Japan, 2020).

Previous studies have revealed the effects of changes in human mobility related to NPIs during the COVID-19 outbreak (Amagasa et al., 2020; Badr et al., 2020; Li et al., 2020; Nagata et al., 2021; Yabe et al., 2020; Zhou et al., 2020). Reduced mobility that effectively reduces the spread of infection could cause physical inactivity, which is concerning (Hall et al., 2021; Lippi et al., 2020). A descriptive study showed that globally, within 30 days of declaration of the pandemic, there was a 27.3% reduction in the mean number of steps taken (Tison et al., 2020). Further, several studies have shown that reduced physical activity during the COVID-19 pandemic is associated with mental health issues, such as depression, loneliness, stress, anxiety, and sadness (Meyer et al., 2020; Pieh et al., 2020; Silva et al., 2020). Additionally, according to the World Health Organization, physical inactivity is a major risk factor for non-communicable diseases (World Health Organization, 2020) and is estimated to cause 6–10% of coronary heart diseases, type 2 diabetes, and breast and colon cancers worldwide (Lee et al., 2012). Therefore, it is important to analyze reduced physical activity caused by the implementation of NPIs to plan long-term measures against the current and any future pandemics.

Much has been discussed on the factors encouraging or discouraging physical activity. Many studies consistently demonstrate that individuals of higher socioeconomic status (SES) are more likely to be physically active during leisure time, while those of lower SES are more likely to engage in job-related physical activity (Beenackers et al., 2012; McNeill et al., 2006). Furthermore, neighborhood environments are also associated with the amount of physical activity. High-walkability neighborhoods, which have mixed land use or favorable esthetic qualities, promote residents' walking behavior (Saelens et al., 2003; Saelens and Handy, 2008; Sallis et al., 2009), but those living in highly-deprived neighborhoods are more likely to be physically inactive (Cubbin et al., 2006; Hillsdon et al., 2008). During the COVID-19 pandemic, people with low incomes in the USA and the UK showed decreased physical activity (Fearnbach et al., 2021; Robinson et al., 2021). Conversely, a study from Bangladesh demonstrated that highly educated individuals with high income is more likely to be physically inactive (Rahman et al., 2020). Considering such differences reflect social structures and the measures taken against COVID-19 in each country; further evaluation based on the situations in different countries is needed.

In Japan, decreased physical activity was observed during the COVID-19 outbreak (Hino and Asami, 2021; Makizako et al., 2021; Yamada et al., 2020). Hino and Asami (2021) suggested that proximity to large parks could effectively mitigate decreased walking among female older adults during the SoE. Hanibuchi et al. (2021) reported that reduced time spent outdoors is associated with individual attributes such as age, gender, income, or residential location and perception of anxiety related to the infection or the stigma. Moreover, Koohsari et al. (2021) revealed that the implementation of working-from-home was associated with decreased work-related physical activity and increased sitting time. However, few studies have attempted to clarify the comprehensive relationships between physical inactivity and individual attributes such as age, residential location, work situation changes, or anxiety related to the pandemic. This study employed data from a smartphone application and an online survey to retrospectively observe changes in physical activity, particularly decreased walking and increased sedentary behaviors, during the first wave of the COVID-19 pandemic in Japan, and explore the relationship between individual attributes, including demographic, socioeconomic, and geographic characteristics, work situation changes, and perception of anxiety.

4.2 Methods

4.2.1 Data collection

We conducted a nationwide online survey among registered panel members of a survey company (Cross Marketing Inc.) from May 19 to May 23, 2020. People aged 20–69 years with diverse demographic and socioeconomic backgrounds, owning iPhones, and living in Japan were recruited from 4.65 million panel members. The quota sample was designed to have the same distribution of population by age, gender, and geographical region based on the 2015 Japan population census. As for the definition of the geographical region, we classified the prefectures into metropolitan areas that consist of Tokyo, Kanagawa, Saitama, Chiba, Aichi, Gifu, Mie, Osaka, Hyogo, Kyoto and Nara and nonmetropolitan areas that consist of the rest. However, this sampling design was not applied to participants aged 60–69 years because of fewer responses from females of this age group.

4.2.2 Measurement of changes in walking and sedentary behaviors

To analyze changes in sedentary behavior, the participants were asked regarding change is duration of sitting since COVID-19 outbreak when compared with before the pandemic. Participants selected answers from the following options: significant reduction, slight reduction, no change, slight rise, significant rise. The answers were converted to integer values (1: significant reduction, 2: slight reduction, 3: no change, 4: slight rise, 5: significant rise) to obtain ordinal variables for statistical analyses.

Additionally, to observe changes in walking behavior objectively and retrospectively, from the participants, we collected screenshot images of the pre-installed "iPhone Health App" (Apple Inc.), which automatically records daily step counts. The screenshots of number of daily steps were captured for the previous 3 months by the participants. We then extracted this information through image processing and optical character recognition methods using Python 3.7.7, OpenCV 4.2.0, and Tesseract 5.0.0. Details of the image processing methods to obtain the step counts in numbers have been described previously (Adachi et al., 2021). Subsequently, we calculated the differences between the number of mean steps before and after the first SoE for each participant and used them for each period to measure the changes in walking behavior. According to a previous study, the pre-SoE period was from February 19, 2020 to March 23, 2020 and the post-SoE period was from April 16, 2020 to May 19, 2020 (Adachi et al., 2021).

4.2.3 Demographic, socioeconomic, and geographic variables

The demographic and socioeconomic attributes of the participants considered as variables were: gender (0: males, 1: females), age (20–29 years, 30–39 years, 40–49 years, 50–59 years, 60–69 years), chronic disease (0: no, 1: yes), educational status (junior high school/high school, junior (technical) college/vocational school, undergraduate/graduate school), occupation (white-collar job including administrators, professionals, and office clerks; gray-collar job including sales clerks and service workers; blue-collar job including security workers and production, construction, and transportation workers; and other/not working), household annual income (<3 million yen, 3–7 million yen, ≥7 million yen, and unknown), living alone (0: no, 1: yes), living with child(ren) under 18 years (0: no, 1: yes), and living with person(s) aged 65 years and older (0: no, 1: yes). The data corresponding to the categorical variables, such as age, educational status, occupation, and household income, were converted to a binary system indicating whether the participants belong to each group or not (0: no, 1: yes).

Neighborhood-level population density and deprivation were considered as geographic variables. The neighborhoods were defined by the postal code of the participants' residential address and were categorized as follows into groups of approximately equal sample sizes: lowest density (non-densely-inhabited-district (non-DID), defined by the 2015 Japan population census), middle-low density (DID with 7,015 people/km2 or fewer), middle-high density (DID with 7,016–10,214 people/km2), and highest density (DID with 10,215 people/km2 or more). The neighborhood-level deprivation indicator was calculated using the area deprivation index (ADI) derived from the 2015 Japan population census, which has been explained previously (Nakaya et al., 2014). A higher ADI indicates that the neighborhood has more deprived conditions. We categorized the neighborhoods based on ADI quartiles as lowest ADI, middle-low ADI, middle-high ADI, and highest ADI groups.

4.2.4 Variables representing changes related to work situation and anxiety

We hypothesized that the work situation changes and perception of anxiety due to COVID-19 are also associated with walking and sedentary behaviors. The variables that indicate changes in work situation were: introduction of work-from-home/standby-at-home measures (0: no, 1: yes) and decreased amount of work (0: no, 1: yes). Three anxiety variables were also used: strong anxiety about getting infected (0: no, 1: yes), spreading the infection to others (0: no, 1: yes), and stigma associated with going out (0: no, 1: yes).

4.2.5 Statistical analysis

To examine the direct and indirect relationships among the individual attributes including demographic, socioeconomic, and geographic variables, changes in work situation, perception of anxiety due to the pandemic, and changes in physical activity, we assumed the following models (Fig. 4.1): model A represents that the individuals' background affected their work situation and perception of anxiety which affected the changes in physical activity; model B assumes the inverse relationship between perception of anxiety and the changes in physical activity represented by model A to account for the possibility that the physical inactivity causes increased anxiety during the pandemic (Silva et al., 2020); model C and D assumes the direct relationship between the work situation changes and perception of anxiety in addition to the frameworks of model A and B. All models assume the direct relationships between the individuals' background and the changes in physical activity.

We examined the relationships by path analysis, a special case of structural equation modeling, and evaluated the most suitable model to explain the comprehensive relationships by comparative fit index (CFI) and root mean square error of approximation (RMSEA) which indicate how well the model fits. CFI is expressed as a value between 0 and 1, and models with a value greater than 0.95 are often interpreted as good fitting (Ullman and Bentler, 2012). RMSEA represents that the smaller the value, the better fitting the model, and values of 0.06 or less can be interpreted as good fitting (Ullman and Bentler, 2012). Furthermore, to evaluate the relationship between each variable, the relationship was considered statistically significant if the path's p-value was less than 0.05. To estimate the coefficients to the dichotomous variables indicating changes in work situation and perception of anxiety and ordinal variables indicating changes in time spent in sedentary behavior, binary probit and ordered probit regression models were employed, respectively. All statistical analyses were performed using R 3.6.1, and the lavaan package, version 0.6-7, was used to run path analysis.

This study was approved by the Research Ethics Committee of the Graduate School of Engineering, Tohoku University (approval number: 20A-3). Informed consent was obtained from all participants.

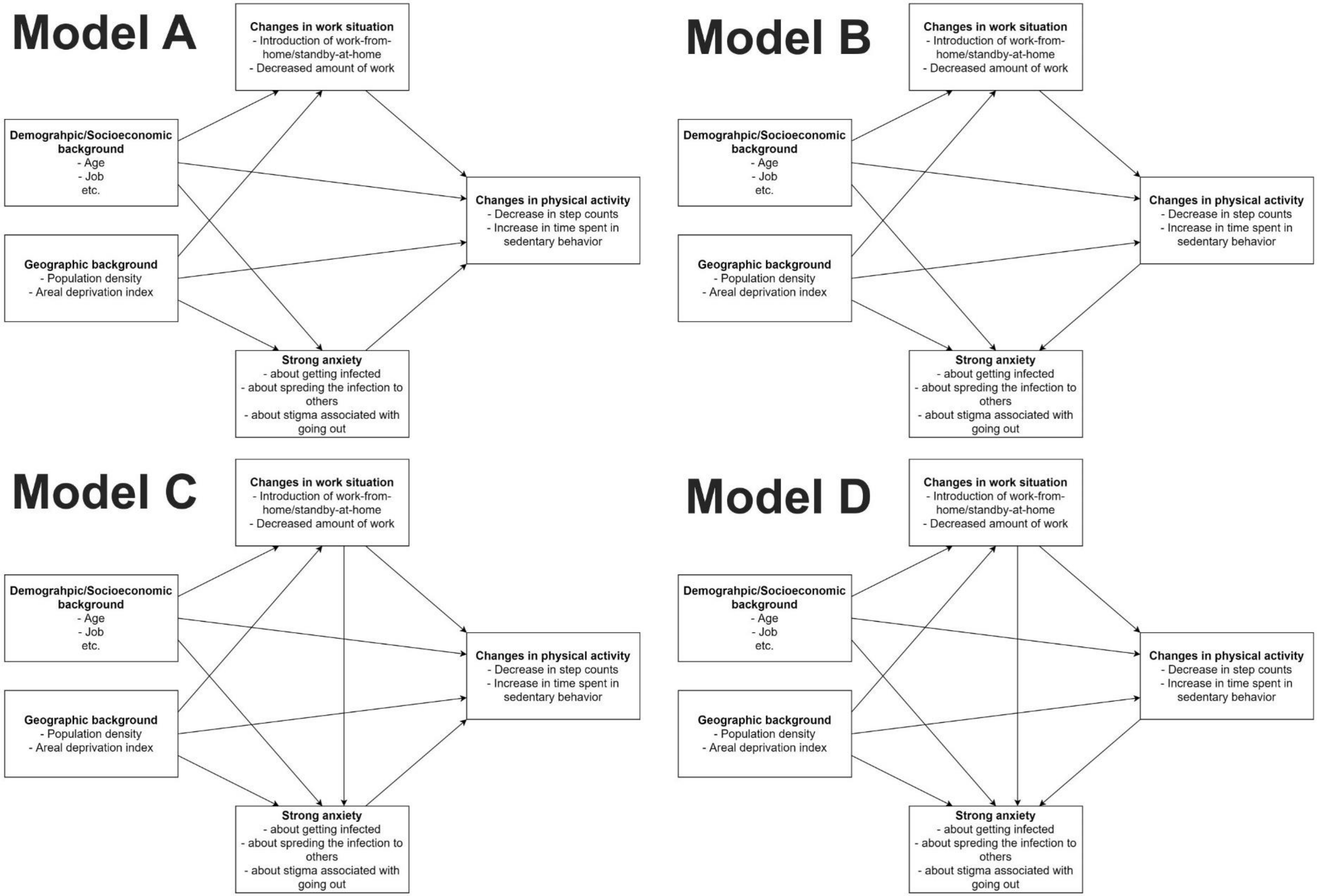


Fig. 4.1. Conceptual frameworks of the models indicating hypotheses of the relationships among individual attributes, work situation changes, perception of anxiety, and changes in physical activity

4.3 Results

In the online survey, 1,200 panel members participated. We excluded the data of 282 participants from whom the daily step counts could not be obtained for more than 15 days both before and after the SoE because of errors such as low image resolution. We excluded the data of five participants whose educational data was unavailable and 17 participants whose postal code was missing. Finally, data of 896 participants were used for analyses (Fig. 4.2).

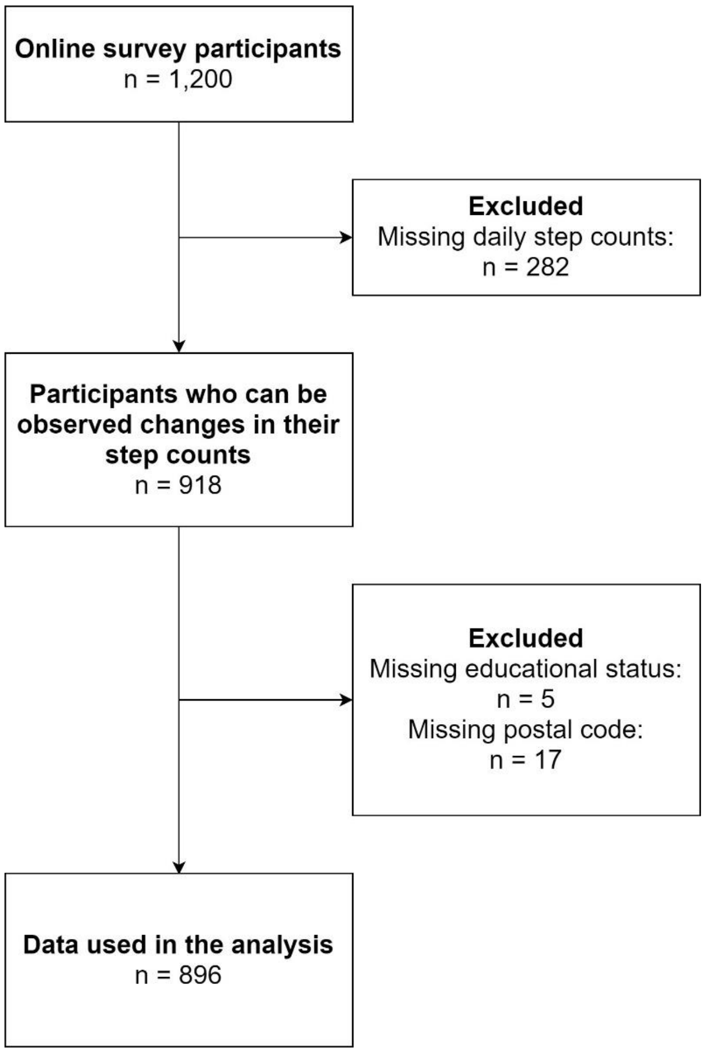


Fig. 4.2. Flow diagram of participant inclusion

Fig. 4.3 shows the differences in mean step counts between late-February and mid-May, 2020. The step counts decreased gradually from late-February, and there was more than 20% reduction after the SoE. Table 4.1 summarizes the changes in walking and sedentary behaviors during the COVID-19 outbreak based on demographic, socioeconomic, and geographic attributes. More than 60% of participants increasingly spent time in sedentary behavior. The average step count consistently decreased across all attributes, while sedentary behavior increased during the outbreak. There were significant differences in step count reductions when considering age, educational status, living with child(ren), neighborhood density, ADI, and introduction of work-from-home/standby-at-home measures. Furthermore, the changes in time spent in sedentary behavior across groups categorized according to gender, educational status, neighborhood density, ADI, introduction of work-from-home/standby-at-home, decreased amount of work, and strong anxiety about getting infected, spreading the infection to others, and the stigma associated with going out, were significant.

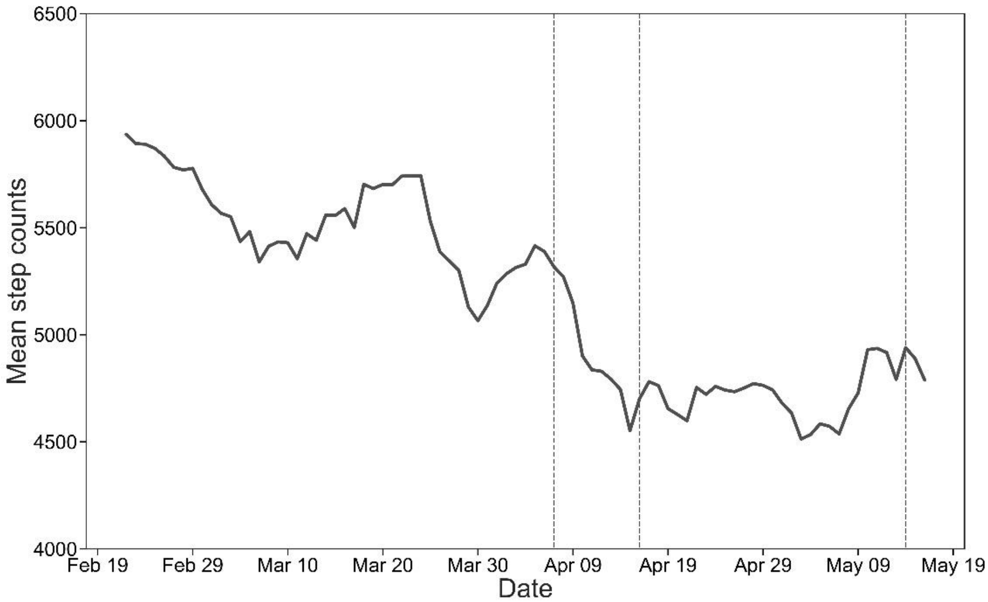


Fig. 4.3. Changes in mean step counts of the participants (7-day moving average). Vertical dash lines represent the start/end date of state of emergency (SoE) declaration (April 7, 2020, SoE declaration for Tokyo, Osaka, Kanagawa, Saitama, Chiba, Hyogo, and Fukuoka; April 16, 2020, SoE declaration for the remaining prefectures; May 14, 2020, lifting of SoE for prefectures excluding Hokkaido, Saitama, Chiba, Tokyo, Kanagawa, Kyoto, Osaka, and Hyogo).

Table 4.1. Changes in walking and sedentary behaviors during the COVID-19 outbreak based on characteristics of respondents

	n	%	Average change in step counts a)b)	Number of participants by change levels of sedentary behavior c)				
				Significant reduction	Slight reduction	No change	Slight rise	Significant rise
Total	896		-918.4 (SD=2276.2)	1 (0.1%)	9 (1.0%)	321 (35.8%)	293 (32.7%)	272 (30.4%)
Gender			*p=0.263*	*p=0.002*				
Males	459	51.2	-1001.5 (SD=2318.7)	1 (0.2%)	5 (1.1%)	178 (38.8%)	160 (34.9%)	115 (25.1%)
Females	437	48.8	-831.2 (SD=2230.0)	0 (0.0%)	4 (0.9%)	143 (32.7%)	133 (30.4%)	157 (35.9%)
Age			*p<0.001*	*p=0.066*				
20-29 years	134	15.0	-1991.5 (SD=2604.2)	0 (0.0%)	3 (2.2%)	40 (29.9%)	34 (25.4%)	57 (42.5%)
30-39 years	180	20.1	-771.0 (SD=2586.5)	0 (0.0%)	2 (1.1%)	60 (33.3%)	64 (35.6%)	54 (30.0%)
40-49 years	214	23.9	-907.6 (SD=1903.6)	0 (0.0%)	1 (0.5%)	78 (36.4%)	71 (33.2%)	64 (29.9%)
50-59 years	171	19.1	-756.1 (SD=1921.4)	1 (0.6%)	1 (0.6%)	73 (42.7%)	52 (30.4%)	44 (25.7%)
60-69 years	197	22.0	-475.9 (SD=2186.2)	0 (0.0%)	2 (1.0%)	70 (35.5%)	72 (36.5%)	53 (26.9%)
Chronic disease			*p=0.388*	*p=0.983*				
No	682	76.1	-952.9 (SD=2338.1)	1 (0.1%)	7 (1.0%)	243 (35.6%)	225 (33.0%)	206 (30.2%)
Yes	214	23.9	-808.5 (SD=2067.8)	0 (0.0%)	2 (0.9%)	78 (36.4%)	68 (31.8%)	66 (30.8%)
Educational status			*p<0.001*	*p=0.025*				
Junior high school/high school	177	19.8	-493.9 (SD=1849.1)	1 (0.6%)	1 (0.6%)	77 (43.5%)	52 (29.4%)	46 (26.0%)
Junior (technical) college/vocational school	219	24.4	-668.6 (SD=2506.6)	0 (0.0%)	3 (1.4%)	84 (38.4%)	69 (31.5%)	63 (28.8%)
Undergraduate/graduate school	500	55.8	-1178.1 (SD=2276.6)	0 (0.0%)	5 (1.0%)	160 (32.0%)	172 (34.4%)	163 (32.6%)
Occupation			*p=0.788*	*p=0.601*				
White-collar job	407	45.4	-901.1 (SD=1876.6)	0 (0.0%)	3 (0.7%)	152 (37.3%)	126 (31.0%)	126 (31.0%)
Gray-collar job	152	17.0	-1067.1 (SD=2910.4)	0 (0.0%)	1 (0.7%)	57 (37.5%)	45 (29.6%)	49 (32.2%)
Blue-collar job	75	8.4	-913.1 (SD=2575.5)	0 (0.0%)	0 (0.0%)	31 (41.3%)	27 (36.0%)	17 (22.7%)
Other/not working	262	29.2	-860.6 (SD=2343.2)	1 (0.4%)	5 (1.9%)	81 (30.9%)	95 (36.3%)	80 (30.5%)

Table 4.1 (continued)

	n	%	Average change in step counts [a)b)]	Number of participants by change levels of sedentary behavior [c)]				
				Significant reduction	Slight reduction	No change	Slight rise	Significant rise
Household annual income			*p=0.347*	*p=0.085*				
Less than 3 million yen	122	13.6	-808.0 (SD=3125.0)	0 (0.0%)	3 (2.5%)	50 (41.0%)	35 (28.7%)	34 (27.9%)
3-7 million yen	377	42.1	-886.4 (SD=2082.5)	0 (0.0%)	2 (0.5%)	128 (34.0%)	121 (32.1%)	126 (33.4%)
7 million yen or more	298	33.3	-950.5 (SD=1965.7)	1 (0.3%)	2 (0.7%)	100 (33.6%)	108 (36.2%)	87 (29.2%)
Unknown	99	11.0	-1079.9 (SD=2619.3)	0 (0.0%)	2 (2.0%)	43 (43.4%)	29 (29.3%)	25 (25.3%)
Living alone			*p=0.134*	*p=0.363*				
No	736	82.1	-856.5 (SD=2159.7)	1 (0.1%)	6 (0.8%)	267 (36.3%)	246 (33.4%)	216 (29.3%)
Yes	160	17.9	-1203.5 (SD=2739.1)	0 (0.0%)	3 (1.9%)	54 (33.8%)	47 (29.4%)	56 (35.0%)
Living with child(ren) under 18 years			*p<0.001*	*p=0.226*				
No	650	72.5	-1084.2 (SD=2295.6)	1 (0.2%)	7 (1.1%)	225 (34.6%)	213 (32.8%)	204 (31.4%)
Yes	246	27.5	-480.3 (SD=2168.3)	0 (0.0%)	2 (0.8%)	96 (39.0%)	80 (32.5%)	68 (27.6%)
Living with person(s) aged 65 years and older			*p=0.423*	*p=0.091*				
No	762	85.0	-942.0 (SD=2314.5)	1 (0.1%)	6 (0.8%)	268 (35.2%)	248 (32.5%)	239 (31.4%)
Yes	134	15.0	-784.7 (SD=2047.5)	0 (0.0%)	3 (2.2%)	53 (39.6%)	45 (33.6%)	33 (24.6%)
Neighborhood density			*p<0.001*	*p<0.001*				
Lowest density	218	24.3	-360.0 (SD=2117.8)	1 (0.5%)	1 (0.5%)	99 (45.4%)	66 (30.3%)	51 (23.4%)
Middle-low density	232	25.9	-506.8 (SD=2046.2)	0 (0.0%)	0 (0.0%)	87 (37.5%)	80 (34.5%)	65 (28.0%)
Middle-high density	229	25.6	-1029.4 (SD=2268.8)	0 (0.0%)	3 (1.3%)	81 (35.4%)	80 (34.9%)	65 (28.4%)
Highest density	217	24.2	-1802.4 (SD=2399.2)	0 (0.0%)	5 (2.3%)	54 (24.9%)	67 (30.9%)	91 (41.9%)

Table 4.1 (continued)

	n	%	Average change in step counts a)b)	Number of participants by change levels of sedentary behavior c)				
				Significant reduction	Slight reduction	No change	Slight rise	Significant rise
Areal deprivation index (ADI)			*p=0.002*	*p=0.019*				
Lowest ADI	224	25.0	-1118.2 (SD=2699.2)	1 (0.4%)	3 (1.3%)	75 (33.5%)	66 (29.5%)	79 (35.3%)
Middle-low ADI	224	25.0	-1278.3 (SD=2359.6)	0 (0.0%)	0 (0.0%)	66 (29.5%)	84 (37.5%)	74 (33.0%)
Middle-high ADI	224	25.0	-661.9 (SD=2055.4)	0 (0.0%)	2 (0.9%)	93 (41.5%)	71 (31.7%)	58 (25.9%)
Highest ADI	224	25.0	-615.3 (SD=1840.5)	0 (0.0%)	4 (1.8%)	87 (38.8%)	72 (32.1%)	61 (27.2%)
Introduction of work-from-home/standby-at-home			*p<0.001*	*p<0.001*				
No	595	66.4	-638.5 (SD=1996.7)	1 (0.2%)	5 (0.8%)	249 (41.8%)	193 (32.4%)	147 (24.7%)
Yes	301	33.6	-1471.8 (SD=2664.6)	0 (0.0%)	4 (1.3%)	72 (23.9%)	100 (33.2%)	125 (41.5%)
Decreased amount of work			*p=0.080*	*p<0.001*				
No	724	80.8	-849.8 (SD=2234.5)	1 (0.1%)	7 (1.0%)	284 (39.2%)	233 (32.2%)	199 (27.5%)
Yes	172	19.2	-1207.2 (SD=2429.5)	0 (0.0%)	2 (1.2%)	37 (21.5%)	60 (34.9%)	73 (42.4%)
Strong anxiety about getting infected			*p=0.806*	*p=0.002*				
No	613	68.4	-932.1 (SD=2112.0)	1 (0.2%)	6 (1.0%)	233 (38.0%)	209 (34.1%)	164 (26.8%)
Yes	283	31.6	-888.8 (SD=2600.3)	0 (0.0%)	3 (1.1%)	88 (31.1%)	84 (29.7%)	108 (38.2%)
Strong anxiety about spreading the infection to others			*p=0.499*	*p=0.002*				
No	668	74.6	-883.5 (SD=2063.6)	1 (0.1%)	6 (0.9%)	253 (37.9%)	226 (33.8%)	182 (27.2%)
Yes	228	25.4	-1020.8 (SD=2810.7)	0 (0.0%)	3 (1.3%)	68 (29.8%)	67 (29.4%)	90 (39.5%)
Strong anxiety about stigma associated with going out			*p=0.942*	*p<0.001*				
No	745	83.1	-915.2 (SD=2070.3)	1 (0.1%)	7 (0.9%)	280 (37.6%)	251 (33.7%)	206 (27.7%)
Yes	151	16.9	-934.4 (SD=3107.0)	0 (0.0%)	2 (1.3%)	41 (27.2%)	42 (27.8%)	66 (43.7%)

a) Changes in step counts were calculated by the differences in the mean step counts between the pre-SoE period (from February 19, 2020 to March 23, 2020) the post-SoE period (from April 16, 2020 to May 19, 2020).

[b] p for ANOVA or t-test

[c] p for Wilcoxon rank sum test or Kruskal-Wallis test

Table 4.2. Fit indices of each model

Model	**CFI**[a]	**RMSEA**[b]
A	0.064	0.753
B	0.996	0.057
C	0.913	0.364
D	0.995	0.124

[a] Comparative Fit Index

[b] Root Mean Square Error of Approximation

Table 4.2 summarizes the fit indices of each model based on path analysis. Judging from CFI and RMSEA, model B best explained the relationships among the demographic, socioeconomic, and geographic variables, changes in work situation, perception of anxiety, and changes in walking and sedentary behaviors (CFI = 0.996, RMSEA = 0.057).

Fig. 4.4 shows the significant paths in model B. Details of all the estimated coefficients of the models are provided in the appendix. Considering individual attributes and the changes in physical activity, respondents aged 20–29 years, aged 40–49 years, and living in the highest-density neighborhoods were more likely to experience reduced step counts. However, white-collar workers and living with child(ren) under 18 years were positively associated with differences in step counts and such individuals were less likely to experience reduced walking behavior. Moreover, females and workers in jobs other than white, gray, and blue-collar jobs or non-working participants were more likely to show increased sedentary behavior, while participants with household income less than 3 million yen were less likely to show increased sedentary behavior.

The work-from-home/standby-at-home group was positively associated with undergraduate/graduate school, and white-collar jobs, along with middle-low density, middle-high density, and highest density neighborhoods, while it was negatively associated with female respondents and the other jobs/not working group. Decreased amount of work was positively associated with an income of less than 3-million-yen group and negatively associated with the other jobs/not working group. The work-from-home/standby-at-home group and the decreased work group were associated with decreased step counts and increased time spent in sedentary behavior.

Female participants, age 30–39 years, and incomes less than 3 million yen were positively associated with strong anxiety about getting infected and about spreading the infection to others. Further, participants aged 20–29 years, aged 30–39 years, living with child(ren) under 18 years were positively associated with strong anxiety about the stigma of going out. Living in middle-low ADI were negatively associated with strong anxiety about spreading the infection to others and living in the highest density neighborhoods were negatively associated with the stigma of going out. Decreased step counts were associated with strong anxiety about spreading the infection to others or about the stigma of going out while increased time spent in sedentary behavior was associated with all anxiety variables.

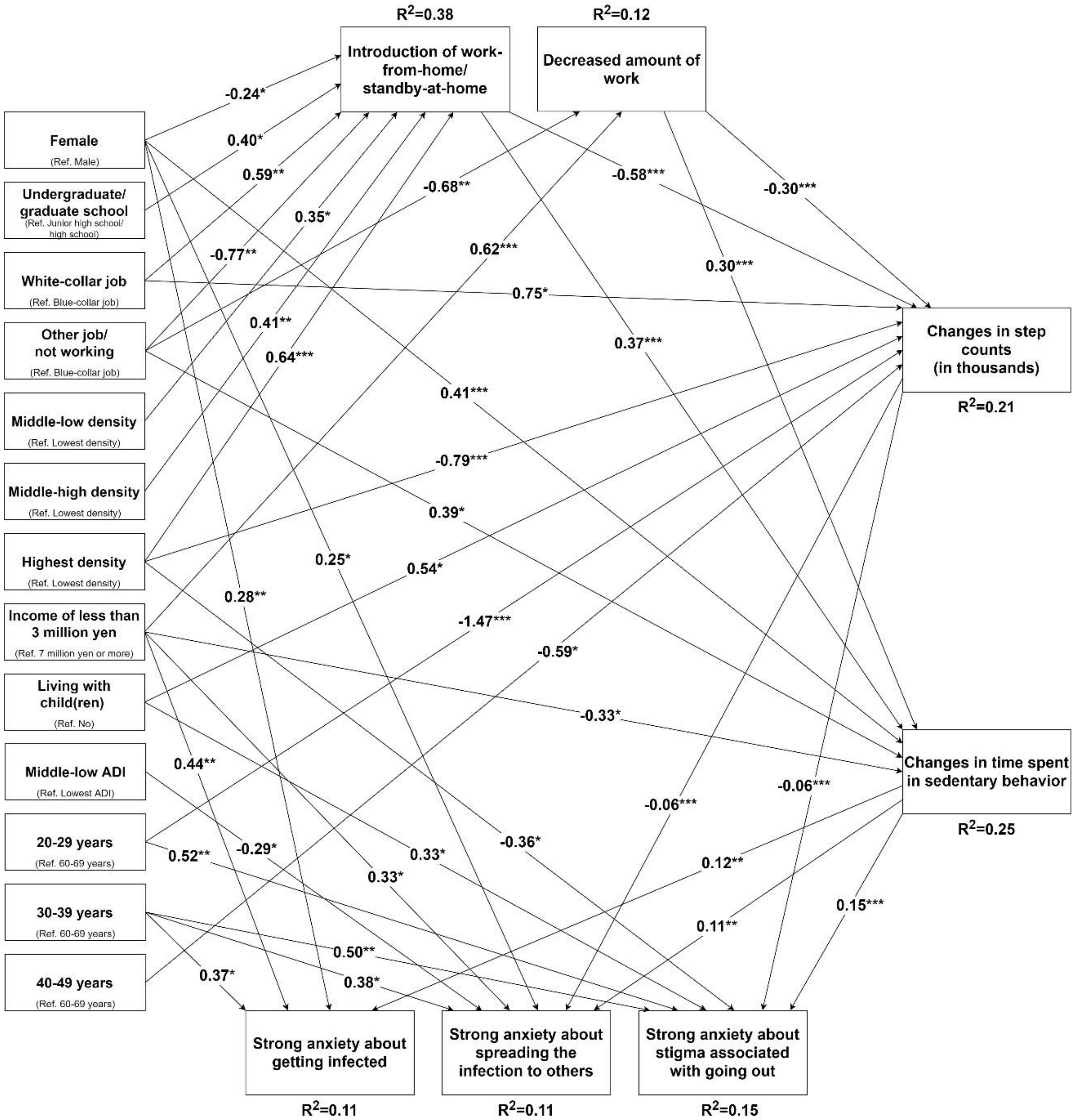


Fig. 4.4. Coefficients of model B estimated by path analysis.

Only significant paths and their coefficients among demographic, socioeconomic, and geographic variables, changes in work situation and perception of anxiety, and changes in walking and sedentary behaviors are shown.

*** statistical significance at 0.1%; ** statistical significance at 1%; * statistical significance at 5%.

CFI = 0.996, RMSEA = 0.057.

Changes in step counts were determined by calculating the difference in the mean step counts between the pre-state of emergency (SoE) period (from February 19, 2020 to March 23, 2020) and the post-SoE period (from April 16, 2020 to May 19, 2020). The ordered categories of change in time spent in sedentary behavior were defined as follows: 1: significant reduction, 2: slight reduction, 3: no change, 4: slight rise, 5: significant rise.

4.4 Discussion

Several studies have documented decreased physical activity during the COVID-19 outbreak in Japan (Adachi et al., 2021; Hino and Asami, 2021; Makizako et al., 2021; Yamada et al., 2020). However, to the best of our knowledge, this is the first study to examine the association of changes in physical activity during the COVID-19 outbreak in Japan with the demographic, socioeconomic, and geographical attributes, and changes in work situation and perception of anxiety, simultaneously.

We found that overall, people became inactive during the first wave of the outbreak; based on the direct relationships estimated by path analysis, especially younger individuals and those living in high-density neighborhoods were more likely have decreased walking behavior. Previous studies have shown a similar trend in outing and walking behaviors (Adachi et al., 2021; Hanibuchi et al., 2021; Hino and Asami, 2021), and this could be attributed to more walks for daily activities before the pandemic among younger individuals and residents in urban area, thereby resulting in a significant decrease in the number of steps. Additionally, sedentary behavior clearly increased among females, similar to previous reports that showed that females became inactive during the outbreak in Japan (Hanibuchi et al., 2021; Hino and Asami, 2021; Makizako et al., 2021). Containment measures such as school closure or self-isolation may have increased the burden of housework on females (Hanibuchi et al., 2021; Power, 2020), making them more inactive.

As for the indirect relationships between individual attributes and the changes in physical activity via changes in work situation, individuals of higher SES, such as undergraduate/graduate school graduates and white-collar job workers, were more likely to implement preventive measures like work-from-home or standby-at-home, which were associated with decreased step counts and increased sedentary behavior. This could be because of decreased walking needed for commuting. Moreover, those living in high-density neighborhoods were more likely to implement work-from-home or standby-at-home strategies. This is expected as companies not requiring on-site work, such as information technology companies, are normally located in urban areas. Moreover, it is suggested that those with incomes less than 3 million yen were more likely to experience decreased work causing decreased step counts and increased sedentary behavior. Therefore, individuals with lower SES were more likely to experience economic problems and decreased physical activity simultaneously. Previous studies have revealed that unemployment is often associated with deterioration of mental health (Paul and Moser, 2009) and increased smoking and drinking behaviors (Montgomery et al., 1998). Individuals with lower SES with decreased work would have particularly high health risks during the pandemic.

Our results showed that changes in physical activity were associated with perception of anxiety, similar to several previous studies (Pieh et al., 2020; Silva et al., 2020). The model assuming that decreased physical activity causes increased anxiety better explained the comprehensive relationships compared to the model assuming that anxiety causes physical inactivity or the models assuming direct relationships between the work situation changes and anxiety. Increased anxiety during the pandemic is a crucial concern as a previous study demonstrated that COVID-19 related anxiety was strongly associated with functional impairment, alcohol or drug coping, negative religious coping, extreme hopelessness, and passive suicidal ideation (Lee, 2020). Our path model showed that females, younger individuals, and those living in high-density neighborhoods were more likely to experience decreased physical activity associated with anxiety. During the pandemic in Japan, several studies reported an increase in the number of females committing suicide (Nomura et al., 2021; Tanaka and Okamoto, 2021) and high urbanization to be associated with severe psychological distress and new-onset suicidal ideation (Okubo et al., 2021). These indicated that decreased physical activity could be one of the factors affecting such serious mental health problems during the pandemic in Japan.

Furthermore, the variables of anxiety regarding spreading the infection to others and stigma associated with going out were related to decreased walking behavior while the variable of anxiety about getting infected was not. This may be because in Japanese society with tight social norms (Gelfand et al., 2021), people are more anxious about disrupting social harmony by spreading the infection or going out than about getting infected. Although Gelfand et al. (2021) suggested that tightening social norms may mitigate the COVID-19 outbreak, in strict societies, social isolation due to decrease in opportunities to go out would increase people's concerns about disturbing others or being criticized by others which may make people more inactive. Appropriate social norms should be considered based on overall health risks including infection, physical inactivity, and mental health.

This study has several limitations. First, the method of sample selection was not random, and the questionnaire has not been validated using external data; therefore, our findings are limited in their generalization. Second, a bias may have occurred due to the method of observation of walking behavior. Although we observed only the steps walked while the participants carried their iPhones, its frequency may vary according to personal attributes such as gender and age. We employed a simple method for quantitatively counting steps before the survey during the emergency; however, measurements by wearing an accelerometer at all times would have ideally reflected the changes in physical activity more accurately. Third, we attempted to explore the relationships between the changes in physical activity and individual attributes, the work situation changes, and perception of anxiety during the COVID-19 pandemic by comparing the path models based on several hypotheses; however, this cross-sectional study could not conclude the causality. To address these limitations, it is important to build an application for simultaneously observing step counts and location, and conducting a social survey for a larger scale and duration.

4.5 Conclusion

Physical inactivity during the COVID-19 pandemic is a serious concern causing various health problems. By examining the relationship of the changes in step count and time spent in sedentary behavior during the first wave of the outbreak in Japan to individual circumstances, the present study revealed that younger individuals, those living in high-density neighborhoods, and females were clearly associated with decreased walking behavior or increased sedentary behavior, and the changes in physical activity were associated with strong anxiety related to the pandemic. Further, while individuals with high SES were more likely to implement preventions such as work-from-home or standby-at-home, lower SES leads to decreased amounts of work, and both of those changes in work situation were related to decreased walking behavior and increased sedentary behavior. The health of people with low SES facing economic burden and females, younger individuals, and those living in urban areas who experience decreased physical activity should be continuously observed. Finally, considering that the pandemic is a changing, evolving situation, further analyses of changes in physical activity are warranted.

5. Discussions and conclusion

In the previous chapters, novel methods to evaluate the urban environment and mobility related to people's health by using spatial big data were discussed. The present chapter discusses the benefits of the proposed approach to health geography research, possibilities in future research, and the challenges of applying urban informatics in geographies of health.

5.1 Benefits of applying urban informatics to geographies of health

Table 5.1 summarizes the main results and benefits discussed in each chapter. A major benefit of urban informatics approaches to geographies of health is the ability to reduce data-dependent spatio-temporal limitations. This thesis demonstrated that streetscape imagery and mobile phone-based data can capture mobility and its related environment with detailed spatio-temporal resolution in a large area.

Miller (2017b) argues that the past failure of macro-geography which seeks general laws is due to poor computer technology and lack of data and that the current development of data-driven geography with big data obtained by ubiquitous and continuous systems will facilitate meso-geographical analysis. Miller (2017b) adds, meso-geography lies between descriptive micro-geography and macro-geography, assuming the existence of general laws but allowing for spatio-temporal specificity. That is, increased availability of detailed dynamic geographic information will allow generalizations about a phenomenon that includes specificity in different spaces and times, rather than generalizations based on one aspect at a specific point in time.

Table 5.1. Summary of main results

Chapter	Data	Resolution		Results	Benefits for geographies of health
		Spatial	Temporal		
2	Streetscape imagery	Micro	A few months to a few years	Developing an automatic evaluation method for the micro-scale environment related to mobility	Micro-scale environment evaluation in any location based on unified criteria
3	Mobile phone network	Micro	Continuous	Identifying places where mobility is particularly related to the COVID-19 infection	Dynamic observation of the human mobility related to the infection at near-real-time
4	Mobile phone data/Online survey	**Mobile phone data:** Does not include spatial information **Online survey:** Zip code	**Mobile phone data:** Continuous **Online survey:** Dependent on time of survey	Exploring social and geographic background of mobility changes during the COVID-19 pandemic	Understanding of social contexts behind human mobility changes at specific events

In case of the context of geographies of health, population density or accessibility to facilities, which can be measured in a wide area by statistical survey data and existing GIS data, were usually used to evaluate the objective walkability. This method enabled to generalize the relationship between neighborhood walkability and walking behavior from a macro perspective at a certain temporal point. However, it often excludes pedestrians' perceptual factors that may influence walking, such as safety and neighborhood aesthetics (Duncan et al., 2011). As a result, it is difficult to quantitatively evaluate the effects of the spatial specificity represented by minute environmental factors, that cannot be captured by density and accessibility, on walking. In addition, traditionally, since the evaluation of such micro-scale neighborhood environments required systematic observations or questionnaire surveys, it is difficult to evaluate consistently over a wide area.

The streetscape image evaluation using semantic segmentation and statistical approaches, as shown in Chapter 2, can strongly present a solution to this dilemma. Currently, streetscape imagery platforms, including Google Street View (GSV), cover a wide area of the world and enable to quantitatively evaluate streetscapes in any location based on unified criteria. Furthermore, observation of the neighborhood environment using streetscape images has been attempted in various micro-scale factors, including not only the aesthetics of the streetscape, but also safety (Wang et al., 2019b) and graffiti (Novack et al., 2020). In the future, it may be possible to cover a wider range of environmental factors related to perceptions of pedestrians. This technological progress will enable to build a model that includes spatial specificity that has been overlooked in conventional objective evaluations and to generalize how human mobility interacts with the macro-scale and the micro-scale factors based on observations in various locations.

In addition, ubiquitous and ongoing data flows have made it possible to observe dynamics that include temporal specificity, owing to events both mundane and unusual (Miller, 2017b). In Chapters 3 and 4, by using data obtained constantly from mobile phones, the dynamic examination of human mobility during specific events was demonstrated. If the data is obtained continuously, the methods can evaluate the impact of events on human mobility and health in near-real-time, regardless of the scale or type of event. Furthermore, most big data are suitable for observing changes over minutes, hours, or days, rather than years or decades (Batty, 2013), allowing studies in geographies of health to analyze data in unprecedented multi-temporal scales. Although not real-time data, GSV images can be used to observe the temporal changes in streetscapes, since they are updated at intervals of several months to several years in major urban areas. In the future, by using the dashboard camera data of taxis, buses, and emergency vehicles, the observation of streetscapes in near-real-time could be possible.

Since the dataset used in Chapter 4 is a small sample size compared to the typical data used in urban informatics and has spatio-temporal limitations, it may not be regarded as big data (Batty, 2013). However, the methodology, which combines the smartphone application and the Internet-based social survey, can be useful in supporting the understanding of the individual and geographical contexts behind human mobility changes in emergencies, and in implementing precise public health measures. In the future, research is expected to be extended to a large-scale with dynamic surveys by building applications that can simultaneously conduct social surveys with GPS-based locations and step observations.

The analysis of people's health and urban environment following the urban informatics approach will contribute greatly to public health measures in the future. Knowledge based on geographies of health and geographic information science has contributed to public health measures, and numerous studies on the health hazards caused by social inequalities and the appropriate allocation of health services have been conducted (Dummer, 2008; Rushton, 2003). However, the application of spatial big data will strongly help to implement appropriate policies in situations that require an immediate response. A good example of this is the mobile phone-based mobility analysis conducted by health geographers at the forefront of the COVID-19 response team in Japan (Ministry of Health, Labour and Welfare, 2020b). Furthermore, extensive unified retrospective environmental observations using big data allow the evaluation of the impact of policy interventions on people's health at a low cost and in a short period of time. The application of urban informatics may be effective in increasing the use of the health geographic approach in public health measures.

5.2 Future possibilities and research

The objective of urban informatics is to use systematic theories and methods based on new information technologies for analyzing urban systems and to apply them to improve urban design (Shi et al., 2021). That is, it is necessary to systematize the individual findings on urban phenomena obtained by big data analysis and reflect them in urban planning. The neighborhood environment evaluation and mobility observation based on spatial big data presented in this thesis, show independent results. However, the goal of this study is to further elaborate and systematize these research approaches, which results in developing a framework to support healthy urban planning. To develop this thesis's approach into a systematic urban environmental assessment, the possibilities of more detailed observations of environment and mobility and the development of the framework will be discussed in this section.

First, to implement a more detailed environmental assessment, future studies will need to increase the variety of micro-scale observation targets. Although the micro-scale evaluation model, as shown in Chapter 2, was developed based on the scores that integrated multiple aspects related to pedestrians' perceptions, it would also be necessary to individually evaluate the relationships between mobility and each environmental element such as safety and aesthetics. Furthermore, there are other micro-scale environment factors that cannot be measured by streetscape images but should be considered, such as air and noise pollution (Cerin et al., 2011; Howell et al., 2019; Saelens and Handy, 2008). It will also be necessary to adopt a citizen scientific approach (Silvertown, 2009) to enable high-resolution and dynamic measurement of these factors. For instance, Apte et al. (2017) have proposed a method for mapping the spatial distribution of air pollution at a 30 meters-scale, using vehicles with a fast-response pollution measurement platform, and stated that high spatial resolution and routine air pollution measurements could be possible by using taxis, delivery vehicles, and public transit. In addition, Ghosh et al. (2019) developed a mobile-phone-based participatory sensing system for measuring urban noise pollution. Similar approaches would be useful in solving the issues discussed in Chapter 4. To develop this area of study further, cooperation of the government and citizens will be essential.

Second, although Chapter 3 of the thesis indicates the observation of the mobility change, which was used hourly population in a 500-m-square grid based on mobile device locations, individual movement can be tracked in detail by using GPS-based location history. By combining detailed trajectories with the high-resolution environmental assessment described above, it is possible to measure the environmental elements people are exposed to during their movement. Furthermore, in recent years, the process of transportation mode estimation from GPS logs has been developing (Dabiri et al., 2020; Yang et al., 2018). The transportation mode is useful to assess detailed health benefits and risks based on the amount of physical activity, frequencies of exposure to noise and air pollution, and road traffic injury rates during travel (Apparicio et al., 2018; Woodcock et al., 2014). Future studies will need to apply these techniques to build a model to evaluate the effect of mobility on people's health from large-scale GPS data obtained in a large area.

Third, in addition to the detailed observation of mobility and environment using the urban informatics approach, future studies will also need to consider the development of a framework for the assessment of the healthy urban environment, by referring to the health impact assessment (HIA) (Centers for Disease Control and Prevention, 2016), which is a systematic method for assessing the impact of urban planning and policy intervention on health. The HIA process consists of the following steps (Centers for Disease Control and Prevention, 2016; National Research Council (US) Committee on Health Impact Assessment, 2011): "Screening" identifies whether HIA is useful for plans and policies; "Scoping" considers the possible benefits and health risks of plans and policies; "Assessment" identifies affected populations and quantifies the health impacts due to plans and policies; "Recommendations" suggests actions to promote positive health impacts and minimize negative impacts; "Reporting" presents the impact of plans or policies to decision-makers, communities, and other stakeholders; and "Monitoring and evaluation" tracks the implementation of plans and policies and evaluates the HIA itself and impact on health outcomes. In the past, HIA has been implemented to evaluate the health impacts of various plans and policies, such as programs to encourage children to walk to school and multimodal transportation systems, from both benefit and risk perspectives (Dannenberg et al., 2008).

Urban informatics techniques, such as big data analysis, simulation, Web and real-time GIS, and urban sensing, can be applied to the HIA process in health evaluation, planning, information disclosure, and monitoring after policy intervention. First, in the Assessment step based on the detailed observation and modeling described above, people's health in the current environment can be quantified. Although the relationship between human mobility and health is complex, Woodcock et al. (2014) quantitatively assessed the impact of introducing a bicycle sharing system on population health by calculating disability-adjusted life years (DALYs) (World Health Organization, 2013) based on physical activity, air pollution exposure, and road traffic injury. Similarly, future research should attempt to quantitatively evaluate the impact of mobility change on people's health by modeling the relationship between travel modes and associated health benefits and risks. Next, to consider the appropriate plans or policy interventions in the Recommendations step, simulation models can be used to predict the behavioral changes and health impacts due to them. Here, the application of microsimulation and agent-based models would be useful to simulate the interaction between individual mobility and the urban environment at a high-resolution spatial scale (Birkin, 2021; Crooks et al., 2021). In addition, Web GIS and real-time GIS technologies, which have developed remarkably in recent years, can strongly support information sharing in the Reporting step and allow continuous monitoring after the implementation of the planning and intervention during the Monitoring and evaluation step (Gong et al., 2015; Mbuh et al., 2020; Nourjou and Hashemipour, 2017). Applying the aforementioned steps, future study will build a systematic and circulative framework for healthy urban planning (Fig. 5.1). Furthermore, future study also aims at evolving the framework to a near-real-time observation and planning system (Silva et al., 2018), which would facilitate smart and healthy city management.

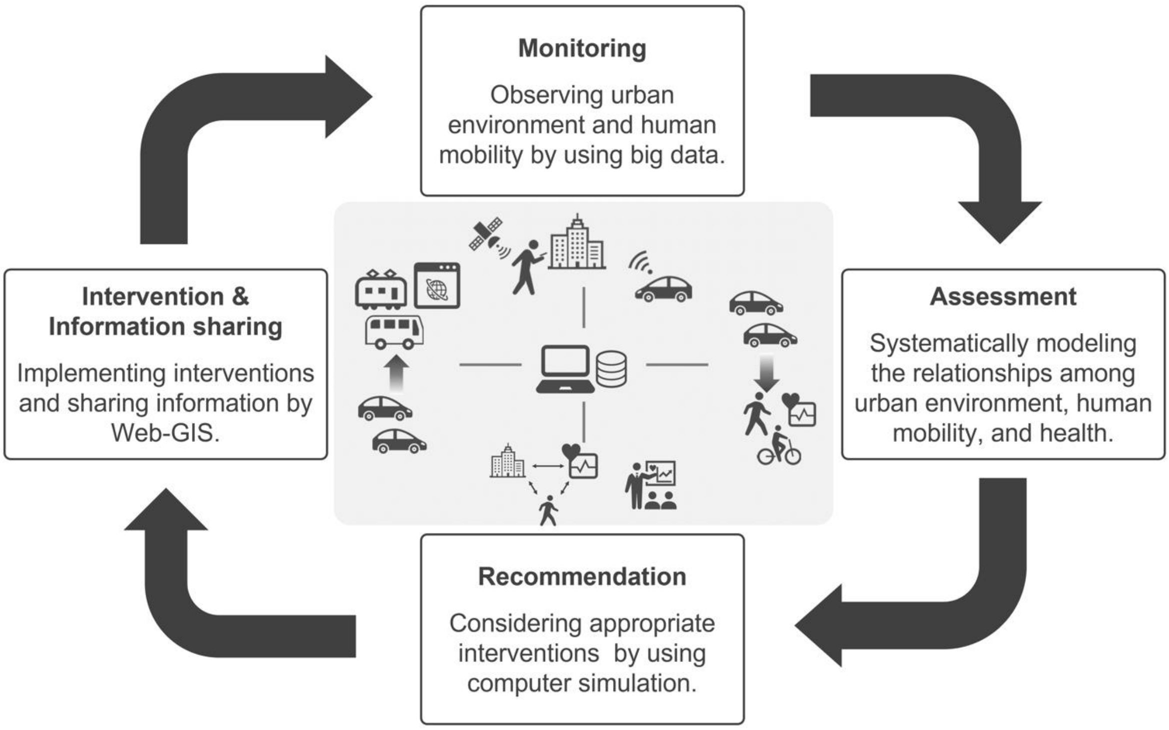


Fig. 5.1. Framework for healthy urban planning based on urban informatics

5.3 Challenges

Although the application of urban informatics will bring many benefits and possibilities to geographies of health, there are challenges that need to be discussed. The first is the issue of technical resources in the field of human geography. Kitchin (2013) argued that most scholars of human geography are largely underprepared for the big data era, although the ongoing data revolution requires a wider appreciation of the various emerging data sources and data types, as well as skills in coding, modeling, and simulation. Additionally, in Japan, given the situation that many laboratories of geography in universities are part of the faculty of letters (The Association of Japanese Geographers, 2021), many geographers may not be able to utilize the abundant computer resources for their research. In this situation, it is of course necessary to promote programming and computer science education in geography programs in universities (Bowlick et al., 2017), in addition to the conventional instructions for field observation and GIS techniques. However, it is not realistic to expect geographers to be responsible for all processes such as building databases to store continuously flowing big data, analyzing spatial laws, and applying the research results in urban planning. For incorporating urban informatics into geographic studies, it is necessary to establish an interdisciplinary research group with specialists in information science, urban planning, public health, and human geography, as well as industry–government–academia collaboration that includes private companies and local governments.

The second is the issue pertaining to the data and machine learning models. Since most of the big data employed for urban observation are accumulated by private companies for commercial purposes, the accuracy and representativeness of the data vary (Kitchin, 2020; Struijs et al., 2014). Therefore, the presence of bias in the data should always be considered. For instance, mobility observation using mobile phone data, as shown in Chapters 3 and 4, may include bias due to the frequencies of carrying the device and users' attributes. Furthermore, tracking data often have a limited demographic context (Kitchin, 2020). To address these biases and limitations, it is necessary to validate big data using public statistical data or survey data based on random sampling.

In addition, the availability of data is also biased. For instance, although GSV images enable the observation of cityscapes of any place in the world at a multi-scale time, its maintenance frequency and area vary by location and time (Cândido et al., 2018; Fry et al., 2020; Rzotkiewicz et al., 2018). Also, the deep learning model used for semantic segmentation, as shown in Chapter 2, was only trained on German cityscape images (Cordts et al., 2016) and cannot identify elements such as graffiti and garbage, which may influence pedestrians' perceptions. It is expected that such limitations due to availability will be relieved with the progress of technology; however, it should be noted that some places and perception-related factors are excluded from the analysis owing to the aforementioned issues in the current situation.

Furthermore, in the context of geographies of health, there is little high-resolution epidemiological data to compare with detailed mobility data. As shown in Chapter 3, the changes in mobility can be observed at high-resolution scales by using the mobile phone data and used in crisis response such as the COVID-19 pandemic. However, the public epidemiological data that correspond to the mobility changes are only available in coarse spatial units such as prefectures during the pandemic. To model how human mobility causes the spread of infections or contributes to human health in detail, it is necessary to increase the availability of high-resolution epidemiological data.

The third is that it is difficult to analyze complex urban phenomena with only quantitative approaches. This is the same as the criticism against positivist geography over the past several decades (Kitchin, 2020). Despite the application of big data, the generalization of urban systems eliminates diverse individuals and complex multi-dimensional social structures (Kitchin, 2020). As argued in this study, urban informatics provides a multi-scale spatio-temporal view of cities, enabling one to observe phenomena within cities from multiple angles. However, as described above, not everything in a city can be data-driven, and some aspects are still impossible to observe. It is necessary to take into account the lack of geographic or temporal objects due to data availability, or lack of cultural or social aspects due to overgeneralization. In addition, there is the concern that correlation is relied on, rather than causality, in a situation of massive data flow in real-time (Miller, 2018).

Although there are no easy solutions to urban problems, big data undoubtedly provide numerous opportunities to examine particular urban systems and issues, and urban science can provide useful insights into the same (Kitchin, 2020). O'Sullivan and Manson (2015) stated that many geographers are moving away from quantitative research when other fields are moving toward the analysis of the geographical topics by using quantitative approach. Additionally, they argued that unquestioningly importing methods from physics is problematic; however, applying quantitative analysis to geography is important (O'Sullivan and Manson, 2015). In this situation, exploring the geographical context behind the phenomenon and avoiding overgeneralization or over-abstraction of space is important for geographers to apply urban informatics (Derudder and van Meeteren, 2019; O'Sullivan and Manson, 2015). In geographies of health, rather than only observing the correlation between big-data-based mobility and health, it will be necessary to explore what environmental factors influence mobility and what social backgrounds make those environmental factors. In addition to big data analysis, traditional social surveys and qualitative approaches continue to play an important role in gaining a more precise and deeper understanding of the relationship between the urban environment and people's health (O'Sullivan and Manson, 2015).

The last is the issue of ethics. Urban informatics and the use of big data raise several ethical issues, which have received little consideration so far (Kitchin, 2020). In general, since much of the data used by researchers is provided by private companies with anonymization, it is difficult to identify individuals using specific data alone. However, combining multiple anonymized big data may make this possible (Herschel and Miori, 2017). In addition, although the applications that obtain people's location information usually seek consent for handling the personal information when users sign up, many do not read the full terms (Sabel et al., 2021). As a result, people may participate in studies without their knowledge and the results may be fed back into governments or private companies for decision-making, affecting people's lives (Kitchin, 2020; Sabel et al., 2021). Furthermore, since the results of big data analysis are often trusted despite their incompleteness and bias, there is a risk of inappropriate decision-making (Herschel and Miori, 2017). It is necessary to consider an appropriate balance between privacy protection and the wider availability of data (Sabel et al., 2021).

5.4 Final remarks

The present thesis attempted the application of urban informatics for enhancing geographies of health in the big data era. The results demonstrated that big data, deep learning, and statistical analysis techniques are useful in facilitating healthy cities and regions by enabling one to observe urban environments, mobility, and health at unprecedented spatio-temporal scales. It is still not enough to solve the complex urban mechanism in spite of the application of big data, and urban informatics would not replace the mainstream of geographic research. However, urban informatics will undoubtedly provide new insights on further understanding of the comprehensive and detailed relationship between the urban environment and people’s health, and will contribute to the progress of geographies of health.

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Appendix

Table A.1

Estimated coefficients of all paths to introduction of work-from-home/standby-at-home measures for model A

From	Coef.	95% CI	p
Gender (Ref. Male)			
Female	-0.24	-0.45 to -0.02	0.029*
Age (Ref. 60-69 years)			
20-29 years	0.05	-0.30 to 0.40	0.795
30-39 years	0.15	-0.18 to 0.49	0.363
40-49 years	0.28	-0.05 to 0.61	0.093
50-59 years	-0.04	-0.37 to 0.29	0.793
Chronic disease (Ref. No)			
Yes	-0.02	-0.28 to 0.23	0.856
Educational status (Ref. Junior high school/high school)			
Junior (technical) college/vocational school	0.28	-0.06 to 0.62	0.110
Undergraduate/graduate school	0.40	0.10 to 0.70	0.010*
Occupation (Ref. Blue-collar job)			
White-collar job	0.59	0.20 to 0.97	0.003**
Gray-collar job	0.24	-0.17 to 0.66	0.256
Other/not working	-0.77	-1.24 to -0.30	<0.001***
Household annual income (Ref. 7 million yen or more)			
Less than 3 million yen	-0.13	-0.48 to 0.22	0.458
3-7 million yen	-0.08	-0.32 to 0.15	0.489
Unknown	-0.09	-0.43 to 0.24	0.586
Living alone (Ref. No)			
Yes	0.16	-0.12 to 0.45	0.257
Living with child(ren) under 18 years (Ref. No)			
Yes	-0.15	-0.41 to 0.11	0.268
Living with person(s) aged 65 years and older (Ref. No)			
Yes	-0.10	-0.40 to 0.19	0.490
Neighborhood density (Ref. Lowest density)			
Middle-low density	0.35	0.07 to 0.64	0.016*
Middle-high density	0.41	0.13 to 0.69	0.004**
Highest density	0.64	0.34 to 0.94	<0.001***
Areal deprivation index (ADI) (Ref. Lowest ADI)			
Middle-low ADI	0.02	-0.26 to 0.29	0.901
Middle-high ADI	-0.12	-0.40 to 0.17	0.429
Highest ADI	-0.11	-0.41 to 0.18	0.463

* Coef.: Coefficient and CI: confidence interval. "***," "**," and "*," denote the statistical significance at 0.1%, 1%, and 5% levels, respectively. The sample size was 896.

Table A.2
Estimated coefficients of all paths to decreased amount of work for model A

From	Coef.	95% CI	p
Gender (Ref. Male)			
Female	0.09	-0.13 to 0.31	0.437
Age (Ref. 60-69 years)			
20-29 years	0.07	-0.30 to 0.43	0.723
30-39 years	0.09	-0.26 to 0.45	0.606
40-49 years	0.08	-0.27 to 0.43	0.653
50-59 years	0.05	-0.29 to 0.40	0.758
Chronic disease (Ref. No)			
Yes	0.00	-0.26 to 0.27	0.981
Educational status (Ref. Junior high school/high school)			
Junior (technical) college/vocational school	-0.01	-0.34 to 0.31	0.938
Undergraduate/graduate school	0.05	-0.24 to 0.33	0.757
Occupation (Ref. Blue-collar job)			
White-collar job	-0.18	-0.56 to 0.19	0.336
Gray-collar job	0.11	-0.29 to 0.50	0.599
Other/not working	-0.68	-1.09 to -0.27	0.001**
Household annual income (Ref. 7 million yen or more)			
Less than 3 million yen	0.62	0.27 to 0.96	<0.001***
3-7 million yen	0.22	-0.03 to 0.47	0.084
Unknown	0.08	-0.31 to 0.48	0.685
Living alone (Ref. No)			
Yes	0.11	-0.18 to 0.40	0.449
Living with child(ren) under 18 years (Ref. No)			
Yes	0.03	-0.24 to 0.31	0.813
Living with person(s) aged 65 years and older (Ref. No)			
Yes	0.01	-0.31 to 0.34	0.932
Neighborhood density (Ref. Lowest density)			
Middle-low density	-0.17	-0.47 to 0.13	0.274
Middle-high density	-0.03	-0.32 to 0.27	0.859
Highest density	0.19	-0.13 to 0.51	0.242
Areal deprivation index (ADI) (Ref. Lowest ADI)			
Middle-low ADI	0.29	-0.02 to 0.59	0.066
Middle-high ADI	0.25	-0.07 to 0.56	0.123
Highest ADI	0.25	-0.09 to 0.58	0.146

* Coef.: Coefficient and CI: confidence interval. "***," "**," and "*," denote the statistical significance at 0.1%, 1%, and 5% levels, respectively. The sample size was 896.

Table A.3
Estimated coefficients of all paths to strong anxiety about getting infected for model A

From	Coef.	95% CI	p
Gender (Ref. Male)			
Female	0.32	0.12 to 0.52	0.002**
Age (Ref. 60-69 years)			
20-29 years	0.03	-0.30 to 0.35	0.873
30-39 years	0.40	0.10 to 0.70	0.009**
40-49 years	0.28	-0.02 to 0.57	0.067
50-59 years	0.28	-0.01 to 0.57	0.057
Chronic disease (Ref. No)			
Yes	0.20	-0.01 to 0.41	0.065
Educational status (Ref. Junior high school/high school)			
Junior (technical) college/vocational school	0.13	-0.15 to 0.41	0.354
Undergraduate/graduate school	0.11	-0.14 to 0.36	0.399
Occupation (Ref. Blue-collar job)			
White-collar job	-0.02	-0.38 to 0.33	0.899
Gray-collar job	0.09	-0.29 to 0.48	0.638
Other/not working	0.06	-0.33 to 0.44	0.772
Household annual income (Ref. 7 million yen or more)			
Less than 3 million yen	0.42	0.10 to 0.73	0.010*
3-7 million yen	0.09	-0.13 to 0.31	0.420
Unknown	0.06	-0.27 to 0.38	0.726
Living alone (Ref. No)			
Yes	-0.19	-0.46 to 0.09	0.190
Living with child(ren) under 18 years (Ref. No)			
Yes	0.16	-0.08 to 0.40	0.187
Living with person(s) aged 65 years and older (Ref. No)			
Yes	-0.13	-0.41 to 0.14	0.347
Neighborhood density (Ref. Lowest density)			
Middle-low density	0.20	-0.05 to 0.46	0.112
Middle-high density	0.00	-0.26 to 0.26	0.990
Highest density	-0.02	-0.29 to 0.25	0.876
Areal deprivation index (ADI) (Ref. Lowest ADI)			
Middle-low ADI	-0.08	-0.33 to 0.18	0.551
Middle-high ADI	-0.01	-0.28 to 0.25	0.919
Highest ADI	-0.01	-0.27 to 0.26	0.956

* Coef.: Coefficient and CI: confidence interval. "***," "**," and "*," denote the statistical significance at 0.1%, 1%, and 5% levels, respectively. The sample size was 896.

Table A.4
Estimated coefficients of all paths to strong anxiety about spreading the infection to others for model A

From	Coef.	95% CI	p
Gender (Ref. Male)			
Female	0.30	0.09 to 0.50	0.005**
Age (Ref. 60-69 years)			
20-29 years	0.13	-0.20 to 0.46	0.445
30-39 years	0.42	0.10 to 0.74	0.009**
40-49 years	0.20	-0.12 to 0.51	0.227
50-59 years	0.15	-0.17 to 0.47	0.366
Chronic disease (Ref. No)			
Yes	0.18	-0.04 to 0.40	0.114
Educational status (Ref. Junior high school/high school)			
Junior (technical) college/vocational school	0.13	-0.16 to 0.42	0.377
Undergraduate/graduate school	0.15	-0.12 to 0.42	0.274
Occupation (Ref. Blue-collar job)			
White-collar job	-0.19	-0.56 to 0.18	0.320
Gray-collar job	0.01	-0.39 to 0.41	0.970
Other/not working	-0.04	-0.44 to 0.36	0.843
Household annual income (Ref. 7 million yen or more)			
Less than 3 million yen	0.30	-0.02 to 0.63	0.065
3-7 million yen	0.04	-0.19 to 0.28	0.722
Unknown	-0.05	-0.39 to 0.29	0.779
Living alone (Ref. No)			
Yes	-0.02	-0.30 to 0.27	0.915
Living with child(ren) under 18 years (Ref. No)			
Yes	0.07	-0.18 to 0.31	0.603
Living with person(s) aged 65 years and older (Ref. No)			
Yes	-0.16	-0.46 to 0.15	0.308
Neighborhood density (Ref. Lowest density)			
Middle-low density	0.18	-0.08 to 0.45	0.175
Middle-high density	0.04	-0.24 to 0.31	0.803
Highest density	-0.04	-0.34 to 0.25	0.766
Areal deprivation index (ADI) (Ref. Lowest ADI)			
Middle-low ADI	-0.26	-0.53 to 0.01	0.057
Middle-high ADI	-0.01	-0.29 to 0.26	0.920
Highest ADI	-0.07	-0.34 to 0.21	0.618

* Coef.: Coefficient and CI: confidence interval. "***," "**," and "*," denote the statistical significance at 0.1%, 1%, and 5% levels, respectively. The sample size was 896.

Table A.5

Estimated coefficients of all paths to strong anxiety about stigma associated with going out for model A

From	Coef.	95% CI	p
Gender (Ref. Male)			
Female	0.02	-0.23 to 0.27	0.896
Age (Ref. 60-69 years)			
20-29 years	0.66	0.28 to 1.04	<0.001***
30-39 years	0.54	0.17 to 0.92	0.004**
40-49 years	0.28	-0.11 to 0.67	0.154
50-59 years	0.35	-0.03 to 0.73	0.07
Chronic disease (Ref. No)			
Yes	0.17	-0.09 to 0.42	0.198
Educational status (Ref. Junior high school/high school)			
Junior (technical) college/vocational school	0.29	-0.04 to 0.62	0.080
Undergraduate/graduate school	0.03	-0.28 to 0.34	0.872
Occupation (Ref. Blue-collar job)			
White-collar job	-0.13	-0.53 to 0.26	0.511
Gray-collar job	-0.14	-0.56 to 0.28	0.517
Other/not working	-0.04	-0.47 to 0.38	0.839
Household annual income (Ref. 7 million yen or more)			
Less than 3 million yen	0.11	-0.26 to 0.47	0.560
3-7 million yen	-0.19	-0.45 to 0.08	0.166
Unknown	-0.12	-0.50 to 0.26	0.534
Living alone (Ref. No)			
Yes	0.17	-0.16 to 0.49	0.312
Living with child(ren) under 18 years (Ref. No)			
Yes	0.27	-0.01 to 0.55	0.055
Living with person(s) aged 65 years and older (Ref. No)			
Yes	-0.11	-0.45 to 0.22	0.506
Neighborhood density (Ref. Lowest density)			
Middle-low density	0.08	-0.21 to 0.38	0.589
Middle-high density	-0.08	-0.39 to 0.23	0.597
Highest density	-0.23	-0.56 to 0.10	0.172
Areal deprivation index (ADI) (Ref. Lowest ADI)			
Middle-low ADI	0.03	-0.28 to 0.35	0.840
Middle-high ADI	0.21	-0.10 to 0.52	0.190
Highest ADI	0.15	-0.16 to 0.47	0.340

* Coef.: Coefficient and CI: confidence interval. "***," "**," and "*," denote the statistical significance at 0.1%, 1%, and 5% levels, respectively. The sample size was 896.

Table A.6

Estimated coefficients of all paths to the changes in step counts (in thousands) between the pre-SoE and post-SoE periods for model A

From	Coef.	95% CI	p
Gender (Ref. Male)			
Female	0.04	-0.37 to 0.44	0.863
Age (Ref. 60-69 years)			
20-29 years	-1.23	-1.80 to -0.65	<0.001***
30-39 years	-0.03	-0.69 to 0.62	0.923
40-49 years	-0.44	-1.04 to 0.15	0.144
50-59 years	-0.15	-0.73 to 0.44	0.628
Chronic disease (Ref. No)			
Yes	0.08	-0.36 to 0.52	0.722
Educational status (Ref. Junior high school/high school)			
Junior (technical) college/vocational school	0.24	-0.39 to 0.86	0.457
Undergraduate/graduate school	-0.13	-0.69 to 0.43	0.648
Occupation (Ref. Blue-collar job)			
White-collar job	0.61	-0.01 to 1.23	0.054
Gray-collar job	0.31	-0.33 to 0.96	0.339
Other/not working	-0.10	-0.77 to 0.58	0.776
Household annual income (Ref. 7 million yen or more)			
Less than 3 million yen	0.27	-0.31 to 0.86	0.360
3-7 million yen	-0.03	-0.49 to 0.42	0.885
Unknown	-0.17	-0.77 to 0.42	0.571
Living alone (Ref. No)			
Yes	0.40	-0.10 to 0.91	0.119
Living with child(ren) under 18 years (Ref. No)			
Yes	0.69	0.18 to 1.19	0.008**
Living with person(s) aged 65 years and older (Ref. No)			
Yes	0.00	-0.56 to 0.57	0.988
Neighborhood density (Ref. Lowest density)			
Middle-low density	0.14	-0.36 to 0.64	0.596
Middle-high density	-0.41	-0.89 to 0.07	0.098
Highest density	-0.99	-1.47 to -0.50	<0.001***
Areal deprivation index (ADI) (Ref. Lowest ADI)			
Middle-low ADI	-0.35	-0.81 to 0.12	0.146
Middle-high ADI	0.14	-0.36 to 0.64	0.575
Highest ADI	0.19	-0.33 to 0.71	0.473

Table A.6 (continued)

From	Coef.	95% CI	p
Introduction of work-from-home/standby-at-home (Ref. No)			
Yes	-0.46	-0.59 to -0.33	<0.001***
Decreased amount of work (Ref. No)			
Yes	-0.14	-0.30 to 0.03	0.104
Strong anxiety about getting infected (Ref. No)			
Yes	-0.16	-0.28 to -0.03	0.014*
Strong anxiety about spreading the infection to others (Ref. No)			
Yes	-0.30	-0.40 to -0.21	<0.001***
Strong anxiety about stigma associated with going out (Ref. No)			
Yes	-0.33	-0.42 to -0.24	<0.001***

* Coef.: Coefficient and CI: confidence interval. "***," "**," and "*," denote the statistical significance at 0.1%, 1%, and 5% levels, respectively. The sample size was 896.

Table A.7
Estimated coefficients of all paths to the changes in time spent in sedentary behavior for model A

From	Coef.	95% CI	p
Gender (Ref. Male)			
Female	0.30	0.11 to 0.49	0.002**
Age (Ref. 60-69 years)			
20-29 years	0.10	-0.20 to 0.39	0.530
30-39 years	-0.22	-0.53 to 0.08	0.157
40-49 years	-0.12	-0.42 to 0.17	0.418
50-59 years	-0.21	-0.50 to 0.09	0.165
Chronic disease (Ref. No)			
Yes	0.00	-0.21 to 0.20	0.990
Educational status (Ref. Junior high school/high school)			
Junior (technical) college/vocational school	-0.12	-0.39 to 0.14	0.366
Undergraduate/graduate school	0.08	-0.17 to 0.32	0.544
Occupation (Ref. Blue-collar job)			
White-collar job	-0.18	-0.52 to 0.15	0.285
Gray-collar job	-0.15	-0.51 to 0.21	0.415
Other/not working	0.30	-0.06 to 0.67	0.105
Household annual income (Ref. 7 million yen or more)			
Less than 3 million yen	-0.44	-0.73 to -0.14	0.004**
3-7 million yen	0.07	-0.14 to 0.28	0.495
Unknown	-0.22	-0.52 to 0.08	0.157
Living alone (Ref. No)			
Yes	-0.14	-0.39 to 0.10	0.253
Living with child(ren) under 18 years (Ref. No)			
Yes	-0.19	-0.42 to 0.04	0.109
Living with person(s) aged 65 years and older (Ref. No)			
Yes	-0.01	-0.26 to 0.23	0.930
Neighborhood density (Ref. Lowest density)			
Middle-low density	0.02	-0.22 to 0.26	0.872
Middle-high density	0.03	-0.23 to 0.29	0.810
Highest density	0.18	-0.07 to 0.44	0.156
Areal deprivation index (ADI) (Ref. Lowest ADI)			
Middle-low ADI	0.11	-0.14 to 0.35	0.399
Middle-high ADI	-0.16	-0.41 to 0.08	0.198
Highest ADI	-0.12	-0.37 to 0.14	0.365

Table A.7 (continued)

From	Coef.	95% CI	p
Introduction of work-from-home/standby-at-home (Ref. No)			
Yes	0.30	0.22 to 0.38	<0.001***
Decreased amount of work (Ref. No)			
Yes	0.25	0.15 to 0.34	<0.001***
Strong anxiety about getting infected (Ref. No)			
Yes	0.15	0.06 to 0.24	<0.001***
Strong anxiety about spreading the infection to others (Ref. No)			
Yes	0.15	0.06 to 0.24	<0.001***
Strong anxiety about stigma associated with going out (Ref. No)			
Yes	0.21	0.12 to 0.31	<0.001***

* Coef.: Coefficient and CI: confidence interval. "***," "**," and "*," denote the statistical significance at 0.1%, 1%, and 5% levels, respectively. The sample size was 896. The ordered categories of change in time spent in sedentary behavior were defined as follows: 1: significant reduction, 2: slight reduction, 3: no change, 4: slight rise, 5: significant rise.

Table A.8
Estimated coefficients of all paths to introduction of work-from-home/standby-at-home measures for model B

From	Coef.	95% CI	p
Gender (Ref. Male)			
Female	-0.24	-0.45 to -0.02	0.029*
Age (Ref. 60-69 years)			
20-29 years	0.05	-0.30 to 0.40	0.796
30-39 years	0.15	-0.18 to 0.49	0.363
40-49 years	0.28	-0.05 to 0.61	0.093
50-59 years	-0.04	-0.37 to 0.29	0.793
Chronic disease (Ref. No)			
Yes	-0.02	-0.28 to 0.23	0.856
Educational attainment (Ref. Junior high school/high school)			
Junior (technical) college/vocational school	0.28	-0.06 to 0.62	0.11
Undergraduate/graduate school	0.40	0.10 to 0.70	0.01*
Occupation (Ref. Blue-collar job)			
White-collar job	0.59	0.20 to 0.97	0.003**
Gray-collar job	0.24	-0.17 to 0.66	0.256
Other/not working	-0.77	-1.24 to -0.30	0.001**
Household annual income (Ref. 7 million yen or more)			
Less than 3 million yen	-0.13	-0.48 to 0.22	0.458
3-7 million yen	-0.08	-0.32 to 0.15	0.489
Unknown	-0.09	-0.43 to 0.24	0.586
Living alone (Ref. No)			
Yes	0.16	-0.12 to 0.45	0.257
Living with child(ren) under 18 years (Ref. No)			
Yes	-0.15	-0.41 to 0.11	0.268
Living with person(s) aged 65 years and older (Ref. No)			
Yes	-0.10	-0.40 to 0.19	0.490
Neighborhood density (Ref. Lowest density)			
Middle-low density	0.35	0.07 to 0.64	0.016*
Middle-high density	0.41	0.13 to 0.69	0.004**
Highest density	0.64	0.34 to 0.94	<0.001***
Areal deprivation index (ADI) (Ref. Lowest ADI)			
Middle-low ADI	0.02	-0.26 to 0.29	0.901
Middle-high ADI	-0.12	-0.40 to 0.17	0.429
Highest ADI	-0.11	-0.41 to 0.18	0.463

* Coef.: Coefficient and CI: confidence interval. "***," "**," and "*," denote the statistical significance at 0.1%, 1%, and 5% levels, respectively. The sample size was 896.

Table A.9
Estimated coefficients of all paths to decreased amount of work for model B

From	Coef.	95% CI	p
Gender (Ref. Male)			
Female	0.09	-0.13 to 0.31	0.437
Age (Ref. 60-69 years)			
20-29 years	0.07	-0.30 to 0.43	0.723
30-39 years	0.09	-0.26 to 0.45	0.606
40-49 years	0.08	-0.27 to 0.43	0.653
50-59 years	0.05	-0.29 to 0.40	0.758
Chronic disease (Ref. No)			
Yes	0.00	-0.26 to 0.27	0.981
Educational attainment (Ref. Junior high school/high school)			
Junior (technical) college/vocational school	-0.01	-0.34 to 0.31	0.938
Undergraduate/graduate school	0.05	-0.24 to 0.33	0.757
Occupation (Ref. Blue-collar job)			
White-collar job	-0.18	-0.56 to 0.19	0.336
Gray-collar job	0.11	-0.29 to 0.50	0.599
Other/not working	-0.68	-1.09 to -0.27	0.001**
Household annual income (Ref. 7 million yen or more)			
Less than 3 million yen	0.62	0.27 to 0.96	<0.001***
3-7 million yen	0.22	-0.03 to 0.47	0.084
Unknown	0.08	-0.31 to 0.48	0.685
Living alone (Ref. No)			
Yes	0.11	-0.18 to 0.40	0.449
Living with child(ren) under 18 years (Ref. No)			
Yes	0.03	-0.24 to 0.31	0.813
Living with person(s) aged 65 years and older (Ref. No)			
Yes	0.01	-0.31 to 0.34	0.932
Neighborhood density (Ref. Lowest density)			
Middle-low density	-0.17	-0.47 to 0.13	0.274
Middle-high density	-0.03	-0.32 to 0.27	0.859
Highest density	0.19	-0.13 to 0.51	0.242
Areal deprivation index (ADI) (Ref. Lowest ADI)			
Middle-low ADI	0.29	-0.02 to 0.59	0.066
Middle-high ADI	0.25	-0.07 to 0.56	0.123
Highest ADI	0.25	-0.09 to 0.58	0.146

* Coef.: Coefficient and CI: confidence interval. "***," "**," and "*," denote the statistical significance at 0.1%, 1%, and 5% levels, respectively. The sample size was 896.

Table A.10
Estimated coefficients of all paths to the changes in step counts (in thousands) between the pre-SoE and post-SoE periods for model B

From	Coef.	95% CI	p
Gender (Ref. Male)			
Female	-0.12	-0.50 to 0.25	0.521
Age (Ref. 60-69 years)			
20-29 years	-1.47	-2.00 to -0.94	<0.001***
30-39 years	-0.37	-0.99 to 0.25	0.246
40-49 years	-0.59	-1.17 to -0.02	0.043*
50-59 years	-0.35	-0.92 to 0.22	0.234
Chronic disease (Ref. No)			
Yes	-0.06	-0.49 to 0.36	0.773
Educational attainment (Ref. Junior high school/high school)			
Junior (technical) college/vocational school	0.11	-0.49 to 0.71	0.721
Undergraduate/graduate school	-0.15	-0.69 to 0.39	0.589
Occupation (Ref. Blue-collar job)			
White-collar job	0.75	0.17 to 1.33	0.012*
Gray-collar job	0.39	-0.20 to 0.98	0.196
Other/not working	-0.28	-0.93 to 0.37	0.397
Household annual income (Ref. 7 million yen or more)			
Less than 3 million yen	0.17	-0.38 to 0.71	0.551
3-7 million yen	0.03	-0.41 to 0.47	0.903
Unknown	-0.12	-0.70 to 0.45	0.673
Living alone (Ref. No)			
Yes	0.42	-0.06 to 0.89	0.086
Living with child(ren) under 18 years (Ref. No)			
Yes	0.54	0.05 to 1.03	0.030*
Living with person(s) aged 65 years and older (Ref. No)			
Yes	0.10	-0.45 to 0.65	0.718
Neighborhood density (Ref. Lowest density)			
Middle-low density	0.03	-0.44 to 0.51	0.889
Middle-high density	-0.35	-0.83 to 0.13	0.157
Highest density	-0.79	-1.25 to -0.32	<0.001***
Areal deprivation index (ADI) (Ref. Lowest ADI)			
Middle-low ADI	-0.22	-0.67 to 0.24	0.354
Middle-high ADI	0.11	-0.38 to 0.60	0.664
Highest ADI	0.19	-0.31 to 0.69	0.459

Table A.10 (continued)

From	Coef.	95% CI	p
Introduction of working-from-home/standby at home (Ref. No)			
Yes	-0.58	-0.71 to -0.45	<0.001***
Decreased amount of work (Ref. No)			
Yes	-0.30	-0.46 to -0.14	<0.001***

* Coef.: Coefficient and CI: confidence interval. "***," "**," and "*," denote the statistical significance at 0.1%, 1%, and 5% levels, respectively. The sample size was 896.

Table A.11
Estimated coefficients of all paths to the changes in time spent in sedentary behavior for model B

From	Coef.	95% CI	p
Gender (Ref. Male)			
Female	0.41	0.24 to 0.58	<0.001***
Age (Ref. 60-69 years)			
20-29 years	0.25	-0.03 to 0.53	0.075
30-39 years	0.01	-0.27 to 0.28	0.968
40-49 years	-0.01	-0.30 to 0.27	0.920
50-59 years	-0.07	-0.33 to 0.20	0.629
Chronic disease (Ref. No)			
Yes	0.09	-0.10 to 0.29	0.347
Educational attainment (Ref. Junior high school/high school)			
Junior (technical) college/vocational school	-0.04	-0.29 to 0.21	0.760
Undergraduate/graduate school	0.09	-0.15 to 0.33	0.462
Occupation (Ref. Blue-collar job)			
White-collar job	-0.28	-0.60 to 0.05	0.099
Gray-collar job	-0.19	-0.52 to 0.15	0.282
Other/not working	0.39	0.03 to 0.75	0.033*
Household annual income (Ref. 7 million yen or more)			
Less than 3 million yen	-0.33	-0.60 to -0.06	0.019*
3-7 million yen	0.05	-0.15 to 0.24	0.645
Unknown	-0.24	-0.53 to 0.05	0.105
Living alone (Ref. No)			
Yes	-0.16	-0.39 to 0.07	0.183
Living with child(ren) under 18 years (Ref. No)			
Yes	-0.09	-0.31 to 0.13	0.429
Living with person(s) aged 65 years and older (Ref. No)			
Yes	-0.07	-0.30 to 0.15	0.521
Neighborhood density (Ref. Lowest density)			
Middle-low density	0.08	-0.16 to 0.32	0.503
Middle-high density	0.00	-0.25 to 0.23	0.941
Highest density	0.07	-0.17 to 0.31	0.579
Areal deprivation index (ADI) (Ref. Lowest ADI)			
Middle-low ADI	0.04	-0.19 to 0.27	0.714
Middle-high ADI	-0.13	-0.36 to 0.10	0.278
Highest ADI	-0.10	-0.34 to 0.13	0.389

Table A.11 (continued)

From	Coef.	95% CI	p
Introduction of working-from-home/standby at home (Ref. No)			
Yes	0.37	0.29 to 0.45	<0.001***
Decreased amount of work (Ref. No)			
Yes	0.30	0.21 to 0.40	<0.001***

* Coef.: Coefficient and CI: confidence interval. "***," "**," and "*," denote the statistical significance at 0.1%, 1%, and 5% levels, respectively. The sample size was 896. The ordered categories of change in time spent in sedentary behavior were defined as follows: 1: significant reduction, 2: slight reduction, 3: no change, 4: slight rise, 5: significant rise.

Table A.12
Estimated coefficients of all paths to strong anxiety about getting infected for model B

From	Coef.	95% CI	p
Gender (Ref. Male)			
Female	0.28	0.08 to 0.48	0.007**
Age (Ref. 60-69 years)			
20-29 years	-0.05	-0.38 to 0.28	0.761
30-39 years	0.37	0.08 to 0.67	0.013*
40-49 years	0.24	-0.05 to 0.53	0.107
50-59 years	0.28	-0.01 to 0.57	0.057
Chronic disease (Ref. No)			
Yes	0.19	-0.02 to 0.40	0.080
Educational attainment (Ref. Junior high school/high school)			
Junior (technical) college/vocational school	0.12	-0.15 to 0.40	0.388
Undergraduate/graduate school	0.07	-0.18 to 0.31	0.605
Occupation (Ref. Blue-collar job)			
White-collar job	0.00	-0.35 to 0.36	0.985
Gray-collar job	0.11	-0.28 to 0.49	0.589
Other/not working	0.08	-0.30 to 0.46	0.683
Household annual income (Ref. 7 million yen or more)			
Less than 3 million yen	0.44	0.12 to 0.76	0.006**
3-7 million yen	0.08	-0.14 to 0.30	0.471
Unknown	0.09	-0.23 to 0.41	0.597
Living alone (Ref. No)			
Yes	-0.17	-0.45 to 0.11	0.232
Living with child(ren) under 18 years (Ref. No)			
Yes	0.19	-0.04 to 0.43	0.108
Living with person(s) aged 65 years and older (Ref. No)			
Yes	-0.11	-0.39 to 0.16	0.409
Neighborhood density (Ref. Lowest density)			
Middle-low density	0.18	-0.07 to 0.43	0.155
Middle-high density	-0.03	-0.29 to 0.22	0.793
Highest density	-0.10	-0.37 to 0.17	0.470
Areal deprivation index (ADI) (Ref. Lowest ADI)			
Middle-low ADI	-0.10	-0.36 to 0.15	0.429
Middle-high ADI	0.00	-0.26 to 0.26	0.994
Highest ADI	0.01	-0.26 to 0.27	0.964

Table A.12 (continued)

From	Coef.	95% CI	p
Changes in step counts (in thousands) between the pre-SoE and the post-SoE periods	-0.03	-0.05 to 0.00	0.052
Changes in time spent sedentary behavior during the COVID-19 outbreak	0.12	0.05 to 0.20	0.001**

* Coef.: Coefficient and CI: confidence interval. "***," "**," and "*," denote the statistical significance at 0.1%, 1%, and 5% levels, respectively. The sample size was 896.

Table A.13
Estimated coefficients of all paths to strong anxiety about spreading the infection to others for model B

From	Coef.	95% CI	p
Gender (Ref. Male)			
Female	0.25	0.05 to 0.46	0.017*
Age (Ref. 60-69 years)			
20-29 years	0.01	-0.33 to 0.34	0.965
30-39 years	0.38	0.07 to 0.70	0.018*
40-49 years	0.14	-0.18 to 0.45	0.394
50-59 years	0.13	-0.18 to 0.45	0.409
Chronic disease (Ref. No)			
Yes	0.17	-0.05 to 0.39	0.137
Educational attainment (Ref. Junior high school/high school)			
Junior (technical) college/vocational school	0.12	-0.17 to 0.41	0.411
Undergraduate/graduate school	0.10	-0.17 to 0.36	0.47
Occupation (Ref. Blue-collar job)			
White-collar job	-0.15	-0.52 to 0.22	0.426
Gray-collar job	0.03	-0.37 to 0.43	0.891
Other/not working	-0.01	-0.40 to 0.38	0.973
Household annual income (Ref. 7 million yen or more)			
Less than 3 million yen	0.33	0.01 to 0.65	0.044*
3-7 million yen	0.03	-0.20 to 0.27	0.776
Unknown	-0.03	-0.36 to 0.31	0.879
Living alone (Ref. No)			
Yes	0.01	-0.27 to 0.29	0.950
Living with child(ren) under 18 years (Ref. No)			
Yes	0.12	-0.13 to 0.36	0.353
Living with person(s) aged 65 years and older (Ref. No)			
Yes	-0.14	-0.44 to 0.16	0.374
Neighborhood density (Ref. Lowest density)			
Middle-low density	0.16	-0.10 to 0.42	0.238
Middle-high density	-0.01	-0.29 to 0.26	0.919
Highest density	-0.16	-0.45 to 0.14	0.291
Areal deprivation index (ADI) (Ref. Lowest ADI)			
Middle-low ADI	-0.29	-0.56 to -0.03	0.031*
Middle-high ADI	0.01	-0.27 to 0.28	0.985
Highest ADI	-0.05	-0.33 to 0.22	0.715

Table A.13 (continued)

From	Coef.	95% CI	p
Changes in step counts (in thousands) between the pre-SoE and the post-SoE periods	-0.06	-0.08 to -0.04	<0.001***
Changes in time spent sedentary behavior during the COVID-19 outbreak	0.11	0.04 to 0.19	0.004**

* Coef.: Coefficient and CI: confidence interval. “***,” “**,” and “*,” denote the statistical significance at 0.1%, 1%, and 5% levels, respectively. The sample size was 896.

Table A.14
Estimated coefficients of all paths to strong anxiety about stigma associated with going out for model B

From	Coef.	95% CI	p
Gender (Ref. Male)			
Female	-0.04	-0.29 to 0.21	0.772
Age (Ref. 60-69 years)			
20-29 years	0.52	0.14 to 0.90	0.007**
30-39 years	0.50	0.13 to 0.87	0.008**
40-49 years	0.22	-0.17 to 0.61	0.270
50-59 years	0.34	-0.04 to 0.72	0.078
Chronic disease (Ref. No)			
Yes	0.15	-0.10 to 0.40	0.239
Educational attainment (Ref. Junior high school/high school)			
Junior (technical) college/vocational school	0.28	-0.05 to 0.61	0.096
Undergraduate/graduate school	-0.04	-0.35 to 0.27	0.814
Occupation (Ref. Blue-collar job)			
White-collar job	-0.09	-0.48 to 0.30	0.660
Gray-collar job	-0.12	-0.53 to 0.30	0.585
Other/not working	-0.01	-0.42 to 0.41	0.979
Household annual income (Ref. 7 million yen or more)			
Less than 3 million yen	0.14	-0.23 to 0.51	0.450
3-7 million yen	-0.20	-0.46 to 0.07	0.139
Unknown	-0.09	-0.47 to 0.29	0.647
Living alone (Ref. No)			
Yes	0.20	-0.13 to 0.52	0.236
Living with child(ren) under 18 years (Ref. No)			
Yes	0.33	0.05 to 0.61	0.020*
Living with person(s) aged 65 years and older (Ref. No)			
Yes	-0.09	-0.42 to 0.25	0.605
Neighborhood density (Ref. Lowest density)			
Middle-low density	0.05	-0.24 to 0.34	0.741
Middle-high density	-0.14	-0.45 to 0.17	0.369
Highest density	-0.36	-0.69 to -0.04	0.030*
Areal deprivation index (ADI) (Ref. Lowest ADI)			
Middle-low ADI	-0.01	-0.32 to 0.31	0.963
Middle-high ADI	0.23	-0.08 to 0.54	0.145
Highest ADI	0.17	-0.14 to 0.49	0.278

Table A.14 (continued)

From	Coef.	95% CI	p
Changes in step counts (in thousands) between the pre-SoE and the post-SoE periods	-0.06	-0.08 to -0.04	<0.001***
Changes in time spent sedentary behavior during the COVID-19 outbreak	0.15	0.07 to 0.23	<0.001***

* Coef.: Coefficient and CI: confidence interval. “***,” “**,” and “*,” denote the statistical significance at 0.1%, 1%, and 5% levels, respectively. The sample size was 896.

Table A.15
Estimated coefficients of all paths to introduction of work-from-home/standby-at-home measures for model C

From	Coef.	95% CI	p
Gender (Ref. Male)			
Female	-0.24	-0.45 to -0.02	0.029*
Age (Ref. 60-69 years)			
20-29 years	0.05	-0.30 to 0.40	0.796
30-39 years	0.15	-0.18 to 0.49	0.363
40-49 years	0.28	-0.05 to 0.61	0.093
50-59 years	-0.04	-0.37 to 0.29	0.793
Chronic disease (Ref. No)			
Yes	-0.02	-0.28 to 0.23	0.856
Educational attainment (Ref. Junior high school/high school)			
Junior (technical) college/vocational school	0.28	-0.06 to 0.62	0.110
Undergraduate/graduate school	0.40	0.10 to 0.70	0.010*
Occupation (Ref. Blue-collar job)			
White-collar job	0.59	0.20 to 0.97	0.003**
Gray-collar job	0.24	-0.17 to 0.66	0.256
Other/not working	-0.77	-1.24 to -0.30	0.001**
Household annual income (Ref. 7 million yen or more)			
Less than 3 million yen	-0.13	-0.48 to 0.22	0.458
3-7 million yen	-0.08	-0.32 to 0.15	0.489
Unknown	-0.09	-0.43 to 0.24	0.586
Living alone (Ref. No)			
Yes	0.16	-0.12 to 0.45	0.258
Living with child(ren) under 18 years (Ref. No)			
Yes	-0.15	-0.41 to 0.11	0.268
Living with person(s) aged 65 years and older (Ref. No)			
Yes	-0.10	-0.40 to 0.19	0.490
Neighborhood density (Ref. Lowest density)			
Middle-low density	0.35	0.07 to 0.64	0.016*
Middle-high density	0.41	0.13 to 0.69	0.004**
Highest density	0.64	0.34 to 0.94	<0.001***
Areal deprivation index (ADI) (Ref. Lowest ADI)			
Middle-low ADI	0.02	-0.26 to 0.29	0.901
Middle-high ADI	-0.12	-0.40 to 0.17	0.429
Highest ADI	-0.11	-0.41 to 0.18	0.463

* Coef.: Coefficient and CI: confidence interval. "***," "**," and "*," denote the statistical significance at 0.1%, 1%, and 5% levels, respectively. The sample size was 896.

Table A.16
Estimated coefficients of all paths to decreased amount of work for model C

From	Coef.	95% CI	p
Gender (Ref. Male)			
Female	0.09	-0.13 to 0.31	0.437
Age (Ref. 60-69 years)			
20-29 years	0.07	-0.30 to 0.43	0.723
30-39 years	0.09	-0.26 to 0.45	0.606
40-49 years	0.08	-0.27 to 0.43	0.653
50-59 years	0.05	-0.29 to 0.40	0.758
Chronic disease (Ref. No)			
Yes	0.00	-0.26 to 0.27	0.981
Educational attainment (Ref. Junior high school/high school)			
Junior (technical) college/vocational school	-0.01	-0.34 to 0.31	0.938
Undergraduate/graduate school	0.05	-0.24 to 0.33	0.757
Occupation (Ref. Blue-collar job)			
White-collar job	-0.18	-0.56 to 0.19	0.335
Gray-collar job	0.11	-0.29 to 0.50	0.599
Other/not working	-0.68	-1.09 to -0.27	0.001**
Household annual income (Ref. 7 million yen or more)			
Less than 3 million yen	0.62	0.27 to 0.96	<0.001***
3-7 million yen	0.22	-0.03 to 0.47	0.084
Unknown	0.08	-0.31 to 0.48	0.685
Living alone (Ref. No)			
Yes	0.11	-0.18 to 0.40	0.449
Living with child(ren) under 18 years (Ref. No)			
Yes	0.03	-0.24 to 0.31	0.813
Living with person(s) aged 65 years and older (Ref. No)			
Yes	0.01	-0.31 to 0.34	0.932
Neighborhood density (Ref. Lowest density)			
Middle-low density	-0.17	-0.47 to 0.13	0.274
Middle-high density	-0.03	-0.32 to 0.27	0.859
Highest density	0.19	-0.13 to 0.51	0.242
Areal deprivation index (ADI) (Ref. Lowest ADI)			
Middle-low ADI	0.29	-0.02 to 0.59	0.066
Middle-high ADI	0.25	-0.07 to 0.56	0.123
Highest ADI	0.25	-0.09 to 0.58	0.146

* Coef.: Coefficient and CI: confidence interval. “***,” “**,” and “*,” denote the statistical significance at 0.1%, 1%, and 5% levels, respectively. The sample size was 896.

Table A.17
Estimated coefficients of all paths to strong anxiety about getting infected for model C

From	Coef.	95% CI	p
Gender (Ref. Male)			
Female	0.40	0.13 to 0.67	0.003**
Age (Ref. 60-69 years)			
20-29 years	-0.05	-0.52 to 0.42	0.837
30-39 years	0.24	-0.19 to 0.67	0.276
40-49 years	0.05	-0.37 to 0.46	0.820
50-59 years	0.27	-0.16 to 0.70	0.213
Chronic disease (Ref. No)			
Yes	0.21	-0.08 to 0.51	0.160
Educational attainment (Ref. Junior high school/high school)			
Junior (technical) college/vocational school	-0.03	-0.43 to 0.37	0.889
Undergraduate/graduate school	-0.17	-0.51 to 0.17	0.330
Occupation (Ref. Blue-collar job)			
White-collar job	-0.25	-0.73 to 0.24	0.319
Gray-collar job	-0.13	-0.65 to 0.39	0.629
Other/not working	1.01	0.49 to 1.54	<0.001***
Household annual income (Ref. 7 million yen or more)			
Less than 3 million yen	0.05	-0.40 to 0.50	0.818
3-7 million yen	-0.02	-0.33 to 0.30	0.917
Unknown	0.06	-0.40 to 0.51	0.81
Living alone (Ref. No)			
Yes	-0.37	-0.74 to 0.01	0.057
Living with child(ren) under 18 years (Ref. No)			
Yes	0.23	-0.10 to 0.55	0.172
Living with person(s) aged 65 years and older (Ref. No)			
Yes	-0.08	-0.46 to 0.30	0.684
Neighborhood density (Ref. Lowest density)			
Middle-low density	0.11	-0.25 to 0.47	0.545
Middle-high density	-0.23	-0.60 to 0.13	0.214
Highest density	-0.55	-0.92 to -0.17	0.004**
Areal deprivation index (ADI) (Ref. Lowest ADI)			
Middle-low ADI	-0.30	-0.65 to 0.05	0.097
Middle-high ADI	-0.12	-0.48 to 0.24	0.512
Highest ADI	-0.12	-0.50 to 0.26	0.545

Table A.17 (continued)

From	Coef.	95% CI	p
Introduction of working-from-home/standby at home (Ref. No)			
Yes	0.61	0.51 to 0.70	<0.001***
Decreased amount of work (Ref. No)			
Yes	0.72	0.63 to 0.80	<0.001***

* Coef.: Coefficient and CI: confidence interval. “***,” “**,” and “*,” denote the statistical significance at 0.1%, 1%, and 5% levels, respectively. The sample size was 896.

Table A.18
Estimated coefficients of all paths to strong anxiety about spreading the infection to others for model C

From	Coef.	95% CI	p
Gender (Ref. Male)			
Female	0.38	0.11 to 0.65	0.006**
Age (Ref. 60-69 years)			
20-29 years	0.06	-0.40 to 0.52	0.815
30-39 years	0.26	-0.17 to 0.69	0.239
40-49 years	-0.03	-0.47 to 0.40	0.880
50-59 years	0.14	-0.31 to 0.58	0.548
Chronic disease (Ref. No)			
Yes	0.19	-0.11 to 0.50	0.218
Educational attainment (Ref. Junior high school/high school)			
Junior (technical) college/vocational school	-0.03	-0.44 to 0.38	0.881
Undergraduate/graduate school	-0.13	-0.48 to 0.22	0.468
Occupation (Ref. Blue-collar job)			
White-collar job	-0.42	-0.90 to 0.05	0.082
Gray-collar job	-0.21	-0.72 to 0.29	0.408
Other/not working	0.91	0.39 to 1.44	<0.001***
Household annual income (Ref. 7 million yen or more)			
Less than 3 million yen	-0.05	-0.51 to 0.41	0.830
3-7 million yen	-0.06	-0.38 to 0.26	0.710
Unknown	-0.05	-0.53 to 0.43	0.841
Living alone (Ref. No)			
Yes	-0.19	-0.56 to 0.17	0.299
Living with child(ren) under 18 years (Ref. No)			
Yes	0.13	-0.20 to 0.47	0.442
Living with person(s) aged 65 years and older (Ref. No)			
Yes	-0.10	-0.49 to 0.29	0.602
Neighborhood density (Ref. Lowest density)			
Middle-low density	0.08	-0.29 to 0.46	0.660
Middle-high density	-0.20	-0.57 to 0.17	0.288
Highest density	-0.57	-0.96 to -0.19	0.003**
Areal deprivation index (ADI) (Ref. Lowest ADI)			
Middle-low ADI	-0.47	-0.83 to -0.12	0.009**
Middle-high ADI	-0.12	-0.49 to 0.25	0.535
Highest ADI	-0.18	-0.57 to 0.22	0.379

Table A.18 (continued)

From	Coef.	95% CI	p
Introduction of working-from-home/standby at home (Ref. No)			
Yes	0.62	0.52 to 0.71	<0.001***
Decreased amount of work (Ref. No)			
Yes	0.70	0.62 to 0.79	<0.001***

* Coef.: Coefficient and CI: confidence interval. "***," "**," and "*," denote the statistical significance at 0.1%, 1%, and 5% levels, respectively. The sample size was 896.

Table A.19

Estimated coefficients of all paths to strong anxiety about stigma associated with going out for model C

From	Coef.	95% CI	p
Gender (Ref. Male)			
Female	0.09	-0.21 to 0.38	0.568
Age (Ref. 60-69 years)			
20-29 years	0.59	0.11 to 1.08	0.017*
30-39 years	0.40	-0.06 to 0.87	0.085
40-49 years	0.09	-0.39 to 0.56	0.719
50-59 years	0.34	-0.12 to 0.81	0.151
Chronic disease (Ref. No)			
Yes	0.18	-0.14 to 0.50	0.280
Educational attainment (Ref. Junior high school/high school)			
Junior (technical) college/vocational school	0.16	-0.27 to 0.58	0.469
Undergraduate/graduate school	-0.21	-0.60 to 0.17	0.280
Occupation (Ref. Blue-collar job)			
White-collar job	-0.33	-0.81 to 0.16	0.190
Gray-collar job	-0.33	-0.84 to 0.17	0.199
Other/not working	0.78	0.26 to 1.31	0.003**
Household annual income (Ref. 7 million yen or more)			
Less than 3 million yen	-0.21	-0.69 to 0.28	0.401
3-7 million yen	-0.28	-0.61 to 0.05	0.092
Unknown	-0.12	-0.62 to 0.37	0.626
Living alone (Ref. No)			
Yes	0.01	-0.38 to 0.41	0.949
Living with child(ren) under 18 years (Ref. No)			
Yes	0.33	-0.01 to 0.67	0.058
Living with person(s) aged 65 years and older (Ref. No)			
Yes	-0.07	-0.48 to 0.34	0.746
Neighborhood density (Ref. Lowest density)			
Middle-low density	0.00	-0.38 to 0.38	0.993
Middle-high density	-0.28	-0.66 to 0.09	0.140
Highest density	-0.69	-1.09 to -0.28	<0.001***
Areal deprivation index (ADI) (Ref. Lowest ADI)			
Middle-low ADI	-0.16	-0.54 to 0.23	0.425
Middle-high ADI	0.11	-0.28 to 0.50	0.564
Highest ADI	0.06	-0.35 to 0.46	0.783

Table A.19 (continued)

From	Coef.	95% CI	p
Introduction of working-from-home/standby at home (Ref. No)			
Yes	0.52	0.42 to 0.63	<0.001***
Decreased amount of work (Ref. No)			
Yes	0.62	0.53 to 0.71	<0.001***

* Coef.: Coefficient and CI: confidence interval. "***," "**," and "*," denote the statistical significance at 0.1%, 1%, and 5% levels, respectively. The sample size was 896.

Table A.20
Estimated coefficients of all paths to the changes in step counts (in thousands) between the pre-SoE and post-SoE periods for model C

From	Coef.	95% CI	p
Gender (Ref. Male)			
Female	-0.23	-0.64 to 0.18	0.270
Age (Ref. 60-69 years)			
20-29 years	-1.48	-2.03 to -0.92	<0.001***
30-39 years	-0.47	-1.12 to 0.17	0.151
40-49 years	-0.65	-1.24 to -0.05	0.033*
50-59 years	-0.42	-1.02 to 0.18	0.170
Chronic disease (Ref. No)			
Yes	-0.12	-0.57 to 0.32	0.588
Educational attainment (Ref. Junior high school/high school)			
Junior (technical) college/vocational school	0.09	-0.52 to 0.70	0.777
Undergraduate/graduate school	-0.15	-0.71 to 0.40	0.586
Occupation (Ref. Blue-collar job)			
White-collar job	0.80	0.18 to 1.42	0.012*
Gray-collar job	0.39	-0.23 to 1.01	0.217
Other/not working	-0.38	-1.24 to 0.48	0.385
Household annual income (Ref. 7 million yen or more)			
Less than 3 million yen	0.07	-0.49 to 0.63	0.801
3-7 million yen	0.01	-0.45 to 0.47	0.967
Unknown	-0.14	-0.73 to 0.46	0.656
Living alone (Ref. No)			
Yes	0.48	-0.03 to 0.98	0.063
Living with child(ren) under 18 years (Ref. No)			
Yes	0.49	-0.02 to 1.01	0.061
Living with person(s) aged 65 years and older (Ref. No)			
Yes	0.14	-0.43 to 0.70	0.635
Neighborhood density (Ref. Lowest density)			
Middle-low density	-0.01	-0.50 to 0.48	0.966
Middle-high density	-0.32	-0.84 to 0.20	0.223
Highest density	-0.73	-1.30 to -0.15	0.013*
Areal deprivation index (ADI) (Ref. Lowest ADI)			
Middle-low ADI	-0.16	-0.66 to 0.34	0.526
Middle-high ADI	0.12	-0.39 to 0.62	0.647
Highest ADI	0.20	-0.32 to 0.72	0.445

Table A.20 (continued)

From	Coef.	95% CI	p
Introduction of working-from-home/standby at home (Ref. No)			
Yes	-0.65	-0.99 to -0.31	<0.001***
Decreased amount of work (Ref. No)			
Yes	-0.35	-0.80 to 0.09	0.118
Strong anxiety about getting infected (Ref. No)			
Yes	0.22	0.04 to 0.40	0.015*
Strong anxiety about spreading the infection to others (Ref. No)			
Yes	0.08	-0.08 to 0.24	0.337
Strong anxiety about stigma associated with going out (Ref. No)			
Yes	0.00	-0.15 to 0.15	0.996

* Coef.: Coefficient and CI: confidence interval. "***," "**," and "*," denote the statistical significance at 0.1%, 1%, and 5% levels, respectively. The sample size was 896.

Table A.21
Estimated coefficients of all paths to the changes in time spent in sedentary behavior for model C

From	Coef.	95% CI	p
Gender (Ref. Male)			
Female	0.57	0.32 to 0.82	<0.001***
Age (Ref. 60-69 years)			
20-29 years	0.32	-0.09 to 0.72	0.122
30-39 years	0.16	-0.23 to 0.55	0.415
40-49 years	0.02	-0.37 to 0.41	0.915
50-59 years	0.05	-0.33 to 0.43	0.797
Chronic disease (Ref. No)			
Yes	0.19	-0.08 to 0.47	0.171
Educational attainment (Ref. Junior high school/high school)			
Junior (technical) college/vocational school	-0.02	-0.37 to 0.33	0.922
Undergraduate/graduate school	0.04	-0.29 to 0.37	0.814
Occupation (Ref. Blue-collar job)			
White-collar job	-0.41	-0.86 to 0.04	0.072
Gray-collar job	-0.26	-0.72 to 0.19	0.251
Other/not working	0.77	0.18 to 1.36	0.011*
Household annual income (Ref. 7 million yen or more)			
Less than 3 million yen	-0.32	-0.71 to 0.06	0.098
3-7 million yen	0.01	-0.27 to 0.29	0.941
Unknown	-0.25	-0.66 to 0.15	0.226
Living alone (Ref. No)			
Yes	-0.25	-0.57 to 0.07	0.119
Living with child(ren) under 18 years (Ref. No)			
Yes	0.01	-0.30 to 0.31	0.961
Living with person(s) aged 65 years and older (Ref. No)			
Yes	-0.12	-0.44 to 0.19	0.442
Neighborhood density (Ref. Lowest density)			
Middle-low density	0.14	-0.19 to 0.47	0.414
Middle-high density	-0.10	-0.43 to 0.23	0.564
Highest density	-0.17	-0.57 to 0.23	0.400
Areal deprivation index (ADI) (Ref. Lowest ADI)			
Middle-low ADI	-0.11	-0.44 to 0.21	0.499
Middle-high ADI	-0.16	-0.47 to 0.15	0.320
Highest ADI	-0.15	-0.47 to 0.17	0.357

Table A.21 (continued)

From	Coef.	95% CI	p
Introduction of working-from-home/standby at home (Ref. No)			
Yes	0.60	0.36 to 0.85	<0.001***
Decreased amount of work (Ref. No)			
Yes	0.60	0.31 to 0.88	<0.001***
Strong anxiety about getting infected (Ref. No)			
Yes	-0.20	-0.32 to -0.09	<0.001***
Strong anxiety about spreading the infection to others (Ref. No)			
Yes	-0.21	-0.32 to -0.09	<0.001***
Strong anxiety about stigma associated with going out (Ref. No)			
Yes	-0.10	-0.22 to 0.03	0.128

* Coef.: Coefficient and CI: confidence interval. "***," "**," and "*," denote the statistical significance at 0.1%, 1%, and 5% levels, respectively. The sample size was 896. The ordered categories of change in time spent in sedentary behavior were defined as follows: 1: significant reduction, 2: slight reduction, 3: no change, 4: slight rise, 5: significant rise.

Table A.22
Estimated coefficients of all paths to introduction of work-from-home/standby-at-home measures for model D

From	Coef.	95% CI	p
Gender (Ref. Male)			
Female	-0.24	-0.45 to -0.02	0.029*
Age (Ref. 60-69 years)			
20-29 years	0.05	-0.30 to 0.40	0.796
30-39 years	0.15	-0.18 to 0.49	0.363
40-49 years	0.28	-0.05 to 0.61	0.093
50-59 years	-0.04	-0.37 to 0.29	0.793
Chronic disease (Ref. No)			
Yes	-0.02	-0.28 to 0.23	0.856
Educational attainment (Ref. Junior high school/high school)			
Junior (technical) college/vocational school	0.28	-0.06 to 0.62	0.110
Undergraduate/graduate school	0.40	0.10 to 0.70	0.010*
Occupation (Ref. Blue-collar job)			
White-collar job	0.59	0.20 to 0.97	0.003**
Gray-collar job	0.24	-0.17 to 0.66	0.256
Other/not working	-0.77	-1.24 to -0.30	0.001**
Household annual income (Ref. 7 million yen or more)			
Less than 3 million yen	-0.13	-0.48 to 0.22	0.458
3-7 million yen	-0.08	-0.32 to 0.15	0.489
Unknown	-0.09	-0.43 to 0.24	0.586
Living alone (Ref. No)			
Yes	0.16	-0.12 to 0.45	0.257
Living with child(ren) under 18 years (Ref. No)			
Yes	-0.15	-0.41 to 0.11	0.268
Living with person(s) aged 65 years and older (Ref. No)			
Yes	-0.10	-0.40 to 0.19	0.490
Neighborhood density (Ref. Lowest density)			
Middle-low density	0.35	0.07 to 0.64	0.016*
Middle-high density	0.41	0.13 to 0.69	0.004**
Highest density	0.64	0.34 to 0.94	<0.001***
Areal deprivation index (ADI) (Ref. Lowest ADI)			
Middle-low ADI	0.02	-0.26 to 0.29	0.901
Middle-high ADI	-0.12	-0.40 to 0.17	0.429
Highest ADI	-0.11	-0.41 to 0.18	0.463

* Coef.: Coefficient and CI: confidence interval. "***," "**," and "*," denote the statistical significance at 0.1%, 1%, and 5% levels, respectively. The sample size was 896.

Table A.23
Estimated coefficients of all paths to decreased amount of work for model D

From	Coef.	95% CI	p
Gender (Ref. Male)			
Female	0.09	-0.13 to 0.31	0.437
Age (Ref. 60-69 years)			
20-29 years	0.07	-0.30 to 0.43	0.723
30-39 years	0.09	-0.26 to 0.45	0.606
40-49 years	0.08	-0.27 to 0.43	0.653
50-59 years	0.05	-0.29 to 0.40	0.758
Chronic disease (Ref. No)			
Yes	0.00	-0.26 to 0.27	0.981
Educational attainment (Ref. Junior high school/high school)			
Junior (technical) college/vocational school	-0.01	-0.34 to 0.31	0.938
Undergraduate/graduate school	0.05	-0.24 to 0.33	0.757
Occupation (Ref. Blue-collar job)			
White-collar job	-0.18	-0.56 to 0.19	0.336
Gray-collar job	0.11	-0.29 to 0.50	0.599
Other/not working	-0.68	-1.09 to -0.27	0.001**
Household annual income (Ref. 7 million yen or more)			
Less than 3 million yen	0.62	0.27 to 0.96	<0.001***
3-7 million yen	0.22	-0.03 to 0.47	0.084
Unknown	0.08	-0.31 to 0.48	0.685
Living alone (Ref. No)			
Yes	0.11	-0.18 to 0.40	0.449
Living with child(ren) under 18 years (Ref. No)			
Yes	0.03	-0.24 to 0.31	0.813
Living with person(s) aged 65 years and older (Ref. No)			
Yes	0.01	-0.31 to 0.34	0.932
Neighborhood density (Ref. Lowest density)			
Middle-low density	-0.17	-0.47 to 0.13	0.274
Middle-high density	-0.03	-0.32 to 0.27	0.859
Highest density	0.19	-0.13 to 0.51	0.242
Areal deprivation index (ADI) (Ref. Lowest ADI)			
Middle-low ADI	0.29	-0.02 to 0.59	0.066
Middle-high ADI	0.25	-0.07 to 0.56	0.123
Highest ADI	0.25	-0.09 to 0.58	0.146

* Coef.: Coefficient and CI: confidence interval. "***," "**," and "*," denote the statistical significance at 0.1%, 1%, and 5% levels, respectively. The sample size was 896.

Table A.24
Estimated coefficients of all paths to the changes in step counts (in thousands) between the pre-SoE and post-SoE periods for model D

From	Coef.	95% CI	p
Gender (Ref. Male)			
Female	-0.13	-0.50 to 0.25	0.513
Age (Ref. 60-69 years)			
20-29 years	-1.47	-2.00 to -0.94	<0.001***
30-39 years	-0.37	-0.99 to 0.25	0.246
40-49 years	-0.59	-1.17 to -0.02	0.043*
50-59 years	-0.35	-0.92 to 0.22	0.233
Chronic disease (Ref. No)			
Yes	-0.06	-0.49 to 0.36	0.773
Educational attainment (Ref. Junior high school/high school)			
Junior (technical) college/vocational school	0.11	-0.49 to 0.71	0.717
Undergraduate/graduate school	-0.15	-0.68 to 0.39	0.594
Occupation (Ref. Blue-collar job)			
White-collar job	0.76	0.17 to 1.34	0.011*
Gray-collar job	0.39	-0.20 to 0.98	0.195
Other/not working	-0.28	-0.93 to 0.37	0.403
Household annual income (Ref. 7 million yen or more)			
Less than 3 million yen	0.16	-0.39 to 0.70	0.570
3-7 million yen	0.02	-0.42 to 0.47	0.914
Unknown	-0.13	-0.70 to 0.45	0.669
Living alone (Ref. No)			
Yes	0.42	-0.06 to 0.89	0.086
Living with child(ren) under 18 years (Ref. No)			
Yes	0.54	0.05 to 1.03	0.030*
Living with person(s) aged 65 years and older (Ref. No)			
Yes	0.10	-0.45 to 0.65	0.720
Neighborhood density (Ref. Lowest density)			
Middle-low density	0.04	-0.44 to 0.51	0.875
Middle-high density	-0.34	-0.82 to 0.14	0.160
Highest density	-0.79	-1.25 to -0.32	<0.001***
Areal deprivation index (ADI) (Ref. Lowest ADI)			
Middle-low ADI	-0.22	-0.68 to 0.24	0.347
Middle-high ADI	0.10	-0.38 to 0.59	0.674
Highest ADI	0.19	-0.32 to 0.69	0.467

Table A.24 (continued)

From	Coef.	95% CI	p
Introduction of working-from-home/standby at home (Ref. No)			
Yes	-0.59	-0.71 to -0.46	<0.001***
Decreased amount of work (Ref. No)			
Yes	-0.29	-0.45 to -0.13	<0.001***

* Coef.: Coefficient and CI: confidence interval. “***,” “**,” and “*,” denote the statistical significance at 0.1%, 1%, and 5% levels, respectively. The sample size was 896.

Table A.25
Estimated coefficients of all paths to the changes in time spent in sedentary behavior for model D

From	Coef.	95% CI	p
Gender (Ref. Male)			
Female	0.42	0.24 to 0.59	<0.001***
Age (Ref. 60-69 years)			
20-29 years	0.25	-0.02 to 0.53	0.074
30-39 years	0.01	-0.27 to 0.28	0.967
40-49 years	-0.02	-0.30 to 0.27	0.917
50-59 years	-0.07	-0.33 to 0.20	0.632
Chronic disease (Ref. No)			
Yes	0.09	-0.10 to 0.29	0.347
Educational attainment (Ref. Junior high school/high school)			
Junior (technical) college/vocational school	-0.04	-0.29 to 0.21	0.751
Undergraduate/graduate school	0.09	-0.15 to 0.33	0.470
Occupation (Ref. Blue-collar job)			
White-collar job	-0.28	-0.61 to 0.05	0.094
Gray-collar job	-0.19	-0.52 to 0.15	0.282
Other/not working	0.39	0.03 to 0.75	0.034*
Household annual income (Ref. 7 million yen or more)			
Less than 3 million yen	-0.32	-0.60 to -0.05	0.021*
3-7 million yen	0.05	-0.15 to 0.25	0.630
Unknown	-0.24	-0.53 to 0.05	0.107
Living alone (Ref. No)			
Yes	-0.16	-0.39 to 0.07	0.183
Living with child(ren) under 18 years (Ref. No)			
Yes	-0.09	-0.31 to 0.13	0.433
Living with person(s) aged 65 years and older (Ref. No)			
Yes	-0.07	-0.30 to 0.15	0.523
Neighborhood density (Ref. Lowest density)			
Middle-low density	0.08	-0.16 to 0.32	0.518
Middle-high density	-0.01	-0.25 to 0.23	0.926
Highest density	0.07	-0.17 to 0.30	0.587
Areal deprivation index (ADI) (Ref. Lowest ADI)			
Middle-low ADI	0.05	-0.18 to 0.27	0.699
Middle-high ADI	-0.12	-0.35 to 0.10	0.287
Highest ADI	-0.10	-0.34 to 0.13	0.400

Table A.25 (continued)

From	Coef.	95% CI	p
Introduction of working-from-home/standby at home (Ref. No)			
Yes	0.38	0.30 to 0.46	<0.001***
Decreased amount of work (Ref. No)			
Yes	0.29	0.20 to 0.39	<0.001***

* Coef.: Coefficient and CI: confidence interval. "***," "**," and "*," denote the statistical significance at 0.1%, 1%, and 5% levels, respectively. The sample size was 896. The ordered categories of change in time spent in sedentary behavior were defined as follows: 1: significant reduction, 2: slight reduction, 3: no change, 4: slight rise, 5: significant rise.

Table A.26
Estimated coefficients of all paths to strong anxiety about getting infected for model D

From	Coef.	95% CI	p
Gender (Ref. Male)			
Female	0.29	0.08 to 0.49	0.006**
Age (Ref. 60-69 years)			
20-29 years	-0.04	-0.37 to 0.29	0.814
30-39 years	0.37	0.07 to 0.67	0.015*
40-49 years	0.24	-0.06 to 0.53	0.114
50-59 years	0.28	-0.01 to 0.57	0.059
Chronic disease (Ref. No)			
Yes	0.19	-0.02 to 0.40	0.074
Educational attainment (Ref. Junior high school/high school)			
Junior (technical) college/vocational school	0.12	-0.16 to 0.40	0.408
Undergraduate/graduate school	0.06	-0.19 to 0.31	0.628
Occupation (Ref. Blue-collar job)			
White-collar job	-0.01	-0.37 to 0.36	0.969
Gray-collar job	0.09	-0.30 to 0.48	0.642
Other/not working	0.13	-0.28 to 0.53	0.533
Household annual income (Ref. 7 million yen or more)			
Less than 3 million yen	0.41	0.08 to 0.74	0.015*
3-7 million yen	0.07	-0.15 to 0.29	0.516
Unknown	0.08	-0.24 to 0.40	0.630
Living alone (Ref. No)			
Yes	-0.18	-0.46 to 0.10	0.204
Living with child(ren) under 18 years (Ref. No)			
Yes	0.19	-0.05 to 0.42	0.117
Living with person(s) aged 65 years and older (Ref. No)			
Yes	-0.12	-0.39 to 0.15	0.401
Neighborhood density (Ref. Lowest density)			
Middle-low density	0.19	-0.07 to 0.44	0.151
Middle-high density	-0.04	-0.30 to 0.22	0.783
Highest density	-0.11	-0.39 to 0.17	0.438
Areal deprivation index (ADI) (Ref. Lowest ADI)			
Middle-low ADI	-0.11	-0.37 to 0.14	0.388
Middle-high ADI	-0.01	-0.28 to 0.25	0.930
Highest ADI	-0.01	-0.27 to 0.26	0.961

Table A.26 (continued)

From	Coef.	95% CI	p
Introduction of working-from-home/standby at home (Ref. No)			
Yes	0.03	-0.12 to 0.17	0.735
Decreased amount of work (Ref. No)			
Yes	0.05	-0.08 to 0.18	0.447
Changes in step counts (in thousands) between the pre-SoE and the post-SoE periods	-0.02	-0.06 to 0.01	0.224
Changes in time spent sedentary behavior during the COVID-19 outbreak	0.10	0.01 to 0.19	0.035*

* Coef.: Coefficient and CI: confidence interval. "***," "**," and "*," denote the statistical significance at 0.1%, 1%, and 5% levels, respectively. The sample size was 896.

Table A.27
Estimated coefficients of all paths to strong anxiety about spreading the infection to others for model D

From	Coef.	95% CI	p
Gender (Ref. Male)			
Female	0.25	0.04 to 0.47	0.020*
Age (Ref. 60-69 years)			
20-29 years	0.01	-0.33 to 0.35	0.954
30-39 years	0.38	0.07 to 0.69	0.018*
40-49 years	0.14	-0.18 to 0.45	0.393
50-59 years	0.13	-0.19 to 0.45	0.424
Chronic disease (Ref. No)			
Yes	0.17	-0.05 to 0.39	0.136
Educational attainment (Ref. Junior high school/high school)			
Junior (technical) college/vocational school	0.13	-0.17 to 0.42	0.398
Undergraduate/graduate school	0.10	-0.16 to 0.37	0.450
Occupation (Ref. Blue-collar job)			
White-collar job	-0.14	-0.51 to 0.24	0.477
Gray-collar job	0.02	-0.38 to 0.42	0.907
Other/not working	0.02	-0.40 to 0.43	0.930
Household annual income (Ref. 7 million yen or more)			
Less than 3 million yen	0.29	-0.04 to 0.63	0.083
3-7 million yen	0.02	-0.21 to 0.26	0.849
Unknown	-0.03	-0.37 to 0.30	0.844
Living alone (Ref. No)			
Yes	0.00	-0.28 to 0.29	0.979
Living with child(ren) under 18 years (Ref. No)			
Yes	0.11	-0.14 to 0.36	0.376
Living with person(s) aged 65 years and older (Ref. No)			
Yes	-0.14	-0.44 to 0.16	0.360
Neighborhood density (Ref. Lowest density)			
Middle-low density	0.17	-0.10 to 0.44	0.207
Middle-high density	-0.01	-0.28 to 0.27	0.963
Highest density	-0.16	-0.46 to 0.14	0.310
Areal deprivation index (ADI) (Ref. Lowest ADI)			
Middle-low ADI	-0.31	-0.57 to -0.04	0.025*
Middle-high ADI	-0.01	-0.29 to 0.26	0.931
Highest ADI	-0.07	-0.34 to 0.21	0.640

Table A.27 (continued)

From	Coef.	95% CI	p
Introduction of working-from-home/standby at home (Ref. No)			
Yes	-0.01	-0.16 to 0.14	0.901
Decreased amount of work (Ref. No)			
Yes	0.05	-0.08 to 0.18	0.457
Changes in step counts (in thousands) between the pre-SoE and the post-SoE periods	-0.06	-0.09 to -0.03	<0.001***
Changes in time spent sedentary behavior during the COVID-19 outbreak	0.10	0.01 to 0.19	0.035*

* Coef.: Coefficient and CI: confidence interval. “***,” “**,” and “*,” denote the statistical significance at 0.1%, 1%, and 5% levels, respectively. The sample size was 896.

Table A.28

Estimated coefficients of all paths to strong anxiety about stigma associated with going out for model D

From	Coef.	95% CI	p
Gender (Ref. Male)			
Female	-0.07	-0.33 to 0.19	0.599
Age (Ref. 60-69 years)			
20-29 years	0.50	0.12 to 0.89	0.011*
30-39 years	0.51	0.14 to 0.87	0.007**
40-49 years	0.23	-0.16 to 0.62	0.244
50-59 years	0.34	-0.04 to 0.72	0.083
Chronic disease (Ref. No)			
Yes	0.14	-0.10 to 0.39	0.255
Educational attainment (Ref. Junior high school/high school)			
Junior (technical) college/vocational school	0.30	-0.03 to 0.64	0.076
Undergraduate/graduate school	-0.01	-0.33 to 0.30	0.929
Occupation (Ref. Blue-collar job)			
White-collar job	-0.03	-0.43 to 0.37	0.887
Gray-collar job	-0.09	-0.51 to 0.33	0.673
Other/not working	-0.07	-0.52 to 0.39	0.765
Household annual income (Ref. 7 million yen or more)			
Less than 3 million yen	0.14	-0.24 to 0.52	0.469
3-7 million yen	-0.21	-0.48 to 0.06	0.127
Unknown	-0.09	-0.47 to 0.29	0.644
Living alone (Ref. No)			
Yes	0.22	-0.11 to 0.54	0.199
Living with child(ren) under 18 years (Ref. No)			
Yes	0.33	0.05 to 0.61	0.021*
Living with person(s) aged 65 years and older (Ref. No)			
Yes	-0.09	-0.43 to 0.24	0.591
Neighborhood density (Ref. Lowest density)			
Middle-low density	0.07	-0.22 to 0.37	0.631
Middle-high density	-0.11	-0.42 to 0.20	0.469
Highest density	-0.33	-0.66 to 0.01	0.054
Areal deprivation index (ADI) (Ref. Lowest ADI)			
Middle-low ADI	-0.01	-0.33 to 0.31	0.941
Middle-high ADI	0.22	-0.09 to 0.54	0.158
Highest ADI	0.17	-0.15 to 0.49	0.292

Table A.28 (continued)

From	Coef.	95% CI	p
Introduction of working-from-home/standby at home (Ref. No)			
Yes	-0.09	-0.25 to 0.08	0.298
Decreased amount of work (Ref. No)			
Yes	-0.01	-0.15 to 0.14	0.942
Changes in step counts (in thousands) between the pre-SoE and the post-SoE periods	-0.07	-0.10 to -0.04	<0.001***
Changes in time spent sedentary behavior during the COVID-19 outbreak	0.18	0.08 to 0.29	<0.001***

* Coef.: Coefficient and CI: confidence interval. “***,” “**,” and “*,” denote the statistical significance at 0.1%, 1%, and 5% levels, respectively. The sample size was 896.