CORRESPONDENCE BETWEEN FEELINGS TOWARDS NEIGHBORS AND APPEARANCE OF NEIGHBORHOOD: ANALYSIS BY COMBINING A MAIL SURVEY AND GOOGLE STREET VIEW

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Recent studies demonstrated associations between physical environment (especially greenery) and people’s health, well-being, and crime rate by using street-level imagery as ‘big data’ and automated image recognition methods. However, few prior studies focused on interrelations between physical environment and residents’ social relationships. This study investigated associations between physical environments and psychological tendencies of neighboring communities in Japan by using a mail survey and Google Street View images. The mail survey was collected from 156 regions across eight prefectures in western Japan. Google Street View images of these regions were collected and classified by machine learning models and human observers. The results indicated mainly negative correlations between the survey items related to feelings towards participants’ neighbors such as social capital and the rate of outdoor gardening by region. Additionally, these correlation patterns differed by type of community, namely, fishing, farming, and other types of communities.

**Key words:** social capital, neighborhood, streetscape, Google Street View, machine learning

**INTRODUCTION**

*Social Capital and Neighborhood Physical Environment*

Social capital in neighborhoods and local communities have been gaining attention of researchers from various fields since studies have suggested effects of social capital on various aspects of residents’ daily life over the last couple of decades (Putnam, 2000; Putnam et al., 1994). Research on public health is one such field, which focused on

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positive effects of social capital on people in local communities from the start and has since been increasing based on quantitative data (Moore & Kawachi, 2017; Shiell et al., 2020). However, associations between social capital and man-made infrastructure or ‘built environment,’ such as local facilities, walkways, and greenery, have been investigated by a limited number of studies (see review by Mazumdar et al., 2018), though neighborhood physical environment seems to be an important factor in discussions on social capital (Wood & Giles-Corti, 2008).

Previous studies suggested significant associations between elements of social capital and some aspects of neighborhood physical environment. A systematic review by Mazumdar et al. (2018) on articles published until 2015, indicated significant positive relations between social cohesion and walkability or access to local destinations such as libraries. As for greenery in the neighborhood, some recent studies argued for its positive relations with social cohesion and safety. Hong et al. (2018) analyzed survey data of the elderly living in Seattle-King County and Baltimore-Washington DC regions in the US. They showed significant positive associations between subjectively reported natural sights, social cohesion and interaction, and similarly between pedestrian safety and social capital, controlling for demographic variables. Moreover, people felt safe, comfortable, and friendly amidst natural greenery, which contrasted with the atmosphere from streetscapes, such as maintained parks or buildings. Heinze et al. (2018) demonstrated the intervention effect of maintaining neighborhood greenery by local people on violent crimes in their neighborhood through a five-year longitudinal survey conducted in Flint in the US. Their analysis statistically controlled for demographic data and the number of violent crimes in the previous year, and results indicated that vacant neighborhood lots maintained by community members in the local government’s program had less violent crimes than abandoned lots. Although this case study focused on collective interventions in the neighborhood’s physical environment, only a limited number of such studies discussed interrelations between social capital and physical environment. Furthermore, previous studies mainly targeted urban or suburban areas and were conducted mostly in the US or Europe (Mazumdar et al., 2018).

Investigation on Physical Environment Using Google Street View
Since mid-2010, automated image recognition through Google Street View (GSV; Google, 2021) has been applied for various purposes, allowing the processing of a huge number of images, resulting in strong consistency in results. On the GSV application first released in the US in 2007, users can see interactive and sequential 360-degree panorama views from roads, which are integrated with map data. These images were usually taken in daylight at intervals of several meters using a camera mounted on top of cars, which was approximately two meters from the ground. However, GSV has limitations in that the update frequency and density of images varies depending on the region or district. In terms of research practice, several studies examined the validity of virtual auditing objects on GSV, which is sometimes termed as virtual systematic social observation. Queralt et al. (2021) compared virtual audit on GSV with physical observation in cities of five different countries. They showed that levels of concordance
for streetscape elements seemed to be high enough between those observations, though physical disorders (e.g., trash) and aesthetics (e.g., trees) tended to be at relatively lower levels of concordance, compared with buildings and roads. Additionally, audit on GSV also seems to have enough validity compared to observations by local residents, especially for aesthetics such as roadside trees, plantings, and other features of landscape on the roads (Chiang et al., 2017).¹ In summary, GSV provides the opportunity to virtually audit streetscapes in any area where GSV imagery data is available, instead of in-person surveillance which was the conventional observational method for streetscapes.

Automated image recognition through GSV has not only been employed to develop alternatives of existing observation methods, such as assessment of infrastructure condition (e.g., Alipour & Harris, 2020) or mapping certain species of trees or crops (e.g., Ringland et al., 2021; Yan & Ryu, 2021), but also used to capture features of certain areas from elements in their streetscapes. Especially, the greenery and walkability of neighborhoods have been the focus of several studies for the purpose of exploring influences of these physical environments on residents’ health (e.g., Jiang et al., 2020; Li et al., 2018; Li, Zhang, Li, Ricard, et al., 2015; Lu et al., 2018; Nagata et al., 2020). Those studies suggested that aesthetics and well-kept streets might encourage people to walk for health benefits, which seemed to be intuitive. Observations of greenery and walkability by automated methods through GSV could also reflect social inequality between areas (Ki & Lee, 2021; Li, 2021; Li, Zhang, Li, Kuzovkina, & Weiner, 2015), and be positively related with the vitality of neighborhood organizations (e.g., sports clubs) and strength of social networks in local communities (Wang & Vermeulen, 2021).

While those findings were based on hypothesis-driven methodologies, associations between greenery or walkability and social conditions of neighborhood (including social capital) can be also uncovered by data-driven methodologies, which could be feasible through GSV and machine learning. Zhang et al. (2018) conducted an online survey where 81,630 participants chose one image from a pair of GSV images that they thought had more features of each of six perceptual indicators (i.e., safe, lively, beautiful, wealthy, depressing, and boring), for a total of 1,169,078 times across all participants. They trained a deep learning model using the results of the above choices, and highlighted objects or features on GSV imagery that contributed to each of the perceptual indicators. Specifically, greenery and walkability had positive effects on human perceptions of safety, beauty, and wealth on the streetscapes. Furthermore, Wijnands et al. (2019) trained a deep learning model with the results of a computer-aided telephone interview survey by the government as annotations of GSV imagery on each targeted area in the Greater Melbourne area, Australia. The model could modify visual features of GSV images based on parameters from the survey including health, happiness, and social capital (i.e., conversation with others). For instance, GSV images of the targeted areas with high social capital were converted by the model to images with features of areas with low social capital, and the difference between images indicated visual features of

¹ However, as for inter-rater and intra-rater agreement, there seems to be relative inconsistencies in virtual audit of physical disorders and aesthetics on the roads (Griew et al., 2013; Kelly et al., 2013; Odgers et al., 2012).
streetscapes related to social capital. With this method, they suggested that high social capital in the neighborhood would be associated with more grass and smaller trees. In other words, these studies indicated that certain streetscape elements affect people’s intuitive impression of a certain area.

In sum, GSV could be an efficient tool through which novel perspectives might be gained by examining the associations between social capital and physical environment within a neighborhood. Specifically, positive relations between social networks and greenery or walkability have been demonstrated by several studies that targeted various cities in different countries using GSV. Importantly, while greenery and walkability are features of the physical environment influenced mainly by urban planning, the direct influence of local residents on their physical environment tends to be overlooked in those discussions. The latter factor, which affects the atmosphere of local communities, would be crucial to deepen and integrate discussions on interrelations between social capital and neighborhood physical environment, especially from a practical standpoint, as shown by Heinze et al. (2018).

Community-Level Socioecological Factors and Contextual Effects on Psychological Tendencies

To explore associations between social capital and physical environment within local communities, social environment and contextual effects at the community level need to be considered. Social ecology comprising the social and physical environment (Oishi & Graham, 2010) is an important factor that could influence individuals’ behavior and psychological tendencies and is reflected in the streetscapes of local communities. Especially, the type of primary industry or socio-economical/ecological factors in a community could explain the difference in collective psychological tendencies of the local residents. Previous studies indicated that primary industries (e.g., farming, rice/wheat agriculture) that required people to cooperate would be more associated with collectivistic tendencies compared to primary industries (e.g., fishing) that required people to make decisions independently (Talhelm et al., 2014; Uchida et al., 2019). Additionally, such cultural tendencies would be shared among people differently, depending on the type of community. Uchida et al. (2019) demonstrated through large-scale surveys in Japan that interdependent tendencies were shared by farmers and the other residents in farming communities, while independent tendencies were dominant among fishermen, but not the other residents in fishing communities. They explained that these differences in psychological tendencies might reflect people’s adaptation to their primary industries and related social activities. Furthermore, cultural tendencies connected to social ecology would explain people’s attitude toward their neighbors. Liu et al. (2019) compared participants’ behavior in a competitive situation between those who were originally from regions in China where either rice or wheat agriculture was dominant. They also compared responses by participants from China and the US, and concluded that people in rice agricultural regions tended to be more vigilant and paid more attention to ingroup members’ vicious intentions. This suggests that trust among community members as a component of social capital could be influenced by socioecological
factors of the community.

Present Study

As discussed above, previous studies using GSV tended to target relatively similar urban or suburban areas, mainly because of the density of available GSV images. However, virtual audit using GSV can be applied not only to conventional targets such as urban or suburban areas, but also to different types of rural areas (e.g., farming and fishing communities). This enables us to explore associations between social capital and neighborhood physical environment in various types of communities, which could be influenced by socioecological factors. In the present study, to explore such interrelations while taking into account community-level factors, we used a large-scale mail survey conducted in several types of communities and compared them to GSV imagery. The mail survey was originally conducted in another study (Uchida, 2019) to investigate associations between happiness, social capital, and types of community, namely, farming, fishing, and urban communities. The scales in the survey included multiple aspects of social capital such as trust, reciprocity, and social networks as defined by Putnam (2000), and items about relationships with neighbors, happiness, health, and economic status. We extracted available samples from the survey, including farming and fishing communities to consider the difference in interrelations between social capital and their physical environment. GSV images were obtained by referring to the geographical area of each target community, and assessed by machine learning models and human raters. We focused on plantings at houses observed from the public road as the target element of the physical environment that might reflect residents’ behavior, because of three reasons. First, the maintenance of outdoor plantings would influence the streetscape by beautifying it (e.g., Heinze et al., 2018); second, residents may find it easier to modify outdoor plantings decorating their houses than the exterior of houses, such as outer walls; and third, plantings need residents’ continuous effort for maintenance in most cases. Regarding the first reason, indoor plantings as private interior decorations are usually hidden from public roads, while outdoor plantings could be part of the streetscape. In addition, regarding the second and third reasons, roadside trees or greenery at public places (e.g., parks and squares) are usually under the control of the local government, while plantings within houses are private property that might reflect local people’s intentional interventions of the physical environment. Finally, we examined correlations in an exploratory manner between several scales in the survey and the frequency of plantings by the target community. Following the discussions in previous studies (Heinze et al., 2018; Wang & Vermeulen, 2021; Wijnands et al., 2019), we predicted that the frequency of plantings at houses, as part of the aesthetics of streetscapes, would be positively correlated with social capital, happiness, and health, reflecting participants’ relationships with neighbors in positive ways.
METHOD

Survey Data

To analyze the psychological aspects and social relationships of people living in different communities, we utilized prior data from a large-scale survey conducted in the Kinki and Shikoku regions of Japan. The survey was conducted in two parts, and the focal data of the current study was collected in the second part during January/February 2016 to compare different types of communities, including farming, fishing, and urban communities. 301 target communities were selected based on ‘the first survey’ conducted in the Western regions of Japan (see Uchida et al., 2019).

In the first survey, 412 communities were sampled from 60,807 eligible communities within the Kinki, Shikoku, and Chugoku regions in January/February 2013. The samples were stratified by two dimensions: geographical region and type of community. Target regions were categorized into seven regional blocks based on climate division, and communities were categorized into five types, namely farming, fishing, urban, mixed, and other. Based on the census data by the Statistics Bureau, Ministry of Internal Affairs and Communications of Japan (2010), they defined farming community and fishing community as communities with relatively high percentage of farmers or fishers respectively (≥ 25%), and urban community as those with a high population density (≥ 4,000 persons/km²). First, all 20 ‘mixed communities’ consisting of any combination of the above types of communities were included in the samples, because of the limited number of those types of communities. Subsequently, 30 farming, five to six urban, and five ‘other’ communities were sampled from each of the seven regional blocks. As the number of fishing communities were less than farming communities within some target regions, a range from 6 to 32 fishing communities were selected from each block. Consequently, the first survey was mailed to all households in the sample communities, and 7,364 individual responses were received from 408 communities.

From those samples, the following survey (‘the second survey’) focused on the selected communities in the Kinki region, and the leftover fishing communities in the Kinki and Shikoku regions (Uchida, 2019). However, fishing communities in Mie prefecture within the Kinki region were not included, because of the limited number. As a result, 156 communities were targeted, which amounted to approximately half of the total sampled communities in the second survey. As with the first survey, the second survey was mailed to all households in those communities, and 1,916 individual responses were received from 152 communities. There were 56 farming, 83 fishing, 19 urban, and nine ‘other’ communities, including 17 ‘mixed communities’ (the categorization of two communities were unknown, because the census data was unavailable). Response rate at the individual-level differed across communities, ranging from 2% to 58% (M = 18%, SD = 11%).

The second survey was approved by the Institutional Review Board at Kyoto University. A statement of consent was included in the second survey. All information offered by participants was anonymized, except for the zip code of each target community, which had been printed on the questionnaires before mailing. No data from the first survey was used for analysis in the current study.

Measures

The survey aimed to explore the structure of individuals’ happiness and social relationships moderated by type of community. For that purpose, it consisted of items that measured participants’ and their neighbors’ health and happiness, social relationships, psychological tendencies, daily feelings, participation in community activities, and demographic data. To analyze target communities’ psychological aspects and social relationships, the present study focused on items which were related to health and happiness, social capital, impression of their community, individual- and community-level wealth.

The survey contained 12 items regarding health and happiness measured using a 11-point Likert scale (0 to 10) that asked about participants’ and their neighbors’ health and happiness, other daily feelings (e.g., life satisfaction) and financial status. There were 30 items regarding social capital and impression of community measured using a 5-point Likert scale that were related to participants’ trust (e.g., “I trust the people who live in my neighborhood.”), reciprocity (e.g., “If people in the neighborhood need help, I will help them.”), community’s norms (e.g., “There are many rules in the neighborhood that we must obey.”), social relationships (e.g., “As a member of my neighborhood, I think it is important to maintain the harmony in the neighborhood.”), and attachment to the community’s values (e.g., “I feel attached to my
neighborhood”). In addition, we also included an item that measured psychological distance between participants and their neighbors (“To what extent do you and people in the neighborhood overlap as represented by two circles [in the figure]”), and an item that asked participants about their economic status within the community. The item measuring household income consisted of nine options from “under 2 million yen” to “16 million yen and above” in intervals of 2 million yen.

**Google Street View Imagery Collection**

For the purpose of the present study, while psychological aspects of the target communities were captured using the survey data, aspects of the physical environment had to be obtained by observing landscapes around residences of the target communities. Therefore, we focused on the visual data around buildings, including houses, in each of the target communities. To obtain imagery of the target communities located in various places in the Kinki and Shikoku regions, we extracted GSV image data through Google’s application programming interface (API). The API needed location coordinates to display the GSV imagery nearby. If the purpose of collecting GSV images is to capture comprehensive streetscapes of target regions regardless of the existence of houses, referring to coordinates spotted at a certain interval on the API would be a common procedure (e.g., Jiang et al., 2020; Ki & Lee, 2021; Li, 2021; Li et al., 2018; Li, Zhang, Li, Kuzovkina, & Weiner, 2015; Zhang et al., 2018). On the other hand, if the purpose of image collection is to observe streetscapes around certain buildings or facilities, using their addresses or coordinates would be a more reasonable procedure (e.g., Wang & Vermeulen, 2021). Thus, we defined the geographical boundaries of the target communities by referencing locations from the census data, and subsequently acquired the coordinates of buildings within each area by referring to another governmental open data which will be elaborated below.

First, because the API allowed users to download only the latest version of GSV imagery at the point of access, coordinates of the target communities needed to be defined based on the most updated boundary on the map. Therefore, we referred to the latest census data from 2015 instead of the earlier version conducted in 2010, from which the target communities were selected. Second, to obtain coordinates of houses in the target communities for the API, we used polygon data of buildings on the geographical information system (GIS), which was distributed as open data by the geographical department of the Japanese government (Geospatial Information Authority of Japan, 2016). In this process, the QGIS 3.4.15 (QGIS Development Team, 2020) was used. The polygon data did not contain the same information as the census data regarding the local communities’ boundaries. Thus, polygons of the buildings within each target communities’ area were extracted by overlaying the boundaries as vector data with the polygon data. As a result, ‘center of gravity’ points of the selected polygons were obtained and used as their coordinates. Groups of those coordinates would correspond to small areas where local people resided within each of the target communities, though those would also include abandoned buildings. Through this process, 39 communities were excluded from the target communities, because they did not match with the boundaries in the open data due to differences in versions of the census data as mentioned above.

GSV imagery of 115 target communities was extracted through the following process. The size of images was set as 640 × 640 pixels, which was the largest available size the free plan of the API allowed users to download. We chose the largest size because the larger the target images were, the more information we could utilize in image classification (described later). The location of images was limited to the outdoors to exclude indoor images. The vertical angle of images was set as horizontal. The horizontal angles were set as 0, 90, 180, and 270 degrees for every single coordinate. This means that four images

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2 While most previous studies did not mention the permissions of use of GSV imagery, there were specific guidelines for use by Google (https://about.google/brand-resource-center/products-and-services/geo-guidelines/#street-view). It mentions ‘fair use’ of the data, which could allow users to use their contents under certain conditions. However, academic use of the data is partially restricted. We emailed Google to clarify the extent the prohibition would be applicable to the present research design. They replied that the prohibition was up to our interpretation. Consequently, we concluded that the restrictions were not applicable to our method, because the use of GSV imagery in the present research design was not a derivative work, and hence would fall outside the restrictions.

3 Addresses of all 154 target communities selected from the survey data set, were compared to the census data conducted in 2015 (National Statistics Center, 2018), though these communities were originally selected from the previous census data.
were obtained from each of the coordinates, which approximated a panorama view from a certain point on GSV (Fig. 1 shows an example).

Following the parameters mentioned above, we downloaded images referring to the buildings’ coordinates of each target community as closely as possible using the Street View Static API from March 11 to 12, 2020. The extracted images were the latest version of each coordinate on GSV at the point of extraction, but there might exist several years gaps between them, sometimes even in the same community. Because the API did not offer metadata, including the date of capture, directly with the images, the exact range of dates of image capture in each community could not be calculated. Therefore, those images were expected to consist of landscapes of the neighborhood of each target community in recent years. However, the same images could be extracted from different coordinates whose nearest points with available GSV images overlapped. Also, blank images could be obtained from coordinates whose nearest available street view image was too far. Hence, after excluding those duplicates and blank images, 39,187 images from 104 target communities remained for the following analyzes. The number of usable images extracted from GSV varied across communities, ranging from 2 to 2,852 ($M = 377, SD = 451$).

Additionally, we obtained another dataset to train the machine learning model (described later) by the same process as above. In this collection of images, 12 communities were randomly selected from the 115 target communities, comprising 10% of the total, and up to two adjacent communities were chosen from each of those communities. If a selected community had more than two adjacent communities, the nearest two communities according to their region codes on the census were chosen. On the other hand, if a selected community had none or only one adjacent community (e.g., island regions), then less than two adjacent communities were chosen. As a result, 19 communities were listed, and 4,812 GSV images were extracted from 17 selected communities, ranging from 40 to 580 ($M = 283, SD = 155$).

**Image Classification**

Each of the extracted image data was classified by machine learning models or human raters to exclude mistakenly downloaded images and calculate the appearance ratio of a certain object in the images of a target community. Because 88 of 104 target communities of which we downloaded GSV images were farming communities, fishing communities, or both, they tended to be located in rural areas, and often included images without any observable buildings (e.g., only forest and road appeared in the frame of an image). Such images were removed from the dataset, as no landscapes of the neighborhood of the target communities were apparent. After this process, we classified the rest of the images into those who had plants alongside the buildings or not.

Through those two image classification processes, we built two machine learning models to identify houses and plants in the extracted GSV images. While image segmentation has been employed to automatically classify objects from a massive number of GSV imagery by many previous studies (e.g., Ki & Lee, 2021; Li, 2021; Li, Zhang, Li, Ricard, et al., 2015; Nagata et al., 2020; Wang & Vermeulen, 2021; Zhang et al., 2018), a deep learning method termed as “chopped picture” (Ise et al., 2017) was applied instead in those models. The “chopped picture” method was originally developed to identify amorphous objects such as groups of various shapes of plants, unlike distinctive objects (e.g., human faces, dogs, and automobiles), which previous machine learning methods had focused on. Importantly, this method would need less effort and images for its training process than previous object detection or semantic segmentation.
Fig. 2. A Building Image Identified by the Deep Learning Model for Houses

Note. Red squares depict the objects identified as ‘house’ by the model, and green squares depict other things.

(Kameoka et al., 2022). Therefore, this method was expected to perform well in identifying houses and plants in 39,187 GSV images. However, this machine learning method could not identify objects by referring to contextual information, namely, other objects around the target objects. In the current process, machine learning models built by the “chopped picture” method could identify plants with similar texture (e.g., green leaves) nearly as well as human raters, but could not further distinguish between plants nearby houses or any buildings from them. Besides, another limitation of the current method was that the 640 × 640 pixels resolution of GSV images would not be enough to classify types of plants which appeared as groups in the images. This means that the models developed by this method would hardly distinguish maintained plants from wild weeds around houses. Thus, we applied this deep learning method for houses and plants (not maintained plants), and subsequently got human raters to identify plants grown alongside buildings. In the process of developing two deep learning models, 531 and 564 clipped images were used for the models to identify houses or plants respectively (details are presented in supplementary materials).

We used the house model to identify houses in each of all the extracted images (Fig. 2 shows an example of object identification by the model) to select images in which houses were seen nearby. Two human raters also independently classified 392 randomly selected images, which made up 1% of the total number of extracted images, into those who had any house within its frame or not. Cohen’s kappa between their judgements was sufficiently high (.87). Unmatched judgements were discussed and resolved by the raters, and 245 images were concluded as ‘building images.’ Afterwards, we defined the threshold for classifying ‘building images’ via the percentage of parts identified as ‘house’ in any image by the model. This threshold needed to be set, in order for the model’s classification to replicate human raters’ judgement of sampled target images well enough, with lower bias for false positives and negatives. As a result, the
threshold rate of 8% for parts containing houses seemed to be feasible enough, because the kappa value with human raters (.66) was higher than the other percentages among threshold rates of 6% to 10% at 0.5-point intervals, and the number of false positives and negatives were relatively balanced (27 and 36 respectively). Using this threshold, 15,171 images classified as not ‘building images’ were excluded from the extracted images, and two communities were removed from the target communities as they had no ‘building images.’

As with classification of ‘building images,’ two human raters independently classified 245 sampled target images into ones in which maintained plants were seen or not (κ = .67). Unmatched judgements were discussed, and 158 images were agreed as ‘plant images.’ The plants model was used to identify plants in each of the 24,019 extracted images classified as ‘building image’ (Fig. 3 shows an example of object identification by the model). Unlike classification of ‘building images,’ the threshold(s) of the percentage of plant parts within an image was set to exclude images in which human raters would hardly identify any plants, such as house walls or bamboo forest taking up most of the frame. ‘Planting image’ classified by human raters from the sampled images ranged from 0% to 39% of plant parts identified in those images by the model, so the threshold was defined as 39%. As a result, 553 images were excluded from all the remaining extracted images.

Lastly, two human raters classified these 23,466 extracted images into ‘planting images’ or not. 941 images making up approximately 4% of the extracted images were independently judged by both raters. Their classifications matched highly enough (κ = .84), and these were randomly chosen as the outcome of each judgement. The rest of the extracted images were classified by either rater. Consequently, 3,224 images were classified as ‘planting images.’

**Fig. 3.** A Plant Image Identified by the Deep Learning Model for Plants

*Note.* Red squares depict the objects identified as plants by the model, and green squares depict other things.
Preprocess of the Analysis

Before analyzing the data, we excluded several samples that did not have enough data for the following statistical analysis. At the community level, samples who had less than 10 ‘building images’ were removed from the target communities, leaving 100 communities and 1,481 individual samples. These remaining target communities consisted of 27 farming, 62 fishing, 10 urban, and nine ‘other’ communities, including nine ‘mixed communities’ (one community’s type was unknown, because of unavailability of the census data). As for the individual samples, participants consisted of 808 males and 575 females (98 individuals’ gender was unknown), and the mode of their age in an ordinal scale was 65 to 69 (the median was the same). Additionally, data of individuals who consecutively chose the same option throughout a series of multiple-choice questions (even when the items covered diverse questions) were not included for those items, because they would not have properly paid attention to the questionnaires. Lastly, if the number of valid responses for an item was less than five by a target community, that item was treated as a missing value for that target community.

RESULTS

Summary of the Data

The survey included 30 items related to participants’ trust, reciprocity, community norms, social relationships, and attachment to the community’s values. To categorize those items into discrete measures using individual level data, we assessed internal consistency through a principal component analysis (PCA). Items that were sufficiently consistent with each other were averaged to form a single measure. Three items were averaged as a measure of ‘trust’ as a component of social capital (Putnam, 2000), as they showed acceptable Cronbach’s coefficient alpha (.69) and McDonald’s coefficient omega (.83). An example of an item asking about participants’ trust toward others would be: “I trust the people who live in my neighborhood.” Six items captured reciprocity as another component of social capital, associated with social support between participants and their neighbors (e.g., “If people in the neighborhood need help, I help them.”). The items showed sufficiently high Cronbach’s coefficient alpha (.84) and McDonald’s coefficient omega (.89). Four items captured participants’ attachment to their community’s values (e.g., “I feel attached to my neighborhood.”) and showed sufficiently high Cronbach’s coefficient alpha (.88) and McDonald’s coefficient omega (.92). As for community norms, two of five items that asked about the strictness of the norms in participants’ community had low factor loadings.4 Hence, only the remaining three items (e.g., “There are many rules in the neighborhood that we must obey.”) were averaged as a measure of community norms, which had acceptable Cronbach’s coefficient alpha (.66) and McDonald’s coefficient omega (.82). Two items regarding cooperativeness in a community, (“I/People in my neighborhood think it is important to maintain the harmony in the neighborhood.”) were positively correlated ($r = .51$, $p < .001$), and thus integrated as a measure of cooperativeness. Items excluded in the above process were used as single item scales in the analysis. The summary of all the measures and items at the individual level is shown in Table 1 (refer to the Appendix for the community level).

The extracted GSV images and classifications by target community are summarized

4 “If someone broke an established rule, they would probably be made to feel they no longer belong to the neighborhood.”; “I try to always follow the established rules of the neighborhood.”
Table 1. Description of the Items and Measures at the Individual Level

| Item                                                                 | N   | Mean | Med | SD  | Min | Max |
|----------------------------------------------------------------------|-----|------|-----|-----|-----|-----|
| Subjective happiness                                                | 1451| 6.78 | 7.00| 1.90| 0.00| 10.00|
| Subjective health                                                   | 1457| 6.53 | 7.00| 2.02| 0.00| 10.00|
| Ideal happiness                                                      | 1448| 7.24 | 8.00| 1.78| 0.00| 10.00|
| I (including the member of my household) am satisfied with the condition of my life. | 1420| 6.64 | 7.00| 2.19| 0.00| 10.00|
| I (including the member of my household) have enough money for living.| 1422| 5.72 | 6.00| 2.37| 0.00| 10.00|
| I am satisfied with the relationships I have with people in my neighborhood. | 1425| 5.87 | 6.00| 2.18| 0.00| 10.00|
| The members of my household are happy.                               | 1288| 6.66 | 7.00| 2.14| 0.00| 10.00|
| I sometimes feel stress in my daily life.                            | 1421| 5.33 | 5.00| 2.42| 0.00| 10.00|
| I sometimes feel angry in my daily life.                             | 1427| 4.82 | 5.00| 2.44| 0.00| 10.00|
| Happiness of people in your neighborhood                             | 1137| 5.80 | 6.00| 1.39| 0.00| 10.00|
| Happiness of minors in your neighborhood (high-school age or under)  | 1022| 6.00 | 6.00| 1.69| 0.00| 10.00|
| Happiness of people 65 years of age or older in your neighborhood     | 1165| 6.08 | 6.00| 1.63| 0.00| 10.00|
| I try to always follow the established rules of the neighborhood.    | 1368| 3.87 | 4.00| 0.87| 1.00| 5.00 |
| If someone broke an established rule, they would probably be made to feel they no longer belong to the neighborhood. | 1357| 2.48 | 2.00| 1.05| 1.00| 5.00 |
| I have relationships with people in my neighborhood that can never be cut from my life (for good or bad). | 1354| 2.68 | 3.00| 1.09| 1.00| 5.00 |
| There is a general sense in my neighborhood that everyone’s opinions will be accepted. | 1338| 2.51 | 3.00| 0.87| 1.00| 5.00 |
| Many children in my neighborhood participate in local festivals.     | 1342| 3.05 | 3.00| 1.19| 1.00| 5.00 |
| Concern for reputation                                               | 1346| 2.41 | 2.00| 1.01| 1.00| 5.00 |
| I clearly express my opinion when talking with people in my neighborhood. | 1346| 3.14 | 3.00| 0.99| 1.00| 5.00 |
| I don’t worry if my ideas or behavior are different from those of my neighbors. | 1353| 3.03 | 3.00| 0.98| 1.00| 5.00 |
| I would be happy if a person from outside of my neighborhood settled in this neighborhood. | 1367| 4.05 | 4.00| 0.87| 1.00| 5.00 |
| People in my neighborhood have many chances to get to know other people. | 1353| 2.69 | 3.00| 1.05| 1.00| 5.00 |
| I might leave this neighborhood and move to a different place.        | 1349| 2.12 | 2.00| 1.31| 1.00| 5.00 |
Table 2. Description of GSV Images and the Classification at the Community Level

|                          | N   | Mean | Med | SD  | Min  | Max  |
|--------------------------|-----|------|-----|-----|------|------|
| Collected GSV images     | 100 | 390.63 | 240.00 | 456.81 | 48.00 | 2852.00 |
| Building images          | 100 | 240.10 | 119.50 | 338.86 | 12.00 | 1929.00 |
| Building images rate     | 100 | 0.54 | 0.55 | 0.19 | 0.16 | 0.97 |
| Planting images          | 100 | 29.53 | 12.00 | 54.15 | 0.00 | 447.00 |
| Planting images rate     | 100 | 0.12 | 0.10 | 0.09 | 0.00 | 0.37 |
| Number of mailed surveys | 100 | 110.82 | 52.00 | 163.24 | 4.00 | 1045.00 |
| Number of responses      | 100 | 14.81 | 7.50 | 21.72 | 1.00 | 134.00 |
| Rate of responses        | 100 | 0.17 | 0.14 | 0.11 | 0.02 | 0.58 |

Note. GSV = Google Street View.

in Table 2. ‘Building image rate’ was the percentage of ‘building images’ over ‘collected GSV images,’ and ‘planting images rate’ was the percentage of ‘planting images’ over ‘building images.’

Correlation Analysis

To explore relationships between participants’ psychological tendency and physical characteristics in the target communities, we calculated the Spearman’s rank correlation coefficient between planting images rate and the other measures from the survey. The
A rank correlation test was applied instead of the Pearson’s product-moment correlation test due to violation of normality in the distribution of planting image rate as detected by the Lilliefors test ($p = .013$; its histogram is shown in Fig. 4). The results of the rank correlation test are shown in Table 3.

As shown in Table 3, the rate of planting images for all target communities was weakly positively correlated with four single item scales: ideal happiness, concern about neighbors, wealth of the neighborhood, and household income. It also had significant weak negative correlations with three measures: trust, cooperativeness, and attachment to the community’s values. However, differentiating between farming and fishing communities produced different patterns of correlations. For farming communities, planting images rate was moderately or strongly positively correlated with four single item scales, in addition to subjective happiness and health, stress and anger in daily life. Furthermore, planting images rate was also moderately negatively correlated with a single-item scale regarding openness toward migrants and the composite measure for trust. Lastly, fishing communities showed less similar patterns of correlations with the overall sample than farming communities. The rate of planting images had a significant moderate positive correlation with the happiness of young neighbors, and significant weak negative correlations with attachment to the community’s values and three single item scales: connection with neighbors, neighbors’ acceptance toward opinions, and closeness with neighbors. Additionally, the rate of planting images was weakly positively correlated with household income.

**Discussion**

The present study explored interrelations between social capital and neighborhood physical environment as a reflection of individuals’ behavior, by examining correlations between several measures from a mail survey and the frequency rate of plantings at
Table 3. Rank Correlations of Planting Images Rate and Various Measures From the Survey

|                                                | All communities (n = 100) | Farming communities (n = 27) | Fishing communities (n = 62) |
|------------------------------------------------|---------------------------|-------------------------------|------------------------------|
| Subjective happiness                           | .12                       | .47*                          | .01                          |
| Subjective health                              | .11                       | .42*                          | .02                          |
| Ideal happiness                                | .20*                      | .42*                          | .10                          |
| I (including the member of my household) have  |                           |                               |                              |
| enough money for living.                        |                           |                               |                              |
| I sometimes feel stress in my daily life.       |                           |                               |                              |
| I sometimes feel angry in my daily life.        |                           |                               |                              |
| Happiness of minors in your neighborhood (high- |                           |                               |                              |
| school age or under)                            |                           |                               |                              |
| If someone broke an established rule, they     |                           |                               |                              |
| would probably be made to feel they no        |                           |                               |                              |
| longer belong to the neighborhood.             |                           |                               |                              |
| I have relationships with people in my         |                           |                               |                              |
| neighborhood that can never be cut from my    |                           |                               |                              |
| life (for good or bad).                        |                           |                               |                              |
| There is a general sense in my neighborhood    |                           |                               |                              |
| that everyone’s opinions will be accepted.     |                           |                               |                              |
| Concern for reputation                         | .24*                      | .46*                          | .14                          |
| I would be happy if a person from outside of   |                           |                               |                              |
| my neighborhood settled in this neighborhood.  |                           |                               |                              |
| Trust [composite variable]                     |                           |                               |                              |
| Reciprocity [composite variable]               |                           |                               |                              |
| Community’s norms [composite variable]         | .14                       | .32                           | .02                          |
| Cooperativeness [composite variable]           |                           |                               |                              |
| Attachment to the community’s values [        |                           |                               |                              |
| composite variable]                            |                           |                               |                              |
| To what extent are you and people in the      |                           |                               |                              |
| neighborhood overlapped as two circles (in the |                           |                               |                              |
| figure).                                       |                           |                               |                              |
| How wealthy you are, compared with people in   |                           |                               |                              |
| the neighborhood.                              | .18†                      | .05                           | .19                          |
| How wealthy your neighborhood is in the county. |                           |                               |                              |
| What was your household’s pre-tax income last  |                           |                               |                              |
| year (including pensions)? (Your response is   |                           |                               |                              |
| optional.)                                      | .35**                     | .29                           | .32*                         |

Note. Results of single item scales whose $p$ value was more than .10 were omitted, because of space constraints. Five communities were categorized as both farming and fishing communities. **$p < .01$, *$p < .05$, †$p < .10$.**
houses observed through the GSV. Additionally, we also investigated differences in correlational patterns depending on types of community, namely farming and fishing communities.

**Associations Between Plantings and Social Relations in the Neighborhood**

First, results for the overall sample showed opposite patterns of correlations from expectations based on previous studies (e.g., Wijnands et al., 2019). In the current research, the frequency rate of plantings had no positive correlations with scales of social capital (i.e., trust and reciprocity), and even had negative correlations with trust, cooperativeness, and attachment to the community’s values. On the other hand, the rate of plantings was positively correlated with subjective wealth of the community, household income, concern for reputation, and ideal happiness. These findings suggest that plantings at houses could reflect residents’ financial freedom, and serve as signals of wealth to other residents, creating competition in the neighborhood. This interpretation could perhaps explain the former negative correlations for plantings, that is, the more plantings the houses had, the more conspicuous the financial competition became in the neighborhood, which contrasts with having cooperative relationships between neighbors.

Second, farming communities showed relatively similar correlation patterns with all communities other than fishing communities, though the rate of farming communities was lower than fishing communities among all the samples. Correlations between plantings, and cooperativeness, attachment to community’s values, or household income were not significant, but the directionality of the relationships were similar to all other communities. Besides, hospitality toward migrants was negatively correlated with plantings, which could also be explained through the earlier mentioned financially competitive relationships signaled by outdoor gardening, because new residents would be potential competitors of old residents. By contrast, subjective happiness and health had positive correlations with plantings, which is consistent with findings by previous studies (e.g., Hart et al., 2018; Wijnands et al., 2019). However, stress and anger in daily life also had moderate positive correlations with plantings, which was unlike previous studies showing that exposure to greenery on the street might have positive influences on people’s mental health (e.g., Hart et al., 2018; Jiang et al., 2020). Rather, our findings suggest that relatively happy or healthy residents might tend to grow plants around their houses, while feeling stress and anger in their daily lives, which would not necessarily contradict with having financially competitive relationships.

Third, unlike farming communities, fishing communities showed different correlational patterns from all other communities, even though fishing communities accounted for more than half of all samples. One of the notable results for fishing communities was the lack of association between subjective wealth of the community and plantings. This

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5 “How wealthy your neighborhood is in the country.”
6 “What was your household’s pre-tax income last year (including pensions)? (Your response is optional.)”
7 “I am concerned about what my neighbors think of me.”
8 “I would be happy if a person from outside of my neighborhood settled in this neighborhood.”
9 “I sometimes feel stress in my daily life.”; “I sometimes feel angry in my daily life.”
contrasts with the positive correlations found for all other communities and farming communities, which was similarly found between household income and plantings. Furthermore, subjective happiness and health had no correlations with plantings in contrast to farming communities. Unique correlation patterns for fishing communities emerged for two scales about psychological connections with neighbors,\textsuperscript{10} which were negatively correlated with plantings. In addition, openness toward each other’s opinion\textsuperscript{11} was also negatively correlated with plantings. These correlation patterns could be understood in the context of independent tendencies in fishing communities in Japan (Uchida et al., 2019). In other words, independent tendencies might motivate the residents to grow plants around their houses as segregations between private spaces and streets in fishing communities. However, independent tendencies are unable to account for the moderate positive correlation between happiness of minors in the neighborhood and plantings, and the current data does not provide sufficient evidence for interpretation.

Through the above discussion, we suggest the following hypothesis on interrelations between social capital and neighborhood physical environment. Plantings around houses could reflect residents’ financial leeway, and this might make the financially competitive relationships more conspicuous in the neighborhood. In such situations, neighborhood cooperative relationships including social capital might be undermined, and plantings around houses could arouse residents’ negative feelings, such as stress or anger. Additionally, that tendency could be more obvious in communities in which interdependence is dominant, such as farming communities. This interpretation of the results corresponds to the discussion by Liu et al. (2019) that people from collectivistic cultures would tend to be more vigilant toward other members in their community under competitive situations than individualistic cultures. Furthermore, we expect that this phenomenon could not occur in individualistic communities, such as fishing communities, where independent tendencies are dominant. Rather, weak psychological connections among neighbors could be reflected in the plantings around houses which acts as additional walls between private and public spaces. The above difference between farming and fishing communities in using plantings could support the discussion of cultural differences associated with socioecological factors in Uchida et al. (2019) from the perspective of observable physical environment.

Consequently, while the previous studies indicated positive associations between social capital and overall greenery on the streets (e.g., Wijnands et al., 2019), our findings suggest that individuals’ direct intervention to the streetscapes, a specific type of greenery in the form of personal landscaping/gardening, could negatively influence social capital in the neighborhood, depending on the type of community. Therefore, the influence of greenery on social capital in local communities would need to be discussed while considering categories and contextual effects of different communities. In terms of contextual effects, while Uchida et al. (2019) pointed out that collective activities (e.g., maintenance of community infrastructure) in a local community could play an important

\textsuperscript{10}“I have relationships with people in my neighborhood that can never be cut from my life (for good or bad).”; “To what extent are you and people in the neighborhood overlapped as two circles (in the figure).”

\textsuperscript{11}“There is a general sense in my neighborhood that everyone’s opinions will be accepted.”
role, our findings suggest that elements (e.g., plantings managed by individuals) observed in streetscapes also could be a mediator of such effects. In other words, the present study extended the theory suggested in the previous study by combining the self-reported survey on psychological aspects and image data of the shared physical environment, which was a more objective measure. This is an important approach to investigate contextual effects and for community building on the ground.

Furthermore, compared with the previous studies in Western countries (e.g., Heinze et al., 2018; Wijnands et al., 2019), the present study focusing on Japanese rural areas showed a country-level cultural difference in the position of plantings around houses within the streetscape. While plantings observed around houses in Japan might be privately owned (see Fig. 3) and function as a boundary for each, outdoor gardening in the Western countries might be parts of the streetscape of public roads. In other words, the former could be more likely controlled by house residents who care about their reputation within the community, while the latter could be more likely influenced by residents who care about the public spaces of the community. Therefore, the present study also suggests that ‘publicness’ of streetscapes around houses could differ by types of communities, regions, or nations, which could be quantitatively investigated as practiced in the present study.

Limitations and Future Studies

The samples used by the present study came from a mail survey that originally focused on farming and fishing communities in certain regions, and thereby had several limitations for statistical analyses and generalization of the results. Specifically, the samples were from the Kinki and Shikoku regions, which may not be representative of all local communities across Japan. Moreover, because of low population in rural areas, the number of valid responses by target community were very low for some items of the survey,\(^\text{12}\) which limited available statistical analysis including multivariate analysis. Ideally, the differences of the correlation patterns between the farming and fishing communities were to be tested through a multiple regression analysis using community type as a moderator. However, the relatively small sample size would make it difficult to detect those differences in that analysis, even if they were fairly large. Therefore, our suggestion from the results needs to be considered with this limitation in mind. Regarding GSV imagery collection, given that the samples were mainly from rural areas, the probability of obtaining GSV imagery from a target community would also be low, because GSV imagery would be relatively sparse in the countryside, compared to urban areas. This shortage of GSV images in some target communities also contributed to the limited availability of sample size for statistical analysis. Another limitation of GSV was that the dates of the latest images were not controlled, and sometimes ranged across several years even within communities. Additionally, the low resolution of GSV imagery hindered the classification of types of plants by machine learning models. The permissions of use of GSV imagery may be another limitation of the present method, as

\(^{12}\) For example, the number of valid responses from farming communities was just six in the measure for ‘happiness of minors in your neighborhood (high-school age or under).’
well as above issues about the image data (see footnote 2). Referring to our discussion in the methods section, users are left to interpret Google’s restrictions by themselves, which might allow studies utilizing GSV imagery to be published continuously as reviewed in the present study. Thus, researchers also need to consider alternative resources (e.g., Mapillary). Lastly, though we focused on the smallest unit of area based on the census, mainly because of the availability of the dataset, the actual geographical range of the ‘local community’ or neighborhood could be smaller than that.

The limitations in size and geographical variety of the samples in the present study could be addressed by conducting larger scale mail or online surveys in future studies. Furthermore, different data and perspectives that were not utilized in the present study can be used to verify the current findings. First, with a satisfactory sample size, the differences in the correlation patterns between the community types can be tested by a multiple regression analysis. For demographic and socioecological factors, governmental statistics (e.g., census data) that objectively show socioeconomic status and governmental policies for certain areas such as urban planning would offer more information to describe actual situations in the target communities. For the physical environment, classifying specific types of plants that might correspond to the type of community could be conducted by using higher resolution GSV images sold by Google. Elements of streetscapes reflecting individuals’ behavior apart from plantings at houses and longitudinal data of GSV, would also be important to further uncover the dynamics of social capital and neighborhood physical environment. Moreover, the influence of neighborhood facilities (e.g., parks, stations, or schools) on associations between social capital and streetscapes also need to be considered especially in urban areas where the density of buildings is much higher than rural areas. Finally, to explore people’s motivation to care for the streetscape, including plants, future studies can tap into the advantage of using GSV to not only compare communities within a country, but also between countries.

In conclusion, the present study shed light on interrelations between social capital and neighborhood physical environment by combining a conventional mail survey and a newly developed virtual systematic social observation. Despite the limitations of the samples, the results suggested that neighborhood socioecological environment could potentially reflect the dynamics of social capital in a community. We encourage future studies to verify the current hypothesis by utilizing geographically larger and more diverse imagery data, and aggregating various statistics about the target areas. Additionally, from a broader psychological perspective, conventional latent values or factors (e.g., social capital) embedded in interactions between individuals and the ‘built environment’ around them could be discussed more comprehensively by utilizing the present method. This is an important step to extend the psychological discussions from data from self-reports and laboratories to behaviors observed in real situations.
AUTHOR’S CONTRIBUTION

A.U. designed the study; participated in creating items of the survey; collected and managed open data provided by the government and images of GSV using API; trained and processed the machine learning models; classified the images; conducted the statistical analysis; wrote and revised the draft. T.I. implemented the machine learning analyses. Y.M. supported the analysis of the mail survey data and discussed the research idea and interpretation of the results. H.H. and K.T. participated in the design of the mail survey. Y.U. contributed to the design of the mail survey and theory model construction.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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### APPENDIX

Description of the Items and Measures at the Community Level

| Item                                                                 | N  | Mean | Med | SD  | Min | Max |
|---------------------------------------------------------------------|----|------|-----|-----|-----|-----|
| Subjective happiness                                               | 75 | 6.68 | 6.82| 0.71| 4.00| 7.80|
| Subjective health                                                  | 75 | 6.44 | 6.50| 0.59| 4.64| 7.50|
| Ideal happiness                                                    | 74 | 7.07 | 7.28| 0.68| 4.80| 8.48|
| I (including the member of my household) am satisfied with the     | 73 | 6.54 | 6.69| 0.75| 5.00| 7.89|
| condition of my life                                               |    |      |     |     |     |     |
| I (including the member of my household) have enough money for    | 73 | 5.53 | 5.64| 0.90| 3.29| 7.36|
| living.                                                             |    |      |     |     |     |     |
| I am satisfied with the relationships I have with people in my     | 74 | 5.83 | 5.87| 0.83| 4.00| 7.80|
| neighborhood.                                                      |    |      |     |     |     |     |
| The members of my household are happy.                             | 72 | 6.59 | 6.68| 0.73| 4.50| 8.20|
| I sometimes feel stress in my daily life.                          | 73 | 5.26 | 5.31| 0.76| 3.50| 7.17|
| I sometimes feel angry in my daily life.                           | 74 | 4.82 | 4.82| 0.70| 3.17| 6.13|
| Happiness of people in your neighborhood                           | 67 | 5.60 | 5.60| 0.61| 3.80| 7.60|
| Happiness of minors in your neighborhood (high-school age or       | 60 | 5.77 | 5.78| 0.74| 3.13| 7.40|
| under)                                                             |    |      |     |     |     |     |
| Happiness of people 65 years of age or older in your neighborhood   | 67 | 5.87 | 6.00| 0.68| 3.00| 7.20|
| I try to always follow the established rules of the neighborhood.  | 72 | 3.91 | 3.91| 0.31| 3.32| 4.60|
| If someone broke an established rule, they would probably be      | 72 | 2.48 | 2.43| 0.44| 1.60| 3.88|
| made to feel they no longer belong to the neighborhood.            |    |      |     |     |     |     |
| I have relationships with people in my neighborhood that can      | 71 | 2.78 | 2.83| 0.47| 1.79| 3.83|
| never be cut from my life (for good or bad).                      |    |      |     |     |     |     |
| There is a general sense in my neighborhood that everyone’s       | 71 | 2.53 | 2.50| 0.31| 1.71| 3.40|
| opinions will be accepted.                                        |    |      |     |     |     |     |
| Many children in my neighborhood participate in local festivals.   | 70 | 2.91 | 2.91| 0.72| 1.40| 4.40|
| Concern for reputation                                            | 72 | 2.45 | 2.45| 0.40| 1.33| 3.50|
| I clearly express my opinion when talking with people in my       | 72 | 3.20 | 3.20| 0.34| 2.20| 3.86|
| neighborhood.                                                      |    |      |     |     |     |     |
| I don’t worry if my ideas or behavior are different from those of | 72 | 3.02 | 3.06| 0.29| 2.00| 3.69|
| my neighbors.                                                      |    |      |     |     |     |     |
| I would be happy if a person from outside of my neighborhood      | 72 | 4.05 | 4.05| 0.37| 2.86| 4.71|
| settled in this neighborhood.                                      |    |      |     |     |     |     |
| People in my neighborhood have many chances to get to know        | 72 | 2.64 | 2.64| 0.43| 1.50| 4.00|
| other people.                                                      |    |      |     |     |     |     |
| I might leave this neighborhood and move to a different place.     | 72 | 2.06 | 2.00| 0.52| 1.17| 4.50|

INTRODUCTION

METHOD

RESULTS

DISCUSSION

(Released online in J-STAGE as advance publication ■ ■ ■ ■)

(Manuscript received ■ ■ ■ ■; Revision accepted ■ ■ ■ ■; Released online in J-STAGE as advance publication ■ ■ ■ ■)
| Statement                                                                 | N  | Mean | Med | SD  | Min | Max |
|--------------------------------------------------------------------------|----|------|-----|-----|-----|-----|
| If I move from the neighborhood, I am sure to get used to life in the new place. | 72 | 3.15 | 3.17 | 0.37 | 2.00 | 4.00 |
| Trust [composite variable]                                               | 70 | 3.03 | 3.00 | 0.21 | 2.60 | 3.67 |
| Reciprocity [composite variable]                                        | 71 | 3.50 | 3.50 | 0.28 | 2.84 | 4.05 |
| Community’s norms [composite variable]                                  | 72 | 2.97 | 2.98 | 0.37 | 1.93 | 4.00 |
| Cooperativeness [composite variable]                                    | 71 | 3.85 | 3.85 | 0.26 | 3.36 | 4.50 |
| Attachment to the community’s values [composite variable]               | 71 | 3.79 | 3.79 | 0.37 | 2.65 | 4.50 |
| To what extent are you and people in the neighborhood overlapped as two circles (in the figure). | 71 | 3.20 | 3.20 | 0.42 | 2.11 | 4.10 |
| How wealthy you are, compared with people in the neighborhood.           | 71 | 3.74 | 3.78 | 0.49 | 2.40 | 5.00 |
| How wealthy your neighborhood is in the country.                         | 74 | 3.28 | 3.34 | 0.58 | 2.00 | 4.57 |
| What was your household’s pre-tax income last year (including pensions)? | 67 | 2.63 | 2.67 | 0.66 | 1.43 | 4.60 |