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Examining the relationship between social context and community attachment through the daily social context averaging effect

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ABSTRACT

This study advances the measurement of community social context by introducing the daily dynamic perspective to promote a better understanding of the relationship between community social context and community attachment. It measured the social context averaging or polarization (SCAP) effect of communities every 3 h using census and cell phone data and investigated residents' community attachment in 71 communities in Guangzhou, China. There are three findings. First, the social contexts of many communities varied during the day, either moving toward the mean of the whole city or away from the mean. Distinct patterns exist during work hours, evening hours, and night hours. Second, considering variations in social contexts during the evening hours significantly enhances the explanation of the heterogeneity in residents' community attachment. Third, variations in social contexts are more likely to influence residents' attachment in old blocks and migrant communities, and communities that may have gated sub-units are less likely to be influenced. The study advocates that context dynamics be taken as a new dimension of community indicators in place perception studies. The study is also instructive in targeting space and time that deserve special attention in community governance practice.

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Community social context; social area; human mobility; daily activity; averaging effect; community attachment

Introduction

Community attachment describes residents' feeling of acceptance of and belonging to the communities in which they live (Matarrita-Cascante and Luloff 2008). Evidence from various fields has confirmed the positive value of residents' attachment to their communities, including but not limited to promoting the formation of place rootedness and environmentally friendly behaviours (Gu

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and Ryan 2008; Trentelman 2009), enabling community support and reducing crime (Nunkoo and Ramkissoon 2012; Matsukawa and Tatsuki 2018), and establishing a stable identity and increasing people's willingness to settle down (Wu 2012). Despite some negative influence on individuals in specific situations (Fried 2000), improving residents' community attachment is still a fundamental goal of local governance and urban planning.

It is generally believed that community attachment is affected by two levels of factors: the individual level and the community level (Lewicka 2011; Gurney et al. 2017). Lewicka (2011) found that previous studies explored a lot about how individual differences influence place attachment and might even have overemphasized their influence. However, with globalization and urbanization, the increasing prominent inter-community heterogeneity of community attachment, which cannot be simply explained by individual difference, was identified by scholars and has attracted wide attention in recent years (Greif 2010; Gurney et al. 2017; Chang et al. 2020). Understanding what makes residents in different communities have such different levels of attachment to their communities has become important for effective management and planning (Bacqué, Charmes, and Vermeersch 2014).

The community social context is often used as a critical factor in explaining inter-community differences in attachment in existing studies, which have concluded that a community's social context is where the residents perceive and represent the social aspects of their lives. Social context significantly influences social interactions in the community and thus may lead to diverse levels of community attachment (Wu 2012; Górny and Toruńczyk-Ruiz 2013; He 2013). However, although the cases examined to date were well explained in the literature, the results obtained varied when they are compared with each other. Similar community social contexts were found to have completely different, and sometimes opposite, effects on residents' community attachment in different studies (Hays and Kogl 2007; Stolle, Soroka, and Johnston 2008; Greif 2010; Wu 2012).

Some scholars have noted that the inconsistent findings may be attributed to measuring the social context using a static perspective based on census tracts or other delineations of residential location or community (Lewicka 2011; Gustafson 2014). In some cases, particularly those in high-density and high-mobility cities, a community's actual social context is quite different from the one reflected by census tracts, as the community's population continuously interacts with the city's entire population throughout the day (Sundblad and Sapp 2011; Gustafson 2014; Gurney et al. 2017). Because of people's daily mobility, an averaging effect may influence people's actual social context, which means that the social context people perceive or experience may be closer to the population mean than that reflected by the pertinent residential census tracts (Petrović, van Ham, and Manley 2018; Kwan 2018b; Xu et al. 2019). Studies also found that effective social interactions only happen in specific activities at specific times (Kwan 2018a). And some residents, especially the residents of disadvantaged communities, can be especially sensitive to changes in the social context of their residential areas (Lees 2008; Sundblad and Sapp 2011; Bailey, Kearns, and Livingston 2012). Thus, understanding community attachment from a static perspective in a high-mobility age can be biased and may sometimes be misleading (Gustafson 2014; Niedzielski, O'Kelly, and Boschmann 2015). To better understand the community-level differences in community attachment, it is necessary to develop methods to capture the dynamics of community social context and re-examine people's place perceptions.

This study seeks to advance the study on the relationship between community attachment and community social context by introducing the notions of daily dynamic social context and social context averaging. The study combines census and cell phone data to depict the dynamic maps of community social contexts in Guangzhou in China and investigates the relationships between these dynamic social contexts and people's place attachment. By considering both residential social composition and the variations in social contexts at different times of the day, the study hopes to promote a better understanding of community attachment and inspire the formulation of relevant policies to improve community governance.

Literature review

Influence of social context on community attachment

Community attachment is one type of place attachment that focuses on residents' feeling of acceptance of and belonging to the communities in which they live (Matarrita-Cascante and Luloff 2008). Besides examining the emotional bonds between individuals and places, as has been done in studies adopting the generalized concept of place attachment, community attachment research also focuses on individuals' connections with the community and other residents in the community (Trentelman 2009), as well as the subjective perception of the functionality of the community (Trentelman 2009; Erickson, Call, and Brown 2012). By examining how individuals perceive their communities emotionally, socially, physically, and functionally, the concept of community attachment can be used to better explain residents' residential satisfaction and willingness to stay, and therefore plays an essential role in the field of place studies and housing studies (Vogt, Allen, and Cordes 2003; Kanakis et al. 2019), especially for Chinese cities in which community is the basic social unit (Chang et al. 2020).

Previous studies have proposed many approaches to understanding community attachment. A well-known approach to examining the social factors that influence community attachment is the linear development model proposed by sociologists who believed that the societal transformation brought by urbanization might weaken social ties and place-related sentiments in communities (Goudy 1990). Hence, attachment to communities tended to weaken with increases in urbanization-related indicators like population size and density (Kasarda and Janowitz 1974; Goudy 1990). The approach provided a straightforward way to bridge community attributes and residents' community attachment and was supported by evidence from some less urbanized areas (Kasarda and Janowitz 1974; Wasserman 1982). However, when examining diverse and heterogeneous communities in highly urbanized big cities, the linear development model was criticized for its low explanatory power (Sundblad and Sapp 2011; Gustafson 2014). Instead, scholars suggested considering the complexities of social ties and the structural social conditions of communities (Sampson 1988; Flaherty and Brown 2010). They found that the influence of community context on individuals' attachment was multi-dimensional. For instance, residents of socially mixed communities might be distinct in their social interaction patterns and willingness to take up long residence and ultimately have radically different levels of attachment when compared to residents of other types of communities (Sampson 1988; Crowe 2010; Flaherty and Brown 2010; Greif 2010). Hence, both the linear development variable and the multi-dimensional social composition of communities should be considered to understand the inter-community differences in community attachment.

Individuals are exposed to multidimensional geographic contexts in their daily activities, among which the social context, that describes the characteristics and relations of people in the geographic context (Kwan 2012), is an essential factor that influences the neighborhood effect of place on people and people's perceptions of places (Kwan 2018a; Petrović 2020). The concept of social context emphasizes the real social composition of the population to which individuals are exposed in their daily activities and thus distinguishes itself from static social environment studies (Tan, Chai, and Chen 2019; Petrović 2020). Some studies examined the attachment of residents living in communities with specific social compositions and obtained meaningful results by comparing them (Wu 2012; Chang et al. 2020). However, when examining the effects of similar community types in different studies, the results can be inconsistent or even contradictory, especially for low-income communities and migrant communities. For example, while many studies confirmed the general negative association between social mixing and neighbourhood attachment (Greif 2010; Lewicka 2011), some studies observed that social status diversity benefits place attachment (Lewicka 2011; Górny and Toruńczyk-Ruiz 2013). Focusing on specific community types in China, Wu (2012) examined 25 low-income neighbourhoods in six cities and concluded that people living in areas dominated by low-income rural migrants were less willing to identify themselves with their neighbourhoods in contrast to those living in areas dominated by unemployed or retired urban residents. Also based on a survey in China, He (2013) examined four typical communities: open-access old neighbourhoods, *danwei* (work unit) compounds, gated commodity housing estates and migrant enclaves. Her result is that urban life in different types of communities was endowed with very different social meanings, with the migrant enclaves and the commodity housing estates fostering stronger community attachment in their residents. And in another study in China, Zhu, Breitung, and Li (2012) investigated 11 commodity communities in Guangzhou and found that only some of them actually promoted residents' community attachment because residents have different social interaction patterns in different communities. The results of these three Chinese studies are incompatible with each other. Moreover, the effects of community social composition on community attachment were claimed to disappear in some studies based on large sample surveys (Li and Wu 2008; Crowe 2010; Flaherty and Brown 2010). Thus, the relationship between community social context and community attachment remains unclear.

Measuring social context from a dynamic perspective

The studies discussed above assumed that the social contexts of urban communities are static throughout the day. However, the social context of a community is also affected by people who work and visit the community at different times during the day. For example, Silm and Ahas (2014) used cell phone data to compare the segregation indices of different city districts during the day, week and year in Tallinn, Estonia. Their results indicated that temporal segregation indices based on mobile phone use are considerably lower than indices based on residential places derived from the census, where variations between the nighttime and the daytime are the most significant. Le Roux, Vallée, and Commenges (2017) focused on the daily dynamic and examined variations in districts' educational and socio-professional composition over 24 h in the Paris region by drawing on a large sample and detailed daily travel survey. They also found that the city is less segregated during the daytime, but their results indicated that the daily dynamic is socially and spatially differentiated. The study argued that dividing the Paris region into different clusters by considering both districts' social composition and daily dynamics is more adaptable to place perception studies and relevant policies. These studies point out a new perspective for understanding the previously unclear community effects.

Some scholars have summarized the general patterns of daily context dynamics and tried to conceptualize them. For example, Kwan (2012) discussed how people's daily mobility may influence and differentiate their exposure to different community contexts by putting forward the notion of the uncertain geographic context problem (UGCoP). She also proposed the concept of the neighbourhood effect averaging problem (NEAP). This notion suggests the tendency that daily mobility will make a resident's actual exposure to the community environment moves toward the average level when compared with the static residence-based environment (Kwan 2018b). Therefore, people who live in highly segregated communities are more likely to experience a lower level of segregation when their daily mobility is taken into account. Daily mobility increases residents' chances of encountering dissimilar citizens and diminishes the neighbourhood effects of their residential communities. Similar averaging problems were also found in other research (Petrović, van Ham, and Manley 2018; Xu et al. 2019) which argued that the actual socio-spatial context people are exposed to at a place is not only determined by the population living at that place but also influenced by the population of surrounding and other places. In addition, for communities with very high or low levels of certain socioeconomic characteristics, the exposure levels of people's who live there would tend towards the population mean of the entire city.

Therefore, the daily dynamic constitutes another essential dimension of community features besides the social composition of communities. The population's daily dynamic means that residents living in similar socially composed communities may be exposed to completely different social contexts throughout the day. Moreover, the averaging problem of the daily social context can make the actual social context of communities trend toward the population mean during the daytime (Figure 1). We refer to this phenomenon as social context averaging and polarization (SCAP) in this paper because sometimes the trend is towards social context polarization rather than averaging (as observed in this study). The existence of SCAP can be a great challenge in studies that seek to understand the impacts of community social contexts on people's place attachment or other behaviours using static residence-based approaches.

Residents' daily activity and their actual social interactions in the community

Another stream of research that challenges studies based on static contexts is research on people's daily activities and social interactions. Scholars emphasized the diversity of residents' activity sites and activity purposes throughout the day and advocated studies that take into account the meaning of specific activities at specific places to the residents (Niedzielski, O'Kelly, and Boschmann 2015; Ellegård 2018). Although residents generally spend the most time in their residential communities, they do not always have social interactions with other people there. Residents may conduct only a

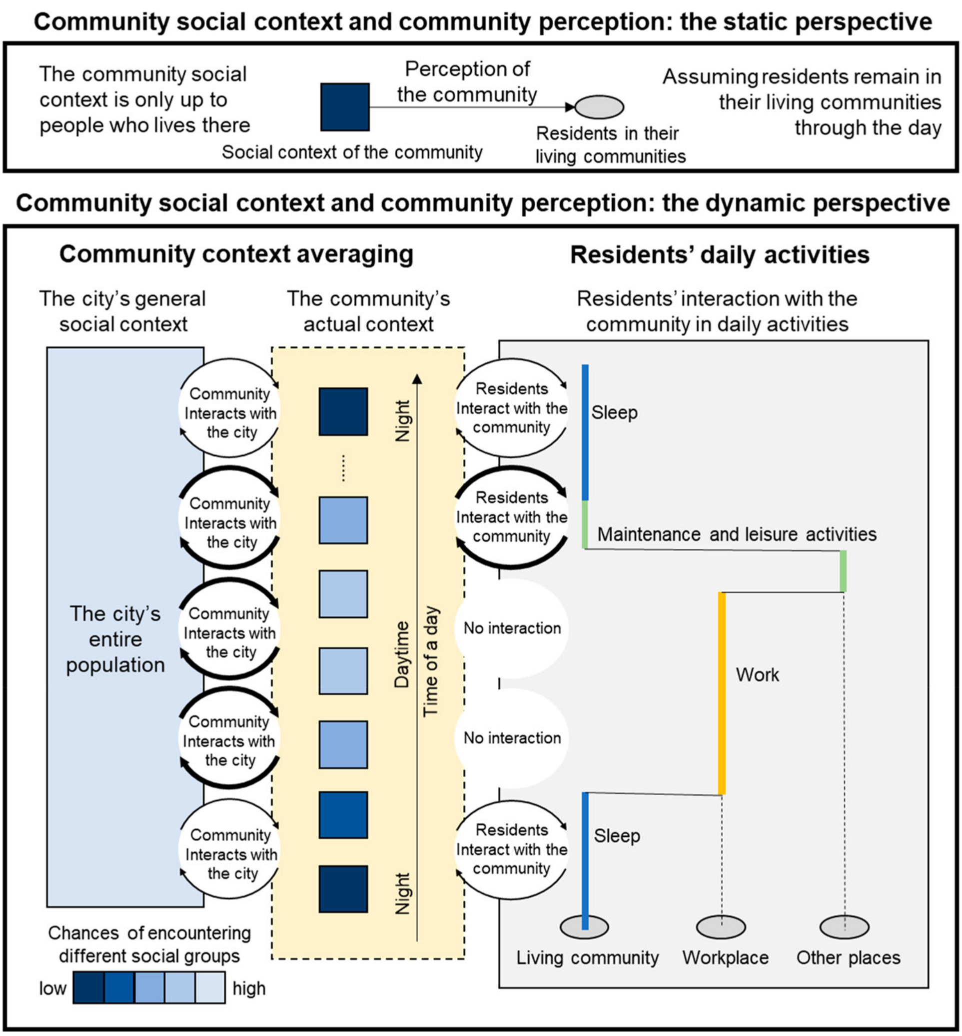

Figure 1. Theoretical perspective.

few activities at their residential locations, with most of their time spent sleeping at home. Hence, the actual social interactions at people's residential locations can be much less than expected and confined within a limited time (Kwan 2012). Based on the meaning of activities to people, some scholars have divided daily activities into three categories: subsistence activities, such as sleep and work; maintenance activities, such as shopping and dining; and leisure activities, such as entertainment and sport. Their results showed that maintenance and leisure activities near people's homes have more inter-group interaction potential (Susilo and Dijst 2010; Browning et al. 2017; Ellegård 2018). Therefore, the actual social interactions that may influence residents' community attachment can only happen in specific activities during limited periods (Lees 2008; Sundblad and Sapp 2011; Bailey, Kearns, and Livingston 2012) (Figure 1). Some advanced studies have attempted to examine residents' actual social interactions and improve existing static context-based attachment research by introducing the community field theory (Sundblad and Sapp 2011) and redefining the concept of community (Gurney et al. 2017). However, research that takes the daily social context dynamic of communities into account is still limited.

Summary

Previous studies have confirmed the influence of social context on people's community attachment with an emphasis on linear development variables (population density) and structural variables (multidimensional social composition and community type). However, these studies did not consider the dynamic nature of high-mobility modern communities and people's daily activities and therefore led to inconsistent results. We identified two streams of recent findings that challenge studies based on static context attachment (Figure 1). The community context averaging problem challenges the conventional community context measure by indicating that a community's actual social context generally deviates from its residence-based context because of the interaction with the city's entire population. The dynamic of the social context of a community can be perceived by its residents. The daily activity studies highlight the significance of activity purpose and interaction intensity and argue that social interactions that may influence residents' community attachment can only happen in specific activities during specific time periods.

We believe that combining the findings of the two streams of work can provide a new perspective to clarify the unclear relationships between inter-community differences in social contexts and people's community attachment. The study thus seeks to address the following three research questions: (1) How do communities' multidimensional social contexts vary with time, and will there be an averaging problem in the variation? (2) Can the daily dynamic perspective explain the inter-community differences in community attachment better than the static approach? (3) Does the impact of social context dynamics vary across communities, and are there communities that need special attention?

Data

Research area

The study area for this research is Guangzhou, the capital of Guangdong province in the south of China. Guangzhou is a nationally historical city and one of China's fastest-growing cities. According to the 2020 statistical yearbook of the city, the population of Guangzhou reaches 18.74 million, the population density of the city's urbanized area approaches 3,000 people per square kilometres, and migrants (permanent population without local registration) comprised more than 40% of the city's total population. The high density and socio-economic diversity make the city a good case for the study. This study focuses on the nine traditional administrative districts which make up the major urbanized area of Guangzhou city (Figure 2). The population of the nine districts comprises over 90% of the registered population in the whole city (Guangzhou Statistics Bureau 2021).

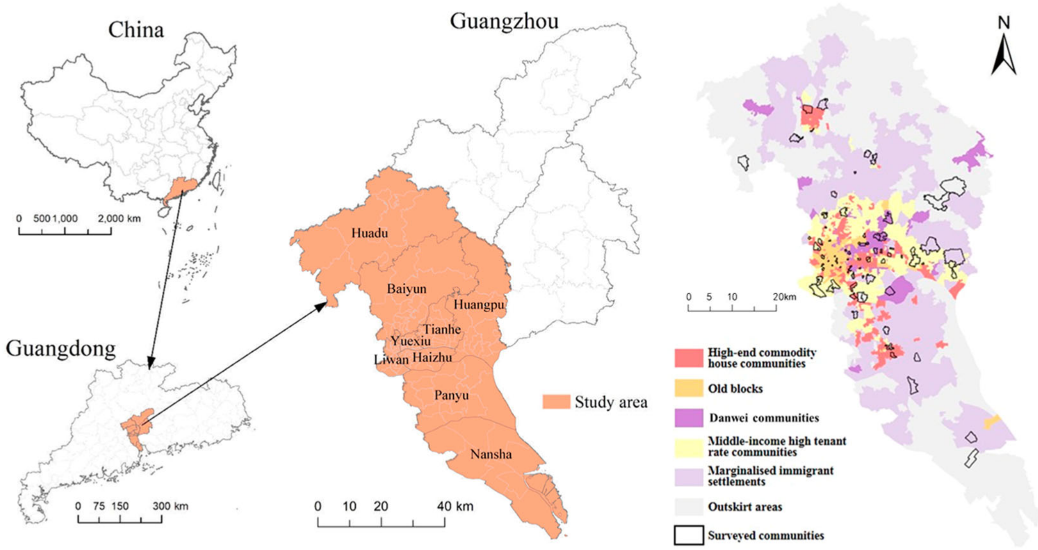

Figure 2. Research area and surveyed communities.

Data collection and processing

Census data

The Sixth National Population Census conducted in 2010 (as the 2020 census data are not yet available, this is the most recent authoritative data) is used to generate the residence-based community social contexts. The census defines the community as the smallest administrative unit in China, which contains one or several independently managed neighbourhoods that are spatially adjacent. Because census communities are also the basic units for primary life services (policing, healthcare, etc.) and logistics delivery in China, residents often need to report which census community they are located in. Also, census community administrators keep in touch with community individuals through online communication platforms in daily life, so residents generally have a clear idea of the community to which they belong. Respondents were asked to give the names of their census communities and to evaluate them in our survey, and we found that they were all able to specify the name of their communities.

Census communities in Chinese cities were delineated following the principles of being easy to manage, easy to self-govern, and easy to allocate resources. Every few thousand residents were assigned to a single community in consideration of the residents' locality, identity, and the neighborhood access control (Ministry of Civil Affairs of the People's Republic of China 2009; Wu and He 2015). Many place-based studies in China were conducted at the census community level (Wu 2012; He 2013; Wu et al. 2014; Chang et al. 2020), and scholars have found that census community residents are not only similar in their socio-economic attributes (Wu et al. 2014), but also close in their self-identity, perceptions, and preferences (He 2013; Chang et al. 2020). Scholars have different definitions for the concept of community. The Chinese census community unit aligns with geographers' viewpoint, in which a community refers to a neighbourhood unit with socially homogeneous and similarly behaved residents (Wu et al. 2014; Gurney et al. 2017). This research takes the census community as the basic unit. In Guangzhou, a community covers approximately 1.7 square kilometres and contains approximately 5400 residents on average.

Five dimensions of census features were synthesized to identify a community's social context types, including the widely discussed social status (Bacqué, Charmes, and Vermeersch 2014; Xu et al. 2019), education level (Le Roux, Vallée, and Commenges 2017) and occupation compositions

(Bailey, Kearns, and Livingston 2012; Le Roux, Vallée, and Commenges 2017), as well as two Chinese city-specific factors of the household registration composition (He 2013; Lin, Wu, and Li 2020), and housing property right type composition (He 2013; Chang et al. 2020). A factor analysis followed by a k-means clustering analysis is used to reduce the feature dimensions and classify the social context types of communities. Finally, the community features are simplified to five main factors. Based on the five main factors, the communities are clustered into six types (see the process of grouping analysis in the Supplemental Materials). As shown in Table 1, the high-end commodity house communities (HC) are characterized by higher housing rent and higher education levels in residents. Most residents entered the communities by purchasing commodity houses. The old blocks (OB) are characterized by more local residents engaged in commerce and service. Danwei communities (DC) have a high proportion of policy houses, with most residents engaged in administration and management. These communities are mostly the once state-owned compounds, representing the type of community which is self-sufficient in residence, employment and service facilities (He 2013). The middle-income high tenant rate communities (MH) are characterized by high rent rates, middle housing rent, and middle education level. The marginalized migrant settlements (MI) are characterized by a higher proportion of migrants living in low-rent houses and engaged in the manufacturing industry. The outskirt areas (OA) are characterized by local residents living in self-built houses. The result is greatly consistent with previous social area research in Guangzhou.

Survey data

A multi-stage probability proportional-to-population size sampling survey was conducted to investigate residents' community attachment. We selected 71 communities as the survey subjects considering both community type and spatial distribution. The communities cover all nine administrative districts and are distributed evenly across the six social context types (Figure 2). For each community, 20–30 respondents were proportionally sampled considering the community's social composition. Professional investigators were employed to conduct face-to-face interviews with the

Table 1. Statistics of different community types.

	Community type					
	HC	OB	DC	MH	MI	OA
N	351	485	157	314	394	341
Housing rent (%)						
Low	11.3	39.0	17.5	11.5	63.6	55.1
Middle	12.1	19.4	18.4	51.7	27.1	35.3
High	76.5	41.5	64.1	36.8	9.3	9.6
Education level (%)						
Middle school or below	15.1	16.2	10.2	15.4	22.1	30.3
High school	52.4	62.7	37.6	67.9	71.2	64.9
College or above	32.5	21.1	52.3	16.7	6.7	4.8
Occupation type (%)						
Administration and management	51.9	38.7	61.1	26.1	16.0	12.9
Manufacturing industry	14.8	16.1	10.5	31.1	56.2	34.2
Commerce and service	32.9	44.9	25.7	41.9	18.1	17.4
Others	0.4	0.3	2.7	0.9	9.7	35.5
Household registration (%)						
Local	49.0	68.8	63.2	29.5	46.7	81.1
Intra-province migrants	37.2	21.4	26.7	35.3	15.1	6.8
Outside-province migrants	13.7	9.7	10.0	35.2	38.2	12.1
How residents obtained the house (%)						
Purchasing commodity house	67.6	20.6	25.6	16.1	6.3	2.7
Policy house	15.6	43.2	50.3	15.9	12.0	6.2
Rent house	12.8	29.4	15.8	55.6	36.7	8.1
Self-built house	4.0	6.9	8.3	12.4	45.0	83.0

Note: high housing rent refers to the top 33% of housing rent in the city, low housing rent refers to the bottom 33%, and middle housing rent is the rent between them.

respondents. The respondents were requested to fill in their detailed socio-economic attributes and complete a Community Attachment Scale.

We use a Community Attachment Scale to measure how individuals perceive their communities emotionally, socially, physically, and functionally, and to examine their willingness to stay. The scale measures residents' community attachment by their responses to four statements: (1) I have a lot of affection for my community; (2) If I have to move out of the community, I would feel reluctant to part with my neighbours; (3) If have to move out of the community, I would feel reluctant to part with the suitable environment; and (4) I feel satisfied with the community management. For each statement, the respondents made self-evaluations using a five-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree. We took the sum of the scores as participants' community attachment scores. The scale is translated from its English version that has been used in other community attachment studies (Lewicka 2011).

The survey was conducted between January and April 2016 under the supervision of the Ethics Committee of Sun Yat-sen University. All participants were fully informed about the study design and provided written consent. In total, 1530 questionnaires were sent out, and 1523 valid ones were retrieved. The reliability and validity of the scale were examined and confirmed to be excellent. The respondents represent their communities well (see the sample representativeness evaluation in the Supplemental Materials).

Cell phone data

Cell phone data is used to examine the daily dynamic of communities' social context. As Guangzhou upgraded its cell phone base stations in 2014 to better cover the city, the data of 2016 was used. The data was provided by a major mobile communication service supplier in China, which holds about 30% market share in Guangzhou. It recorded the one-day trajectory of more than 3 million cell phone users on 28 December 2016, an ordinary Wednesday with no important events or extreme weather. Considering possible changes between 2010 and 2016, we excluded two communities that underwent an urban renewal project during the period. Other communities remained relatively stable during the six years. We also excluded communities assigned less than 50 cell phone users from the research. For each user, the data record one base station that the cell phone signal is connected to the longest every hour. The base stations are densely distributed in Guangzhou, at intervals of 100–1000 m, being denser in the centre and further apart the further away from the centre. Considering the service range of each base station, we generate Thiessen polygons for the base stations to represent their service range. The dataset has been desensitized to protect users' privacy.

Generating the dynamic social context

The study combines census and cell phone data to examine communities' multi-dimensional social contexts at different times of the day. First, the study assigns the base station population to communities. To better distribute the population of marginal polygons, we adopt an area-weighted approach. We assume cell phone users are evenly distributed in the Thiessen polygons. If the proportion of a Thiessen polygon intersecting with a community is large, then the probability that the polygon's population is assigned to this community is high. Thus, users in marginal polygons have probabilities of belonging to more than one community, with an accumulated probability of 100%. When calculating the number of actual active cell phone users in communities, we add up all the probabilities (Figure 3).

Second, the study labels the cell phone users with probabilities of having specific socio-economic attributes according to the population composition of their residential community. Drawing on the previous literature (Xu et al. 2019; Zhou et al. 2019), the study identifies places where the users stayed the longest between 0:00 and 6:00 as their residential places. Considering we currently have no access to residents' exact socio-economic attributes, we label them with probabilities. Each resident is labelled with probabilities of belonging to specific social groups based on the

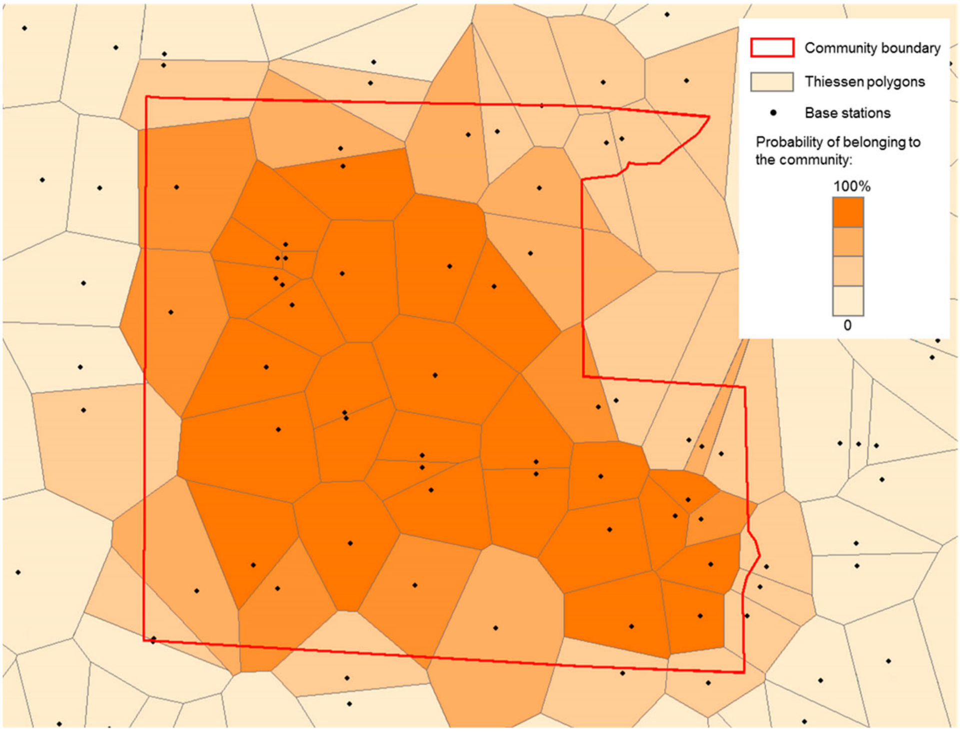

Figure 3. Distributing base station population to a community.

groups' proportions in their living communities. In this way, we identified the residential communities for nearly 2.6 million users, which account for 17.3% of the city's total population, and labelled them with speculated probabilities of having specific socio-economic attributes.

Third, the study aggregates the dynamic population of communities by time periods. A complete day is decomposed into six 3-hour periods from 6:00 to 24:00 and one 6-hour period from 0:00 to 6:00. The study focuses on the six 3-hour periods, which have also been examined in previous social context temporal variation research (Silm and Ahas 2014; Park and Kwan 2018). For each time period, we aggregate the real-time population's social composition based on the speculated attribute probabilities. For residents who appear in more than one community during the study period, we define the longest stay community as their activity place in that period. The community social compositions are calculated as the sum of the probabilities (Figure 4). Finally, the dynamic social context was generated for 2040 communities, accounting for 99.3% of all communities in the study area.

Methods

Quantifying community social context variation

A variation index was developed to quantify the temporal change of the community social context. The index describes the extent to which a community's social context approaches the global mean throughout the day. Each community's comprehensive social context is represented by the five main factors generated in the factor analysis. The formula of the index is as follows:

$$VI_t = \frac{(\overrightarrow{MF_t} - \overrightarrow{MF_{census}}) \cdot (-\overrightarrow{MF_{census}})}{|\overrightarrow{MF_{census}}|}, \tag{1}$$

where t refers to time periods, VI_t is the variation index at t, $\overrightarrow{MF_t}$ is the five-dimensional vector

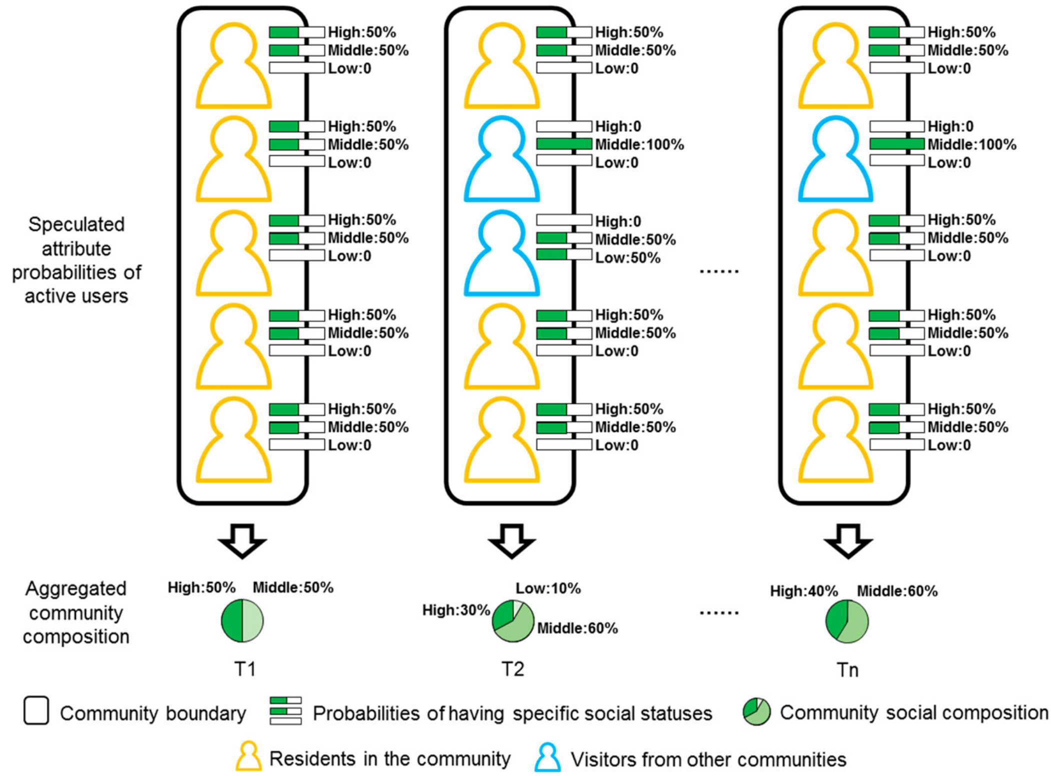

Figure 4. Aggregating users' attribute probabilities to communities.

from the main factors' global mean to their values at t, and $\overrightarrow{MF_{census}}$ is the five-dimensional vector from the global mean to the census-based values. Hence, VI_t equals the projection of $\overrightarrow{MF_t} - \overrightarrow{MF_{census}}$ on $-\overrightarrow{MF_{census}}$. A positive VI_t indicates that the community's social context gets closer to the global mean (averaged) at t, whereas a negative one indicates the community's social context becomes even more polarized. Figure 5 illustrates how the variation index characterizes community social context change in two examples.

Hierarchical linear modelling

The study used hierarchical linear models to examine how variables at different levels influence the community attachment of the 1523 residents. The unconditional means model (Null model) was developed to examine the variance component at the individual level and community level and evaluate model suitability. Equations (2) to (4) demonstrate the Null model:

$$\text{Individual level: } Y = \beta_0 + \gamma \tag{2}$$

$$\text{Community level: } \beta_0 = \gamma_{00} + \mu_0 \tag{3}$$

$$\sigma^2 = Var(\gamma),\ \tau_{00} = Var(\mu_0), \tag{4}$$

$$ICC1 = \frac{\tau_{00}}{\sigma^2 + \tau_{00}}, \tag{5}$$

$$ICC2 = \frac{k(ICC1)}{1 + (k-1)ICC1}, \tag{6}$$

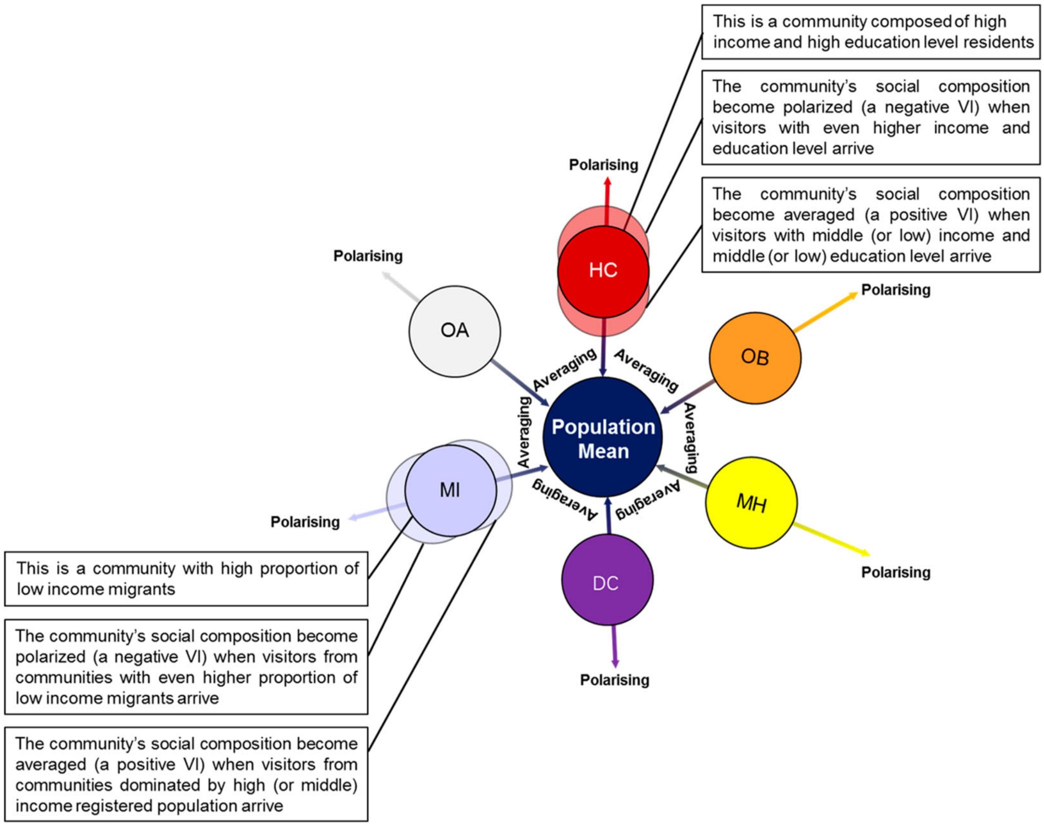

Figure 5. Examples of averaging and polarizing effects of community social context.

where Y is an individual's community attachment; β_0 and γ are the individual-level fixed and random effects; γ_{00} and μ_0 are the community-level fixed and random effects; σ^2 and τ_{00} are the variance of γ and μ_0. Equations (5) and (6) are the Intra Correlation Coefficients (ICCs), in which k refers to the mean sample size of the surveyed communities. ICC1 captures the reliability of the score within a group, and ICC2 reflects the reliability of the mean group score. An ICC1 greater than 0.05 ensures significant variation at the community level. Moreover, an ICC2 greater than 0.5 ensures that the individual-level samples of each community are sufficient to represent that community (Bliese 2000).

The Static Context model was developed to examine the effects of linear development variable and community social context type:

$$\begin{aligned}\text{Individual level: } Y = {} & \beta_0 + \beta_1(social\ status) + \beta_2(education\ \ level) \\ & + \beta_3(occupation) + \beta_4(household\ \ registration) \\ & + \beta_5(housing\ \ acquisition\ \ mode) + \gamma,\end{aligned} \tag{7}$$

$$\begin{aligned}\text{Community level: } \beta_0 = {} & \gamma_{00} + \gamma_{01}(population\ density) \\ & + \gamma_{02}(social\ context\ type) + \mu_0,\end{aligned} \tag{8}$$

where the five-dimensional socio-economic attributes were controlled at the individual level, β_1 to β_5 refer to the individual attribute variables' coefficients, γ_{01} and γ_{02} refer to the coefficients of population density and community social context type variables.

The Dynamic Context models were developed to examine the effect of communities' daily social context dynamic and its interaction effect with the community social context type variable:

$$\begin{aligned}\text{Individual level: } Y_t = &\beta_{0t} + \beta_{1t}(\textit{social status}) + \beta_{2t}(\textit{education level}) \\ &+ \beta_{3t}(\textit{occupation}) + \beta_{4t}(\textit{household registration}) \\ &+ \beta_{5t}(\textit{housing acquisition mode}) + \gamma_t,\end{aligned} \tag{9}$$

$$\begin{aligned}\text{Community level: } \beta_{0t} = &\gamma_{00t} + \gamma_{01t}(\textit{population density}) \\ &+ \gamma_{02t}(\textit{social context type}) + \gamma_{03t}(VI_t) \\ &+ \gamma_{04t}(VI_t \times \textit{social context type}) + \mu_{0t},\end{aligned} \tag{10}$$

where t refers to time period, $VI_t \times$ *social context type* refers to the multiplicative interaction term of the variation index at t and the community social context type variable.

Results

Inter-community difference of community attachment

The survey reveals that most participants have moderate community attachment scores, but the scores are different between communities (Figure 6). An analysis of variance (ANOVA) shows the F-statistic of community attachment of different communities is 3.473, indicating the inter-community difference of community attachment is significant at $p < 0.001$. Figure 6 also shows that community attachment varies by social context type. For example, the community attachment of old blocks (OB) and *danwei* communities (DC) is generally slightly higher than other types. However, community attachment of the same social context type also varies greatly, which is worth investigating.

Temporal variation of community social context

Communities' social context varies with time. Figure 7(a) shows that communities have wide ranges of variation indices (VI) during daytime (9:00–18:00) and relatively narrow variations in other periods, indicating that communities' social context can change dramatically with daytime activities. In addition, most of the communities have positive indices, indicating that the social context of the city's communities generally approaches the global mean in daily activities. However, approximately one-third of the communities have negative indices, indicating not only averaging effects but also polarizing effects towards the community social context.

A combined analysis of the Gini index and the Global Moran's I index was conducted to examine the distribution of the variation index (see equations in the Supplemental Materials). As shown in Figure 7(b), the Gini index of the variation index decreases and the Global Moran's I index of the variation index increases during the daytime, indicating that the variation index becomes increasingly proportionally distributed but spatially concentrated as daily activities occur. Three typical distribution types can be identified from the results. First, the night type (T1 and T6) has variation indices with a relatively higher Gini index but a lower Global Moran's I index. Second, the worktime type (T2, T3 and T4) has variation indices with a relatively lower Gini index but a higher Global Moran's I index. Finally, the evening type (T5) has variation indices with a high Gini index and a relatively high Global Moran's I index. As the distributions of T4, T5 and T6 are the most different from each other, we take them as representatives of each distribution type.

The results indicate that the community social context is relatively stable at night. In comparison, communities' social context varies greatly at worktime, and the variations are concentrated in

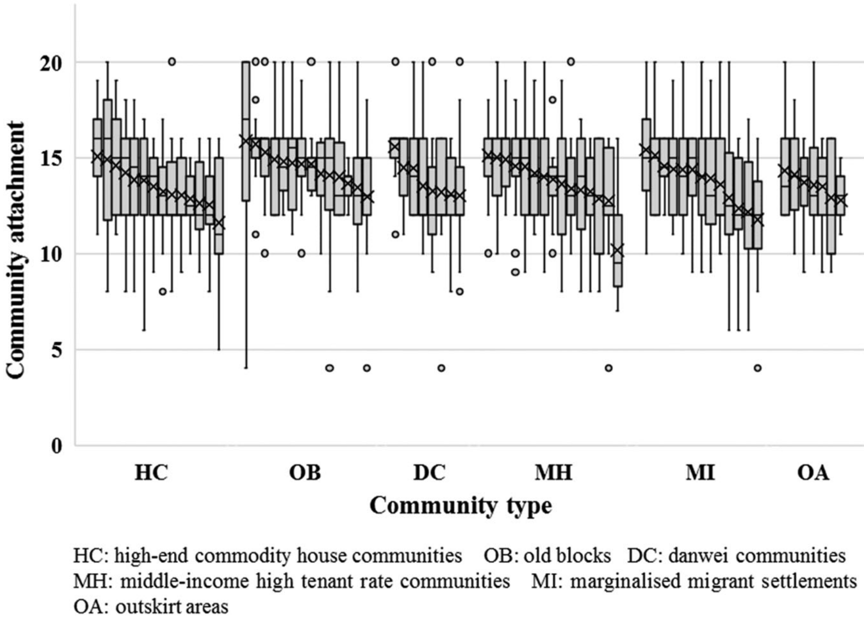

Figure 6. Distribution of community attachment of each communities.

space. And in the evening, the range of the variation reduces but the social context of specific concentrated places still deviates from its census-based condition and approaches the global mean (Figure 8). The daily social context dynamic indicates the social areas are variable during the day.

The variation index also varies among community types. As shown in Table 2, different types of communities have very different variation indices at each time period. Despite the overall variation index of the city being the highest at worktime (T4), the average variation indices of MH and MI are negative. And in the evening (T5), the average variation index of OB also becomes negative. Indicating that different types of communities have distinctive social context variation patterns over time. While the city's overall social context is becoming averaged in general, the social context of the MH, MI, and OB becomes polarized at specific periods. Therefore, it is necessary to further investigate the influence of the social context dynamic on different types of communities.

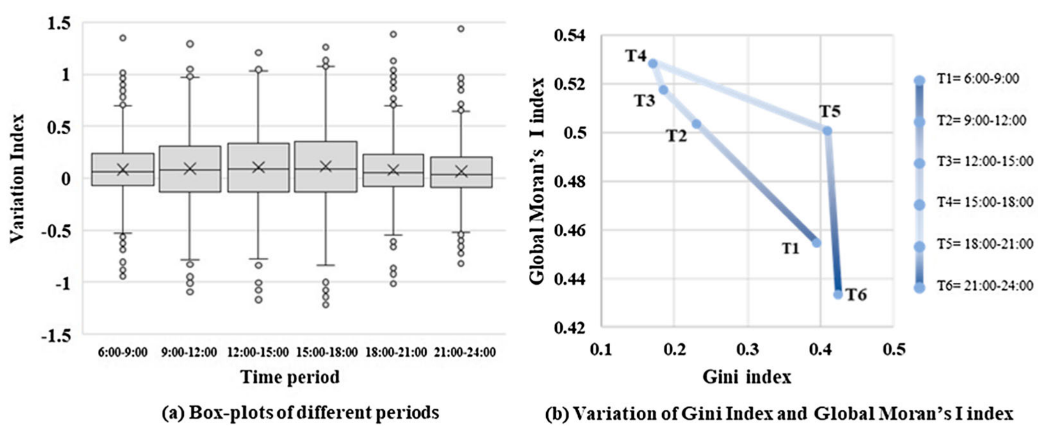

Figure 7. Temporal variation of the Variation Index.

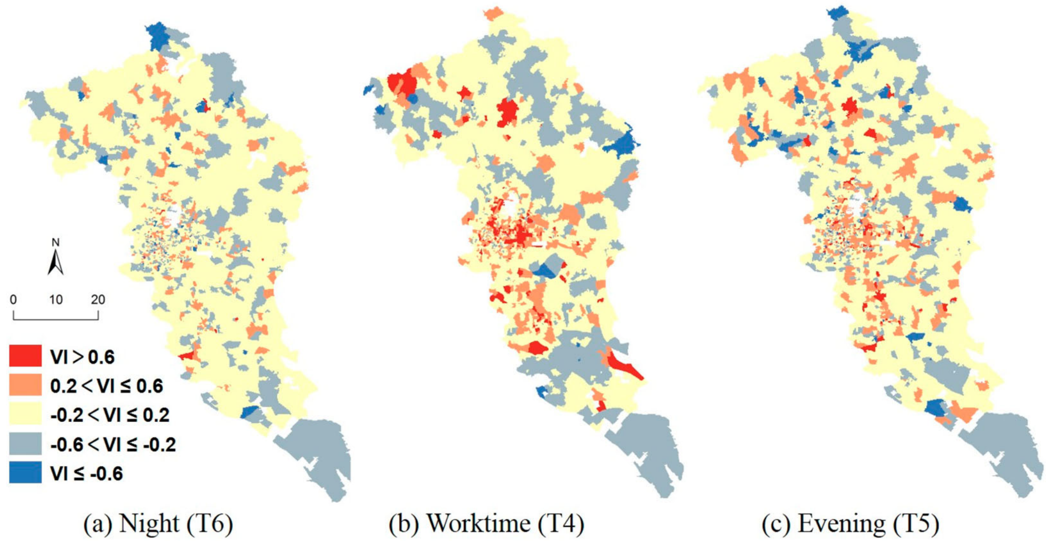

Figure 8. Spatial distribution of variation index at T4, T5 and T6.

Daily social context dynamic and community attachment

The effect of daily social context variation on respondents' community attachment was further examined using hierarchical linear models. The Null model shows ICC1 = 0.105 and ICC2 = 0.714, indicating that the inter-community heterogeneity is significant, and the sample size of each community is sufficient. As shown in Table 3, the Static Context model explained 9.2% of the community-level variance, and the Dynamic Context models performed differently in different periods. In the night period (T6), the Dynamic Context model only explained 7.5% of the community-level variance, which shows no improvement compared to the Static Context model. However, in the worktime and evening periods, the models explained 14.9% and 25.7% of the community-level variance, respectively, showing significant improvements. The result indicates that communities with similar census composition can still be quite different in their residents' community attachment, and communities' daily social context dynamics can further explain the difference. The dynamics of periods when people are active and have strong interaction intensity (worktime and evening) have more substantial explanatory power. Furthermore, the dynamic of the evening period, when people are active and more likely to be in their residential communities, has the strongest explanatory power.

Specifically, residents' community attachment is influenced by both individual and community-level variables. As shown in Table 4, people with higher education levels and those with non-local household registration tend to have a lower attachment to their residential communities. The policy house residents and self-built house residents have a significantly higher level of community

Table 2. Variation index of different types of communities at T4,T5,T6.

	Mean value of the variation index		
	Night (T6)	Worktime (T4)	Evening (T5)
HC	−0.005	0.219	0.151
OB	0.009	0.207	−0.039
DC	0.045	0.378	0.330
MH	−0.017	−0.059	−0.042
MI	−0.032	−0.052	−0.044
OA	0.106	0.326	0.129

Table 3. Performance of hierarchical linear models.

	Variance Component (ratio explained)	
	Community Level	Individual Level
Null model	0.754	6.415
Static Context model	0.685 (9.2%)	6.102 (4.9%)
Dynamic Context models		
Night (T6)	0.697 (7.5%)	6.102 (4.9%)
Worktime (T4)	0.642 (14.9%)	6.102 (4.9%)
Evening (T5)	0.559 (25.7%)	6.102 (4.9%)

attachment. The reason may be that these attributes reflect individuals' access to social resources and differentiated ability to construct their social networks (Chang et al. 2020). By controlling for the individual variables, Table 4 shows that the community level variables perform differently

Table 4. Results of hierarchical linear models.

	Static context model		Dynamic context models					
			Night (T6)		Worktime (T4)		Evening (T5)	
	Coefficient	*P*-value	Coefficient	*P*-value	Coefficient	*P*-value	Coefficient	*P*-value
Individual-level variables								
Social status								
Middle = 1	0.180	0.358	0.160	0.404	0.168	0.381	0.160	0.405
High = 1	−0.015	0.950	−0.043	0.856	−0.040	0.866	−0.045	0.849
Low (reference)								
Education level								
College or above = 1	**−0.347****	0.014	**−0.345****	0.015	**−0.350****	0.014	**−0.346****	0.015
High school = 1	**−0.751*****	0.000	**−0.735*****	0.000	**−0.764*****	0.000	**−0.757*****	0.000
Middle school or below (reference)								
Occupation type								
Administration and management = 1	−0.165	0.461	−0.156	0.485	−0.164	0.461	−0.163	0.465
Commerce and service = 1	−0.225	0.281	−0.226	0.277	−0.228	0.277	−0.225	0.284
Industry = 1	−0.203	0.391	−0.192	0.417	−0.202	0.393	−0.195	0.409
Others (reference)								
Household registration								
Intra-province migrants = 1	**−0.514****	0.017	**−0.521****	0.014	**−0.509****	0.017	**−0.501****	0.018
Outside-province migrants = 1	**−0.977 *****	0.000	**−0.973*****	0.000	**−0.988*****	0.000	**−0.985*****	0.000
Local (reference)								
Housing type								
Commodity = 1	0.084	0.753	0.091	0.728	0.081	0.757	0.096	0.714
Policy = 1	**0.419****	0.038	**0.427****	0.038	**0.411****	0.043	**0.413****	0.045
Self-built = 1	**0.649****	0.019	**0.643****	0.020	**0.641****	0.020	**0.647****	0.018
Others (reference)								
Community-level variables								
Intercept	**14.409*****	0.000	**14.387*****	0.000	**14.404*****	0.000	**14.377*****	0.000
Population density	0.174	0.261	0.161	0.328	0.145	0.354	0.134	0.406
Social context type								
HC = 1	−0.287	0.430	−0.253	0.510	−0.293	0.390	−0.257	0.459
OB = 1	0.459	0.251	0.516	0.209	0.539	0.158	0.515	0.168
DC = 1	0.164	0.646	0.092	0.794	0.023	0.939	0.037	0.900
MH = 1	0.015	0.968	−0.014	0.973	−0.024	0.946	0.007	0.985
MI = 1	0.155	0.686	0.086	0.832	0.141	0.697	0.131	0.703
OA (reference)								
Variation Index (VI)			0.092	0.886	0.010	0.978	0.255	0.694
Social context type × VI								
HC × VI			−0.425	0.768	0.590	0.465	0.480	0.597
OB × VI			−1.019	0.239	−0.415	0.513	**−1.710***	0.056
DC × VI			1.054	0.454	1.180	0.258	1.180	0.364
MH × VI			−1.515	0.285	−0.955	0.443	**−2.665***	0.06
MI × VI			−1.666	0.232	**−2.560****	0.037	**−3.120****	0.033
OA × VI (reference)								

Note: High social status residents are those with the top 20% individual monthly income in Guangzhou, low social status residents are those in the bottom 20% of monthly income, and middle social status residents are those between them. * indicates significant at $p < 0.05$, ** indicates significant at $p < 0.01$, *** indicates significant at $p < 0.001$.

in the models. In the Static Context model, the population density and social context type variables showed no significant effect on residents' community attachment alone. However, the Dynamic Context models show that the interaction term of social context type and variation index can have significant effects on community attachment. The variation index for worktime (T4) has a negative effect on people's community attachment in type MI, and the variation index for the evening (T5) has negative effects in types OB, MH and MI. We provide two possible explanations for the results considering residents' daily activity and each community type's characteristics. First, for the negative effects of averaging effect on people's community attachment in OB, MH and MI, the reason is probably that these three types of communities are places where groups typically considered vulnerable (old block residents and migrants) concentrate. Vulnerable residents tend to build networks of acquaintances and avoid visitors who are different from them (Li and Wu 2008; Wu 2012). This is also indicated by the variation indices of the three types of communities which show their social context becomes polarized in the evening period(T5) (Table 2). Thus, the context change towards the average can have an adverse effect on the formation of their community attachment. This notion likely explains why communities where vulnerable groups live have more inconsistent findings. Second, the HC and DC community types generally have gated sub-units, which is probably why the social context dynamic does not influence their residents' attachment in any single period.

Discussion and conclusions

In view of the inconsistent results of past research based on static context-based community attachment, the study proposed a new perspective to understand the heterogeneity in people's attachment among different communities by considering the daily social context dynamic and people's activity patterns. The study has three major findings. (1) The social context of communities vary during the day. This context can be either averaged or polarized with time and generates three typical distribution patterns at night (21:00–24:00), work time (15:00–18:00) and the evening (18:00–21:00). (2) Communities' daily social context dynamics can further explain the heterogeneity in residents' attachment among communities, where the dynamic of the evening period has the strongest explanatory power. (3) The averaging of the community social context is more likely to reduce the community attachment of the residents of old blocks and migrant communities, and communities that may have gated sub-units are less likely to be influenced by the variation in social context over the course of the day.

The study contributes to previous research in three ways. First, this study developed a method to quantify the averaging of the multi-dimensional social contexts of communities by combining census and cell phone data. The results confirmed the existence of social context averaging in most of the city's communities. In addition, these results extended previous findings by revealing that the effect is unevenly distributed over the day, and social context polarization also exists in some communities. Second, the study proposed a framework for examining residents' community perception from a social context dynamic perspective. The results confirmed the importance of examining residents' community perception considering variations in ambient social contexts and the intensity of residents' interactions with their residential communities. Third, the study identified communities that are more likely to be influenced by the social context dynamic and those that are not. The results provide explanations for some previously inconsistent findings and can help targeted policymaking and planning. Although our research is conducted in the Chinese context, disadvantaged communities located in older urban areas and immigrant settlements can be found in many cities worldwide. The danwei compounds and the high-end commodity house communities, which may not exist in some cities, actually represent the type of communities based on institutional advantages and income advantages, respectively. So our findings shed light on urban research in various contexts. More generally, the study contributes to human geography research by emphasising the dynamics of human activity in space. There has been a long-standing distinction between place-based and people-based paradigms in human geography research. This study, however, proposes an approach to studying people's social perception in urban space from the perspective of people-space interaction, which overcomes the limitations of static spatial studies and breaks the boundaries of research paradigms. The study highlights that space is the carrier of human activity, and human geography researchers should consider human activity in space as an essential variable in place perception studies.

The study focuses on introducing the daily dynamic perspective. The results revealed the relationship between daily social context dynamic and residents' inter-community differences in community attachment. However, the study did not address the causality between variables and the causal pathways from varied social contexts to differentiated community attachment. Our subsequent study will examine the mediator effects of residents' activity decisions, willingness to interact and social-network construction on their community attachment. We recognize that identifying cell phone users' residences using only one-day's trajectories can be cursory. In addition, although the survey data and cell phone data we used were both from 2016, the census data available is from 2010. There is a mismatch in the time of the data. Therefore, the social context we obtained may deviate from the reality to some extent. However, the general trend of the city's multi-dimensional social context variation revealed in this study is likely to be valid, which is the main concern of the research. Socio-economic attributes of cell phone users are imputed based on community-level census data in this study, assuming that community members are homogeneous. However, residents in the same community can also have diverse socio-economic attributes and travel preferences, making our imputations biased. The solution to this problem is to use data that records both individual socio-economic attributes and mobility, which is difficult to get and involves personal privacy. Therefore, our approach can be a compromise solution in many situations. Furthermore, while we did our best to increase the survey coverage, we still have limited community-level samples, which prevented us from controlling for more community-level covariables. The study assumes all individuals perceive the community social context in the same way, which simplifies the interaction between individuals and places and therefore has some limitations. In fact, individuals' perceptions of the dynamics and the deviations of the social context can be different or even completely opposite. Hence the study results do not represent the reality of all residents in the communities we studied. The size of Thiessen polygons and communities were both correlated with population density, with smaller sizes in densely populated areas and larger sizes in sparsely populated areas. Therefore, changes in population density and facility density can also affect residents' community attachments. The study focuses on the effect of the composition of social context, but the effect of density is also worth investigating. However, as an initial finding, our results supported the overall associations between community social context dynamic and residents' community attachment. With large sample sizes and high-quality data, the study can be further extended.

The high-density and high-mobility features of modern cities call for new perspectives for understanding conventional problems. As an important by-product of human mobility, the multi-dimensional and dynamic social contexts of communities challenge conventional community perception studies that misidentified residents' perceived or experienced social contexts. Recent concepts like the NEAP (Kwan 2018b) have highlighted that individual exposures can be different when we compare residence-based and mobility-based measurements. This idea has attracted considerable attention in geographic and health research. But the notion was derived from observations at the individual level. This study highlights another important aspect of the effect of people's daily mobility which is based on places, namely the social context averaging or polarization (SCAP) effect, which means that the socioeconomic characteristics of places can also change over the course of a day because of people's daily mobility. The SCAP effect indicates that previous residence-based studies that are based on the distribution of nighttime population may misrepresent the social contexts of people in different communities. Thus, in both theory and practice, the study highlights that the dynamics of social context should be taken as a new dimension of community indicators that determine residents' place perception and attachment in addition to the conventional linear development and structural variables. Additional attention should be paid to indicators of the dynamic dimension to promote a better understanding of urban systems and make informed decisions. For example, more attention should be given to places where vulnerable groups live and face a high level of daily social context dynamic. Also, policymakers should keep in mind that the social context of the evening period when people interact intensely with their residential community is critical in effective community governance.

Disclosure statement

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