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ENCOUNTER AND ITS CONFIGURATIONAL LOGIC:

Understanding spatiotemporal co-presence with road network and social media check-in data

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ABSTRACT

Public space facilitates the social interaction between people. It is widely accepted that the connection between spaces creates the possibility of the mutual visibility between people. The relationship between spatial configuration and the spatiotemporal encounters, however, has rarely been investigated explicitly in empirical cases. The focus of this study is two folded: firstly, it examines the way to measure spatiotemporal encounters between different groups of people based on their mobility records; secondly, it investigates how the design of the built environment contributes to physical co-presence on spatial and temporal dimensions. Using ubiquitous individual social media check-in data in Central Shanghai, China, this study proposes a framework for quantifying physical face-to-face co-presence patterns between the defined local random walkers and the remote visitors across time in every street. In the introduced People-Space-Time (PST) model, social capital is conceptualised as an integration among social difference, spatial distance (metric and geometrical distance) and time distance. The reliability of the applied data and the effectiveness of the introduced methods are validated by the investigations of the scaling nature of the extracted mobility patterns and the correlation between the outputs and surveyed data. The produced spatiotemporal patterns of face-to-face co-presence reveal that city centres and the large-scale urban complexes (e.g., transport hubs, shopping malls, stadiums, etc.) are ideal places for people to encounter. The results of the regression analyses demonstrate that spatial and functional centrality measures are significant variables for predicting spatiotemporal co-presence in streets, but in which the functional centrality structures maintain a higher standard of explanatory power than the spatial network. The temporal complexity of the co-presence is revealed by the temporally shifting performance of the integrated regression models across time. The findings in this study yield that it is the spatio-functional interaction influencing spatiotemporal variation of the physical encounter between people, and reclaim the necessity of adding fine-scale land-use patterns in the traditional configurational analysis for deeply understanding the social processes with urban big data in the contemporary digitalised cities.

KEYWORDS

Co-presence, spatial configuration, spatio-functional interaction, social media check-in, space syntax

1. INTRODUCTION

The city is a complex system for interaction. In geography, the linkage between the theory of spatial from and other temporal process has been explored theoretically and empirically (Harvey 1969). Geographical landscape shapes the spatial generator for the (re)production of the temporal process from place to place. Such an idea has formed the theoretical foundation for configurational studies focusing on the interrelation between the spatial configuration and the movement. The concept of 'co-presence' in space syntax theory has been argued as a by-product of the organisation of the built environment that often manifests itself in people's 'movement' due to the fact that connections between spaces create the possibility of the mutual visibility between people (Hiller and Hanson 1989). By combining the concept of 'co-presence' in space syntax and social science, Marcus (2010) provided the possibility of liking the so-called spatial capital with social capital. Some studies have been conducted to prove the interdependency between them, but the relationship between the spatial configuration and spatiotemporal encounter patterns has rarely been investigated explicitly with the city-wide observation in the empirical studies.

The main scope of this study is to empirically explore the extent to which the spatial design influences the physical face-to-face interaction between different groups of people, the social media users more precisely, in the contemporary digitalised society. Two types of people are focused in this study: the random walkers who frequently move in a space, and the remote visitors who only visit the space irregularly. The co-presence between these two groups is quantified as an interplay between various social capital, including social difference, spatial distance (metric and geometric distance) and the time cost. Relevant results are mapped in street segments to illustrate fine-resolution distributions of the co-presence intensity. Meanwhile, streets are indexed by quantifying their spatial and function contexts to reflect the urban spatial and functional centrality structures. A multivariate regression is used in this research to explore the explanative power of the spatial and functional centrality variables for the spatiotemporal co-presence intensities in streets. The remainder of this research is structured as follows. Section 2 introduces the background of this research followed by the descriptions of the methodology as well as data. Section 5 documented the empirical results in detail. At last, section 6 concludes the papers with a summary and a discussion on the further steps.

2. BACKGROUND

A society is a system of social interaction, and co-presence is one of the essential conditions for the occurrence of social interaction (Giddens 1984). Its definitions are ambiguous owing to the variation of theories, methodologies, and spatial scales for analysis. It can also be defined as a sense of co-existence between people in their virtual communications via various sharing behaviours, such as photo sharing or social media interaction (Ito and Okabe 2005). In social geography, co-presence can be adequately understood from its antithesis - segregation - which describes the passive separation of certain group(s) of people from other population (Massey and Denton 1993). Owing to its natural linkage to the demographic characteristics of the population, segregation is conventionally explored in the resolution of areas/districts that are artificially defined for spatial statistics, e.g., census units or administrative boundaries (e.g., Ernest Burgess 1928; Wong 1993). The spatial dimension of segregation at the intra-urban scale has been argued as also being critical (O'Sullivan and Wong 2007) and many methods have been developed to model the potential spatial interaction across the activity space, including k-nearest neighbouring aggregation (Osth et al. 2014), kernel density estimation (O'Sullivan and Wong 2007), activity-based modelling (Wong and Shaw 2011), etc. Although the spatial distance between analysis units has been considered in these models, the effects of urban design have rarely been involved in relevant studies.

Physical co-presence, face-to-face encounters, in particular, reflects urban vitality in public space and its publicness (Mitchell 1995). In configurational studies, co-presence is a fundamental concept binding spatial connectivity to urban movement (Peponis et al. 1997), which has been verified by experiments with an agent-based simulation (Penn and Turner 2001). Recently, Marcus (2007; 2010) has reconceptualised spatial centrality as 'spatial capital' and emphasised its quintessence for understanding social performativity. Furthermore, geographical accessibility metrics for different sections of the population and job opportunities through spatial networks were adopted to estimate co-presence patterns (Legeby 2011; 2013; Marcus and Legeby 2012). These efforts have suggested that structural centralities are capable of affecting the co-presence patterns. Nevertheless, these studies were basically on the basis of static spatial data without proper consideration of the dynamics of people's mobility patterns. Consequently, the interdependency between the spatial configuration and spatiotemporal encounters has rarely been investigated explicitly in these empirical cases.

Co-presence is also a critical dimension in mobility patterns indicating that social interaction is associated with people's travel choices. This idea has been widely accepted in transport geography with a focus on the collective results of many individual trips (Kenyon et al. 2002; Gonzalez et al. 2008). Related studies have highlighted the importance of the temporal processes of physical encounters. Some attempts based on human contact networks have been conducted (e.g., Stehlé et al. 2011; Isella et al. 2011). With the help of Bluetooth sensors, Kostakos et al. (2010) have clarified the spatiotemporal patterns of mobility, presence and encounters. Sun et al. (2013) evaluate repeated face-to-face encounters using a time-resolved social encounter network on public buses. However, the datasets adopted in these studies are either embedded in limited samples within small areas or are constrained to one type of transport, thereby failing to produce fine-scaled physical co-presence patterns covering the large landscape.

3. THE METHOD

3.1 THE FRAMEWORK

The framework of this study is shown in Figure 1. There are four modules including (a) data processing, (b) measuring co-presence patterns, (c) measuring centralities and (d) exploring the configurational logic of co-presence. In the first module, required datasets are mined and then processed for abstracting the most reliable information for the initial data gathered from the open data resources. For instance, place-based check-ins records (check-ined Points-of-interest (POIs)) are spatially assigned to their nearest street segments, and individual check-in records should be aggregated to trips and filtered by removing the invalid information for making them as an exact description of the mobility patterns. In the next module, trajectory patterns obtained from the social media data are applied to compute the presence and co-presence patterns across time with the street network data. Simultaneously, social groups of people are identified according to their travelling behaviours that are recorded in mobility patterns. The physical presence of people based on metric distance and the angular distance are combined to take into account the influence of the public space on the patterns of the face-to-face encounters. The presences of people in different groups across time are joined to capture spatiotemporal patterns of their co-presence.

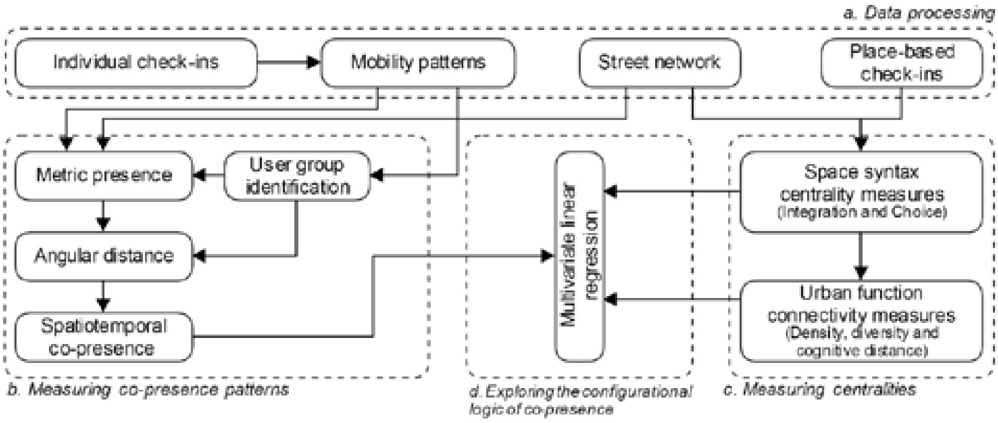

Figure 1 -The research framework

In module (c), the street network and placed-based check-ins data are employed in the calculations of the spatial and functional centrality indices. At the last step, computed co-presence patterns and centrality patterns in streets are used as the dependent variables and the independent factors in regression models, respectively. The multivariate linear regression model is adopted to capture the impact of urban form and functions on the hourly varying co-presence intensity patterns. By doing so, this study investigates the spatial logic of the temporal significance of physical co-presence and its inherent differentiation from street to street.

3.2 MEASURING THE PHYSICAL CO-PRESENCE

3.2.1 THE PEOPLE-SPACE-TIME (PST) MODEL

Co-presence is a multidimensional concept reflecting the interplay among different types of social capital. This study proposes an integrated model in which these interactions between various forms of social capital can be comprehensively addressed. These interactions can be summarised as the social capital of people, space and time, which have been acknowledged to be essential for the creation of social ties (Crandall et al. 2010). Social capital for people denotes to social difference between people, which can be captured by their demographic features, such as social classes, educational backgrounds, etc. Social difference denotes the fundamental cost of human interaction because it captures the internal variance between people. Social capital in space and social capital in time, on the other hand, are the external conditions for people's interaction.

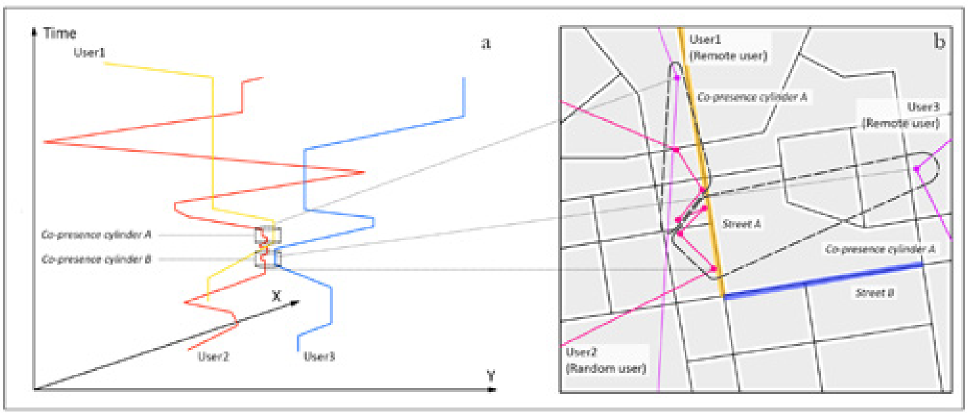

Figure 2 - Interactions between people in the People-Space-Time (PST) model. (a) The 3D spatiotemporal scatter diagram plotting the movement patterns of citizens as location coordinates (x, y) against time, (b) The planar representation of the 3D spatiotemporal scatter diagram.

The social capital in space, or 'spatial capital' can be reflected by the spatial cost that people need to overcome in their trips to see one another. There are two types of spatial capital: metric distance, which reflects the energy cost for people to travel and encounter; the other is angular distance, which captures the cognitive efforts that directly impact the mutual visibility between people. The more two individuals are metrically and geometrically proximal to one another, the more likely they will see one another in the space. Additionally, time constraints are also very important since people could hardly to encounter one another if they are present at the same place at different times

In Figure 2a, the hypothesised moving trajectories of three users are mapped, and two co-presence cylinders are used to capture the co-presence between them occurring at different time periods. Cylinders A and B capture the co-presence between users 1 and 2 and between users 1 and 3 within the same area, respectively. In a planar representation of the spatiotemporal cube with the street network, it is recognised that the average cognitive distance between the users in the two cylinders varies (Figure 2b). Street A is more likely to be the place where users 1 and 2 can encounter one another, while street B is the place for users 2 and 3 to meet. Since street B is more configurationally distanced from the actual places where these two users are present compared to street A, street A will maintain a higher degree of co-presence intensity than B.

Co-presence can be measured in different ways with different spatial unit settings. One typical method is individual-based, in which the personal social network is focused and every person can be treated as a node in his/her social network. Another method is place-based. In those models, the co-presence in place is concentrated by mapping the exposure of people in certain places. These models are also similar to those mapping the spatial segregation of people. This study applies the latter model as it emphasises the role of space in connecting people and it enables a comparison between the co-presence patterns and other features of the built environment.

3.2.2 CO-PRESENCE MEASURES

3.2.2.1 IDENTIFICATION OF USER GROUPS

This study focuses on two specified social groups of people (social media users) based on their differentiation in travel (check-in) behaviours, including local users and remote users of the public space as detected by social media. The random users for location i refer to people who walk randomly between places in the neighbouring area within a fixed time interval. The so-called remote users for location i are external visitors who use incoming flows towards the neighbouring area of location i from somewhere outside. In other words, the local users are part of the internal flow, and the remote users are parts of the incoming flow. In Figure 6-2-b, user 2 is a local random user in the nearby streets, whereas users 1 and 3 are defined as remote users with a far less frequent presence. Based on these definitions of user groups according to their mobility variations, this study focus on the relative, perceived difference in terms of their travelling behaviours instead of the absolute inherent difference between people in their social classes. In reality, few people can directly judge if the persons they encounter in the street are local or non-local for a certain place. Instead, they can tell if they met someone somewhere. That is to say, people define others as locals or not according to their encounter frequency, which is directly related to mobility patterns in urban space. If someone is continuously present in a place, new visitors would feel familiar with him/her when they travel to that place at the same time. This study suggests that using the observable mobility backgrounds of people to define their place-related social groups is closer to the real mechanism that people use to define others in the built environment (e.g., Bourdieu 1987; Crane 2012). Moreover, this method, in some sense, is consistent with methods that are applied in transport geography to detect housing and job addresses, in which visitation frequency is a key factor in determining the place-identities of citizens. In addition, the identification of user groups for a co-presence analysis in this research is movement associated. The agglomeration of random travel behaviours is close to pedestrian movement illustrating the capability to retain people in space; by contrast, long trips are purposeful, reflecting attractiveness on a city-wide scale. Thus, the co-presence between local and non-local users, in this sense, is not only an observation of physical interaction, but also a measure representing the publicness of a place from a mobility perspective, which is one of the core issues in urban design.

3.2.2.2 SPATIOTEMPORAL PRESENCE

SPATIOTEMPORAL PRESENCE INTENSITY OF THE LOCAL RANDOM USERS

The spatio-temporal presence intensity index of local random users ($PRE^{Random}_{(i,r,\Delta t)}$) measures the configurational accumulation of transitions between the venues inside the neighbouring area for a location defined by a given radius within a fixed time interval. Formally, it can be represented in the equation shown below, where presence intensity is the ratio of the metric presence density ($Den^{Local}_{(i,r,\Delta t)}$) to the cognitive distance ($Dis^{Local}_{(i,r,\Delta t)}$).

This idea originates from the spatial interaction model, but transforms its initial form to a simpler version. The metric presence density is calculated as the sum of the weights ($W_{(j,t)}$) of all the reachable check-ins at radius r within time interval Δt .

This analysis uses the mean angular step depth to all accessible check-ins ($MDep_{(j,t)}$) under the fixed spatial and time situations as the extra cost beyond the energy expenditure reflected by radius r. Apart from the traditional spatial interaction model in which a distance decay function is adopted with a calibrated parameter, this model maintains the methodological conciseness for result interpretation by using the mean angular step depth as a denominator. By assuming the trips for a user l can be represented as a set of checked-in locations in sequence: $Trip_l = (C^l_1, C^l_2, C^l_3, \dots, C^l_{t-1}, C^l_t, C^l_{t+1}, \dots, C^l_n)$, this analysis applies the walking distance ($dist_{(i,j_t)}$) between the checked-in location j and the location of public space i and the network distance between ($dist_{(i,j_{t-1})}$) the origin (C^l_{t-1}) towards the destination (C^l_t,) and the location i in question to extract the local random users for a specific location from the mobility patterns. The criterion for this spatial selection is constraining these two distances to a shorter degree than the given radius to identify the buffer zone for location i

$$PRE^{Random}_{(i,r,\Delta t)} = \frac{Den^{Random}_{(i,r,\Delta t)}}{Dis^{Random}_{(i,r,\Delta t)}} = \frac{\sum_{j=1}^{J} W_{(j,t)}}{MDep_{(j,t)}}, \{dist_{(i,j_t)} \le r, dist_{(i,j_{t-1})} \le r, t \in \Delta t\} \quad \text{.................} (1)$$

SPATIO-TEMPORAL PRESENCE INTENSITY OF REMOTE VISITORS

The spatiotemporal presence intensity index of the local random users ($PRE^{Remote}_{(i,r,\Delta t)}$) measures the configurational accumulation of the transitions towards the neighbouring area for location i in question from the places outside within a fixed time interval. Being similar to the presence intensity of random users, this index is defined as the interplay between co-presence density ($Den^{Remote}_{(i,r,\Delta t)}$) and distance ($Dis^{Remote}_{(i,r,\Delta t)}$) for the remote visitors.

The mathematical expression is shown below, in which, $dist_{(i,j,t)}$ represents the distance between location i and the checked-in destination (C^l_t) within the same given time interval (Δt), while $dist_{(i,j,t-1)}$ and $dist_{(i,j,t+1)}$ denotes the distances from location i to the previous checked-in location (C^l_{t-1}), and to the subsequent checked-in location (C^l_{t-1}), respectively. Though controlling these distance metrics (having C^l_t located in a local area for the targeted location, but its predecessor and successor outside that buffer), remote visitors can be successfully identified.

$$PRE^{Remote}_{(i,r,\Delta t)} = \frac{Den^{Remote}_{(i,r,\Delta t)}}{Dis^{Remote}_{(i,r,\Delta t)}} = \frac{\sum_{j=1}^{J} W_{(j,t)}}{MDep_{(j,t)}},$$

$$\{dist_{(i,j,t)} \le r, dist_{(i,j,t-1)} \ge r, dist_{(i,j,t+1)} \ge r, t \in \Delta t\} \quad \text{...} (2)$$

3.2.2.3 SPATIO-TEMPORAL PRESENCE BALANCE

The spatiotemporal balance index measures the equilibrium between the presence densities of predefined social groups of people. Normalised information entropy is applied to quantify the degree of balance. Assuming there are K (k=1,2,3,…,K) groups of people in question, this research calculates the temporal presence probability ($P_{(i,k,r,\Delta t)}$) for each group by subdividing its presence density ($Den^{k}_{(i,r,\Delta t)}$) by the total presence density of all groups. In this study, only two complementary social groups of people are accounted for (k1= random, k2= remote).

$$BAL_{(i,r,\Delta t)} = \frac{-\sum_{k=1}^{K} P^{k}_{(i,r,\Delta t)} \times \ln\left(P^{k}_{(i,k,\Delta t)}\right)}{\ln(K)}, \quad \{dist_{(i,j,t)} \leq r, t \in \Delta t\} \quad \text{(3)}$$

$$P^{k}_{(i,k,\Delta t)} = \frac{Den^{k}_{(i,r,\Delta t)}}{\sum_{k=1}^{K} Den^{k}_{(i,k,\Delta t)}} \quad \text{(4)}$$

3.2.2.4 SPATIOTEMPORAL CO-PRESENCE INTENSITY

The spatiotemporal co-presence intensity index measures the extent to which various complementary groups of people cluster at the local area around location i at radius r within a given time interval. The formal expression is shown in equation 5 which is similar to the form of calculating the presence intensity by combining the presence density and diversity. But this measure takes into account the balance factor as a weighting parameter for presence density. In so doing, this research conceptualises the spatiotemporal face-to-face co-presence as the interplay among density, distance and their balance with the people, space and time constraints.

$$COP_{(i,r,\Delta t)} = \frac{{Den_{(i,r,\Delta t)}}^{BAL_{(i,r,\Delta t)}}}{Dis_{(i,r,\Delta t)}}, \{dist_{(i,j,t)} \leq r, t \in \Delta t\} \quad \text{(5)}$$

3.2.2.5 SETTINGS

The proposed framework and detailed measures are extendable to the applications of relevant questions at various spatial scales. In this study, street segments are selected as the basic units for analysis since they are real spaces where face-to-face co-presence occurs with the metric and geometrical distance metrics, and it is vector-based without the modifiable areal unit problem that would impact the robustness of the analysis. The other two basic parameters in the introduced measures are the radius r for defining the local area of the segment i and the time interval Δt for identifying the time resolution. This study utilises a 750 m walking distance as the radius that defines the buffer zone for segment i based on an assumption that the average walking speed is approximately 5 km/h and the average waking time is 9 min (Bohannon 1997; Long and Thill 2015). Additionally, 1 hour is used as the interval because it was found that 1 hour is an optimised time scale for the proposed analysis, as making the time scale smaller would risk compromising the reliability of data since the average sample size would be accordingly smaller. Face-to-face encounters normally occurs within a short time, maybe a few seconds or a few minutes. Nevertheless, such a fine-scale co-presence pattern may generate bias with a large amount of variability but less regularity thereby constraining the production of reasonable patterns. Thus, it is argued that selecting 1 hour as the time interval is a rational choice for producing robust results with a good balance between temporal singularity and regularity.

3.3 INDEXING THE CENTRALITIES OF SPATIAL CONFIGURATION

The spatial configuration contains two interdependent sub-systems: the spatial network and land-use patterns. By converting these two systems into graph-based representations, this study computes the graph centralities of these two systems separately, including the space syntax centrality and urban function connectivity measures. The former measures the shallowness between space and space, while the latter covers critical aspects of relatedness between urban functions along the spatial grids.

	Abbreviation	Definition
Space syntax centrality measures		
Integration	INT %Radius%	The angular closeness of street network at a radius
Choice	**CHO %Radius%**	**The angular betweeness of street network at a radius**
Urban function centrality measures		
Density	DEN %Radius%	The accessible function density of POIs through the street network at a radius weighted by place-based social media check-ins
Diversity	DIV %Radius%	The accessible function diversity of POIs through the street network at a radius weighted by place-based social media check-ins
Distance	DIS %Radius%	The mean angular step depth to the reachable POIs through the street network at a radius

Table 1 - Centrality measures of spatial configuration

3.4 REGRESSION ANALYSIS

To explore the influence of the configurational centrality measures on the spatiotemporal co-presence intensity and the related community structure, a multivariate linear regression model is applied. This study employs the stepwise technology in the regression models to select the most important factors determining the observed variation of the dependent variables by filtering out the factors with less contribution to the model goodness-of-fit. This method can efficiently control the risk of over-fitting and produce an essential variable structure. Before the stepwise variable filter method is applied, the variables maintaining the higher risk of multicollinearity are detected and removed. The principle is defined by setting the threshold of the variance inflation factor (VIF) for each variable. In this study, the variables with VIF values bigger than 10 are removed from the models.

4 THE MATERIALS

4.1 STUDY AREA

Central Shanghai is selected as the case for the empirical investigation in this research. Shanghai is one of the mega-cities in current urban China (Figure 3). Per the national economic capital growth, it has been growing dramatically since the 1860s. The urbanisation process in Shanghai is Chinese modernisation in miniature. The spatial expansion and the shift of the spatio-social structures provide an ideal case to examine the interactive relationship between the spatial form and temporal social processes. Meanwhile, as one of the most developed cities in China, Shanghai maintains the largest group of social media users due to its large population base and a high rate of social media penetration, which enables the presupposition of using the social media dataset to precast people’s movements within the city.

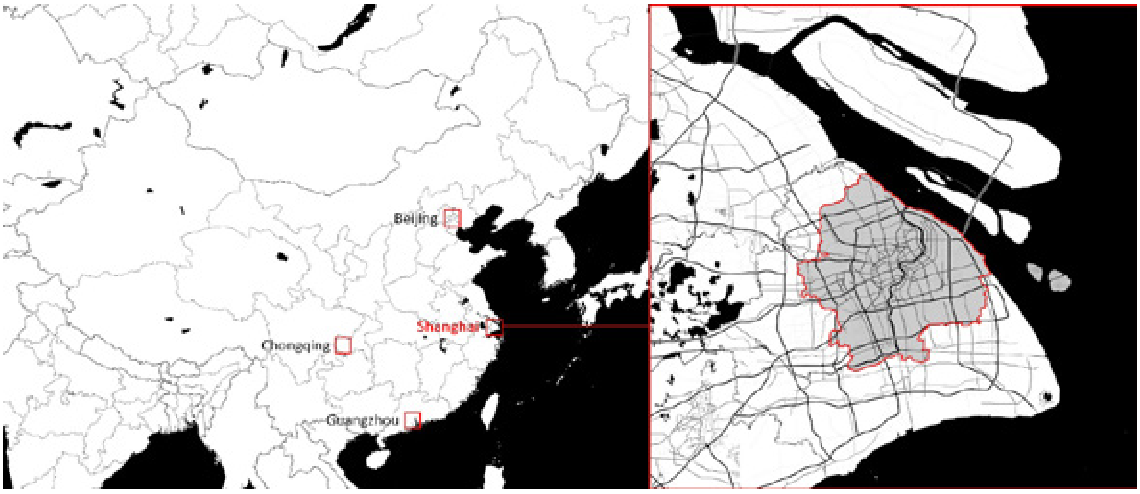

Figure 3 - The study area

4.2 STREET NETWORK AND CHECKED-IN POIS

The street network of Shanghai was gathered from an online navigation service provider with detailed spatial information. The street network data in Central Shanghai were spatially clipped from the raw data and transformed into a segmental map by maintaining the spatial axiality of the streets, which represents the topo-geometrical nature of the spatial grid. The processed segmental map consists of 92,920 street segments.

POI data and the associated check-in information were obtained through an application programming interface (API) of a Chinese social media service provider – Sina microblog, which is equivalent to Twitter in western countries. This dataset consists of a type of place-based data recording the total accumulated check-ins and the number of users who checked-in. Other features include the typology of the POIs and their coordinates. There are 191,035 checked-in POIs within the study area, which are categorised into eleven main types of complementary non-residential land-uses, including retail, catering, hotel, office, recreation, public service, park, education, hospital, culture and transport. The criteria used to classify the land-uses is the intergroup similarity of the check-in behaviours. This process can reduce the dimensions of land-use types by maintaining the most inherent information regarding land-use typology. In this study, 256 types of land-uses in the social media location-based service system are summarised according to the defined active land-uses.

4.3 SPATIOTEMPORAL TRIPS IN SOCIAL MEDIA CHECK-IN DATA

The intra-city trajectory patterns of social media users are extracted from individual check-in records collected on workdays for a quarter-long period from March to May 2016. The raw dataset includes 2,868,972 records of 73,427 users across 48,234 venues within the boundary of the study area. Even though social media check-in records are a type of fine-scale location data regarding the spatiotemporal presence of smart-phone users, they can hardly be directly used to estimate the real mobility distributions due to the existence of fake check-in records. Following the method proposed in the study conducted by Wu et al. (2014), this study applies a rule-based method to produce a spatiotemporal dataset regarding the trips of individual social media users on a typical workday. The steps to extract the spatiotemporal trips include: 1) removing invalid check-in records in which the actual locations of the smartphone users do not match the locations of the venues to which they want to check in; 2) removing the users who have only checked in once; 3) producing spatiotemporal trips of a person based on his/her consecutive check-ins; 4) eliminating anomalous trips with unexpected travel speed or duration (the thresholds of speed and duration are 400 km/hour and 12 hours, respectively); 5) merging extracted trips into a typical workday (the initial check-in trajectories for a user on different days are segmented as substantive groups with unique IDs); and 6) eradicating the trips that do not move towards the locations in the study area. The data that were ultimately obtained include 584,746 trips towards destinations in Central Shanghai. The aggregated results between the census units are shown in Figure 4, in which the directional polycentric structure is illustrated.

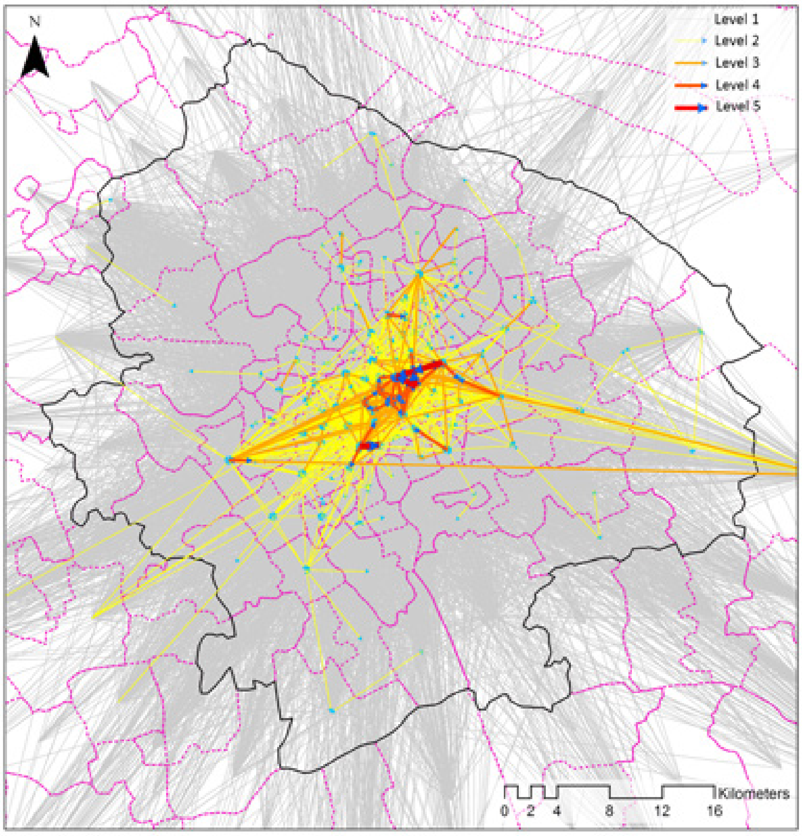

Figure 4 - The aggregated trips between census units in Cantal Shanghai

4.4 GATE COUNTS

Gate count data were collected on several workdays in November 2016, covering the main streets in 10 census areas that were randomly selected (Figure 5). In each gate for an individual street segment, the aggregated flows in three one-hour-long intervals are counted. These are the time periods from 9:00 to 10:00, 14:00 to 15:00, and 21:00 to 22:00. These data are prepared to validate the reliability of social media check-in data in describing urban movement and to prove the effectiveness of the proposed method to quantify the co-presence intensity.

Figure 5 - Gate count data in the randomly selected census areas

5 EMPIRICAL RESULTS

5.1 PRELIMINARY VALIDATION

Before the introduction of the empirical results, one primary task is to validate the reliability of the extracted trajectories and the computed patterns of the spatiotemporal co-presence between the random users and remote users. This aim is achieved in the present study by conducting two comparisons. The first comparison concerns the scaling nature of the mobility data in social media check-in records, while the second concerns the goodness of the correlation between the calculated co-presence intensity and the surveyed gate counts. In this regard, this study verifies the effectiveness and applicability of the proposed methods and the framework.

5.1.1 SCALING NATURE

It has been widely discussed that scaling phenomena are common in mobility patterns. The scaling property of a distribution can be specified and modelled in several ways. For instance, it can be fitted by a pow-law function ($f(x) \sim kx^{-\beta}$) or an exponential function ($f(x) \sim e^{-\alpha x}$).

In this study, both models are tested. It is found that individual movement records in social media check-in data are more likely to be governed by an exponential law. As shown in Figure 6-6, the pattern of the trip length has a good fit (R2=0.952) with an exponent of $\alpha = 0.121$, and the duration distribution is well modelled with a larger exponent $\alpha = 0.144$ (R2=0.977). These results are in accordance with the findings in previous studies (e.g., Liang et al. 2012; Liu et al. 2014; Wu et al. 2015). This is evidence that the extracted trips in this study maintain the inherent scaling structures of human movement distribution, indicating the feasibility of using the social media check-in records in relevant studies.

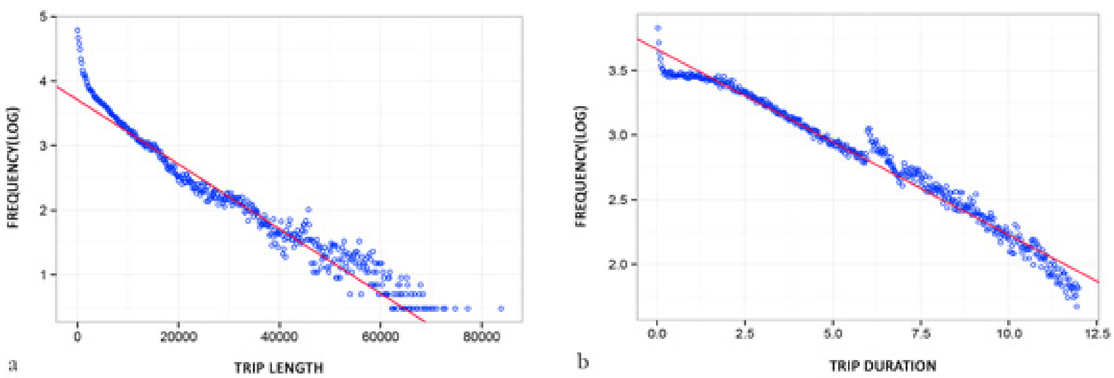

Figure 6 - Distributions of trip length and duration ((a) the exponent fit of the trip length pattern; (b) the exponent fit of the trip duration pattern)

5.1.2 CORRELATION WITH GATE COURTS

Co-presence patterns are rooted in urban mobility distributions. Despite the fact that co-presence patterns are more complex than the flow volume, the urban flow volume is the primary factor determining the underlying probability of people's physical interactions. Spatially varying co-presence patterns should be reasonable estimations of pedestrian flows. Consequently, the accuracy of the produced results is evaluated preliminarily by the examination of their correlation with the survey data. Figure 6-7 illustrates the scatter plots in which the gate count is understood to be a function of the co-presence variable over three time periods. The results indicate that spatiotemporal co-presence patterns generated by the proposed method are highly correlated with the survey data and this trend is sTable 6-across time, with R-square values larger than 80%. These findings show that the dynamic co-presence patterns can not only capture the spatial discrepancy of urban flows but also portray their temporal disparity.

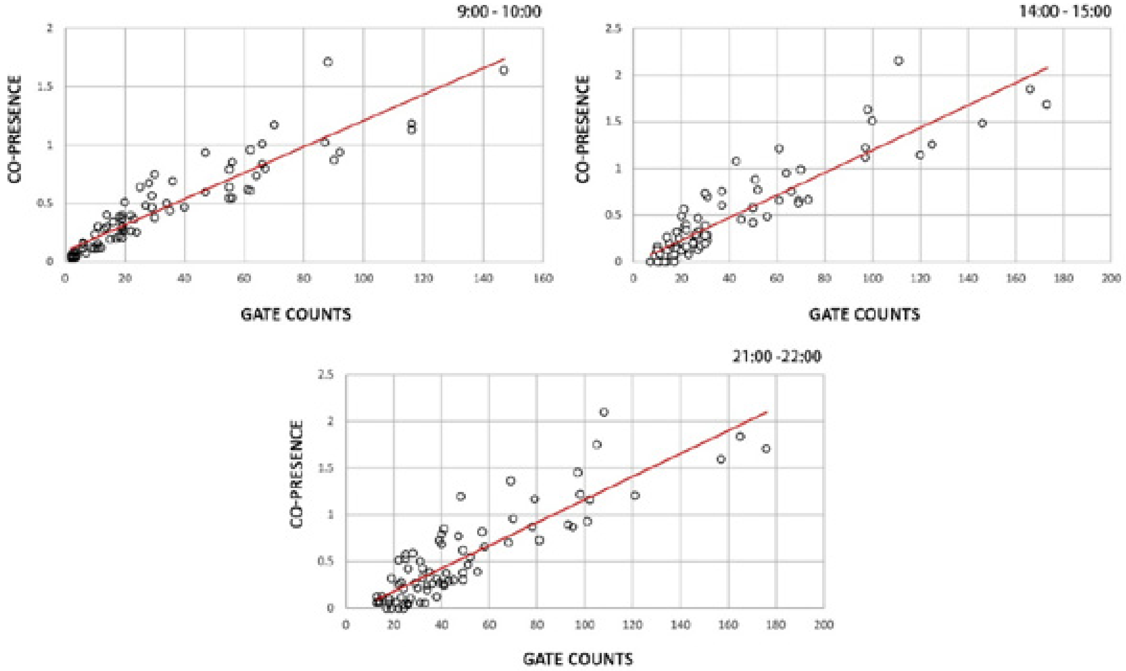

Figure 7 - Scatter plots of gate counts against co-presence index and (Correlation (9:00-10:00) - R2:0.8522, (14:00-15:00)-b – R2: 0.8207, (21:00-22:00)-c – R2; 0.8068)

5.2 SPATIOTEMPORAL CO-PRESENCE PATTERNS

5.2.1 DESCRIPTIVE STATISTICS

5.2.1.1 FREQUENCY DISTRIBUTION OF TRIPS

Figure 8 shows the frequency distributions of all trips extracted from individual social media check-in records. This pattern demonstrates that the check-in behaviours of social media users tend to be more frequent in the evening. There are two peaks that can be clearly observed in the distribution: one is the morning rush-hour at approximately 8 am to 9 am, and the other is dinner time, at approximately 6 pm, which is similar to what has been found in other studies (e.g., Wu et al. 2014). This distribution is different from the patterns observed in transport hubs, in which the morning and evening frequency peaks are typically equal. The main reason for this dissimilarity is that social media behaviours will be more frequent at non-working times when users are engaging in daily leisure activities, such as catering, recreation, etc. Although the trip datasets extracted from various data resources might vary in terms of the frequency distributions, their trends are comparable, indicating the representativeness of social media data regarding human movement.

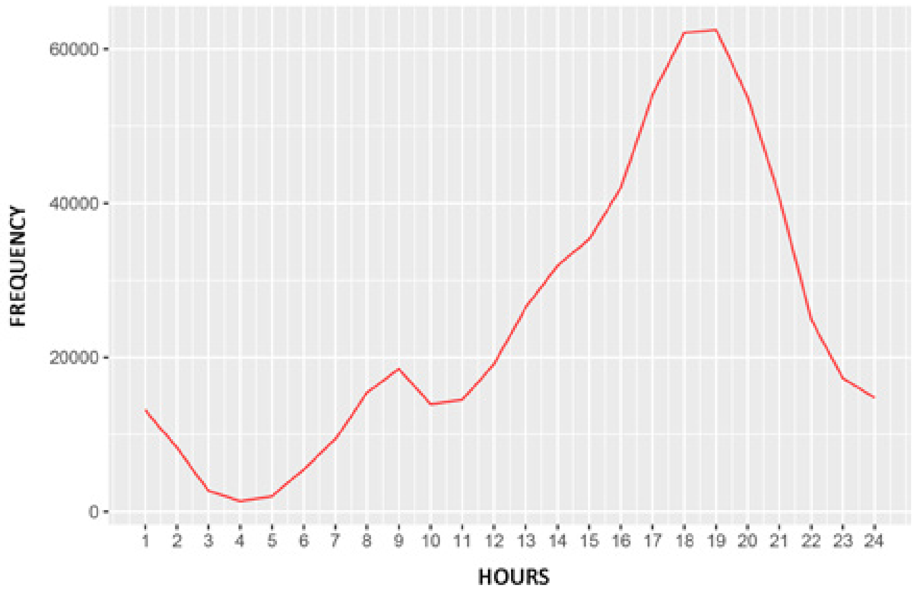

Figure 8 - Temporal distribution of detected trips

5.2.1.2 TEMPORAL PATTERNS OF PRESENCE/CO-PRESENCE

Figure 9 describes the temporal changes of the average presence and co-presence measures. In terms of co-presence density (Figure 9a), the average degree of the clustering of random users in streets is higher than that of the agglomeration of remote users during most time periods with the expectation that the latter is slightly stronger than the former from 12 am to 2 pm. The temporal shift of the balance degree is captured in Figure 9b, in which the interaction between the presence of random and remote users is lowest at 3 o'clock in the morning and moves to over 0.4 after 8 am. The lower values observed before 8 am indicate the spatial differentiation between the local and non-local people flows because many trips occurring during this period are towards residential communities where few people will be active at typical sleeping times. The balance index then decreases to 0.45 at 11 am and increases back to 0.5 after 2 pm. This may result from the reallocation of destinations during lunch time. Similar to the trend observed in the change of the balance index across time, the value of the cognitive distance for the presence of both remote and random users reaches the lowest point and moves to the peak, but a short time collapse is also seen around lunch-time (Figure 9c). This trend demonstrates that the presence of people is more geometrically concentrated in some places but is more dispersed from a city-wide perspective during the periods when the presence density and balance degree are temporally lower.

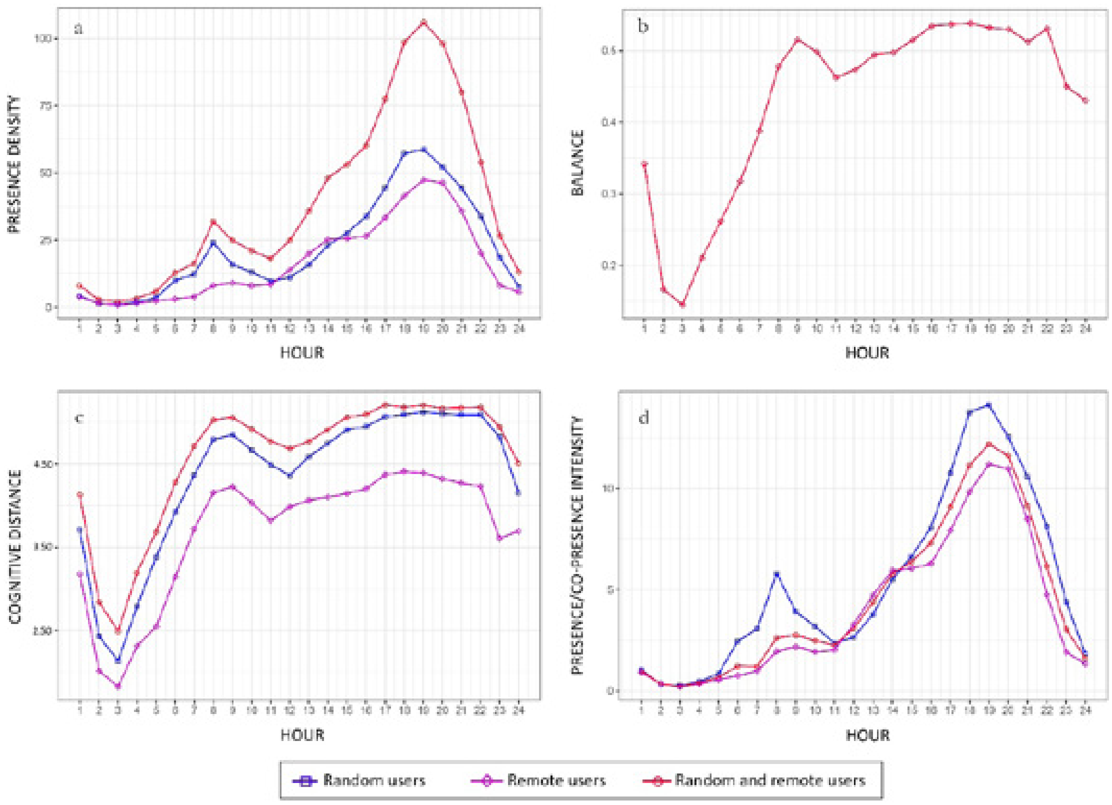

Figure 9 - Change of the average presence/co-presence measures across time in Central Shanghai. ((a) Presence density; (b) Co-presence balance; (c) Mean cognitive distance (angular step depth); (d) Presence/co-presence intensity

It can also be noticed that the average cognitive distance for all users is always higher than the mean angular distance between people in the same group. Furthermore, the mean angular distance for local users encountering one another in the street is higher than that for remote users, which suggests that destinations for non-local users are more configurationally closed, whereas the journey's ends for local random walkers are geometrically scatted but are metrically concentrated. The maps of presence/co-presence intensity indices are illustrated in Figure 9d. The gap between the presence patterns of local and non-local users in terms of presence density is shortened when the cognitive distance is taken into account. The co-presence intensity index exhibits a relatively smooth change and is located in the interval between the two presence intensities of individual groups. In short, the significant fluctuation of the presence and co-presence intensity patterns reveals the temporal complexity of co-presence patterns which is difficult to capture in aggregated descriptions of urban flows.

5.2.2 SPATIOTEMPORAL CO-PRESENCE MAPS

The spatiotemporal change of the co-presence intensity is mapped in Figure 10 with the same symbolising method. The overall urban polycentric structure can be discovered across time based on visual judgement, although the shape of the co-presence cores changes dynamically. This suggests that the co-presence pattern has its roots in the urban structure. In the early morning, the co-presence pattern becomes compact around the city centres, particularly from 4 am to 5 am. When the commuting time approaches, the co-presence intensity turns to be more spatially homogeneous since people are travelling to workplaces that are distributed in a more scattered manner. The global city centre regains its dominance after 9 am in the morning, and this trend remains significant during the rest period. Notably, some locations are also highlighted for an all-day period. Hongqiao Airport, for instance, maintains a high degree of physical co-presence values at all times. This is evidence that modern mix-used complexes, such as transport hubs, shopping malls, etc., and the streets connected to them are emerging places for human interaction.

5.3 THE CONFIGURATIONAL LOGIC OF THE SPATIOTEMPORAL CO-PRESENCE

This study applies a stepwise multivariate regression method to explore the impact of every centrality measure on the variation of co-presence intensity at every hour of a workday by controlling the influences of other factors. The regression results are shown in Table 2. It is standard for all model specifications that accessible function densities at the microscale and mesoscale are the main determinants significantly correlated with co-presence intensity. The global density, however, exerts negative effects on it. This suggests that land-use clustering at smaller scales provides the basic landscape for physical interaction between local and non-local citizens. Another general trend documented is that pedestrian land-use diversity is a suppressed factor but the global diversity is an augmented factor, which yields a tendency where the local mixture of urban functions is not simultaneously preferred by the two defined groups of people if the density effects are fixed. Likewise, the places where people are more likely to be co-present are inferred by a longer angular distance at the local scale, but less cognitive efforts at the global scale. These results imply that co-presence occurs at the locations that are metrically proximal to but configurationally distanced from the areas where the clustering of urban functions manifests at the middle scale. In other words, the stages for physical co-presence may not always be high streets; rather, they are more likely to be the places connected to central streets as the interfaces between centre and centre.

Angular integration and choice variables at low levels are also positively associated with the change of co-presence intensity across time, but their statistical significance varies. Angular integration variables are more significant in specific models before 12 am. In the afternoon, angular choice variables are more significant than the integration elements. What results this might be the fact that the co-presence that occurs in the morning is related to the to-movements driven by the closeness between spaces. This demonstrates that developing areas – the places lacking sufficient local amenities but being fulfilled with adequate housing and employment opportunities – are captured by integration variables at local scales, play more important roles in the spatial co-presence patterns in the morning work hours and late night, when people are committing across the city to their workplaces and homes. By contrast, non-working and non-residential activities are more dominant during other periods within a typical workday; thereby, the impact of angular integration becomes less statistically significant. In a nutshell, spatial centrality measures are significant factors for predicting temporal co-presence patterns using functional centrality indices, and the dynamic change of their significance reveals the composition of various types of urban movements across time.

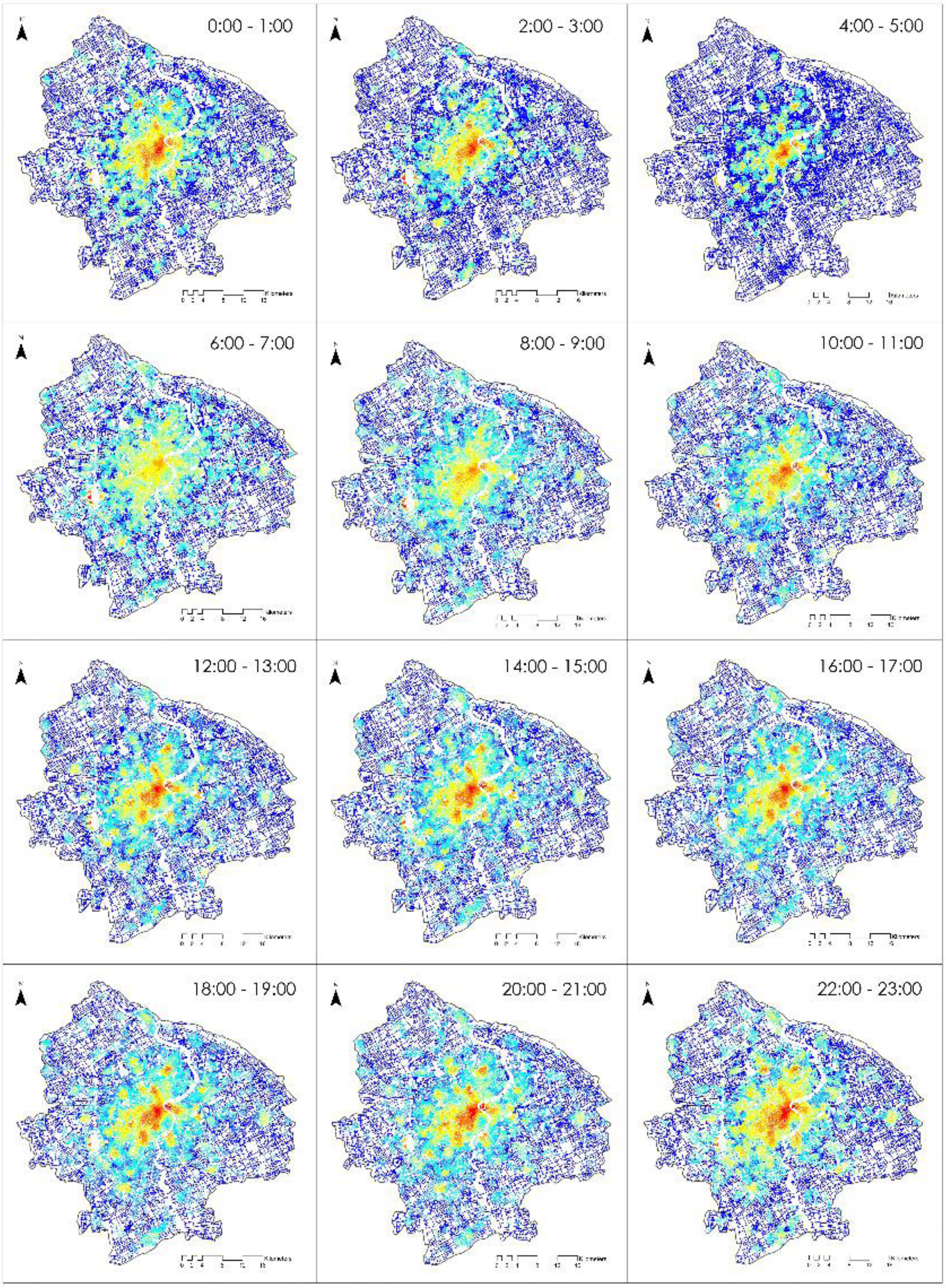

Figure 10 - Spatiotemporal co-presence maps in Central Shanghai

		Time series											
		0:00 - 1:00	1:00 - 2:00	2:00 - 300	3:00 - 4:00	4:00 - 5:00	5:00 - 6:00	6:00 - 7:00	7:00 - 8:00	8:00 - 9:00	9:00 - 10:00	10:00 - 11:00	11:00 - 12:00
Urban function connectivity measures	DEN_R500	0.575	0.516	0.574	0.572	0.597	0.606	0.614	0.367	0.645	0.577	0.636	0.684
	DEN_R2500	0.429	0.465	0.417	0.350	0.414	0.434	0.228	0.157	0.326	0.360	0.330	0.366
	DEN_R10000	-0.263	-0.282	-3.353	-0.31	-0.302	-0.231	-0.146		-0.190	-0.112	-0.113	-0.157
	DIV_R500	-0.132	-0.124	-0.153	-0.113	-0.12	-0.112	-0.079		-0.084	-0.082	-0.099	-0.094
	DIV_R1000												
	DIV_R2500							**-0.078**	**-0.121**	**-0.057**			
	DIV_R5000								**-0.032**				
	DIV_R10000	**0.025**	**0.028**	**0.037**	**0.037**		**0.043**	**0.067**	**0.096**	**0.057**	**0.033**		**0.029**
	DIS_R500								**0.023**				
	DIS_R1000											**-0.052**	
	DIS_R2500	**0.064**	**0.056**		**0.037**	**0.038**	**0.063**	**0.073**	**0.062**	**0.069**	**0.096**	**0.077**	**0.068**
	DIS_R5000			**0.052**									
	DIS_R10000	**-0.065**	**-0.066**	**-0.080**	**-0.055**	**-0.069**	**-0.048**	**-0.043**		**-0.047**	**-0.044**		**-0.041**
Space syntax metrics connectivity measures	**INT_500**	**0.076**	**0.053**	**0.047**			**0.082**	**0.052**	**0.067**		**0.078**	**0.107**	
	INT_2500	**0.151**	**0.180**	**0.175**	**0.170**	**0.163**		**0.076**		**0.103**			
	CHO_500	**-0.026**					**-0.029**		**-0.047**		**-0.068**	**-0.064**	
	CHO_1000			**0.032**	**0.091**								
	CHO_2500		**0.021**			**0.047**	**0.038**				**0.034**		**0.045**
	CHO_100000				**-0.012**							**0.029**	**0.025**
Performance	**Adj. R2**	**0.777**	**0.743**	**0.714**	**0.664**	**0.748**	**0.734**	**0.575**	**0.349**	**0.701**	**0.671**	**0.723**	**0.787**
	Adj. R2(SSX)	**0.474**	**0.462**	**0.430**	**0.405**	**0.442**	**0.399**	**0.309**	**0.233**	**0.378**	**0.368**	**0.394**	**0.425**
	Adj. R2(UFC)	**0.717**	**0.669**	**0.642**	**0.607**	**0.703**	**0.684**	**0.547**	**0.328**	**0.667**	**0.634**	**0.688**	**0.751**
	Enhancement	**7.722%**	**9.960%**	**10.084%**	**8.584%**	**6.016%**	**6.812%**	**4.870%**	**6.017%**	**4.850%**	**5.514%**	**4.841%**	**4.574%**

denotes to the change of the correlation coefficient in the model with only urban function connectivity measures to the model with both urban function connectivity and space syntax centralities, DEN: accessible function density; DIV: accessible function diversity; DIS: cognitive distance to the reachable land-uses; INT: angular integration; CHO: angular choice

Table 2 - Centrality performance against encounter intensity (Only significant variables are shown)

		Time series											
		0:00 - 1:00	1:00 - 2:00	2:00 - 3:00	3:00 - 4:00	4:00 - 5:00	5:00 - 6:00	6:00 - 7:00	7:00 - 8:00	8:00 - 9:00	9:00 - 10:00	10:00 - 11:00	11:00 - 12:00
Urban function connectivity measures	DEN_R500	0.699	0.755	0.728	0.751	0.759	0.806	0.824	0.815	0.789	0.772	0.660	0.576
	DEN_R2500	0.388	0.329	0.364	0.322	0.286	0.227	0.234	0.263	0.292	0.306	0.398	0.469
	DEN_R10000	-0.205	-0.203	-0.220	-0.201	-0.203	-0.198	-0.173	-0.196	-0.200	-0.249	-0.264	-0.281
	DIV_R500	-0.096	-0.106	-0.110	-0.115	-0.123	-0.124	-0.141	-0.140	-0.136	-0.124	-0.128	-0.117
	DIV_R1000							0.033	0.038	0.036			
	DIV_R2500												
	DIV_R5000												
	DIV_R10000	**0.039**	**0.039**	**0.039**	**0.036**	**0.030**	**0.028**	**0.033**	**0.028**	**0.029**	**0.040**	**0.038**	
	DIS_R500												
	DIS_R1000												
	DIS_R2500	**0.061**	**0.055**	**0.047**	**0.05**	**0.049**	**0.041**	**0.016**	**0.041**	**0.045**	**0.040**	**0.052**	**0.056**
	DIS_R5000												
	DIS_R10000	**-0.047**	**-0.046**	**-0.044**	**-0.048**	**-0.052**	**-0.050**		**-0.04**	**-0.042**	**-0.048**	**-0.048**	**-0.068**
Space syntax metrics connectivity measures	**INT_500**											**0.037**	**0.042**
	INT_2500					**0.054**	**0.056**				**0.060**	**0.092**	**0.124**
	CHO_500												
	CHO_1000												
	CHO_2500	**0.044**	**0.049**	**0.053**	**0.048**	**0.032**	**0.028**	**0.040**	**0.041**	**0.046**	**0.025**		**0.016**
	CHO_100000	**0.024**											
Performance	**Adj. R2**	**0.804**	**0.803**	**0.793**	**0.782**	**0.785**	**0.787**	**0.801**	**0.806**	**0.805**	**0.805**	**0.784**	**0.785**
	Adj. R2(SSX)	**0.421**	**0.403**	**0.397**	**0.382**	**0.394**	**0.382**	**0.381**	**0.379**	**0.389**	**0.393**	**0.422**	**0.458**
	Adj. R2(UFC)	**0.765**	**0.771**	**0.756**	**0.760**	**0.754**	**0.76**	**0.775**	**0.778**	**0.775**	**0.769**	**0.735**	**0.718**
	Enhancement	**4.851%**	**3.985%**	**4.666%**	**2.813%**	**3.949%**	**3.431%**	**3.246%**	**3.474%**	**3.727%**	**4.472%**	**6.250%**	**8.535%**

denotes to the change of the correlation coefficient in the model with only urban function connectivity measures to the model with both urban function connectivity and space syntax centralities, DEN: accessible function density; DIV: accessible function diversity; DIS: cognitive distance to the reachable land-uses; INT: angular integration; CHO: angular

Table 2 - Centrality performance against encounter intensity (Only significant variables are shown)

When the goodness-of-fit for every model is scrutinised, co-presence patterns in streets are proven to be properly captured by the centralities of the spatio-functional context where they are embedded. For most of a typical workday, the models with both families of configurational centralities maintain correlation coefficients greater than 0.65. However, this trend is interrupted during the period around the morning peak from 6 am to 8 am. This result implies that the co-presence patterns may be simultaneously driven by other variables that are currently absent from the present models in a more complex sense. For models with spatial and functional centrality measures, their predictability is higher than the other two types of models with either spatial or function centrality indices, suggesting the theoretical proposition that spatio-functional interaction is the essential determinant of spatiotemporal encounter patterns. In addition, models with urban function connectivity measures perform better than those with space syntax centrality metrics in terms of the size of the correlation coefficients. Nevertheless, this does not mean that the impact of the spatial network can be substituted by the influences exerted by the land-use system. Instead, these findings suggest a complimentary relationship between urban form and functions for an in-depth understanding of people's interactions in the streets. These results further exhibit that the physical co-presence that happens in an urban reality is far more complex than was expected and hypothesised in the theory of space syntax. Additionally, the spatial centrality and land-use patterns are more important in the formulation of the landscape for people to communicate and to make a space socially public. More importantly, in comparison to the roles that the spatial grid plays, the effects of the geometrical properties of land-use patterns on the spatiotemporal encounter are more direct and powerful.

6. DISCUSSION AND CONCLUSION

This research examines the spatial logics of the spatiotemporal co-presence between the local and non-local people in Central Shanghai. Two main tasks are expected to be achieved. The first one is to quantify the spatiotemporal patterns based on the individual's check-in records and street network. The second one is to investigate the role that the urban design plays in the sensed spatiotemporal co-presence intensity. The main scope of this study is to empirically explore the extent to which the spatial design influences the physical face-to-face interaction between different groups of people, the social media users more precisely, in contemporary digitalised society.

This study delivers a PST model in which the social capital for people to interact includes three principal dimensions including the social difference between people, the spatial distance (the metric and geometrical distance), and the time cost of people's presence. It is proposed that people can be profiled by their mobility patterns which can further depict the citizens' place identity from place to place and from time to time. Within a given time, interval, social media users who visit a local area for a location frequently are defined as the 'local random users' for that location, while the users who have a short time visit towards the local area for a location and travel back to somewhere outside the local area are identified as the 'remote users'. From an aggregated scope, the local random users and the remote users are the parts of the internal flow and the incoming flow for a location in question, respectively. Given these definitions, this study anchored its specific focus on the physical encounter between the local random users and the remote users by considering comprehensively the required energy expenditure and cognitive cost. By giving a time radius and a distance radius, the delivered co-presence intensity addresses the interplay among the co-presence density, balance and mean cognitive distance in every street. Portraying spatiotemporal patterns is not only related to the perceived publicness of space but also helpful for producing the deeper knowledge on how the offline built environment is used by the online population in the current digitised world.

Individual's trajectory pattern is extracted from their consecutive check-in records and then used to produce the spatiotemporal co-presence intensity in streets with the street network dataset. The reliability of the mined data and the effectiveness of the proposed method are proven by the observation that the processed spatiotemporal trips follow exponential laws in terms of the trip length and duration and a good correlation between the outputs and the small sized survey data. The co-presence patterns across time reveal their temporal complexity. Not only the city centres but also the planned centres and the large-scale social complexes, such as transport hubs, shopping malls, etc. are the crucial spaces for people to encounter. Regression results suggest that physical co-presence between the random and remote users are not always in high streets as expected, but their nearby streets where the pedestrian land-use mixture is less and the angular distance to the land-use is longer. The impacts of the angular integration in the regression models for describing the deviation of co-presence patterns are more significant in the morning when developing areas are more likely to be the destinations in the commuting time. It is validated that the urban function connectivity measures maintain higher standards of predictability than the space syntax centralities, though the model performance can be further enhanced if both types of configurational centrality variables are used. It is also noteworthy that the goodness-of-fit in the integrated model is significantly lower in the morning peak hour.

The potential contribution of this work relying on several aspects. Firstly, it is proven that social media dataset can be adopted to understand human's mobility and presence with a large coverage and a fine spatial resolution. Secondly, it proposes a street-based framework to quantify the spatiotemporal co-presence between defined groups of people. This framework is flexible and can be extended and used to measure other co-presence phenomena. Thirdly, this work suggests that it is the spatio-functional interaction through streets that influences the spatiotemporal variation of the encounter between people, which could be a reference for the further studies on the relevant directions. Fourthly, it is recognised that land-use patterns are theoretically and methodologically necessary for understanding the social processes in contemporary society where people's travelling decision making is biased by the online location services. Lastly, the introduced measure of co-presence intensity in this study could be considered as a spatiotemporal centrality index across places. It extends the current space syntax integration purely focusing on spatial network, to a more comprehensive centrality with land-use, spatial network, temporal and individual components, the four domains in accessibility measurements (Geurs and Wee 2004).

Further work can be conducted in, but not limited to, the following aspects. The time interval for computing the co-presence intensity in this study is set for 1 hour in order to avoid the bias caused by the data's scarceness. In the next step, the time interval can be further divided with a better data support to produce the results with more temporal singularity. Moreover, the information of the individual check-in trajectories can be enriched by combining it with other big data resources, such as the cell phone datasets, etc. Besides, more empirical studies should be conducted in other cases to validate the generality of the conclusions in this study.

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