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Exploring human mutuality in cyber and physical spaces using mobile big data and network analysis

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ABSTRACT

Partially due to the limited access to datasets of human activities in cyber and physical (online and offline) spaces, the exploration of weak human interactions, defined as human mutuality in this work (i.e. co-location in physical space, and co-domain in cyber space) and their networks in the two spaces have been constrained to some extent in recent years. To bridge this gap, this study establishes a unified framework for directly comparing individual-level human mutuality networks across physical and cyber spaces, based on large-scale Uniform Resource Locators (URLs) data from tens of thousands of users in Jilin, China. Within this framework, human mutuality networks are constructed with users as nodes and mutuality events as edges, based on shared locations or shared website visits. The networks are systematically analyzed through three dimensions: fundamental network properties (such as clustering coefficient and average shortest path length), degree and strength distributions, and community structures. The results show distinct structural differences between the two spaces. Cyber space displays a significantly shorter average shortest path length (2.4) than the physical space (7.6), suggesting faster information transmission and the potential to alleviate digital inequalities by accelerating access to resources. Both networks present heavy-tailed degree distributions, indicating heterogeneous structures shaped by a few highly connected individuals. Furthermore, while physical space exhibits numerous small communities with strong local clustering, cyber space contains fewer but larger communities, with weaker local cohesion. This reduced local clustering may increase the risk of rapid misinformation diffusion. Additionally, the formation of cyber communities based on shared online behaviors reveals potential socioeconomic similarities among users despite differences in their physical attributes. Together, these insights offer a foundation for understanding human interactions across hybrid spaces and inform strategies for managing cyber and physical social dynamics.

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Cyber space; human mutuality; complex network; community detection

1. Introduction

As digital technology advances, human activities (e.g. shopping, banking) are increasingly transitioning from offline (physical space) to online (cyber space), resulting in the change of human interaction to a mixed mode, i.e. co-location in physical space and co-domain (website) in cyber space simultaneously (Assimakopoulos 2000; Liu et al. 2021). Based upon human interaction, different human interaction networks can be constructed based on the locations and domains that users visited in chronological order in cyber and physical spaces, respectively.

In physical space, human interaction is commonly divided into strong interactions (e.g. face-to-face communication) and weak interactions (e.g. co-presence at a shared location) (Liu et al. 2023a; Liu et al. 2023b; Zhang et al. 2023). To model these interactions, early research focused on individual-level behaviors using statistical models such as Brownian motion, Lévy flight, continuous-time

random walk, and preferential return. However, these models are often limited in capturing large-scale spatial patterns and heterogeneity. To address these gaps, population-level and place-based models, including gravity, radiation, intervening opportunities, and social-based models, have been developed, offering insights into flows and relationships across regions (Barbosa et al. 2018; Schneider et al. 2013). These models have been widely applied in fields such as migration (Simini et al. 2012), trade (Silva and Nelson 2012), and tourism demand (Morley, Rosselló, and Santana-Gallego 2014). In recent years, with the rise of big data, human interaction models have further evolved by integrating multi-source datasets, such as demographic and social media data (Iacopini, Karsai, and Barrat 2024), and advanced methods such as machine learning and deep learning, enabling more accurate and individualized predictions of complex spatiotemporal behaviors (Gao et al. 2024; Liu et al. 2024; Shi et al. 2024). Meanwhile, weak interactions have gained

growing attention as a new form of social phenomenon. A notable example of the long-term influences of weak interaction is place identity and attachment, where individuals from the same hometown are more likely to form connections in metropolitan regions.

In cyber space, both strong interactions (e.g. direct communication through phone calls or messaging) and weak interactions (e.g. passive co-visitation of the same websites) may exist and exert influence. Given the prevalence of such weak forms of interaction, it is hypothesized that weak interactions in cyber space, such as co-visiting the same websites, might play a crucial role in reflecting human demographic and socio-economic attributes, facilitating information diffusion, and potentially bridging digital inequality. This hypothesis motivates the exploration of human mutuality in cyber space and further supports the comparative analysis of human mutuality across physical and cyber spaces.

However, most research focuses predominantly on human interaction in physical space, often oversimplifying or neglecting their cyber counterparts. Although some studies have examined strong cyber interaction using data from social platforms like Weibo and Zcool (Fang et al. 2020; He, Wang, and Zeng 2022; Hu et al. 2020), weak interaction in cyber space remains under-explored. Furthermore, studies on cyber human interaction are typically conducted at an aggregate level, such as city-level, neglecting the characteristics of human interaction at the individual level. Despite extensive research on cyber and physical human interaction networks separately, there's a scarcity of studies that directly and quantitatively compare these two types of networks for the same group of people at the individual level. This gap, largely due to the lack of datasets capturing both cyber and physical interaction for the same users, is critical for advancing current research and addressing practical concerns, such as managing information dissemination.

Additionally, aside from the examination of static networks, there's been growing attention to the temporal patterns of networks. While many studies have explored the temporal patterns of mobility networks, few have delved into the potential dynamism of human interaction. For example, studies have shown strong correlations between community transformations and cycles of human movement (Walsh and Pozdnoukhov 2011), and notable variations in temporal characteristics of human mobility across different cities (Sparks et al. 2022; Zhou et al. 2016). Nevertheless, given that human interaction might have significant changes during different periods, comprehending the temporal characteristics of human interaction networks is essential to grasping the dynamics of human behavior and completing the existing literature.

To address the research gaps, the study first defines weak human interaction in cyber and physical spaces as human mutuality, and then constructs the corresponding networks, which are further compared with reference networks and between two spaces. This study offers several distinct contributions that set it apart from previous research: (1) Our work theoretically defines weak human interaction (hereafter referred to as human mutuality) in cyber and physical spaces based on currently available data, URL; (2) the utilization of URL data in this study effectively resolves data mismatch problems, enabling a direct comparison of human mutuality network between cyber and physical spaces and providing reliable comparative results; (3) the characteristic of human mutuality network is investigated and compared between spaces at the individual level; (4) this study further examines the temporal characteristic of network structures in cyber and physical spaces, using dynamics human mutuality networks. The experiments were conducted in Jilin Province, where unique users extracted from the URL datasets were considered as nodes in the networks. The edges in the cyber and physical spaces were determined based on the order of time, location, and website records following specified rules outlined in the methodology section. Four types of networks were built, including static human mutuality networks in cyber and physical spaces containing all data used in the study, as well as dynamic human mutuality networks based on partial data within different periods. These networks were evaluated and compared from three perspectives: network property, network structure, and community detection.

The remainder of the paper is organized as follows: [Section 2](#) introduces the study area and URL datasets. [Section 3](#) presents how human mutuality networks are constructed, and the evaluation methods. [Section 4](#) reports the results. [Section 5](#) discusses the main findings, limitations, and suggestions for future research, and conclusions are drawn in [Section 6](#).

2. Study area and datasets

2.1. Study area

This study was conducted in Jilin Province, located in northeastern China, bordering Russia and North Korea, as depicted on the left side of [Figure 1](#). In the 1980s, Jilin Province experienced significant industrial growth and became a prominent industrial region. However, subsequent national policy changes led to the relocation of resources and talent to southern China, resulting in a gradual decline in Jilin's development compared to other regions. Jilin Province covers approximately 191,202 km² and has a population of 24.07 million according to the seventh



Figure 1. The study area of Jilin Province in the northeast of China (left), and the 9 secondary administrative regions and 12,800 cellular towers in blue dots (right).

census. It comprises nine secondary administrative regions, represented by colorful asterisks on the right side of Figure 1, with Changchun as the capital city. The figure also shows the distribution of 12,800 cellular towers (depicted as blue dots) across the province, highlighting significant clusters in the more developed areas.

2.2. Dataset

In this study, human mutuality is defined as a form of weak human interaction, representing the subtle influence of co-presence in both physical and cyber space. To explore human mutuality in cyber space, Uniform Resource Locator (URL) data is used in the study, which is one type of mobile phone data. The process of generating URL data is displayed in Figure 2. Users' smart mobile devices can visit the internet through

signal communication with cellular towers. These towers are maintained by the service providers, which not only provide access to the public network but also monitor users' internet usage. The metadata of usage is stored in the URL database, which includes all information from the data transmission chain of "user devices- cellular towers- servers of websites." However, to safeguard individuals' privacy, only partial data is utilized as URL data in the study, as depicted in Table 1. The User ID serves as a unique identity for each user when accessing mobile internet; CELL ID records the users' connected cellular towers; Longitude and Latitude are the geographical coordinates of the cellular towers; Request Time records the time of website access, and the URLs encompass the domain of the websites visited by the users.

Given the sensitive nature of mobile big data, strict privacy protection measures were implemented in this

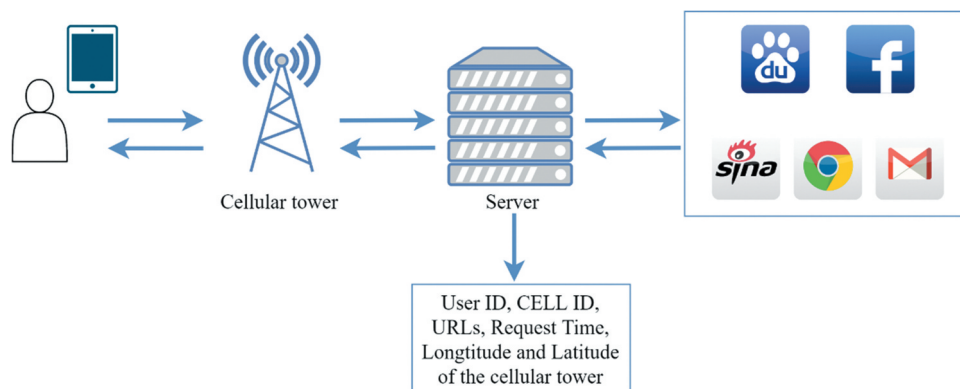


Figure 2. The process of the generation of URL data.

Table 1. The sample from Uniform Resource Locator data.

User ID	CELL ID	URLs	Request time	Longitude	Latitude
46000**83987	7162	szextshort.sweixin.qq.com	2016-12-20 00:39:07	123.94101	43.79141
46007**00041	40083	mmsns.qpic.cn	2016-12-20 00:39:03	128.91792	43.11605

study. The dataset was provided by China Unicom, with all personally identifiable information, such as user IDs, device identifiers, and other sensitive attributes, fully anonymized and masked at the source in accordance with relevant data protection regulations. Prior to analysis, an additional layer of data masking and aggregation was applied to further minimize any potential risk of individual identification, as detailed in Table 1. The final dataset used in this study contains only anonymized records that cannot be traced back to any specific individual. All procedures comply with ethical standards to ensure the privacy and security of user information throughout the research process.

The data used in this research was collected on Tuesday, 20 December 2016, and consists of approximately 20 million records, from which we extracted 84,052 users and 12,800 cell towers. In physical space, the geographical locations of connected cellular towers can serve as an estimate of their physical locations. Therefore, the data comprising User ID, CELL ID, Longitude, Latitude, and Request Time are used for the construction of a physical human mutuality network, while the data comprising User ID, CELL ID, URLs, and Request Time are used for the construction of a cyber human mutuality network.

3. Methodology

A framework has been proposed to define and characterize human mutuality networks in cyber and physical spaces in this study. The framework includes three stages, as displayed in Figure 3. The first stage defines human mutuality in cyber and physical spaces and constructs corresponding networks from URL data. The second stage characterizes these networks from three aspects: network property, network structure, and community detection. The third stage involves conducting separate comparisons of network

structures, first between cyber and physical spaces, and second between dynamic and static aspects.

3.1. Constructing human mutuality networks

This subsection details the process of defining human mutuality and constructing static and dynamic human mutuality networks in both cyber and physical spaces using massive URL data. It also includes direct comparisons of human mutuality definitions in cyber and physical spaces. Additionally, two reference networks are introduced and constructed as baselines to evaluate the structures of the human mutuality networks.

3.1.1. Static human mutuality networks

Static human mutuality networks are constructed using all records saved within a day. These networks include two types: Cyber Static Human Mutuality Network (CSHMN) and Physical Static Human Mutuality Network (PSHMN), both of which are undirected and weighted. The definitions for CSHMN and PSHMN are as follows:

$$G_{\text{CSHMN}} \text{ or } G_{\text{PSHMN}} = (V, E) \quad (1)$$

$$V = \text{unique} \left(\sum_d V(d) \text{ while } d \in \text{URL} \right) \quad (2)$$

$$E = \sum_d f(\text{UserA}, \text{UserB}, \text{Time}, \text{Place or Web}) \text{ while } d \in \text{URL} \quad (3)$$

where V represents all nodes and E represents all edges. In this study, V is defined as all unique users extracted from the URL data, as presented in Equation (2), and E represents all human mutuality between users, as presented in Equation (3). Physical human mutuality is defined as weak interaction

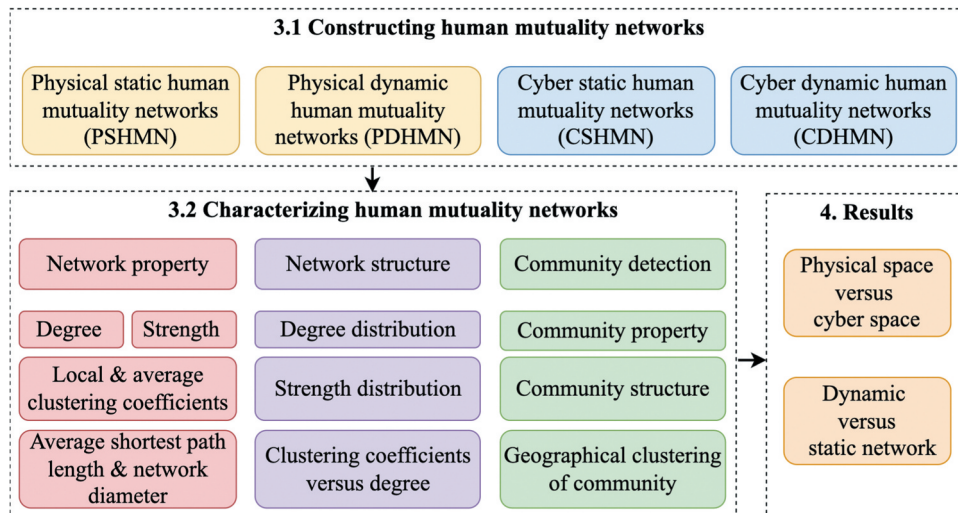


Figure 3. The workflow of the proposed analytical framework, including three stages (i.e. constructing human mutuality networks, characterizing human mutuality networks, and comparative results).

between different users who have visited the same place within a short time frame (Zheng 2011). Cyber human mutuality is similarly defined, based on the premise that visited websites and locations both reflect people's interests, cognition, and culture. Therefore, cyber human mutuality is defined as weak interaction between different users who visit the same websites within a short time frame. The time interval for mutuality in physical space is set to 1 minute, reflecting typical pause times at locations according to previous studies (Alessandretti et al. 2017), while in cyber space, it is set to 1 second to account for the high frequency of online activities.

The example in Figure 4 illustrates the definitions of human mutuality in cyber and physical spaces. In Figure 4(a), we have the mutuality between USER, WEBSITE, and PLACE. For instance, t_{A1} denotes the first visit of User A to Google, while T_{A1} represents the first visit of User A to Place X, and so on. The corresponding human mutuality networks are shown in Figure 4(b, c). In Figure 4(b), an edge is formed between User A and User B because both of them visited Google for the first time. This pattern continues for other users as well, such as User B and User C. In Figure 4(c), an edge with a weight of 2 is created between User B and User C since they visited Place X for the first time and Place Y for the second time. Similar patterns are observed for the rest edges in the network.

3.1.2. Dynamic human mutuality networks

To investigate the temporal variation of human mutuality networks between cyber and physical spaces, dynamic human mutuality networks are constructed, comprising a series of subnetworks. The construction process for these subnetworks is similar to

that of static networks, with the primary difference being the data utilized. These subnetworks are built by aggregating data from different periods separately. The mathematical definition of dynamic human mutuality networks is as follows:

$$G_{CDHMN} \text{ or } G_{PDHMN} = \sum_1^t (V^t, E^t) \quad (4)$$

where t is the number of time intervals, (V^t, E^t) represents one subnetwork constructed from the data belonging to the t period, V^t includes all active users, E^t includes all human mutuality during this period, CDHMN represents cyber dynamics human mutuality networks, while PDHMN represents physical dynamics human mutuality networks. In this study, four periods are selected (Zhang, Shen, and Zhao 2021): 7 a.m. to 10 a.m. (morning); 11 a.m. to 2 p.m. (noon); 5 p.m. to 8 p.m. (late afternoon); 9 p.m. to 12 a.m. (night).

3.1.3. Reference networks

Two reference networks, namely random networks and scale-free networks, are included in this study as they represent two extreme types of network structures, providing a basis for cross-comparisons. The random network is entirely homogeneous, generated by purely random connections between different nodes. Typically, these networks have small clustering coefficients, and their degree distributions follow a Poisson distribution (Erdős and Rényi 1960; Frieze and Karoński 2016). In this study, random networks are generated by random walks between nodes, with the average node degrees matching those of the explored networks. On the other hand, the scale-free network is a typical heterogeneous network, where a few nodes account for many connections. This

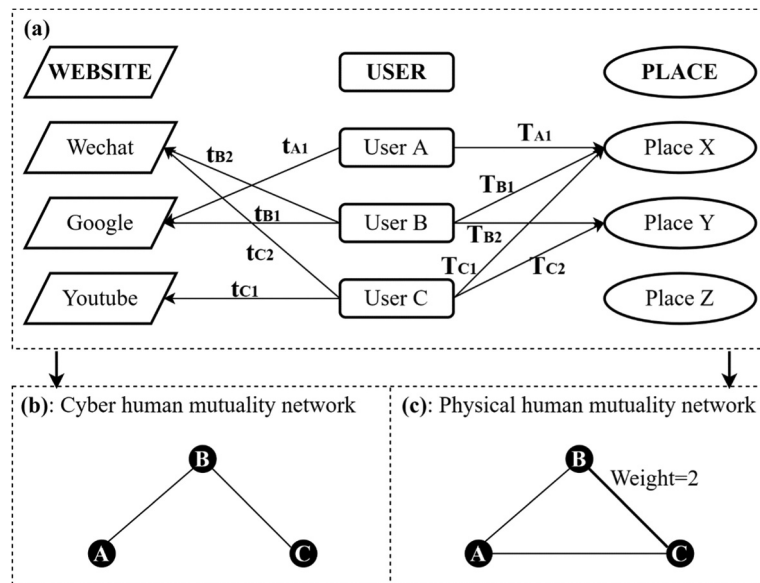


Figure 4. The definition of human mutuality in cyber and physical spaces.

imbalance is reflected in the heavy-tailed degree distribution, a key characteristic of scale-free networks (Hein, Schwind, and König 2006). Another important feature is the negative correlation between the clustering coefficient and node degree (Morita 2006). The scale-free networks in this study are constructed based on preferential attachment, with the node distribution following a power law (Barabási and Albert 1999).

3.2. Characterizing human mutuality networks

The human mutuality networks in the study are characterized in three aspects: network properties include the number of nodes, the number of human mutuality, the number of edges, node degree, node strength, clustering coefficient, average shortest path length, and network diameter; network structures include degree distribution, strength distribution, and scaling relation between degree and clustering coefficient, which are further compared with two reference networks; community detection to examine the similarities and difference of community structure in cyber and physical spaces. Additionally, all analyses are performed on both static and dynamic networks.

3.2.1. Network property and structure

3.2.1.1. Node degree K_i and degree distribution $P(k)$. Node degree and degree distribution are two important measures to reflect the heterogeneities of networks (Borgatti et al. 2009). Node degree measures the number of connections each individual (node) has in the network. For example, in a physical setting, it represents how many different people a person shares a public space with during a certain period. In cyber space, it reflects how many other users someone is indirectly connected to through co-visiting the same websites. The nodes with higher degrees represent people who are more connected in the networks. Because the human mutuality networks in the study are undirected, the in-degree and out-degree are not considered. The mathematical definition of node degree k_i is shown in Equation (5), which measures the number of nodes to which node i is connected.

$$k_i = \sum_{j \in V} N(v_i, v_j) \quad (5)$$

In this formulation, v_i and v_j represent nodes i and j in the network, V denotes the set of all nodes, and the summation iterates over all nodes $j \in V$ except i . The term $N(v_i, v_j)$ is an indicator function that equals 1 when a link exists between node v_i and node v_j and 0 otherwise. Consequently, k_i quantifies the total number of direct neighbors of node i . The degree distribution $P(k)$ characterizes the proportion of nodes with degree k in the human mutuality networks. In the random network, $P(k)$ is a Poisson distribution; in the scale-free networks, $P(k)$ is a power-law distribution.

3.2.1.2. Node strength s_i and strength distribution $P(s)$. The node strength is employed to reflect the degree of weight networks. Node strength captures the intensity of connections, considering how frequently the ties are between individuals. For instance, in physical space, this could reflect how frequently two people stay together in the same place and same time, while in cyber space, it might indicate how often two users browse the same website within overlapping time windows. Higher strength suggests more repeated interactions. The nodes with high strength represent people who have more mutuality with others and are possibly the hub nodes. The mathematical definition of node strength s_i is displayed in Equation (6), which measures the sum of the weights of the edges connected to node i . The strength distribution $P(s)$ captures the number of nodes with a specific strength s in the human mutuality networks.

$$s_i = \sum_{j \in V} W(v_i, v_j) \quad (6)$$

In this equation, v_i and v_j denote nodes i and j in the network, V represents the set of all nodes, and the summation iterates over all nodes $j \in V$ except i . The term $W(v_i, v_j)$ denotes the weight of the connection between nodes v_i and v_j , which reflects the interaction intensity or frequency between the two nodes. Consequently, s_i quantifies the total interaction weight associated with node i . The strength distribution $P(s)$ then describes the proportion of nodes with strength s in the human mutuality networks.

3.2.1.3. Local $C(v)$ and average clustering coefficients $\langle C \rangle$.

The clustering coefficients measure the degree of clustering of the networks. Two types of clustering coefficients are adopted in the study. The local clustering coefficients measure the likelihood that two of an individual's contacts are also connected to each other, forming small groups or "triangles" in the network. For example, in physical space, high clustering may occur in office environments where many colleagues regularly meet, while in cyber space, lower clustering suggests that users who browse the same website are less likely to have common browsing behaviors elsewhere. This is important because lower clustering in cyber space could reflect weaker online community cohesion and may affect phenomena like the rapid spread of misinformation, where tightly-knit groups often amplify messages. The mathematical definition of locally weighted clustering coefficients is shown in Equation (7), where $w_{i,j}$ is the weight between node i and node j , a_{ij} are the elements of the adjacency matrix (Barrat et al. 2004).

$$c_w(i) = \frac{1}{s_i(k_i - 1)} \sum_{j,h} \frac{(w_{i,j} + w_{i,h})}{2} a_{ij} a_{ih} a_{jh} \quad (7)$$

The second type is the average clustering coefficient, which is used to quantify the density of the entire network. It is calculated based on Equation (8), where N is the number of nodes in the networks.

$$\langle C \rangle = \frac{\sum_{i \in V} c_w(i)}{N} \quad (8)$$

3.2.1.4. Average shortest path length L and network diameter D . The average shortest path length in a network is a measure of the average number of steps along the shortest paths for all possible pairs of nodes. It provides insight into the typical separation between nodes, reflecting how efficiently information or influence can spread across the network (Watts and Strogatz 1998), such as the average number of people you will need to connect with a stranger. For example, in physical space, it might reflect how many shared locations link two otherwise unconnected people, while in cyber space, it shows how quickly information or behaviors could spread through shared online activities. Shorter paths imply more efficient connectivity. Mathematically, it is the sum of the shortest path lengths between all pairs of nodes divided by the number of such pairs, as displayed in Equation (9). Network diameter, on the other hand, is the length of the longest shortest path between any two nodes in the network, as shown in Equation (10). It represents the maximum distance between any pair of nodes, indicating the extent of the network. A larger diameter suggests that the network is more spread out, while a smaller diameter indicates a tightly connected structure. In physical space, this could imply how far apart different groups are in terms of shared locations, whereas in cyber space, it may reflect the maximum steps needed for information to potentially reach all users. Both metrics are fundamental in the study of network structure, helping to understand connectivity and the potential speed of communication within the network.

$$L = \frac{1}{\frac{n(n-1)}{2}} \sum_{i < j} d(i, j) \quad (9)$$

$$D = \max_{i,j} d(i, j) \quad (10)$$

where n represents the number of nodes in the network, and $d(i, j)$ is the shortest path length between node i and node j .

3.2.1.5. Clustering coefficients versus degree. The weighted clustering coefficient $C_w(k)$ of the nodes with a specific degree k is calculated based on Equation (11).

$$C_w(k) = \frac{1}{N(k)} \sum_{i/k_i=k} C(i) \quad (11)$$

In the equation, k_i denotes the degree of node i , and summation is performed over all nodes i with degree $k_i = k$. $C(i)$ represents the weighted clustering coefficient of node i , and $N(k)$ is the total number of nodes with degree k , serving as a normalization factor to compute the average clustering coefficient for nodes of degree k . The scaling relationship between the weighted clustering coefficient and degree is expressed in Equation (12):

$$C_w(k) \propto k^{-\gamma} \quad (12)$$

where γ is a scaling exponent that captures how the clustering coefficient changes as a function of node degree. A decreasing scaling relation suggests that denser clusters tend to have lower connectivity.

3.2.2. Community detection

Community detection is a fundamental step in network analysis for understanding the group structure of networks. There are many algorithms designed for community detection, such as Infomap (Edler, Bohlin, and Rosvall 2017) and the edge betweenness method (Newman and Girvan 2004). Considering the computation efficiency, the method proposed by Blondel et al. (2008) is selected in this study, which is a heuristic method based on modularity optimization. Modularity is proposed by Newman and Girvan (2004), and designed to evaluate how good a particular partition of a network is. Communities are analyzed from three aspects: community structure, community properties, and geographical clustering. To quantify the similarity of community structures across different time intervals, this study employs the Normalized Mutual Information (NMI) method proposed by Danon et al. (2005). NMI is a widely used metric for comparing community partitions in complex networks, with values ranging from 0 to 1. An NMI value close to 1 indicates a high degree of similarity between two community structures, while a value near 0 reflects significant differences. By applying NMI, the temporal stability of community structures in both cyber and physical human mutuality networks can be systematically assessed. The geographical clustering is determined through the following process: first, each user is mapped to a geographical location based on the center point of their activity space in physical space; second, Kernel Density Estimation (KDE) is performed for each community, with the bandwidth set to the average distance of all nearest points based on the head/tail break (Jiang 2013), finally, the geographical clustering for each community is defined as areas with a density value greater than three standard deviations, as shown in Equation (13).

$$D_{c,i} \geq 3\sigma_c \quad (13)$$

where $D_{c,i}$ is the KDE value of i -th unit within the c th community, and σ_c is the standard deviation of all units within the community.

4. Results

The following three subsections compare the human mutuality networks between cyber and physical spaces from three aspects: 1) network properties in subsection 4.1, such as clustering coefficient, degree, strength, average shortest path length, and network diameter, 2) network structures in subsection 4.2, and community properties and structures in subsection 4.3

4.1. Network properties

We first present the results of a comparative analysis between the CSHMN and the PSHMN. As shown in Table 2, PSHMN comprises 66,082 nodes, 220,185 edges, and 49,055,635 weights, indicating frequent human mutuality despite relatively lower connectivity. This suggests that human mutuality in physical space primarily occurs among acquaintances or familiar individuals. Additionally, PSHMN exhibits a significantly larger clustering coefficient ($\langle C_{wp} \rangle = 0.494$) compared to the corresponding random network ($\langle C_w \rangle = 0.0113$). In contrast, CSHMN consists of 82,121 nodes 38,209,519 edges, and 158,393,745 weights, indicating more frequent mutuality in cyber space compared to physical space. CSHMN also exhibits larger average degree and strength ($\langle K \rangle = 930.6$, $\langle S \rangle = 3857.6$) compared to PSHMN ($\langle K \rangle = 6.6$, $\langle S \rangle = 1484.6$), suggesting more frequent mutuality in cyber space likely due to the absence of geographic constraints. However, CSHMN has a relatively smaller clustering coefficient ($\langle C_{wc} \rangle = 0.454$) compared to PSHMN, although it is still significantly larger than that of the cyber static random network ($\langle C_w \rangle = 9.801 \times 10^{-5}$). This

indicates evident clustering in both spaces, with a more pronounced effect in physical space. Regarding the average shortest path length, PSHMN has an average of 7.6, roughly adhering to the concept of six degrees of separation, which posits that all people are six or fewer social connections apart. In contrast, CSHMN exhibits a significantly shorter average shortest path length of 2.4, indicating that individuals need only an average of three social connections to connect with anyone in cyber space. Furthermore, the network diameter in CSHMN is one-third that of PSHMN, underscoring the more interconnected nature of cyber space compared to physical space.

In this subsection, we present a comparative quantitative analysis of network properties between cyber and dynamic human mutuality networks (CDHMN) and physical dynamic human mutuality networks (PDHMN). Table 2 provides an overview of the statistical properties of PDHMN and CDHMN. Generally, the statistical properties in cyber space, except for clustering coefficients, network diameter, and average shortest path length, exhibit larger magnitudes compared to those in physical space, consistent with findings from static networks. Regarding dynamic characteristics, the trends of these statistical measures between the two spaces are generally similar, with four exceptions. First, the number of edges and average degree from noon to late afternoon show an increasing trend in cyber space and a decreasing trend in physical space. This difference suggests that individuals engage more in cyber human mutuality during work hours and reduce physical human mutuality, contrasting with leisure times. Second, clustering coefficients ($\langle C_w \rangle$ and $\langle C \rangle$) decrease in cyber space from late afternoon to night, while they increase in physical space. This divergence implies that during leisure hours, people tend to cluster more in physical space, possibly for social activities, whereas in cyber space, clustering decreases. These temporal variations in human mutuality networks between cyber and physical spaces highlight a strong correlation between network structure and individuals' lifestyle states (leisure

Table 2. Properties of human mutuality networks in cyber and physical spaces.

Property	Physical space					Cyber space				
	PSHMN	Network in the morning	Network at noon	Network in the late afternoon	Network at night	CSHMN	Network in the morning	Network at noon	Network in the late afternoon	Network at night
The number of nodes	66,082	25,920	28,824	26,294	14,601	82,121	34,369	37,554	34,640	21,086
The number of human mutuality	49,055,635	11,311,268	7,870,208	9,865,799	4,689,220	38,209,519	35,616,259	24,267,937	34,965,129	12,912,233
The number of edges	220,185	47,742	57,724	50,133	19,742	158,393,745	7,132,140	8,191,639	10,889,741	3,642,212
$\langle K \rangle$	6.6	3.667	3.991	3.796	2.696	930.6	388.494	408.124	577.979	325.807
$\langle S \rangle$	1484.6	872.783	546.087	750.422	642.315	3857.6	2072.580	1292.429	2018.772	1224.721
$\langle C \rangle$	0.449	0.533	0.538	0.555	0.599	0.429	0.351	0.365	0.418	0.393
$\langle C_w \rangle$	0.494	0.571	0.581	0.603	0.637	0.454	0.374	0.390	0.446	0.425
D	25	59	50	63	34	9	11	14	13	12
L	7.6	18.6	15.0	17.5	13.1	2.4	2.5	2.5	2.4	2.5

or work). Regarding network diameter and average shortest path length, the values in PDHMN are twice those in PSHMN, indicating a significant difference. However, in CDHMN, these two metrics are relatively stable across different periods in comparison to CSHMN. This stability is likely due to more cyber human mutuality compared to physical space, ensuring sufficient human mutuality within each period to maintain shorter connections to others.

4.2. Network structures

Figure 5(a, b) depicts the Complementary Cumulative Distribution Function (CCDF) of degree in cyber and physical spaces on a log-log plot. The red points represent empirical data used for constructing PSHMN and CSHMN, while the purple lines depict exponential fits based on the method by Clauset, Shalizi, and Newman (2009). Additionally, degree distributions from random networks (green lines) and scale-free networks (yellow lines) with the same average degree $\langle K \rangle$ as the explored networks are shown. It is evident that for intermediate node degrees, both

PSHMN and CSHMN follow exponential distributions ($P(k) \propto e^{-\zeta k}$ with $\zeta_p = 0.092$, $\zeta_c = 0.0007$). Figure 5(c, d) displays the CCDF of strength in physical and cyber spaces on a log-log plot. The strength distributions $P(s)$ in both spaces are fitted with Weibull distributions ($P(s) \propto (\frac{s}{\lambda})^{\beta-1} e^{-(\frac{s}{\lambda})^\beta}$ with $\beta_p = 0.38$, $\beta_c = 0.491$). The Weibull distribution, characterized by shape parameter β , is analyzed here focusing on its shape rather than the scale parameter λ , which relates to data magnitude. First, the deviation of the empirical data from random networks and scale-free networks suggests that neither CSHMN nor PSHMN can be purely characterized by these network models. Moreover, both exponential and Weibull distributions exhibit heavy-tailed characteristics, indicating a universal feature of human mutuality networks in cyber and physical spaces. This heavy-tailed structure signifies that some individuals are highly connected and interactive, while others remain relatively isolated. Comparing PSHMN and CSHMN, the exponential parameter in PSHMN is larger, indicating sharper distinctions between higher and lower degree values and a greater departure from Poisson

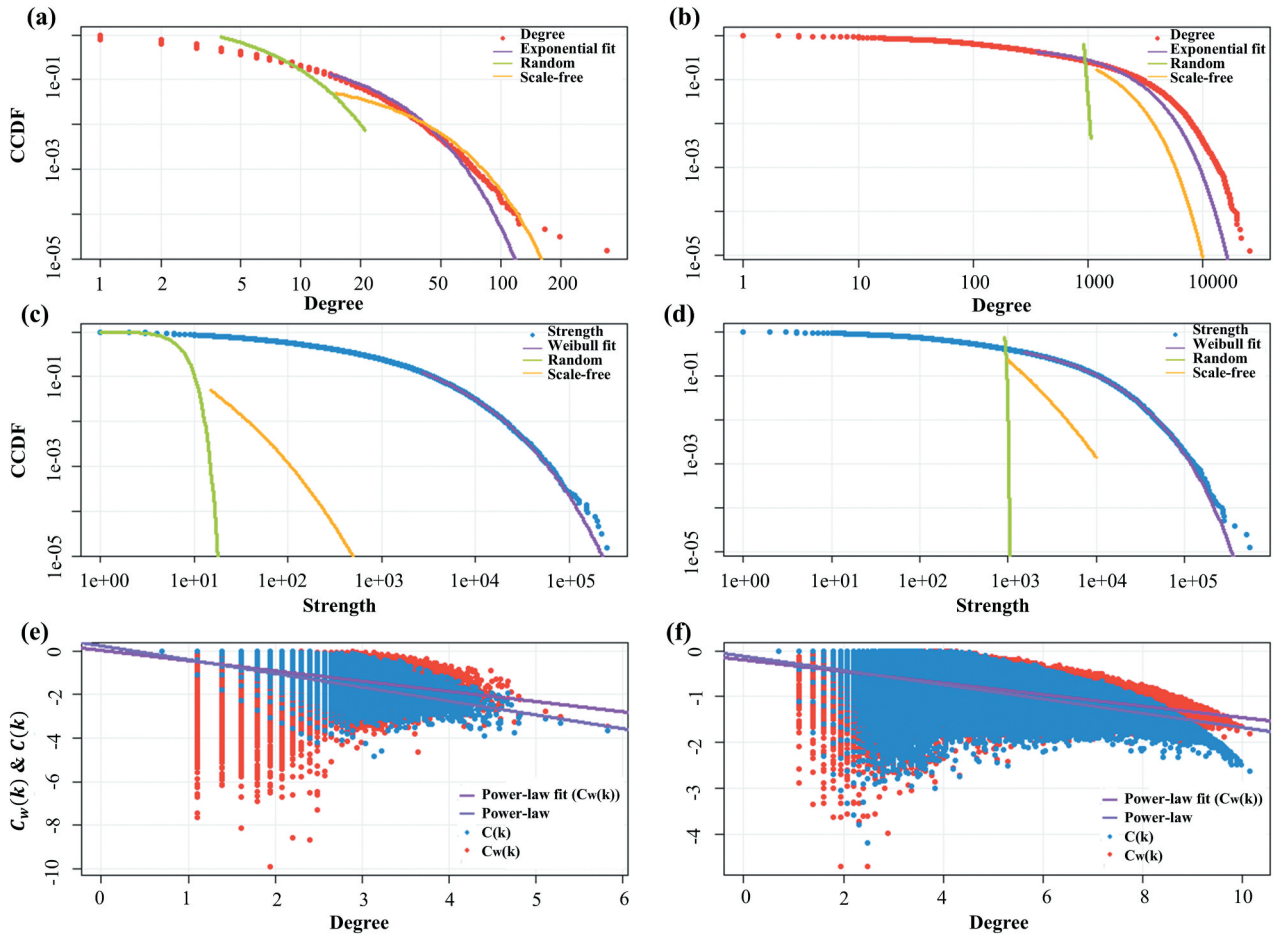


Figure 5. CCDF of the degrees in physical static human mutuality network (a) and cyber static human mutuality network (b); CCDF of the strengths in physical static human mutuality network (c) and cyber static human mutuality network (d); scaling relation between clustering coefficient and degree in physical static human mutuality network (e) and cyber static human mutuality network (f).

distribution. Conversely, the shape parameter in CSHMN is larger, indicating a more pronounced heavy-tailed distribution and highlighting greater network vulnerability (Solé et al. 2008).

To further explore the structure of networks, we analyzed the scaling relation between clustering coefficients and degree. In Figure 5(e, f), the red points and blue points correspond to $C_w(k)$ and $C(k)$ respectively. The two different purple lines are the corresponding power-law fits, where $C_w(k) \propto k^{-\gamma}$ with $\gamma_p = 0.465$ and $\gamma_c = 0.126$; $C(k) \propto k^{-\delta}$ with $\delta_p = 0.628$ and $\delta_c = 0.157$. First, in both CSHMN and PSHMN, the parameters in $C_w(k)$ is larger than those in $C(k)$, which suggests that people who have higher connectivity accumulate a larger number of human mutuality. However, the accumulating rate is larger in physical space than that in cyber space. Secondly, as proven by Dorogovtsev, Goltsev, and Mendes (2002), the completely hierarchical polycentric networks display the scaling relation of $\gamma = 1$. The hierarchical polycentric networks describe the characteristic of the highly clustered parts dividing into sparsely connected parts, which are connected by a few hubs. The finding ($\gamma_p = 0.465, \gamma_c = 0.126$) suggests that the PSHMN is closer to the completely hierarchical polycentric network.

As for the dynamic networks, the degree and strength distributions exhibit similar patterns as the static networks, with fit parameters differing as shown in Table 3. For degree distributions, ζ ranges from 0.000987 to 0.00162 in cyber space and 0.191 to 0.359 in physical space; for strength distributions, β ranges from 0.449 to 0.497 in cyber space and 0.315 to 0.399 in physical space. Comparing the magnitude of ζ and β separately between cyber and physical spaces, it is clear that ζ is larger in physical space, while β is larger in cyber space, aligning with the results of CSHMN and PSHMN and indicating the relatively stable quantitative relationship between two spaces regardless of time. Regarding the dynamic aspect, significant variations in the temporal trends of ζ and β can be observed between cyber and physical spaces. The highest physical ζ and β values occur at night and in the morning, while the highest cyber ζ and β values appear at noon

and in the afternoon, suggesting a greater vulnerability of network structures in physical space during free time (night and morning) and in cyber space during working time (noon and afternoon).

As for the scaling relation between clustering coefficients and degree, similarly, all distributions show similar patterns, which are fit by power-law distributions. Regardless of space and time, γ is always smaller than the corresponding δ , which follows the same rule as static human mutuality networks. Moreover, γ can reflect the extent of the hierarchical polycentric structures of networks. As indicated in Table 3, $\gamma_p > \gamma_c$ always exists for all periods, which implies that hierarchical polycentric structures are more significant in physical space than in cyber space. As for the dynamic characteristic, it is observed that the δ and γ generally move toward different directions as time passes by: the parameters in cyber spaces become smaller, while they become larger in physical space.

4.3. Community properties and structures

This subsection investigated the results of community detection in both cyber and physical spaces, revealing notable differences and similarities. From the perspective of the number of detected communities, we identified a total of 1153 communities in physical space and only 151 in cyber space, indicating a significant reduction in the influence of geographical distance in the cyber environment. This contrast underscores the diminished impact of geographical distance in cyber mutuality.

Further analysis was conducted by plotting the community sizes in descending order for both cyber and physical spaces, as illustrated in Figure 6(a, b). Both distributions adhered to a heavy-tailed structure, yet exhibited notable differences. In physical space, community sizes decreased gradually, indicating a relatively even distribution of community sizes. Conversely, cyber space demonstrated a steep decline from 30,000 to 10,000, signifying a more skewed distribution where only a few communities dominate in size.

Table 3. Fit parameters to describe degree and strength distributions and scaling relations in the cyber and physical dynamic human mutuality networks.

Property	Physical space				Cyber space			
	Network in the morning	Network at noon	Network in the late afternoon	Network at night	Network in the morning	Network at noon	Network in the late afternoon	Network at night
ζ (degree)	0.228	0.191	0.223	0.359	0.00158	0.00169	0.000987	0.00162
β (strength)	0.399	0.378	0.354	0.315	0.484	0.473	0.497	0.449
δ (non-weight)	-0.680	-0.627	-0.628	-0.701	-0.244	-0.236	-0.168	-0.171
γ (weight)	-0.563	-0.480	-0.477	-0.563	-0.207	-0.195	-0.131	-0.122

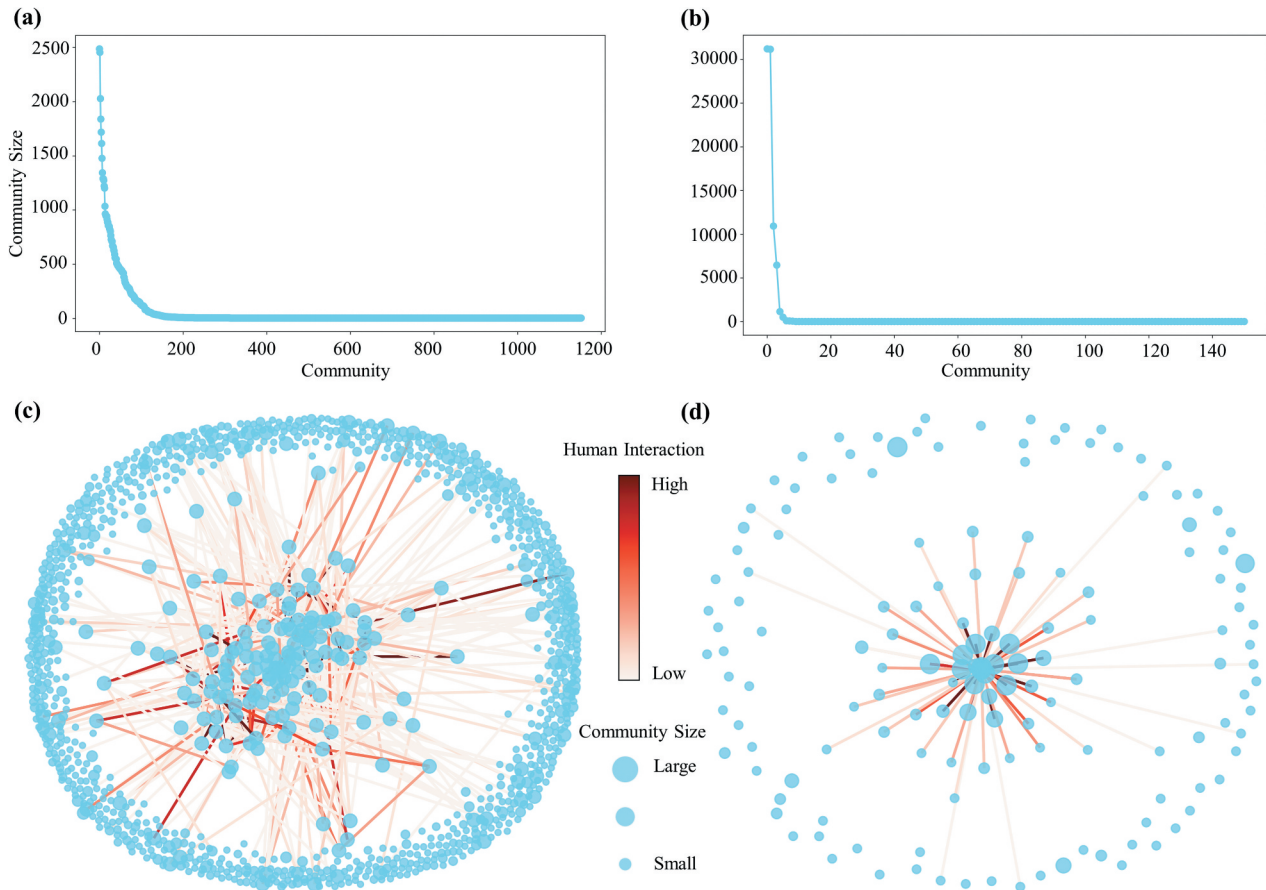


Figure 6. The plots of community sizes in descending order for physical (a) and cyber spaces (b). The community network for physical (c) and cyber spaces (d), where edge color represents the number of human mutuality between communities, every node represents one community, and node size represents the community size.

Examining the community structure from another angle, as displayed in Figure 6(c, d), both cyber and physical spaces displayed a core-periphery structure, characterized by a dense central region and more dispersed peripheral communities. Central communities showed strong interconnections, indicated by darker red edges, suggesting frequent mutuality. In contrast, connections between central and peripheral communities were weaker, as evidenced by lighter red edges. Moreover, central communities tended to be larger, while peripheral communities were relatively smaller. However, some differences were observed. First, the central communities in cyber space were larger than those in physical space, suggesting stronger cohesion in the cyber environment. Second, the mutuality between central and peripheral communities differed significantly. In physical space, there remained some connections between central and peripheral communities, reflecting the fluidity and diversity of social activities in real life. In contrast, in cyber space, there was almost no connection between central and peripheral communities, indicating that social mutuality in cyber space is more concentrated and isolated. Specifically, users in cyber space tend to interact within a few specific communities. The discovery of the core-periphery structure, especially the central

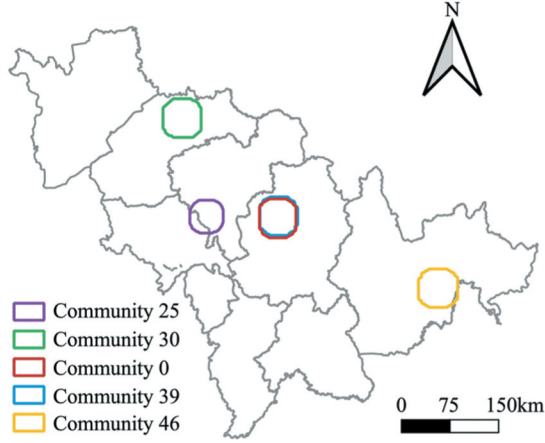
communities, highlights their potential role as key hubs for information dissemination and social influence.

In this study, we selected the five largest communities from both cyber and physical spaces for further investigation. Figure 7(a) presents a table listing various measures for these communities. In physical space, community sizes are relatively uniform, indicating a more evenly distributed mutuality among users. In contrast, cyber space exhibits a significant disparity, with the two largest communities dominating in size. This suggests that user mutuality in cyber spaces is highly concentrated within a few large communities. Analyzing community density, the higher community density in cyber space indicates more tightly-knit mutuality among users within these communities. Regarding network diameter and average shortest path length, the values for each community in cyber space do not differ significantly from those of CSHMN. The stability of network diameter and shortest path length in cyber space across different communities suggests uniformity in the structural characteristics of cyber mutuality. Conversely, in physical space, the network diameter of the top five communities is roughly half that of PSHMN, and their average

(a)

Community ID	Physical space					Cyber space				
	25	30	0	39	46	2	3	1	0	4
Community size	2488	2456	2029	1839	1719	31,214	31,174	10,929	6458	1141
Community density	0.00217	0.00311	0.00249	0.00403	0.00412	0.0219	0.0260	0.0078	0.0269	0.0316
D	14	13	13	12	11	6	6	9	8	11
L	5.526	4.371	5.359	4.513	4.427	2.287	2.156	2.747	2.495	2.822
<C>	0.239	0.201	0.207	0.260	0.212	0.258	0.266	0.278	0.269	0.342
<K>	5.384	7.630	5.046	7.397	7.069	685.033	809.943	85.171	173.461	36.016
<S>	1092.591	1649.399	1002.469	1759.532	1616.570	2375.752	3249.538	780.793	2047.977	69.727

(b)



(c)

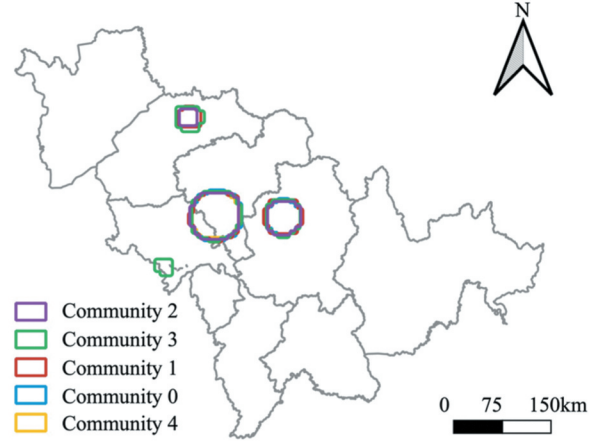


Figure 7. (a) The summaries of measures to characterize the five largest communities in cyber and physical spaces; the geographical clustering of the five largest communities in physical (b) and cyber (c) spaces.

shortest path lengths are smaller than PSHMN's. The variation in these metrics in physical space highlights a more diverse mutuality pattern, with individual communities being more compact and interconnected than the overall network. The higher clustering coefficient in cyber communities suggests a greater tendency for users within the same community to form tightly-knit groups, which contrasts with the physical space where such clustering is less pronounced. The significant fluctuations in degree and strength within cyber space, particularly the lower values in communities 1 and 4, indicate that mutuality in these communities is less frequent or less intense compared to others. This variability is less evident in physical space, where these metrics remain more consistent.

The geographical clustering of the five largest communities in both physical and cyber spaces is visualized in Figure 7(b, c). The spatial distribution reveals distinct patterns: in cyber space, the geographical locations of different communities highly overlap, whereas in physical space, community locations are relatively dispersed. This disparity can be attributed to the inherent characteristics of physical and cyber spaces. In physical space, the relative geographical dispersion of communities underscores the impact of spatial constraints on human mutuality. Physical proximity and geographical features significantly influence where and how communities form and interact. In contrast, these spatial constraints are diminished in cyber space,

allowing for greater geographical overlap among communities.

To further investigate the temporal dynamics of community structures, modularity comparison and NMI method are employed, as shown in Figure 8. The modularity values across these periods suggest that the overall community structures remain relatively stable throughout the day in both spaces. However, the NMI results reveal more significant differences: while communities in physical space maintain high structural similarity across different times, cyber space communities exhibit greater temporal variability. This contrast likely reflects the stronger temporal regularity and spatial constraints of physical activities, whereas online behaviors are more dynamic and responsive to contextual factors throughout the day.

5. Discussion

This study defines and quantifies human mutuality in cyber space and conducts a comparative analysis of human mutuality (weak human interaction) networks between cyber and physical spaces from both static and dynamic perspectives using complex network methods based on massive URL data. Compared with existing research, three key contributions are made. First, a new framework is proposed that treats websites as proxy locations in cyber space, providing a novel approach to analyze online human activity. This framework also creates opportunities for future

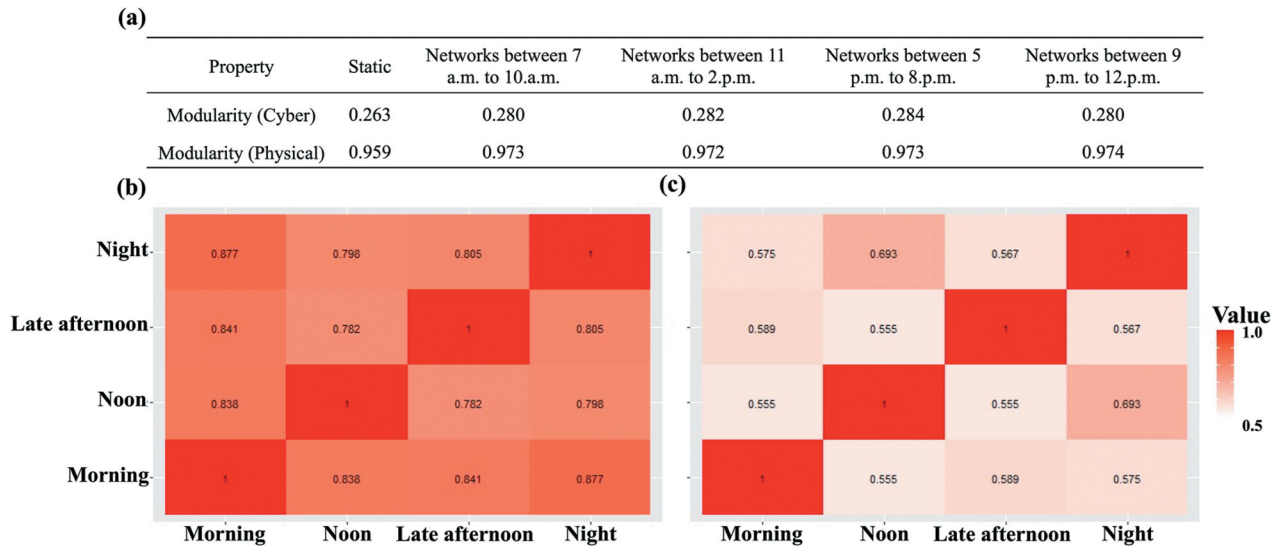


Figure 8. (a) The modularity values of dynamic human mutuality networks in two spaces. The comparison results of the community structures between PDHMN (b) and CDHMN (c).

research to apply advanced methods, such as multi-layer network analysis and temporal community detection, to further explore interactions across cyber-physical spaces. Second, this study offers a new perspective to capture subtle, low-intensity social connections online, which have been largely overlooked in previous studies focused on strong ties or explicit communications. Third, the use of synchronized datasets that record user behaviors in both spaces simultaneously allows for a direct and reliable comparison between cyber and physical human mutuality, addressing the common problem of data mismatch in many earlier studies. Further discussion of the findings and limitations of the study are presented as follows.

First, our results reveal clear temporal variations in network properties, such as average degree, average strength, and clustering coefficient, as well as in the statistical distributions of degree and strength, across both physical and cyber spaces. Specifically, physical networks exhibit higher ζ and β values during night and morning hours, typically associated with individuals' leisure time, whereas cyber networks peak during noon and afternoon, aligning with typical working hours. These patterns suggest that individual daily routines and status may play a critical role in shaping the temporal dynamics of human mutuality structures. Beyond personal schedules, external factors like the built environment have also been shown to influence such temporal variations (Zheng et al. 2022), highlighting the complex interplay between individual behavior and environmental context. However, fully unraveling these multivariable influences remains a challenging task that warrants further research. Understanding these temporal shifts carries meaningful implications. For instance, recognizing when and where strong or weak connections dominate

could inform the optimization of urban spaces, digital platform design, or public health interventions.

Second, this study finds a stark contrast in the average shortest path lengths between physical and cyber spaces: approximately 7.6 in physical space, echoing the classic “six degrees of separation” theory, and just 2.4 in cyber space. This result highlights the exceptional interconnectedness of cyber space, where individuals are, on average, only a few steps away from anyone else. Such heightened connectivity in cyber space has profound implications. On one hand, it enhances the speed and reach of beneficial information flow. Critical updates like disaster warnings, health advisories, or public service announcements can rapidly reach vast populations, potentially save lives and reduce societal disruptions. On the other hand, the same structural advantages enable the swift spread of misinformation, magnifying risks of public panic, reputational harm, and social instability. These dual effects stress the need for effective governance mechanisms that not only promote the advantages of rapid communication but also mitigate its vulnerabilities. Beyond speed, this compressed network structure also carries important implications for social equity. By reducing the number of steps required to bridge diverse individuals and groups, cyber space holds the potential to narrow information gaps, ensuring that marginalized or geographically isolated communities have better access to timely, critical information. This highlights an opportunity to leverage online networks to support more inclusive knowledge dissemination, public health outreach, and social integration, ultimately fostering fairer, more resilient societies.

Third, this study confirms that heavy-tailed distributions of degree and strength are a fundamental feature of human mutuality networks in both cyber

and physical spaces, regardless of time. This consistent presence of heterogeneity means that while most individuals engage in only a few weak interactions, a small number serve as highly connected hubs, a pattern widely observed in prior research on both online and offline networks (Hu et al. 2020; Zignani et al. 2014). It is further found that this uneven structure manifests differently across spaces. Physical human mutuality networks display a stronger hierarchical polycentric structure, as revealed by the relationship between clustering coefficients and degree. This is likely shaped by urban planning strategies designed to distribute populations and resources across multiple centers to mitigate congestion and housing pressures. The result is a spatially localized clustering pattern, where mutual interactions concentrate within distinct urban hubs. In contrast, cyber space shows a weaker polycentric tendency, as online interactions are freed from the constraints of geography, time, and physical infrastructure, allowing connections to form fluidly across diverse locations and contexts. These findings are essential for designing resilient systems, whether optimizing transportation networks, managing crowd flows, or safeguarding online platforms against systemic risks.

Fourth, this study reveals clear differences in the community structures of cyber and physical human mutuality networks: cyber space features fewer but larger communities (151), while physical space contains many more, yet smaller communities (1151). This contrast highlights how cyber space reduces the constraints of geography, enabling broader, more globally connected communities, whereas physical space remains shaped by localized, fragmented clusters tied to physical proximity. These structural differences carry meaningful implications. In cyber space, weaker local clustering and the dominance of a few large communities can accelerate the uncontrolled spread of misinformation, as fewer tightly-knit subgroups exist to absorb, question, or slow down false narratives. Conversely, the stronger localized clustering in physical communities promotes cohesion and resilience, supporting targeted interventions such as neighborhood-based public health campaigns or disaster response efforts. Beyond structural patterns, our findings also suggest that cyber communities may reflect underlying socioeconomic characteristics. Unlike physical communities, which often form around shared geography, cyber communities connect individuals who may differ in age, occupation, or location but converge through shared online behaviors, such as visiting the same websites at similar times. These latent similarities point to the potential of cyber mutuality as a lens to detect hidden social patterns, offering valuable insights for personalized digital marketing, and inclusive policy design aimed

at bridging social divides across both physical and digital spaces.

The findings of this study can also be linked to key theories in urban sociology. Castells' concept of the "network society" highlights how information flows and social ties extend beyond physical proximity, which is echoed in this study's observation of overlapping cyber communities and the shorter path lengths that facilitate faster information flow (Castells 2000). Bauman's idea of "liquid modernity," describing fluid and transient relationships, is reflected in the flexible and shifting patterns of cyber interactions identified in the study (Bauman 2013). Differences in network structures align with Sennett's view on community and individualism: physical communities are shaped by shared spaces, while cyber communities are more individual-driven and less spatially bound (Sennett 2017). The weak human interactions analyzed in this study also parallel Turkle's work on how digital technologies reshape everyday connections, with co-visiting behaviors representing subtle but meaningful forms of online engagement (Turkle 2011). Finally, the core-periphery structures found in cyber communities may signal shared socio-economic characteristics among users, resonating with Sassen's perspective on how digital spaces reflect broader urban and economic patterns (Sassen 2008).

Beyond the current analysis, the scalability of the proposed framework is an important consideration, particularly in light of the growing availability of large-scale mobile big data. Although this study focuses on a single day's dataset, the methodological design, including the construction of weak human interaction networks based on spatiotemporal co-presence and the application of traditional network analysis techniques such as community detection, is inherently scalable. These methods have been widely applied in large-scale mobility studies and are computationally efficient. Moreover, the framework is adaptable to various types of cyber datasets beyond website visit records, such as social media platforms, where weak interactions can be similarly defined through shared content engagement within short time windows. From a technical perspective, the modular structure of the framework allows for parallel processing across temporal intervals or spatial regions, supporting its extension to distributed computing environments for handling larger datasets.

Nevertheless, it is important to acknowledge the limitations of this study. This study is based on data from a single day, which limits the ability to explore temporal dynamics in human mutuality networks. While the one-day dataset is sufficient to demonstrate the feasibility of the proposed framework, it does not capture longitudinal patterns or structural evolution over time. If multi-day datasets become available in

the future, further research could examine the temporal stability and evolution of cyber-physical human mutuality networks, such as analyzing differences between weekdays and weekends, identifying seasonal or periodic variations, detecting structural changes triggered by major events such as the COVID-19 pandemic, and identifying specific structural roles of central and peripheral communities in cyber and physical spaces. To enhance the understanding of their temporal dynamics, future studies could also incorporate interactive network dashboards or animated community evolution maps, which would facilitate intuitive exploration of the evolution of network properties and community structures, particularly when extended time-series data becomes available. Future work will also focus on applying the framework to long-term and large-scale datasets to evaluate its performance and optimize computational efficiency. What's more, while the URL data captures synchronized cyber and physical activities, future research could also further enhance the understanding of cyber-physical human mutuality by integrating additional data sources, such as social media interactions and location-based services from diverse regions and periods, to validate and extend these findings. Such comparative studies would not only provide deeper insights into how weak human interactions manifest across varying platforms, contexts, and regions, but also offer richer contextual information, like individual activity purposes or social attributes, to further explore interaction mechanisms.

6. Conclusions

This study develops an analytical framework to quantify and compare human mutuality, defined as a form of weak interaction, across physical and cyber spaces. By constructing human mutuality networks from extensive URL data that capture both online and offline behaviors, the study proposes an innovative method of substituting websites for locations in cyber space. This framework can also apply to other forms of behavioral data, such as social media data, enabling further comparative research on human interactions across multiple digital contexts.

The analysis of these networks reveals several key findings that contribute to the theoretical understanding of human interactions in dual spaces. First, the average shortest path length of 7.6 in physical space supports the classic six degrees of separation theory, while the shorter path length of 2.4 in cyber space suggests faster and broader information dissemination, contributing to the reduction of information gaps between users. Second, the presence of heavy-tailed degree and strength distributions in both spaces, consistent across time, reinforces findings from previous studies on heterogeneous network structures, while expanding their validity to comparable dual-space datasets. Third, temporal differences between the networks,

reflected in variations in network properties and distribution coefficients, possibly reflect how daily routines, work schedules, and leisure activities shape interactions in physical and cyber spaces. Finally, the core-periphery structures found in both spaces reveal how central groups are strongly connected while peripheral users are more loosely linked. In cyber space, these community structures may also reflect shared socioeconomic characteristics, as individuals within the same cyber community often exhibit similar backgrounds, interests, or consumption behaviors, highlighting cyber space as a parallel dimension of social life.

Future research could extend this framework by incorporating more diverse behavioral datasets and applying the methodology across different geographical regions and longer periods. Such work would contribute to a more comprehensive understanding of human interactions in increasingly integrated cyber-physical spaces.

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Data availability statement

The mobile phone data used in the study cannot be shared publicly due to restrictions.

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