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Understanding interurban networks from a multiplexity perspective

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ABSTRACT

Urban networks are typical multiplex networks with different forms of spatial interactions between cities, including spatial interactions among humans, material and information. It is important to systemically explore multiplex urban networks to understand the operation of complex urban systems and formulate policies for urban planning and regional development. However, studies investigating interurban networks from the multiplexity-based perspective are still in their infancy. Therefore, this study collects records from social media to construct a multiplex urban network with two layers that represent information flows and population mobility. The results of the topological properties analysis confirm that a high correlation exists between information resources and human capital, and there is a strong driving force from human capital to information flows. In addition, the joint effects of these two types of resources on urban development are analyzed, and the cross-layer resource clustering ability of cities is discussed. Several implications for urban economic development planning and orientation that could support macroscopic policy-making are provided.

1. Introduction

Multiplex networks, namely, a set of coupled and layered networks, provide an effective analytical framework for understanding many complex giant systems, such as social networks and biochemical networks (Gomez et al., 2013). Interurban networks are recognized as a type of multiplex network that involves multidirectional flows based on multiple relationships, i.e., economic, social, cultural and environmental activities (Burger, Van Der Knaap, & Wall, 2014; Zhen, Qin, Ye, Sun, & Luosang, 2019). For instance, cities are connected not only by physical transportation networks but also by virtual telecommunication networks, trade networks, labor-market networks, and even water supply networks (Bertolini & Dijst, 2003). Modeling multiplex interurban networks improves our understanding of the complex interrelationships and interactions of these individual networks in the urban domain and can act as a guide for urban policy and practice (Laprie, Kanoun, & Kaâniche, 2007; Rinaldi, Peerenboom, & Kelly, 2001).

However, studies on interurban networks are still in their infancy. Most existing works have focused on single-layer interurban networks, e.g., interurban transportation networks (Dong, Li, Zhang, & Di, 2016; Farahani, Miandoabchi, Szeto, & Rashidi, 2013), interurban telecommunication networks (Krings, Calabrese, Ratti, & Blondel, 2009), interurban corporate networks (Zhao, Derudder, & Huang, 2017) and interurban population mobility networks (Li, Wang, & Di, 2017; Pan & Lai, 2019). Some studies have investigated multilayer interurban networks but focused only on multilayer transportation networks (Gallotti & Barthelemy, 2014; Morris & Barthelemy, 2012; Strano, Shai, Dobson, & Barthelemy, 2015). Therefore, previous studies lack a detailed examination of the diverse interactions among the different layers of interurban networks. Modeling the interurban networks in terms of a multiplex network framework provides more interpretable ways to understand interurban networks. Humans, material and information form cities, and they are the ideal elements for constructing an interurban topology (Smith & Timberlake, 1995). However, in practice, the construction of such interurban networks is very difficult due to a notable gap between the actual capabilities of information sources and our expectations in terms of how the data can be used (Derudder, 2008). The traditional survey-based data used in previous studies (Barthélemy, 2011; De Goei, Burger, Van Oort, & Kitson, 2010; Hubert & Toint, 2006) limit intensive exploration because of the long cycle, high cost and small scale of the data.

The advent of Sina Weibo (Weibo; a Twitter-like service in China) provides an unprecedented opportunity to capture users' trajectories and to simultaneously explore information flows (online footprints) and

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population mobility (offline footprints) on a large scale. In this study, we use data obtained from Weibo to build a two-layer network (an online-offline interaction network) and to conduct a spatial-temporal analysis to enhance our understanding of interurban networks. This study focuses on the following three research questions:

(1) What are the characteristics of multiplex interurban networks?
(2) How do information flows interact with population mobility in multiplex interurban networks?
(3) What are the impacts of multiplex interurban networks on urban policy outcomes?

The contributions of this study are summarized as follows. (1) Existing works mainly discuss single-layer networks from the perspective of information flows or population mobility. However, this study constructs a multiplex interurban network to portray information flows and population mobility by using micro data to overcome the limitations of traditional macro data. This study lays a foundation for systematically exploring interurban network structures from a multiplexity-based view at the country level. (2) This study reveals the correlation and reinforcement between information resources and human capital by using China's multiplex interurban network as an example. (3) The proposed multiplex network-based approach offers a new perspective for understanding urban economic development orientation and planning and shows how network-scientific thinking facilitates our understanding of cities. Due to the widespread use of social networks, the proposed approach can be easily extended to other countries.

The structure of this paper is as follows. Section 2 summarizes the related literature. Section 3 briefly describes the database and methods. Section 4 characterizes the structure of the multiplex interurban network, reveals the interaction between online information flows and offline population mobility, and provides implications for urban policy. Section 5 sets out the conclusions and future works.

2. Literature review

2.1. Multiplex network

In recent years, multiplex networks have gained increasing attention in the theoretical interpretation of complex systems. Fig. 1 illustrates a multiplex network with two layers. The same nodes and edges of the network in layers 1 and 2 are shown in blue and black, respectively. In addition, the nodes common to both networks are shown by dashed lines.

Kivelä et al. (2014) discussed the historical development of multilayer networks and summarized the related concepts. Some studies have characterized the dynamics and the structural properties of multiplex networks, especially in terms of diffusion dynamics (Cozzo, Banos, Meloni, & Moreno, 2013; Gomez et al., 2013; Li, Tang, & Hui, 2013), robustness (De Domenico, Solé-Ribalta, Gómez, & Arenas, 2014), community detection and evolution (Arinik, Figueiredo, & Labatut, 2020; Mucha, Richardson, Macon, Porter, & Onnela, 2010; Vörös & Snijders, 2017), cooperation (Gómez-Gardenes, Reinares, Arenas, & Floría, 2012) and synchronization (Nicosia, Valencia, Chavez, Díaz-Guilera, & Latora, 2013). Interconnected networks are verified to be more resilient to random failures than individual layers (De Domenico et al., 2014). Furthermore, the most resilience is shown to be related to a non-trivial organization of cooperation in the multilayers (Gómez-Gardenes et al., 2012).

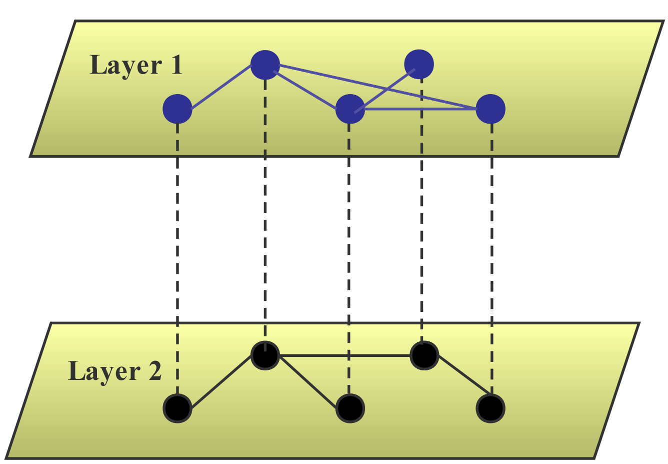

Fig. 1. Schematic illustration of a multiplex network.

Moreover, many empirical studies have been conducted in diverse real-world contexts, including online games (Szell, Lambiotte, & Thurner, 2010; Szell & Thurner, 2010), international trade (Barigozzi, Fagiolo, & Garlaschelli, 2010; Barigozzi, Fagiolo, & Mangioni, 2011; Ducruet, 2013), interbanks (Bargigli, Di Iasio, Infante, Lillo, & Pierobon, 2015) and linguistic systems (Martinčić-Ipšić, Margan, & Meštrović, 2016). Baggio et al. (2016) analyzed the multiplex social ecological network and revealed that changes in social relationships affected community robustness more than changes in food resources. Strano et al. (2015) compared the connected underground and street multilayer networks in Greater London and New York. Their results showed that the underground networks unexpectedly led to congestion in places located at the ends of underground lines. Moreover, a study on financial multi-layer networks (Poledna, Molina-Borboa, Martínez-Jaramillo, Van Der Leij, & Thurner, 2015) showed that market-based systemic risk indicators systematically underestimated expected systemic losses. Therefore, the theory of complex networks provides an effective tool to understand a multiplex interurban system.

2.2. Urban complex network

Leonhard Euler proposed the Seven Bridges of Königsberg problem (Euler, 1736) and thereby began pioneering work to understand cities through graph theory. Since then, the related work has increased rapidly in the literature. There has been a long-lasting interest for scholars, especially transportation geographers, to simplify the interurban network as graphs, including global urban networks (Short & Kim, 1999), world city networks (Taylor, 2001), and transnational urban systems (Derudder, 2006). For more detailed information, please see the related review works (Farahani et al., 2013; Taylor & Derudder, 2015; Xie & Levinson, 2009). However, network analysis remained rather simple before the last millennium (Ducruet & Beauguitte, 2014). Planar and technical networks are two widely used network analysis models.

At the dawn of the 21st century, network science began to emerge (Barabási, 2016) that provided a better way to understand how cities interact. One can naturally map the structures of cities' interaction as a complex network, where nodes denote cities, and links are airplane routes, railway lines, or telecommunication circuits. For example, Guimera, Mossa, Turtschi, and Amaral (2005) constructed a worldwide air transportation network and identified each city's global role based on its pattern of intercommunity and intracommunity connections. Krings et al. (2009) collected the anonymized mobile phone communications from a Belgian operator and studied the interaction between 571 cities. However, most existing works have focused on single-layer interurban networks and built the network structure in terms of infrastructure, e.g., physical transportation and telecommunications. A few studies have used the multilayer network framework to describe interurban networks (Gallotti & Barthelemy, 2014, 2015; Morris & Barthelemy, 2012; Strano et al., 2015). Due to the lack of multi-sourced data, these studies have only focused on multilayer transportation networks to discuss the joint effects of the multi-modal features of an integrated transportation system on the reachability of cities or regions.

2.3. Urban policies and network science

Uncovering the links between urban studies and network science provide policy-makers a new avenue for understanding and formulating urban policies. Network science approaches are applied to answer theoretical and empirical questions arising from urban studies (Derudder & Neal, 2018). The objects of previous studies can be categorized into two levels of urban networks, including intraurban networks and interurban networks. Furthermore, distinct types of practical problems are considered at these two levels.

Intraurban networks, such as commuting networks and transportation networks, focus on analyze the urban structure and layout of urban functions. Wang et al. (2020) revealed the significant influence of the spatial distribution of nodes and community structure on the spatial planning of urban bus systems. The urban bus spatial network of Hangzhou in China is used to provide some planning implications. Bielik, König, Schneider, and Varoudis (2018) analyzed the urban street network in Weimar, Germany and found that the street network configuration, access to people and walkability of the environment were closely related, providing implications for urban street planning. Hajrasouliha and Yin (2015) studied the pedestrian volume in 302 street segments in Buffalo and revealed the impacts of street network connectivity on pedestrian volumes. These authors suggested that the planners of urban street networks should pay attention to both physical connectivity and visual connectivity.

Interurban networks are always used to analyze the regional settlement systems and provide some macro-policy implications. Hui, Li, Chen, and Lang (2018) focused on the urban network in the Greater Bay Area of China and suggested to motivate the partnership and synergies of Hong Kong and Macao for the long-term success of this megacity region. Liu, Derudder, and Wu (2016) analyzed the interurban transportation networks in 22 urban regions in China and found that most urban regions in western China lack any form of polycentricity. Hu, Zhao, Li, and Wu (2019) analyzed the interurban workforce migration network and revealed a malfunction in megacities in regional development. Thus, some policy implications for the effective agglomeration of core urban areas were provided. De Goei et al. (2010) analyzed census commuting interaction data from the Greater South East UK in 1981 and 2001 and provided some policy implications for urban transport planning, i.e., these authors suggested that more investments should be focused on secondary roads in cities instead of the high-speed roads between cities. Meijers, Burger, and Hoogerbrugge (2016) discussed the distribution of metropolitan functions across Western European cities and showed that the planning of urban functions should enhance the local size of urbanization economies and small-medium-sized cities.

Existing studies extend the analytical boundaries of the application of network science in urban policy studies, but there is still ample room for improvement due to the following limitations. First, policy implications are obtained based on a single-layer urban network, especially transportation networks and commuting networks, which ignores the multiple relationships between cities. Second, research activities related to urban orientation from a macro perspective are in the minority thus far, and more research focuses on construction planning in urban light rails, buildings and other specific facilities. Because fundamental strategic policies, such as the strategic orientation of national and regional centers, are essential for the development of urban systems in the long term, urban orientation from a macro perspective can be regarded as an important research direction.

Therefore, this study attempts to understand the interurban network by considering multiple spatial interactions and provides some implications for urban orientation from a macro perspective. With the emergence of social media, the acquisition of large-scale social media data becomes possible. Additionally, social media, as an important part of open data, is identified as a promising complement to conventional authoritative data to understand cities with more social and environmental dimensions (Liu et al., 2015). Liu et al., 2014 employed social media check-in data in China to unveil interurban population mobility in 370 cities. Zhen, Cao, Qin, and Wang (2017) delineated the boundary of the Yangtze River Delta urban agglomeration in China based on the check-in records of Weibo. Wu and Wang (2015) collected location-based social media data from China and explored the geographical ties of interurban network patterns.

However, the description of an interurban network as a multiplex network via social media data has not been attempted. Until now, no studies have explored information flows (online footprints) and population mobility (offline footprints) at the spatial level (the city-pair level) to understand interurban networks. To achieve this purpose, first, we study the topological properties of each layer in the network and reveal the interactions between the two layers. Second, we investigate the joint effects of the multiplex network on the city's central position (ranking) and its capacity for cross-layer resource clustering. Finally, we discuss the implications for urban orientation and planning.

3. Data and methodology

3.1. Data description

3.1.1. Weibo data

Weibo is the most widely used Twitter-like social media platform in China and was launched three years after Twitter. It is estimated that Weibo has 446 million active users each month and officially has more users than Twitter, as announced by Sina Corporation in 2018. We collected all the September 2013 posts on Weibo to construct a multiplex interurban network. Each microblogging post has attributes that describe its unique user identifier, posting time and geographical location of the user at the city level. Each repost also includes its originator's identification and geographical location. In general, the dataset contains approximately four billion posts.

3.1.2. Economic surveys

To discuss the relationship between the topological characteristics of multiplex interurban networks and urban economic development, we collected city-level data from the Provincial Statistical Yearbook of 2014 and used the gross domestic product (GDP) to measure urban economic development.

3.2. Construction of the multiplex interurban network

In this study, the multiplex interurban network consists of an online information flow network and an offline population mobility network. For the information flow network, it is well known that when microblogging posts have been reposted, the original information is diffused among people. Thus, we generate an undirected information flow network among the cities $G^{[I]} = (V^{[I]}, E^{[I]})$ by using nodes to represent the cities where users post, and we aggregate the amount of reposting between users in two cities as the edge weight. Regarding the population mobility network, a set of posts on Weibo record the positional trajectories of all users. Considering the users' trajectories between their homes and destinations for business, we identify a user's home as the city where she/he posted most frequently. The population mobility network is constructed as $G^{[T]} = (V^{[T]}, E^{[T]})$, where the nodes represent cities, and the weights of the edges are given by the number of journeys between cities.

To establish a multiplex interurban network, we combine a single-layer information flow network and a single-layer population mobility network to form a two-layer interurban network, i.e., a multiplex interurban network ($G^{[M]} = (V^{[M]}, E^{[M]})$). $G^{[M]}$ is specified by a vector of the signal adjacency matrices, $\mathbf{A} = [A^{[I]}, A^{[T]}]$, and for each layer $l \in \{I, T\}$, $A^{[l]} = \{a_{ij}{}^{[l]}\}$. When node i is connected to node j at layer l, we have $a_{ij}{}^{[l]} = 1$; otherwise, $a_{ij}{}^{[l]} = 0$. Similar to the case of the signal adjacency matrices, the weighted adjacency matrices are defined as

$\mathbf{W} = [W^{[I]}, W^{[T]}]$, where $W^{[l]} = \{w_{ij}{}^{[l]}\}$ and $w_{ij}{}^{[l]}$ denote the weight of the edge (i,j) at layer l.

Notably, the nodes in $V^{[I]}$ do not appear identically in $V^{[T]}$. Some cities only exist in either $V^{[I]}$ or $V^{[T]}$. If node $i \in V^{[I]}$ and $i \notin V^{[T]}$, we add this node as an isolated node in layer T for unification in the multiplex network; that is, $a_{ij}{}^{[T]} = 0$ for each node j in layer T. Furthermore, we extend this notation to the case of directed and weighted layers, the information flow network $G_d{}^{[I]}$, the population mobility network $G_d{}^{[T]}$, and the multiplex interurban network $G_d{}^{[M]}$ with directed and weighted edges. Similarly, $G_d{}^{[M]}$ is specified by a vector of the signal adjacency matrices $\mathbf{Ad} = [Ad^{[I]}, Ad^{[T]}]$ and the weighted matrices $\mathbf{Wd} = [Wd^{[I]}, Wd^{[T]}]$, and for each layer $l \in \{I, T\}$, $Ad^{[l]} = \{ad_{ij}{}^{[l]}\}$ and $Wd^{[l]} = \{wd_{ij}{}^{[l]}\}$.

4. Results and discussion

4.1. Basic topological characteristics of two single-layer networks

We explore the basic structural properties of the information flow network and the population mobility network, which are defined in the following: (1) node degree $k_i{}^{[l]}$: the degree of node i on a given layer l, which is defined as $k_i{}^{[l]} = \Sigma_j a_{ij}{}^{[l]}$, where $j \in V^{[l]}$ and $j \neq i$; (2) node strength $s_i{}^{[l]}$: the strength of node i on a given layer l, which is defined as $s_i{}^{[l]} = \Sigma_j w_{ij}{}^{[l]}$, where $j \in V^{[l]}$ and $j \neq i$; (3) unweighted clustering coefficient $cc_i{}^{[l]}$ (Watts & Strogatz, 1998): for node i in $G^{[l]}$, $cc_i{}^{[l]} = \Sigma_{i \in V^{[l]}} 2T_i{}^{[l]}/(k_i{}^{[l]}(k_i{}^{[l]} - 1))$, where $T_i{}^{[l]}$ is the number of triangles through node i on the given layer l; (4) weighted clustering coefficient $wcc_i{}^{[l]}$ (Saramäki, Kivelä, Onnela, Kaski, & Kertesz, 2007): given network $G^{[l]}$, it is defined as $wcc_i^{[l]} = \frac{1}{k_i^{[l]}(k_i^{[l]}-1)} \sum_{(i,j)\in E^{[l]}} (\widehat{w}_{ij}^{[l]} \widehat{w}_{ik}^{[l]} \widehat{w}_{jk}^{[l]})^{1/3}$, where $\widehat{w}_{ij}^{[l]}$ is normalized by the maximum weight in the network $\widehat{w}_{ij}^{[l]} = w_{ij}^{[l]}/\max(w_{ij}^{[l]})$; and (5) the scaling exponent e in the power-law distribution of node strength. The results are summarized in Table 1.

Table 1 shows that most cities are involved in both layers. There are 355 and 376 nodes in the information flow network and the population mobility network, respectively. A few cities only exist in one of these two networks, which indicates that these cities have very weak connections to other cities and can be regarded as isolated nodes. The population mobility network has a lower average node degree and a lower clustering coefficient than the information flow network. This result indicates that cities have closer relationships in terms of information resources rather than human capital. This result aligns with the common view that online information dissemination breaks spatial and temporal barriers, while human mobility is circumscribed by the cost of travel (Noulas, Scellato, Lambiotte, Pontil, & Mascolo, 2012; Simini, González, Maritan, & Barabási, 2012; Windzio, 2018).

Table 1
Structural properties of the information flow network and the population mobility network.

Topological properties	$G^{[I]}$	$G^{[T]}$	$G_d{}^{[I]}$	$G_d{}^{[T]}$
N	355	376	355	376
E	99,012	59,300	53,896	35,888
$\bar{k}$	303	190	557	315
$\bar{s}$	991,133	143,607	991,133	143,607
$\overline{cc}$	0.935	0.766	–	–
$\overline{wcc}$	1.3e-04	5.4e-05	–	–
$\overline{w}$	3264	752	1776	455
e	−1.6	−1.8	–	–

Note: Topological properties of the information network and the mobility network. The number of nodes and edges is represented by N and E, respectively. The average node degree is expressed as $\bar{k}$, and the average node strength is defined as $\bar{s}$. In addition, we show the average unweighted clustering coefficient $\overline{cc}$, the average weighted clustering coefficient $\overline{wcc}$ and the average weight of edges $\overline{w}$. The average unweighted clustering coefficient of $G^{[l]}$ is defined as $\overline{cc} = \sum_{i \in V^{[l]}} cc_i^{[l]}/N^{[l]}$, and the average weighted clustering coefficient is defined as $\overline{wcc} = \sum_{i \in V^{[l]}} wcc_i^{[l]}/N^{[l]}$.

In addition, both single-layer networks have scale-free characteristics. The strength distribution in the information flow network and the population mobility network obeys the power-law form with the fitting parameters of −1.6 and −1.8, respectively. As shown in Table 1, there is a great difference between the average unweighted and weighted clustering coefficient in both networks. The results suggest that although most cities are interconnected in terms of information resources and human capital, most resources are absorbed by a few metropolises. Therefore, the information resources and human capital are characterized by large inequality in terms of spatial agglomeration and diffusion in China's urbanization process. This result is consistent with the disparities and imbalance in China's urban development. For instance, the GDP per capita of Beijing was 4.5 times the GDP per capita of Gansu Province in 2017 (128,994 RMB vs 28,497 RMB).

The basic structural properties in Table 1 provide an intuitional understanding of two individual networks at the macroscopic scale. It is necessary to further investigate the relationship between the topological characteristics of the two layers. In this study, the Pearson correlation coefficient and Spearman's rank correlation coefficient are employed to quantify such correlations. The Pearson correlation coefficient is a measure of the linear correlation between the distribution of two resources in cities, and the Spearman's rank correlation is a nonparametric measure of rank correlation and assesses monotonic relationships.

In addition to the above topological indicators defined in the undirected network, we also use some indicators defined in the directed network, including the directed edge weight wd_{ij}, in-strength si_i, out-strength so_i, and average neighbor in-strength ai_i and out-strength ao_i. Here, in-strength si_i (out-strength so_i) measures the city's inflows (outflows) in terms of information resources (human capital), which is defined as the aggregation of all weights associated with the in-links (or out-links) of a node $si_i = \sum_j wd_{ji}$ ($so_i = \sum_j wd_{ij}$). The indicators ai_i and ao_i account for the average node in-strength and out-strength of a node's neighbors, respectively.

The topological properties in Table 2 show a positive relationship between the information flow network and the population mobility network. Except for the lower correlation coefficients of indicators cc_i, w_{ij} and ao_i, almost all other metrics have high correlation coefficients (> 0.8). Intuitively, compared to indicator cc_i, index wcc_i not only reflects the links between cities, but also embodies the link strength. wcc_i captures more comprehensive information about the interurban networks; thus, the correlation between the two layers is higher for wcc_i than that for cc_i. Moreover, the definition of w_{ij} neglects the direction of edges, which is different from wd_{ij}. Thus, the correlation for w_{ij} is lower than the correlation for wd_{ij}. Additionally, the lower correlation for ao_i, compared to ai_i, is supposed to indicate that there is a greater difference in the node average neighbor out-strength between the two layers than in the node average neighbor in-strength. Although the value is low, the correlation coefficient of these three indicators is still significant (the p-value is lower than 0.001). Therefore, these results indicate that the information resources of cities are highly positively correlated with their human capital. That is, a city with rich information resources tends to have more human capital and vice versa. These findings align with existing studies. Some scholars (Bettencourt, Lobo, Helbing, Kühnert, & West, 2007; Marshall, 2009; Raspe & van Oort, 2011) find that information transferring among cities spurs the accumulation of human capital, and some scholars (Faggian, Rajbhandari, & Dotzel, 2017; Trippl, 2013) confirm that population mobility among cities exerts a discernible influence on information distribution.

Table 2
Correlations between the structural properties of the information network and the mobility network.

Correlation coefficient	s_i	cc_i	wcc_i	w_{ij}	wd_{ij}	si_i	so_i	ai_i	ao_i
P_{cc}	0.916	0.250	0.948	0.567	0.870	0.810	0.856	0.793	0.475
S_{cc}	0.906	0.585	0.770	0.639	0.870	0.903	0.810	0.844	0.566

Note: We discuss the correlation between the topological characteristics of layer I and layer T in a multiplex interurban network based on the Pearson correlation coefficient P_{cc} and the Spearman's rank correlation coefficient S_{cc}. All correlation coefficients pass the significance test, and the p-value is lower than 0.001.

4.2. Reinforcement between two single-layer networks

Section 4.1 discusses the basic properties of the two single-layer networks and reveals their high relevance in the interurban networks. This sub-section explains the phenomenon in which the existence of edges in one layer fosters the creation of links in the other layers, which aims to quantify the reinforcement between the two types of resources. Therefore, the conditional probability is introduced in Eq. (1) (Battiston, Nicosia, & Latora, 2014) that two cities connect in one layer given the existence of an edge between this city pair in the other layer,

$$P(A^{[l]} \mid A^{[l']}) = \frac{\sum_{ij} a_{ij}^{[l]} a_{ij}^{[l']}}{\sum_{ij} a_{ij}^{[l']}} \tag{1}$$

where $a_{ij}^{[l]}$ shows whether the link between city i and j in layer l exists in the multiplex network $G^{[M]}$and $l \in \{I, T\}$. The value of $P(A^{[l]}|A^{[l']})$ ranges between 0 and 1, and a higher value indicates that city i is more likely to connect to city j in layer l given the link between the same city pair that exists in layer l'.

The reinforcement between information flows and population mobility is reported in Fig. 2(a). This figure reflects a high conditional probability (0.94), indicating that a city pair connected in the population mobility layer also has a link in the information layer. Accordingly, if people move from one city to the other city, it is more likely to lead to the transfers of information resources between the two cities. Compared to $P(A^{[I]}|A^{[T]})$, $P(A^{[T]}|A^{[I]})$ is lower (0.63) but is still remarkable. Both of the high probabilities emphasize the interactions between information resources and human capital and reconfirm the results obtained in previous studies (Marshall, 2009; Miguélez & Moreno, 2014; Raspe & van Oort, 2011; Trippl, 2013); that is, information dissemination and human mobility each spur the flow of the other. In addition, the disparity between $P(A^{[T]}|A^{[I]})$ and $P(A^{[I]}|A^{[T]})$ indicates that the reinforcement from human capital to information resources is stronger than the reinforcement from information resources to human capital.

Considering the influence of distance, economic development and the closeness of the connections between city pairs, we extend the definition of conditional probability $P(A^{[l]}|A^{[l']})$ given these characteristics of city pairs in layer l'. Therefore, the conditional probability of

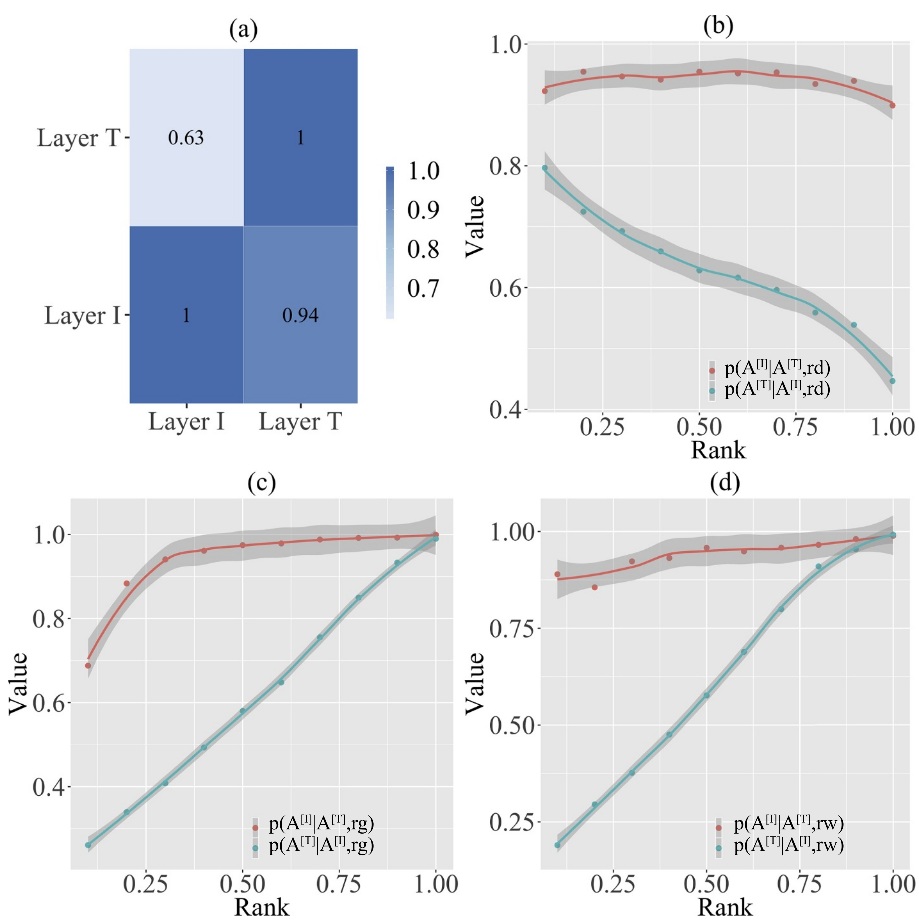

Fig. 2. Reinforcement between the information flow layer and the population mobility layer.
Note: (a) For the information flow layer I (respectively, population mobility layer T), the heat map shows the fraction of the edges that also exist in layer T (respectively, layer I). (b) (c) (d) The probability of finding a certain edge (i,j) at layer T (layer I) conditional on the normalized rank of distance rd, the normalized rank of GDP rg, and the normalized rank of weight rw of the same link at layer T (layer I).

having a link in layer l given its distance in the leading layer l' is introduced:

$$P\left(A^{[l]} \mid A^{[l']}, rd\right) = \frac{\sum_{(i,j)\in E^{[l']}(rd)} a_{ij}^{[l]} a_{ij}^{[l']}}{\sum_{(i,j)\in E^{[l']}(rd)} a_{ij}^{[l']}} \tag{2}$$

where rd denotes the normalized ranking for the distance of edges. For example, the distance of edge (i,j) ranks at 1 out of all 100 edges in layer l in ascending order, and, thus, rd is 0.01. In addition, $E^{[l]}(rd)$ represents the collection of edges with the same normalized rank of distance rd in layer l and $l \in \{I, T\}$. The distance between cities i and j is obtained by their geographical distance, which is obtained by the longitude and latitude. Similarly, the conditional probability of economic development $P(A^{[l]}|A^{[l']}, rg)$ and the closeness of the connections $P(A^{[l]}|A^{[l']}, rw)$ are also defined, where rg denotes the normalized ranking of the geometric average of the city pair's GDP, and rw denotes the normalized ranking of the link weight in layer l'.

Fig. 2(b) illustrates the probability that a link exists in one single-layer network, given the normalized rank of the distance in the other layer. The distance exerts a significant effect on the reinforcement from information resources to human capital, which gradually decreases as the distance between cities increases. This result indicates that the driving force from information flows to population mobility diminishes as the distance of city pairs increases. Conditional probability $P(A^{[I]}|A^{[T]}, rd)$ is consistently maintained at a high level, approximately 0.95, which implies that the distance between city pairs has no discernible impact on the creation of information flows driven by population mobility.

Fig. 2(c) shows the influence of the economy on reinforcement. According to the overall trend of $P(A^{[I]}|A^{[T]}, rg)$ and $P(A^{[T]}|A^{[I]}, rg)$, the mutual reinforcement between these two types of resources is stronger in city pairs with better economic status. These results are consistent with previous studies in the economic field. On the one hand, compared to developing/undeveloped areas, developed cities attract more skilled workers and experts. As the main bearers of information/knowledge, developed cities easily promote information diffusion (Miguélez & Moreno, 2014; Trippl, 2013). Consequently, the reinforcement from population mobility to information flows is stronger between developed regions than between less-developed areas. On the other hand, the growth trend of $P(A^{[T]}|A^{[I]}, rg)$ can be explained by the subjective goal of population mobility, namely, profit maximization (De Haas, 2010). Given the same reinforcement from information flows, people prefer to move to developed areas, where more opportunities are available. Although $P(A^{[I]}|A^{[T]}, rg)$ and $P(A^{[T]}|A^{[I]}, rg)$ have the same tendency, the variations in the two indicators are clearly different. We find that the reinforcement from information flows to population mobility is more sensitive to the economic status of the city pairs.

The function of the closeness of links is also explored and is shown in Fig. 2(d). It can be seen that $P(A^{[T]}|A^{[I]}, rw)$ is an increasing function, which suggests that when the connections between cities are stronger in terms of information flow, the probability is higher that human capital will flow between the same city pairs. Notably, the reinforcement from population mobility to information flows remains at a high level regardless of how close their connection is in terms of population mobility.

4.3. Joint effects on cities

Information resources and human capital have been regarded as critical elements for urban economic growth (Gennaioli, La Porta, Lopez-de-Silanes, & Shleifer, 2012; Van Oort, 2017). It is of great importance to comprehensively utilize both resources for boosting urban development. The reachability of nodes in a network is known to reflect their core status. In a multiplex interurban network, if the reachability of a city depends mainly on just one type of resource, this implies that this resource is more important to the city's development and that this city lacks the capacity to utilize resources comprehensively. Therefore, the joint effects of information resources and human capital in a multiplex interurban system provides insight into urban development patterns.

Here, we introduce an indicator of edge interdependence, which is similar to the central quantity. This value was proposed by Strano et al. (2015) to measure the significance of intermodality. The edge interdependence captures the contribution of information flows and population mobility to the connection between city i and city j in the network,

$$\lambda(i,j) = \frac{\varphi_{ij}}{\sigma_{ij}} \tag{3}$$

where σ_{ij} is the number of shortest paths between nodes i and j in the multiplex network, and φ_{ij} is the sum of the ratio of the links in the shortest paths that exist in both layers. For example, there are two shortest paths (length of 4) between node i and node j, which are named the shortest paths I and II, respectively. The shortest paths I and II have 3 links and 2 links that exist in both layers, respectively. In this case, the sum of the ratio of the links that exist in both layers can be calculated as $\varphi_{ij} = 3/4 + 2/4$. Therefore, when all the shortest paths between the two nodes comprise edges in both layers, the edge interdependence of

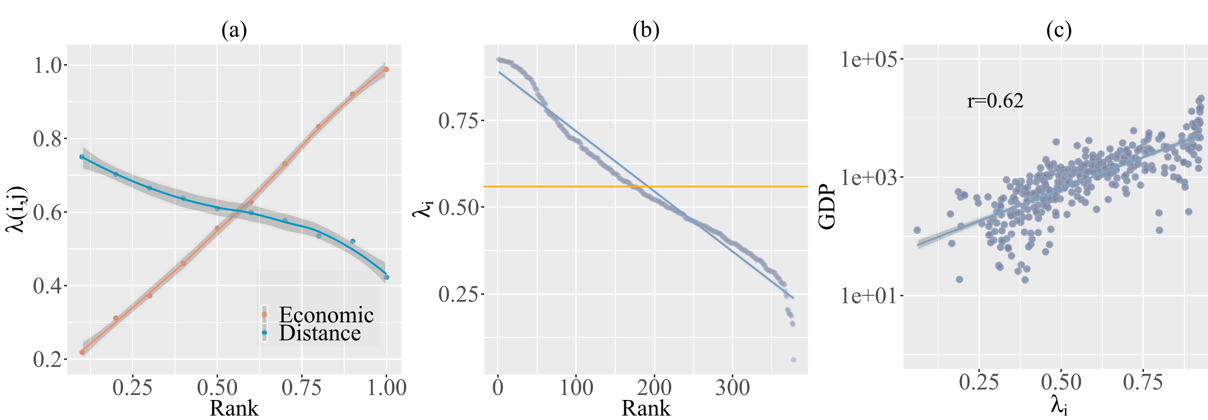

Fig. 3. Interdependence of edges and nodes.
Note: (a) Variation of the edge interdependence $\lambda(i,j)$ with economic and distance growth in the city pairs. The city pairs are ranked according to their geometric average GDP of two cities and geographical distance in ascending order, and edge interdependence is shown with the growth of its normalized rank. (b) Rank distribution of the node interdependence λ_i. The orange line shows the average λ_i in the entire multiplex network. (c) Relationship between node interdependence and the GDP of city i. λ_i is highly correlated with the city's economic development (r = 0.62), and the significance test is passed (significance test: $p < 0.001$). Additionally, the unit of GDP is one hundred million RMB.

the corresponding edges equals 1. λ(*i*,*j*) equals 0 when all the shortest paths between *i* and *j* are only in one layer.

To better understand the relationship between the properties of the city pairs and the added value of interlayer coupling to the reachability of edges, we explore the change in λ(*i*,*j*) by ranking the edges in ascending order according to the distance and average GDP of two cities. Fig. 3(a) shows that λ(*i*,*j*) declines sharply as the distance between city *i* and city *j* increases, which means that the joint effects of the two types of resources are greater when the city pairs are close. Considering the gradual economic development of city pairs, the additional value of the coupling effect to the pair's connection is higher.

Similarly, we introduce an indicator named node interdependence to quantify the additional value of interlayer coupling to the importance of the cities in the entire urban system (Battiston et al., 2014; Morris & Barthelemy, 2012; Strano et al., 2015),

$$\lambda_i = \frac{1}{N^{[M]}} \sum_{j \neq i} \frac{\varphi_{ij}}{\sigma_{ij}} \tag{4}$$

where $N^{[M]}$ is the total number of nodes in network $G^{[M]}$, and the value of λ_i ranges between 0 and 1. A higher value indicates that both types of resources lay a foundation for the central status of the city. Conversely, cities may depend only on a single type of resource. As shown in Fig. 3(b), the cities in the multiplex network have a large variety of node interdependence λ_i, which ranges from 0.06 to 0.93, and the average value of the indicator is obtained by $\lambda = \Sigma_i \lambda_i / N^{[M]}$, which is approximately 0.56.

Fig. 3(c) shows that there is a high correlation between λ_i and the GDP of city *i* ($r = 0.62$), which confirms the importance of the joint effects of information resources and human capital. These results confirm the results of previous studies that information resources and human capital are both key elements for urban development and stimulate one another (Marshall, 2009; Miguélez & Moreno, 2014; Raspe & van Oort, 2011; Trippl, 2013). Thus, it is suggested to promote urban development by increasing the joint effects of the two types of resources, i.e., by improving node interdependence λ_i.

Moreover, because information resources and human capital play vital roles in urban sustainable economic growth (Gennaioli et al., 2012; Li et al., 2017; Van Oort, 2017), node interdependence λ_i can also be interpreted as an indicator used to measure the rationality and economic sustainability of a city's development pattern. Therefore, Fig. 4 displays the joint effects of the two types of resources on cities as a heat map, which evaluates urban economic development patterns. Clearly, indicator λ_i varies, and cities with strong joint effects are dispersed across China but are concentrated in Eastern China. The uneven distribution of indicator λ_i reflects the disproportion and irrationality of the economic development patterns in some regions, especially Western China and Northeastern China.

Furthermore, Table 3 summarizes the top 20 cities obtained in Fig. 4 (see the full ranking list in Appendix A1). This table shows that most cities with strong joint effects are regional centers. For instance, among the top 10 cities, Guangzhou, Hefei, Hangzhou, Nanjing and Chengdu are all provincial capitals. Shanghai, Chongqing, and Beijing are not only regional centers but also national centers. Surprisingly, Jiaxing, Dongguan and Qingdao also display good performance despite their status as nonprovincial capitals. However, these cities are considered to be well-developed cities in their respective provinces.

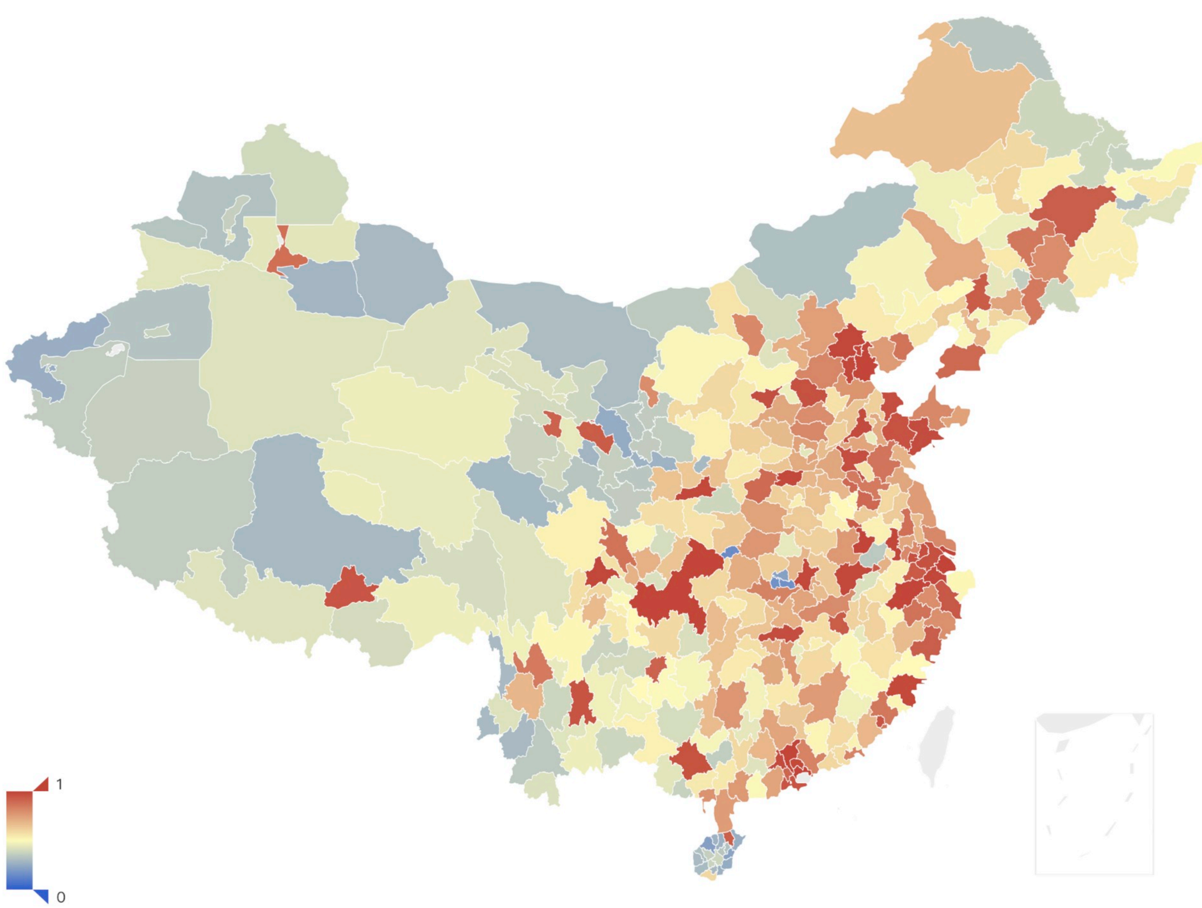

Fig. 4. Geographical distribution of node interdependence.
Note: The deeper red colour indicates a higher value for node interdependence λ_i. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 3
Ranking of node interdependence.

Rank	City (Province)	Rank	City (Province)	Rank	City (Province)	Rank	City (Province)
1	Shanghai (Shanghai)	6	Shenzhen (Guangdong)	11	Jiaxing (Zhejiang)	16	Wuhan (Hubei)
2	Guangzhou (Guangdong)	7	Tianjin (Tianjin)	12	Anqing (Anhui)	17	Fuzhou (Fujian)
3	Hefei (Anhui)	8	Nanjing (Jiangsu)	13	Zhengzhou (Henan)	18	Dongguan (Guangdong)
4	Chongqing (Chongqing)	9	Chengdu (Sichuan)	14	Langfang (Hebei)	19	Qingdao (Shandong)
5	Hangzhou (Zhejiang)	10	Beijing (Beijing)	15	Xi'an (Shaanxi)	20	Ji'nan (Shandong)

4.4. Multilayer clustering

Economic theories show that the cooperative and competitive interactions between the workforce and information bring externality (Gennaioli et al., 2012; Van Oort, 2017). The enhancement of knowledge sharing and technical skills produces external economic returns. Enhancing the information flows and population mobility between cities facilitates the economic growth of the entire country. Therefore, understanding cities' capability of promoting resource flows could benefit policy-makers in designing urban orientation and adjusting urban planning.

To reveal the interaction between information resources and human capital, we introduce the multilayer clustering coefficient to study cities' ability to affect the formation of cross-layer triangles. In single-layer networks, the clustering coefficient, as is well known, quantifies the probability that two neighbors of one node are connected, and these three nodes form triangles. Analogously, in multilayer networks, the multilayer clustering coefficient of one node measures the likelihood of its two neighbors in one layer being connected in the other layer and forming a cross-layer triangle. This metric indicates a city's ability to use the connection in terms of one resource to promote the transfer of the other resource between its neighboring cities. A cross-layer triangle is defined as one-triad that is centered at node i, where edge (i,j) and edge (i,q) belong to layer l. In this case, the multilayer clustering coefficient describes the tendency of the formation of edge (j,q) in the other layer l'. Based on the work published by Battiston et al. (2014), we extend multilayer clustering to the weighted multiplex network scenario, which is defined as follows:

$$wcc_i^{[l,l']} = \frac{1}{k_i^{[l]}(k_i^{[l]}-1)} \sum_{(i,j)\in E^{[l]}} (\hat{w}_{ij}^{[l]}\hat{w}_{iq}^{[l]}\hat{w}_{jq}^{[l']})^{1/3} \tag{5}$$

where $l,\ l' \in \{I,T\}$ and $wcc_i^{[l,l']} \in [0,1]$, $\hat{w}_{ij}^{[l]}$ is normalized by the maximum weight in layer l, and $\hat{w}_{ij}^{[l]} = w_{ij}^{[l]}/\max(w_{ij}^{[l]})$. A higher value for $wcc_i^{[l,l']}$ means that city i has a greater ability to fully mobilize resources in layer l to promote the flows of resources in layer l'.

The cities' geographical information is combined, and the multilayer clustering coefficient of all cities is displayed in Fig. 5. As shown, the cities' cross-layer clustering abilities vary. The cities with a high cross-clustering ability are scattered across the country. In addition, the geographical distribution of $wcc_i^{[I,T]}$ and $wcc_i^{[T,I]}$ presents a hierarchical structure that increases from Western China to Eastern China. However, compared to the geographical distribution of $wcc_i^{[T,I]}$, the distribution of $wcc_i^{[I,T]}$ is more uneven, indicating that most cities do not perform well in using information resources to enhance human capital clustering.

In addition, we find that $wcc_i^{[I,T]}$ and $wcc_i^{[T,I]}$ are both highly relevant to the GDP of city i, as shown in Fig. 6. This result indicates that developed cities have a strong ability to promote population mobility (information flows) because of their information flows (population mobility). Due to the existence of a high correlation, the multilayer

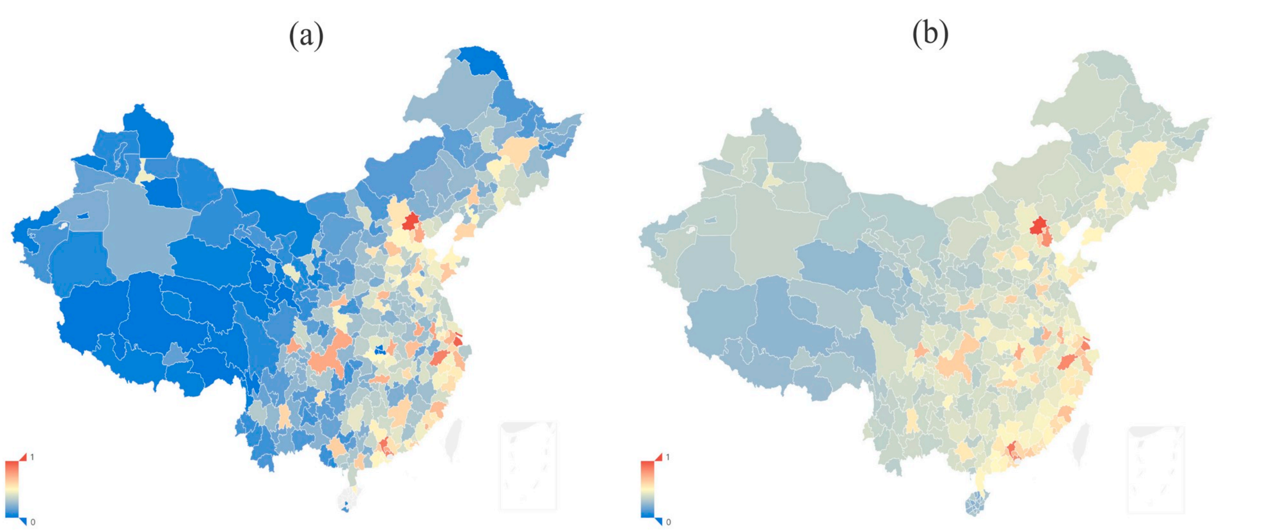

Fig. 5. Geographical distribution of multilayer clustering.
Note: (a) Distribution of $wcc_i^{[I,T]}$(b) Distribution of $wcc_i^{[T,I]}$. Because of the small value of $wcc_i^{[I,T]}$ and $wcc_i^{[T,I]}$, we normalize the indicators and set the maximum value equal to 1 to clearly show the disparity among the cities on the map. We take the logarithm of value $wcc_i^{[l,l']}$ as $\hat{c}_i^{[l,l']}$ and obtain the normalized value $(\hat{c}_i^{[l,l']} - \min(\hat{c}_i^{[l,l']}))/(\max(\hat{c}_i^{[l,l']} - \min(\hat{c}_i^{[l,l']})))$. The normalized value ranges from 0 to 1, and a higher value means that the city has a stronger ability of cross-layer resource clustering. The deeper red colour reflects the indicators with higher values. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

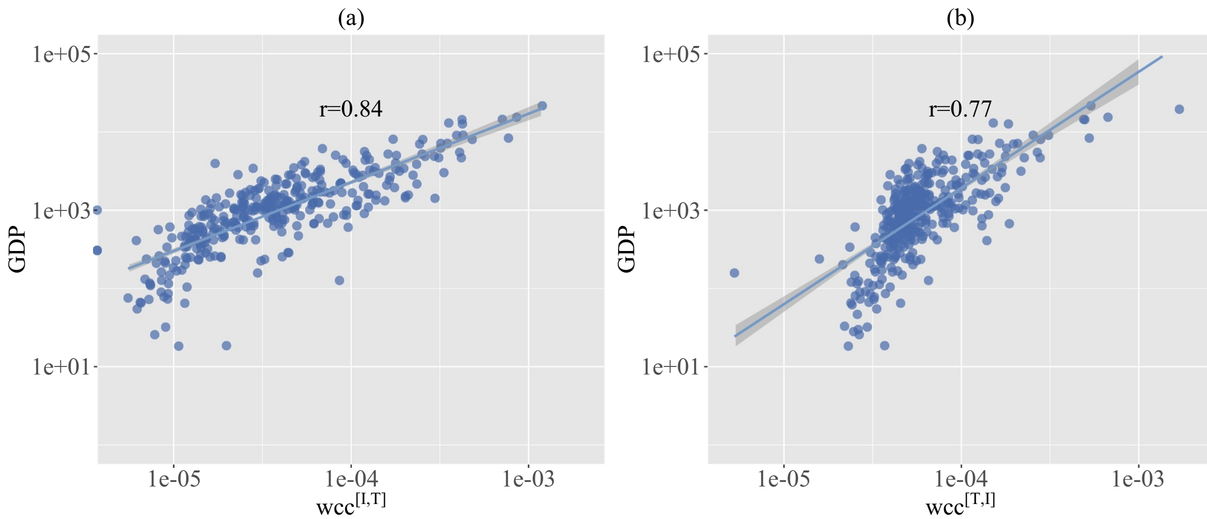

Fig. 6. Relation between GDP and multilayer clustering.
Note: GDP is highly correlated with cross-layer clustering, $wcc_i^{[I,T]}$ and $wcc_i^{[T,I]}$. In addition, the significance tests are all passed with $p < 0.001$. The unit of GDP is one hundred million RMB.

clustering coefficient may be an alternative indicator of GDP to evaluate urban development. Furthermore, compared to the GDP, which requires a long accounting period (monthly, quarterly, or annual) and a time-consuming process to obtain, our indicator based on social media data presents the obvious advantages of low cost and high efficiency. In addition, the multilayer clustering coefficient can provide some insight into the urban industrial layout and implications for urban planning at the national level. As one of the main instruments used by governments to ensure urban or region development in a sustainable way, urban planning plays a crucial role in national development. However, planning in some developing countries is often ineffective and inefficient (Zhao, 2015). Under this circumstance, the multiplayer clustering coefficient is of great significance for developing countries to establish a policy of urban planning. Notably, it is interesting that the correlation between GDP and $wcc_i^{[I,T]}/wcc_j^{[T,I]}$ is higher than the correlation between GDP and the node interdependence λ_i. By comparing the definitions, the node interdependence is based on a global perspective, while the multilayer clustering captures a local structure. Previous studies have verified that population mobility (Hu et al., 2019; Liu et al., 2014) and trade activities (Melitz, 2007; Narayan & Nguyen, 2016) are limited by distance. The interurban interaction has certain locality characteristics; thus, the indicators $wcc_i^{[I,T]}/wcc_j^{[T,I]}$ that capture the local structures are more significant.

The top 20 cities of $wcc_i^{[I,T]}$ and $wcc_i^{[T,I]}$ are tabulated in Table 4 (see the full ranking list in Appendices A2 and A3). Three features of this list are noteworthy.

- This list shows that the top cities are local core cities, in particular, provincial capitals and municipalities. More specifically, 14 provincial capitals and municipalities perform well and rank in the top 20 cities in terms of $wcc_i^{[I,T]}$, and similarly, 13 provincial capitals and municipalities are among the top 20 cities in terms of $wcc_i^{[T,I]}$.
- The city ranking in Table 4 provides insight on cities' industrial focus. High-tech cities have a greater ability to use information flows to facilitate population mobility, and labor-intensive cities tend to utilize population mobility to promote information flow. We find that Suzhou has different rankings in terms of $wcc_i^{[I,T]}$ and $wcc_i^{[T,I]}$(Nos. 13 and 27). This result indicates that Suzhou has a stronger capability of utilizing information flows to promote human activities. Based on the statistical bulletin of Suzhou's national economic and social development in 2017 (Statistics Bureau of Suzhou, 2018), the annual output of high-tech industries was 1.5 trillion RMB and comprised 47.8% of the total industrial output. In addition, due to its development of high-tech industries, Suzhou is regarded as an important city in the G60 Science & Technology Innovation Valley, which is one of the most urbanized regions in China.
- Guangdong Province exhibits its predominance, with five cities in $wcc_i^{[T,I]}$, followed distantly by Zhejiang Province with three cities. The results indicate that Guangdong Province has a strong capability to utilize human capital to promote the transfer of information resources. As reported by the Statistics Bureau of Guangdong Province (Statistics Bureau of Guangdong, 2015), labor-concentrated industries, such as the textile and apparel industry and the electronic and telecommunication equipment industry, are still the pillar industries in Guangdong Province. Our results are consistent with the current status of Guangdong Province with a traditional edge in labor-intensive industries.

Table 4 also provides implications for urban planning and orientation. In the comprehensive urban plans approved by the State Council of China, 54 cities have clearly defined positions and development directions; these cities can roughly be categorized as national central cities, regional hub cities and special function cities. We show the relationship among cities' economic development level, urban orientation and multilayer clustering indicators in Fig. 7. This relationship shows that as the multilayer clustering indicators increase, cities have more important statuses and more developed economic levels.

5. Implications for urban policy

5.1. Enhancement of the joint effects of two resources

To boost the development of cities, it is of significance to promote the comprehensive utilization of human capital and information resources. The crucial role of these two resources in urban economic development has been acknowledged in previous studies (Li, Dong, et al., 2017; Van Oort, 2017). The coordinated development of the population, resources, and societies is the central purpose of urban agglomeration (Fang & Yu, 2017; Frideman, 1986). However, the comprehensive utilization of human capital and information resources has not gained enough attention in evaluations of cities' performance. Therefore, in this study, the indicator of node interdependence, which measures the additional value of interlayer coupling to urban reachability, provides a new tool

Table 4
Ranking of indicator $wcc_i^{[I,T]}$ and $wcc_i^{[T,I]}$.

$wcc_i^{[I,T]}$				$wcc_i^{[T,I]}$			
Rank	City (Province)	Rank	City (Province)	Rank	City (Province)	Rank	City (Province)
1	Beijing (Beijing)	11	Dongguan (Guangdong)	1	Beijing (Beijing)	11	Chengdu (Sichuan)
2	Shanghai (Shanghai)	12	Wuhan (Hubei)	2	Guangzhou (Guangdong)	12	Fuzhou (Fujian)
3	Guangzhou (Guangdong)	13	Suzhou (Jiangsu)	3	Shanghai (Shanghai)	13	Jiaxing (Zhejiang)
4	Hangzhou (Zhejiang)	14	Changsha (Hunan)	4	Hangzhou (Zhejiang)	14	Ningbo (Zhejiang)
5	Shenzhen (Guangdong)	15	Xiamen (Fujian)	5	Tianjin (Tianjin)	15	Foshan (Guangdong)
6	Nanjing (Jiangsu)	16	Ningbo (Zhejiang)	6	Shenzhen (Guangdong)	16	Shanwei (Guangdong)
7	Chengdu (Sichuan)	17	Zhengzhou (Henan)	7	Wuhan (Hubei)	17	Chongqing (Chongqing)
8	Chongqing (Chongqing)	18	Fuzhou (Fujian)	8	Nanjing (Jiangsu)	18	Zhengzhou (Henan)
9	Tianjin (Tianjin)	19	Anqing (Anhui)	9	Hefei (Anhui)	19	Xi'an (Shaanxi)
10	Hefei (Anhui)	20	Xi'an (Shaanxi)	10	Dongguan (Guangdong)	20	Langfang (Hebei)

to evaluate the joint effect of two resources on cities and further provide some implications for urban development.

By considering the case of China, this paper shows how the proposed indicator could be used to support the development of urban systems. First, to a certain degree, the evaluation of the cities proves that most national centers and provincial capitals in China have strong joint effects on human capital and information resources. As shown in Table 3, half of the top 20 cities are provincial capitals, including Guangzhou, Hefei, Hangzhou, Nanjing, Chengdu, Zhengzhou, etc. Second, some underperforming cities in the joint effect of the two resources are revealed. As shown in Appendix A1, Shenyang, Harbin and Changchun, which are the provincial capitals of three northeastern provinces (Liaoning, Heilongjiang, and Jilin) in China, are ranked as the top 41, 42 and 57, respectively, rendering these cities in the fourth quartile of all provincial capitals. As traditional heavy industry bases, these three northeastern provinces gain minimal added value from the joint effects of information resources and human capital, which may impede economic growth. Our findings are consistent with the fact that the northeastern provinces have been suffering from a relative economic decline for years and currently form the rust belt in China. Liaoning Province even reported negative economic growth in 2016, while the growth rate of China's GDP was 6.7%. Therefore, the governments of these cities should deeply consider how to comprehensively use human capital and information resources to boost the development of these cities.

5.2. Urban planning based on the capability of multilayer clustering

It is necessary to consider the urban capability to promote cross-layer resource flows when making policies related to urban planning and orientation. In recent years, urban agglomeration, which is a highly developed spatial form of integrated cities (Fang & Yu, 2017), is

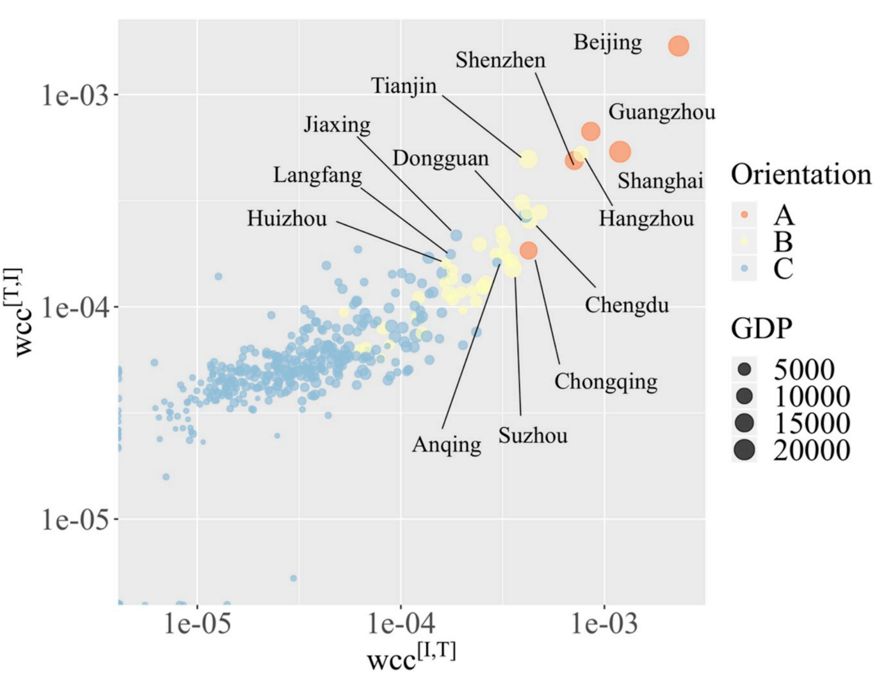

Fig. 7. Relationship between cities' orientation and characteristics.
Note: Cities' orientation in the national urban plan are categorized into three groups, including national central cities (marked as orange points with capital "A"), regional central cities (marked as yellow points with capital "B") and other cities (marked as blue points with capital "C"). In addition, the node size is proportional to the city's GDP, and the unit is one hundred million RMB. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

acknowledged as among the most important directions for urban planning. Core urbans in different scales are the critical parts of organizing and interconnecting other urbans to promote regional or even national development. However, in traditional studies, core urbans have always been identified in terms of the population size and economic development level (Fang & Yu, 2017; Ning, 2015; Portnov & Erell, 2001). In particular, the Japanese Department of Administrative Management defined that the core city should have > 1 million people (Zhang, 2003). The United States proposed that Metropolitan Areas should have a core urbanized location with > 50,000 people (Li and Stough, 2007). The above studies did not consider the cities' essential ability to transfer resources to directly promote regional development. However, the close connection between city groups and the ample liquidity of resources driven by central cities is critical for building urban agglomeration. Therefore, our study proposes indicators to evaluate the urban capability to promote resource flows from the perspective of multiplex networks. In addition, the analytical results show how to use these indicators to support the formulation of policies regarding urban planning and orientation while using China as an example.

By comparing with the comprehensive urban planning approved by the State Council of China, the analytical results support the strategic orientation of most cities. However, some misalignments are revealed between urban capability and orientation. Particularly, three highlights in terms of different city ranks are obtained from Fig. 7 and Appendices A2 and A3.

First, it is necessary to review the orientation rationality of Chongqing as one of China's national central cities and study how to improve Chongqing's capability to meet the requirements as a national center. Based on the urban plans approved by the State Council of China, five cities are defined as national central cities in national urban planning, including Beijing, Shanghai, Guangzhou, Shenzhen and Chongqing. These five cities are all located in the top right of Fig. 7, which indicates their good performance in multilayer clustering. Chongqing, however, is far behind the other four cities. According to indicators $wcc_i^{[I,T]}$ and $wcc_i^{[T,I]}$, the five cities are ranked as follows: Beijing > Shanghai/Guangzhou > Shenzhen > Chongqing. Surprisingly, the national central city of Chongqing has a weak capacity for cross-layer clustering. The $wcc_i^{[I,T]}$ of Chongqing is only ranked 17th, which is even worse than Chengdu, which is something of a "sister city" to Chongqing. Thus, there is a mismatch between the orientation of national centers and Chongqing's capacity.

Second, the polycentric development policies at the national level (Burger et al., 2014) are supported by our indicators. The large urban agglomeration, which aims to achieve cohesion and synergy, is functionally linked by the regional central cities. Due to the importance of regional central cities in the polycentric structure at the national level, the well-performing regional centers are identified in Fig. 7 by the proposed indicators. For example, Suzhou is one of the important central cities in the Yangtze River Delta and is the base for state-level high-tech industrialization, which has a high value of $wcc_i^{[I,T]}$. Huizhou is considered to be one of the central cities in the Pearl River Delta and performs well in terms of cross-layer clustering. In addition, Hangzhou, the capital of Zhejiang Province, which is defined as the regional center of the Yangtze River Delta, demonstrates outstanding performance in multilayer clustering.

Finally, some cities with good performance in promoting cross-layer resource flows do not gain a reasonable orientation to promote regional development. Therefore, it is necessary for authorities to rethink the orientation of these cities to allow their abilities to be fully utilized. As shown in Fig. 7 and Table 4, Jiaxing has a good capacity to use human interactions for clustering information resources, but it is defined merely as a tourist city. Dongguan, which is ranked after Guangzhou and Shenzhen in the Pearl River Delta, does not have a specific orientation in national urban planning. Langfang has the second-best capability in Hebei Province, which is weaker only than the provincial capital Shijiazhuang, and shows the huge potential for supporting the Beijing-Tianjin-Hebei urban integration plan; however, it also lacks orientation in the national plan.

5.3. Integrating social networks into the toolkit of urban planning

It is urgent to integrate social networks into the toolkit of urban planning to support the formulation of urban policy. It is acknowledged that urban systems represent a classical interdisciplinary issue (Yu et al., 2018). Based on different disciplines, traditional methods can be summarized into four types, including quantitative optimization modeling, spatial optimization modeling, agent-based modeling and economic modeling (Arefiev, Terleev, & Badenko, 2015). In these methods, urban economic statistics and geographic information systems (GIS), including maps, remote sensing images, statistical data, etc., are the major analysis and modeling tools. For example, Arefiev et al. (2015) comprehensively utilized the fuzzy set theory and GIS to propose evaluation methods to support urban planning in St. Petersburg in Russia. In addition, a series of interviews with stakeholders was conducted to explore the urban agglomeration development planning of Sarbagita Metropolitan in Indonesia (Rahayu, Haigh, & Amaratunga, 2018). However, there are still some limitations related to these traditional tools. Data collection for GIS and macroeconomic surveys is constrained by financial resources, related facilities and trained personnel, especially in developing countries (Blumenstock, Cadamuro, & On, 2015; Jerven, 2014; Yeh, 1999). In addition, up-to-date data represent an important bottleneck for developing countries in formulating timely and effective urban planning policies (Yeh, 1999).

In the age of the information economy, information diffusion among urbans implies the distribution of essential productive factors, which should be considered in urban planning. Furthermore, it is difficult for the existing toolkit to provide related information. In addition, as a crucial element in urban systems, people affect the functioning of urban systems through their daily performance. In this context, social networks that record the various microscopic behaviors of massive users, to a certain degree, are witnesses of urban system operation and development. Therefore, such networks can be regarded as important supplements to the traditional toolkit to support urban policy-making. In this study, social networks describe the picture of information flows and population mobility among cities in China, which is difficult to achieve by the traditional toolkit. Thus, social networks provide an opportunity to evaluate cities' capability in cross-layer resource clustering and rethink urban orientation in the current urban planning policy.

6. Conclusion and future works

There is increasing awareness that urban networks are multiplex networks characterized by dynamic spatial-temporal interactions between various layers. The national-level urban development policies should capture this complexity. This study uses data collected from Weibo and constructs a multiplex urban network for a pilot investigation. To the best of our knowledge, this is the first attempt to study urban networks from the perspective of a multiplex network by using social media data. First, we explore the topological properties of the network and the dynamic interactions between the information flow layer and the population mobility layer. Second, we investigate their joint effects on the central position of cities, which provides insight into the cities' development patterns. Finally, we discuss the cities' abilities in cross-layer resource clustering and provide some implications for urban orientation and planning. Some notable results are detailed as follows.

- This study verifies the high correlation between information flows and population mobility, which confirms the results in the existing economic literature. Furthermore, the results reveal the strong interactions between the two types of resources. In particular, the reinforcement from population mobility to information flows is stronger than the reinforcement from information flows to population mobility, and it is susceptible to the distance, economic status and tightness of the connection between cities.

- This study reveals the significance of the joint effects of information resources and human capital on the central position of cities in the complex urban system. The joint effects of these resources provide a new perspective for evaluating the economic development pattern of cities. These results show that most cities with strong joint effects are national centers and regional centers. Moreover, it is surprising to find that Jiaxing, Dongguan and Qingdao, which are non-provincial capitals, also display good performance. Moreover, as provincial capitals, Shenyang, Harbin and Changchun have low values of joint effects, which indicates that these three cities gain little added value from the joint effects of information resources and human capital.
- This study reexamines the current city orientation strategy. Although most of the information in the urban plan of the State Council is consistent with our results, the orientation of some cities, such as Chongqing, Jiaxing and Dongguan, requires consideration. In particular, as a national center, Chongqing does not match other cities' ability in consolidating information resources and human capital, as its capacity is even weaker than the capacity of Chengdu, which is something of a “sister city” to Chongqing. In addition, Dongguan and Jiaxing perform well in terms of the proposed indicators; however, neither has specific orientation in the national urban planning.
- This study offers a new multiplex network-based method to the toolkit pool of urban planning. The traditional methods for urban planning and orientation are constrained by several issues, such as time-consuming and inefficiency. Due to the widespread use of social networks, the proposed network-scientific thinking approach can be easily extended to other countries to facilitate our understanding of cities.

This study has some limitations. First, humans, material and information form cities, and these are the ideal elements for constructing urban topology. This study builds a multiplex interurban network in terms of humans and information. In future work, we will incorporate material flows and construct a full multiplex interurban network with three layers that represent population mobility, material flows, and information flows. Second, this study examines the correlation between the multilayer clustering coefficient and GDP and shows that the multilayer clustering coefficient may be an alternative indicator of GDP that evaluates urban economic sustainability. It is well known that for the sake of rapid economic growth, cities ignore environmental costs in China. If China's government launches “green GDP” in the future, which incorporates the environmental costs of economic growth into the conventional GDP, we will examine the correlation between the multilayer clustering coefficient and “green GDP”. The proposed multilayer clustering coefficient may serve as a good indicator to evaluate environmental sustainability in urban development.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A1 shows the full ranking list according to the joint effects of the two types of resources on cities. Appendix A2 and Appendix A3 tabulate the full ranking list of cities according to $wcc_i^{[I,T]}$ and $wcc_i^{[T,I]}$, respectively. Supplementary data to this article can be found online at doi: https://doi.org/10.1016/j.cities.2020.102625

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