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The dynamic process of social capital transformation and the emergence of E-commerce diffusion networks

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ABSTRACT

The emergence of the e-commerce village, which has become prevalent in rural China in recent years, could be regarded as a result of innovation diffusion. To explore the dynamic process of social capital transformation in rural China, this study carried out a field survey in a typical e-commerce village in Northern China named Dinglou Village. We used TERGM and SAOM to analyze the e-commerce diffusion network and found that the neighborhood, family, and peer-group networks all influenced the formation of the e-commerce diffusion network in this village. The contributions of three social networks were not depleted even with external interventions. In conclusion, it is suggested that the existing rural social capital did transform and positively influenced the development of the e-commerce village, which could serve as a case study for understanding the dynamic process of social capital transformation in rural China.

1. Introduction

With the proliferation of ICT applications, E-commerce Villages (ECV) emerged rapidly and became popular in rural China. In China, people prefer to call the E-commerce Village *Taobao Village* because of Taobao.com, the well-known e-commerce platform built by Alibaba. From 2009 to 2022, Taobao Villages[1] has grown from 3 to 7780 (Ali Research Institute, 2019, 2022). In these villages, peasant households sell native produce, handicrafts, or industrial materials on e-commerce platforms such as Alibaba, and these households cluster to a particular scale. E-commerce has enlightened the economic and social development in many under-developed rural areas and has had a broader impact on the transformation of rural livelihoods and daily life (Lin et al., 2016; Wang et al., 2021). In 2019, China's practice of reducing rural poverty through e-commerce received recognition from the World Bank. The World Bank's report stated that e-commerce provided more job opportunities in these Taobao villages, fostered rural entrepreneurship, and restored the social fabric disrupted by labor emigration. The report showed that participation in e-commerce significantly correlated with higher household income for individual households. Such developments, they believed, "offer hope that e-commerce can be a powerful instrument for rural vitalization and poverty reduction" (World Bank and Alibaba Group, 2019).

Many studies shed light on the emergence of China's E-commerce villages (Leong et al., 2016; Liu and Chu, 2017; Tang and Zhou, 2018; Zhou et al., 2021). From our perspective, the critical factor of ECV formation is to acquire most peasants' acceptance of modern e-commerce technology in traditional Chinese villages. Thus, how e-commerce diffuses in Chinese villages is a topic of research importance. As innovation diffusion has always been a research focus in sociology, this paper intends to view the diffusion of e-commerce as a subcontext of innovation diffusion research. The existing research on innovation diffusion has two major approaches, namely the Ryan model and the Coleman model. The Ryan model (Ryan and Gross, 1943) was formed earlier and had a profound impact, but it was also criticized for the problem of "the individual-blame bias." The Coleman model (Coleman et al., 1957, 1966; Menzel and Katz, 1955) valued the role of social networks and quantified it as a measure of the social system. Compared to the former,

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[1] *Taobao villages* are defined as villages where at least 10% of households actively engage in E-commerce business activities (or where there are at least 100 active e-shops in the village) with annual online sales of at least 10 million yuan (or $1,5 million) (Ali Research Institute, 2019).

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this approach is blessed with the advantage of avoiding the problem of the individual-blame bias.

Sociologists typically posit that social networks contain structural social capital, usually functional. In some rural areas of China, the diffusion of e-commerce as an innovation has occurred with the help of rural social networks, enabling rural communities and their residents to obtain technological dividends and achieve development. This process reflects the transformation of social capital. However, although previous studies on rural e-commerce development in China have discussed how acquaintance networks in rural communities influence the diffusion of e-commerce, there remains insufficient empirical evidence to support these claims. Furthermore, few studies have investigated the dynamic process of social capital transformation in promoting the diffusion of e-commerce. The advancement of generative network statistical models allows us to study the transformation of social capital that supports the diffusion of e-commerce in rural communities. Therefore, this study aims to collect data on the formation of the e-commerce diffusion network in a typical ECV by tracing the trajectories of e-commerce diffusion. Using dynamic network models that can address these data, we will examine the impact of existing social networks on e-commerce diffusion to analyze the dynamic process of social capital transformation in innovation diffusion.

The second section of this paper will review existing relevant literature. The third section will introduce the data and network analysis models used in this study. The fourth section will report the analysis results, and the last section will conclude and discuss relevant issues involved in the study.

2. Innovation diffusion and social capital transformation

2.1. Two approaches of innovation diffusion research

Innovation diffusion research can be traced back to the early 20th century. Since then, innovation diffusion has become a prominent sociological research topic for more than a century (Wejnert, 2002). We divide the research on innovation diffusion into two significant streams here, namely Ryan's approach and Coleman's approach. For interpreting the results of innovation diffusion, Ryan's approach emphasizes individual-level factors, while Coleman's model pays more attention to social structural systems measured by interpersonal networks.

Ryan's innovation diffusion research approach. The classic study by Ryan and Gross on the diffusion of agricultural technology (Ryan and Gross, 1943) is considered to have created a paradigm of innovation diffusion research and "left an indelible stamp on the history of all diffusion research" (Rogers, 2010). The primary methodological approach employed in their study was to investigate the behavior of individual innovation adoption. Numerous studies related to innovation diffusion followed this approach, which has become the dominant approach in innovation diffusion research for a considerable period. Everett Rogers, the authoritative scholar in innovation diffusion research, whose book *Diffusion of Innovations* is recognized as a masterpiece in this field, also followed Ryan's research path during his early academic career. His early studies also primarily focused on the individual adopters of agricultural technology. For example, he discussed the classification and characteristics of technology adopters (Rogers, 1958, 1961) and depicted opinion leaders in the agricultural community (Rogers and Cartano, 1962; Rogers and Van Es, 1964).

Since the 1960s, Rogers has dedicated himself to systematically summarizing and generalizing theoretical innovation diffusion research. During this time, he reflected on the potential weaknesses of Ryan's approach and tried to address them. He asserted that the major challenge facing Ryan's approach was *the individual-blame bias*. Specifically, this bias refers to researchers seeking explanations for innovation diffusion cases from individual factors rather than considering the broader social system. The focus of Ryan and Gross's research on the innovation adoption behavior of individual farmers is a typical manifestation of individual-blame bias.

Rogers (2010) identified the individual-blame bias partly due to research methods. Individuals were more accessible to collect data, and individual-level variables were relatively easy to measure. Most innovation diffusion research obtained data through random sampling surveys, which assume each individual is a unit of response, ignoring the importance of the social networks in which individuals are embedded. Rogers cited Barton (1968) to illustrate the problem posed by this research method: *Using random sampling of individuals, the survey is a sociological meat-grinder, tearing the individual from his social context and guaranteeing that nobody in the study interacts with anyone else.* Rogers also tried to conceptually solve the individual-blame bias problem when integrating the innovation diffusion research. He placed the social system as a key element among the four innovation diffusion components. Rogers perceived the social system to have rich content, of which the social network reflecting interpersonal relationships was an important aspect. However, Ryan and Gross and the scholars who followed their approach did not collect data on various network types among individuals and analyze their impacts on the diffusion outcome. James Coleman originated another vital approach to innovation diffusion research, which focused on the interpersonal networks among individuals in the social system. In this approach, the relationships between latent adopters become the unit of analysis instead of individuals.

Coleman's innovation diffusion research approach. In their studies on the diffusion of tetracyclines among physicians, Coleman and his colleagues incorporated the structural social context into their study (Coleman et al., 1957, 1966; Menzel and Katz, 1955). They measured various types of networks among physicians by sociometric methods to reflect interpersonal communication structures. Then, they attempted to compare the individual-attribute perspective with the friendship network perspective through specific analysis in their study. In the individual-attribute perspective, physicians were classified as either *professional-oriented* or *patient-oriented* based on their individual characteristics, and the impact of these attributes on their personal medical prescription decisions was analyzed. In contrast, the friendship network perspective focused on analyzing results related to the degree of integration among physicians and the correlation between this degree of integration and their application of the new drug. This approach differed from Ryan's in that it made efforts to avoid individual-blame bias. Based on their analysis, Coleman and his colleagues considered that the social contact factor has greater explanatory power than individual attributes for the decision to use a new drug.

After the publication of these studies, researchers became increasingly interested in the impact of social network structures reflecting interpersonal interactions on innovation diffusion (Marsden and Podolny, 1990; Strang and Tuma, 1993). Although some subsequent studies questioned Coleman's original work by re-analyzing the data they collected (Burt, 1987b; Van den Bulte and Lilien, 2001), these studies could not deny the influence of social networks on the adoption of new drugs (Friedkin, 2010). However, each of these studies made significant contributions towards a better understanding of how social networks affect innovation diffusion, as well as enhancing research methodologies in this field.

The studies above were carried out under Coleman's approach. Compared to Ryan's approach, which primarily focused on individual adopters, these studies were advantageous because they placed more emphasis on the social network as a measure of the social system. As such, they could help overcome the so-called individual-blame bias inherent in Ryan's approach by not overlooking the social context and investigating how social structural factors influence innovation diffusion.

2.2. Social capital and the development of ECV in China

Social capital is a theoretical concept that emerged from the dialogue between sociology and economics. Sociologists aim to provide alternative explanations for advantage acquisition, as opposed to the perspectives of human capital and economic capital commonly used by economists. Since the introduction of the concept of social capital (Bourdieu, 1986; Coleman, 1988), it has been extensively employed to elucidate individual development (Lin, 1999, 2002; Mouw, 2003; Chen and Volker, 2016; Shen and Bian, 2018) and community development (Putnam, 2000; Portes, 1998; Portes and Mooney, 2003; Aldrich and Meyer, 2015). While there may be some inconsistencies in the understanding of social capital within sociology, it is generally accepted that social capital has a productive function and is related to the social structure and relationships among people (Coleman, 1994). Burt (2005) suggested that social capital is more akin to a metaphor for the advantages of social structure.

Suppose we view the widespread adoption of a particular technological innovation within a community as a form of gaining an advantage. In that case, the fundamental issue at the core of Coleman's approach to the impact of social networks on innovation diffusion is whether social capital's productive functionality facilitates the acquisition of advantages for the community or group. The development of ECVs can be seen as the outcome of the diffusion of e-commerce in rural communities. Therefore, to comprehend the development of ECV in China, a crucial endeavor is to discern how the diffusion of technological innovation takes place in these rural areas. Several scholars have noted that the diffusion of technological innovation, which allows numerous ECVs to achieve overall community development, is closely linked to the transformation of existing social capital in rural communities (Qiu et al., 2019; Zeng et al., 2019; Wei et al., 2020). As a result, farmers involved in these ECVs have gained new technological dividends (Liu et al., 2021; Li and Qin, 2022). However, there is still scope for further research about social capital transformation that supports the diffusion of innovation in the ECV of China.

Firstly, few studies have provided quantitative empirical evidence on how social networks influenced the diffusion of e-commerce as an innovation following Coleman's approach. Leong and her colleagues conducted a case study of ECVs in Suichang and Jinyun counties in Zhejiang Province, China, and attempted to demonstrate the effect of social networks on the rapid diffusion of e-commerce knowledge and related skills. Similarly, Liu and Zheng (2011) identified social networks as the primary factor leading to the formation of e-commerce entrepreneurship aggregation in Dongfeng Village, Suining County, Jiangsu Province. They also discussed the underlying mechanisms in detail. They proposed that social networks played a crucial role in identifying opportunities and mobilizing resources during e-commerce entrepreneurship aggregation. However, these studies are predominantly based on qualitative observations and interviews, with few researchers systematically collecting quantitative data on social networks in rural villages regarding ECVs. It is rare to employ quantitative methods in relevant studies, either to test rural social networks' impact on the diffusion of e-commerce in villages or to test whether the development of rural communities benefits from the transformation of social capital.

Secondly, social network types have yet to be adequately distinguished in previous studies. In the literature on social capital, there is a notable emphasis on distinguishing between types of social networks across various dimensions. The classic literature focused on the strength dimension of relationships, specifically weak or strong ties (Granovetter, 1973; Bian, 1997). Relationships can also be differentiated based on their instrumental or emotional dimensions, frequently explored in research on understanding social support from a social capital perspective (Zhang and Ruan, 2001; Lee et al., 2005). In organization studies, scholars have also emphasized the importance of differentiating between various network types and exploring possible multiple dimensions of social capital (Inkpen and Tsang, 2005). However, in the current studies on the relationship between social capital and the development of ECV in China, few distinguished various types of social networks. This may be partly due to the need for measurement of rural social networks in villages, which limited researchers' ability to examine the impact of specific social network types. Among the various types of networks, peer-group networks were the focus of Coleman et al.'s drug diffusion studies (Coleman et al., 1957, 1966). Apart from that, kinship is a form of relationship valued by Chinese people, particularly in rural areas where family ties based on kinship are often of the most significant importance, and family networks influence many community activities (Fei, 1992). Moreover, neighborhood ties may be second to family ties in traditional rural Chinese society. Proximity of living may also reflect kinship (Fei, 1992), although the two do not always coincide. At times, close neighborhood relationships may even surpass family relationships. Families residing next to each other in rural areas typically have some social obligations to provide mutual aid and support, and there exists a Chinese adage that "close neighbors are better than distant relatives," highlighting the significance of neighborhood networks. In recent years, Chinese sociologists have explored and emphasized the value of the social capital formed by neighborhood networks in urban communities (Liu, 2007; Fang and Xia, 2019). Our study seeks to investigate the impact of three types of rural social networks, namely peer-group, family, and neighborhood networks, and to determine their contributions to the diffusion of innovation in ECV.

Thirdly, previous relevant studies need to focus more on investigating the dynamic process of social capital transformation. Dynamics are highly valued in innovation diffusion research (Granovetter, 1978; Rogers, 2010). However, few studies examine the dynamic of e-commerce diffusion and explore the dynamic changes of the impact of social capital in this process. The dynamic process of social capital transformation is also crucial and requires detailed examination since the impact of social networks on e-commerce diffusion in ECV may be dynamic. Leong et al. (2016) proposed a three-stage framework for the development of ECV, namely birth, expansion, and self-renewal. They argued that social networks played a more significant role in the initial stages of ECV growth. In contrast, third-party supporters, such as e-commerce service providers and local governments, played a more crucial role in later stages. This situation has been observed in many ECVs in China, especially when many local governments in China realized the potential for developing rural e-commerce as a means of promoting poverty alleviation and rural revitalization. In such cases, they become very willing to support and encourage villagers to participate in e-commerce operations (Liang et al., 2016). Therefore, with the involvement of these third-party supporters, the diffusion of e-commerce has ceased to be a purely spontaneous process within the rural community. If empowered by external actors, such as the government, and their supportive actions, would the farmers still depend on the social network? By adopting a dynamic process perspective on social capital transformation, we can address the following question: Will the impact of social capital diminish after external forces enter?

This study has collected longitudinal network panel data on e-commerce diffusion dynamics in a village in China to investigate the transformation of social capital from a dynamic perspective. The use of longitudinal network panel data, which tracks the dynamic evolution of networks over time, enables us to examine the dynamic process of social capital transformation and to take advantage of dynamic network models. Incorporating dynamic network models increases the persuasiveness of the study and surpasses the limitations of relying solely on static cross-sectional network data and related models to infer network formation. The following section will introduce the methodological advancements in network modeling and their relevance to this study.

2.3. Methodological advancements in network modeling

In recent years, the exponential random graph model (ERGM) family has gained popularity as a network modeling and analysis method in social science research. The origins of this model can be traced back to Erdős and Rényi's work in the late 1950s. These models were designed to simulate networks and answer questions about how a given network emerges from several localized processes. Researchers can employ these models to verify mechanisms that impact network formation. ERGMs are also commonly referred to as statistical network models (Goldenberg et al., 2010; Snijders, 2011b) due to their ability to provide packaged tools for empirical analysis, allowing researchers to estimate and test parameters with relative ease. Additionally, this family of models is highly extensible and can address various types of network data, including multivariate, bipartite, valued, and multilevel networks. Related models, such as TERGM and LERGM, can incorporate time dependence and enable researchers to model longitudinal network panel data that reflect network evolution dynamics (Hanneke et al., 2010; Desmarais & Cranmer, 2012a; Koskinen et al., 2015). A comprehensive literature review regarding the application of ERGMs has been conducted and is accessible (Amati et al., 2018).

A similar model is assumed by the stochastic actor-oriented model (SAOM), often mentioned in the same breath with ERGMs. SAOM is also a frequently used approach for modeling dynamic networks. Because SAOM and ERGM infer the process and mechanism of network formation through generative simulation of the observed network, they are commonly referred to as generative network models. The developers of SAOM believe that it was inspired by applications in sociology and other social sciences, and therefore, the model terminology and basic assumption have a social science flavor (Snijders, 2017). Therefore, it is more favored by social science researchers (Benton, 2016; Schaefer and Kreager, 2020). For example, in SAOM, network nodes are assumed to be social actors with agency, such as humans and organizations, et cetera. These actors can potentially change their outgoing ties and drive the network evolution. The observed network dynamics result from the sequences of active choices these actors make. Conversely, ERGMs do not necessarily assume nodes' agency. Therefore, it is generally supposed that SAOM is an "actor-oriented" model, whereas ERGMs are "tie-oriented" models (Snijders, 2011a; Desmarais and Cranmer, 2012b; Block et al., 2019; Lusher et al., 2013). Section 3.4 will provide a detailed explanation that both are suitable for analyzing the research questions of this study.

Portraying the network composed of ties that identify the trajectories of innovation diffusion and modeling the dynamics of the diffusion network by applying TERGM and SAOM represents a novel approach to the methodology of innovation diffusion research. While innovation diffusion studies following Coleman's approach are beneficial in overcoming individual-blame bias, they often share commonality with Ryan's approach in using the variability in individual attributes of innovation adoption, referred to as *innovativeness* by Rogers (2010), as their primary dependent variable for studying innovation diffusion. Although this measurement does reflect whether actors adopt innovation, it cannot capture the specific trajectory of innovation diffusion. Burt and other researchers applied the network autocorrelation model to examine the impact of social networks on innovation diffusion (Burt, 1987b; Galaskiewicz and Burt, 1991). This method assumes that social influences such as imitation and learning occur along social ties or other structural relationships reflected in social networks. Although they claimed to distinguish among various types of influence patterns present in social networks – such as those between adjacent actors, structural equivalent actors, and non-adjacent actors with indirect paths (Leenders, 2002) – it is unclear whether there exist direct links between the paths of innovation diffusion observed in reality and the ties in social networks, because the trajectories of diffusion were not dependent variables.

The innovation diffusion network, composed of ties indicating the actual trajectories of diffusion, can record and restore the entire dynamic process of innovation diffusion in greater detail, thereby clearly reflecting specific mechanisms of diffusion like the direction of information flow. However, studies that take individuals' attributes–innovation adoption–as the outcome variable cannot match this level of detail. The development of generative network models, such as ERGMs, enables the full analysis of diffusion network data. By using them to model the observed diffusion network, mechanisms and processes of diffusion can be inferred. Extensions of ERGM and SAOM assist in addressing multivariate network data and analyzing the effects of other network covariates in network formation (Snijders et al., 2010; Lusher et al., 2013; Amati et al., 2018). Therefore, these methods can be fully utilized to answer whether the e-commerce diffusion network in Chinese ECV is based on the existing rural social networks in the village. In recent years, a growing body of literature has used diffusion network modeling to study diffusion phenomena. Lubell et al. (2012) proposed that the generative network model offers some advantageous features when studying policy diffusion. An and VanderWeele (2022) collected the data that recorded how treatment information from a smoking prevention intervention diffused among students and used ERGM to model this diffusion network data to examine personal characteristics and social processes associated with treatment diffusion. For conducting network modeling analysis of e-commerce diffusion in ECV and answering the above research questions, it is essential to have access to network datasets that record the dynamic diffusion of e-commerce within the specific village being studied, as well as network datasets that record the existing rural social network of the village. Section 3 will provide a detailed introduction to how this study collected these datasets.

3. Data and methods

In order to answer the above research questions, the authors conducted a field study in Dinglou Village, a typical ECV. Dinglou Village started E-commerce very early and is known as "the first Taobao Village in Shandong." It is also one of the first 14 Taobao Villages in China, identified by the Ali Research Institute in 2013. The authors stayed in Dinglou Village from September to October 2019 and collected data for this study.

3.1. Field and household survey in Dinglou Village

Located in Cao County, southwest of Shandong Province, Dinglou Village is a typical rural area of Northern China, and it has been among the underdeveloped areas in the past years. The geographical location of Cao County is shown in Fig. 1 (a).

Since the 1980s, individual households in Dinglou Village and nearby villages began to produce and sell equipment for photographic studios, including specific clothes, but the business scale was small until around 2010. In 2009, a family in Dinglou Village opened an online store on Alibaba (*1688.com*) selling photographic costumes, which some households in the village had produced for years. Then, a few villagers began to imitate and open their online stores. Later, more and more households engaged in e-commerce business. In the spring of 2013, the local government noticed this phenomenon in Dinglou Village. In the first "China Taobao Village Summit" at the end of 2013, Ali Research Institute identified Dinglou Village as one of the first batches of 14 "China Taobao Villages." According to the authors' field survey, as of 2019, more than half of the households in the village were engaging (or had engaged) in e-commerce entrepreneurship, and many of them had improved their living standards through e-commerce activities. The development of e-commerce in Dinglou Village also influenced and engaged other villages nearby.

As Dinglou's e-commerce started early and there was little intervention in the first three to four years, the proliferation of e-commerce mainly depended on villagers' mutual learning and teaching through

Fig. 1. Maps of research site
(a) the geographical location of field survey (Cao County in Shandong Province, China)
(b) the Google Earth snapshot of Dinglou Village
(c) the detailed spatial distribution map of the houses in Dinglou Village, respectively.

their daily communication. Thus, it provides an ideal case to study the e-commerce diffusion network. Additionally, Dinglou is a natural village with clear boundaries, which provides convenience for interviewing every household thoroughly and collecting their social network information. Fig. 1 (b) shows a Google Earth snapshot of Dinglou Village and its surroundings, with the red circle outlining the village as the survey's scope.

Dinglou Village is a typical village of mixed surnames in northern China, with five relatively big clans (of the same surnames) and several small clans with only two or three households. In the survey, we code these clans from 1 to 6. All households in Dinglou were divided into five production teams,[2] the village's organizational structure. This research also examined the correlation between its organizational structure and the e-commerce diffusion networks.

In the survey, the subjects included all the native permanent households living in Dinglou Village. The reason for choosing permanent households[3] was that labor outflow was expected to be normal in rural Northern China. Many villagers kept their *hukou* registration in the village but worked and lived outside, and it was challenging to conduct face-to-face interviews. The native households referred to households with family members born and raised in this village. Since 2013, Dinglou Village has become famous, attracting people from nearby counties and other provinces. They rented places or stores in the village to engage in e-commerce-related activities. These outcomers came and left and had business interactions with native villagers, but were hardly involved in the village's e-commerce diffusion network. Therefore, the non-native households were out of our survey target list. From the villagers' namelist (*hukou* register) provided by the village council, we could theoretically exclude outcomers from native residents. However, at the time-point of the survey, the villagers' namelist provided by the village council was not fully equipped, so it was hard to identify who lived there. We used three methods to solve this problem.

First, we found the critical persons in the village (the village's Party secretary and the village accountant) and asked them about each household in the namelist in turn, mainly about whether they were still living in the village. This process might encounter a problem of memory biases, but it still narrowed down our survey scope.

Second, at the beginning of our survey, we drew a detailed spatial distribution map of the houses in the village and assigned a number to

[2] A production team is a form of a grassroots organization that gradually formed during a series of transformations and campaigns in the countryside after the founding of the People's Republic of China. In addition to economic activities such as production, the daily political life and various public affairs decisions in rural areas were made within the production team as the basic organizational unit. Some studies have argued that the production team was not only the basic unit for organizing production in Chinese rural society during that historical period, but also the basement of the community, which replaced the traditional family community, broke the foundation of a rural society based on blood ties, and to some extent reconstructed social relations in rural China (Wu, 2018). Along with the rural reform in the 1980s, villagers' autonomy in production and management increased, and production teams no longer constituted the most basic level of rural grassroots organization. However, such an organizational form persisted, and many places called them "production teams," as in Dinglou Village. This form of rural organization also continues to influence daily life and social interactions in rural China to a considerable extent.

[3] Permanent household refers to those households who have lived in one place for more than three months, regardless of whether their *hukou* is registered there.

Fig. 1. (*continued*).

each house, as depicted in Fig. 1 (c). This map proved invaluable in familiarizing us with each house in the village and expedited our ability to locate them efficiently. Subsequently, we verified the information of householders by systematically approaching and talking to the residents of each house. If the houses were vacant or no one responded, we asked their neighbors about the owners' whereabouts. If the houses' information remained uncertain, we would verify it by asking other households in the same production team during the survey. After these efforts, we found 245 native permanent households residing in Dinglou Village, which accounted for three-quarters of all the households in the Village Council's namelist. We were confident that our filtered list of native permanent resident households satisfies the requirements.

The survey faced coverage bias even with the filtered list, because some resident households could not be interviewed. According to our statistics, all 245 households were the eligible target respondents, and we completed interviews with 210 of them. The remaining 35 households refused our interview due to medical or personal reasons (more details present in Table S1 of Supplementary Materials). The successful interview rate was around 86%. Although missing data was a curse to relational network surveys (Burt, 1987a), in practice, non-response was inevitable. Stork and Richards (1992) reviewed previous studies using social network data and found that their response rates were between 65% and 90%. They suggested that researchers could use this range as a reference. According to this thumb rule, the non-response rate of this survey was within the acceptable range.

We took each household as an investigation unit in this survey. The households were viewed as nodes when constructing various village networks. In terms of operation, according to the convenience principle, we selected adult respondents in each household who were familiar with the family's basic information and e-commerce practices. Then, we conducted face-to-face interviews with prepared questionnaires and recorded the conversations. The Supplementary Materials will include a partial questionnaire containing relevant questions for this study.

3.2. *E-commerce diffusion network*

In order to depict the diffusion process of e-commerce in the village, the first duty of our survey was to collect information about edges (social ties) connecting the nodes (households), which indicated the trajectory of the diffusion network. We used the name-generator to obtain the ties (edges) of the e-commerce diffusion network. If the households were participating in e-commerce activities or had the experience of e-commerce, we would continue to ask them, "Who taught you how to open an online store?" (referred to as *learning edge*) and ask them to list the names of the villagers they had learned from. Similarly, we would ask them, "Whom you have taught how to open an online store" (*teaching*

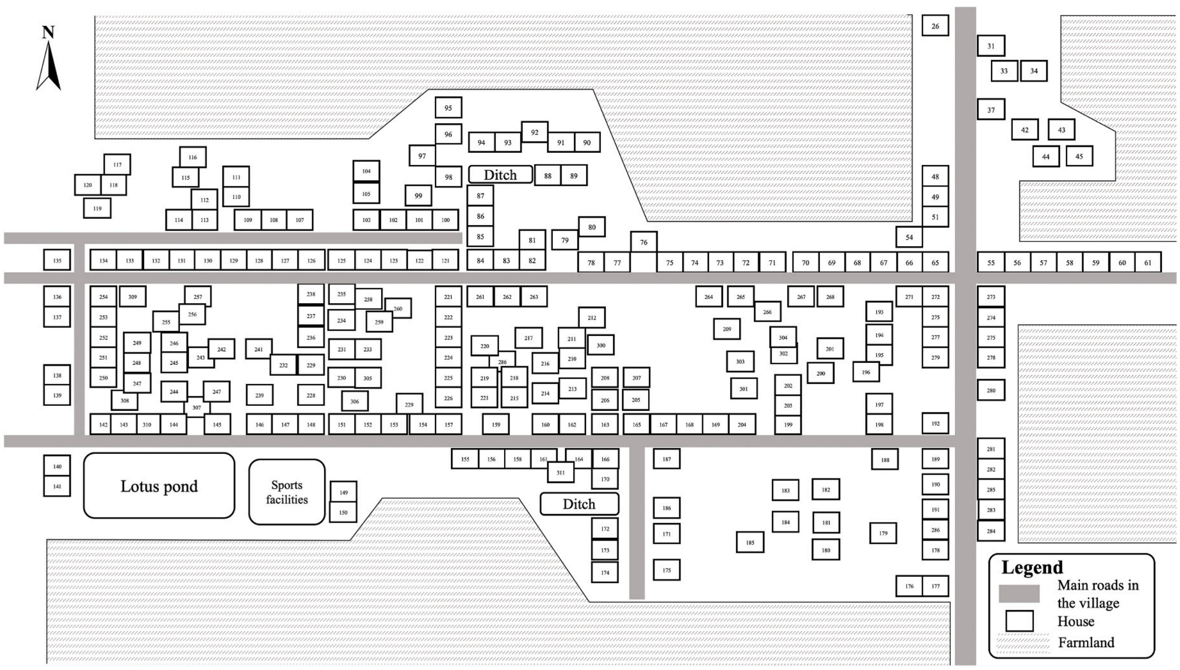

Fig. 1. (*continued*).

edge) and also ask them to list the names of the villagers they had taught. We did not set a limit to the number of ties that the respondents would nominate. When respondents faced recall difficulties, we would use some tricks to help them. We would list the key steps of operating an online store, such as store registration and web page design. Then, we might ask further questions like, "Do you remember who helped you register your online store," "Did you help anyone register their online stores," and "Did you consult anyone (or who consulted you) on designing the web pages." This way, we tried to avoid response bias due to memory failures. The original network data were processed according to the research's requirements. First, exclude the nodes nominated by the respondents who are not native permanent resident households from the network. Second, in the survey, some people nominated by respondents were not householders in the village but family members. Since we considered a household as a network node, all the family members in the same household nominated by respondents would be counted as the same node, according to the family member information in the Village Council's namelist.

Among the 210 households interviewed, 124 e-commerce households were operating e-shops online or had experience operating e-shops online. In the network, they are represented as 124 nodes. The e-commerce diffusion network we construct contains *learning edges* and *teaching edges* obtained using name-generators. The network is a directed graph. Specifically, if household A says they have learned the skills of operating the e-shop from household B, or household B says they have taught the skills of operating the e-shop to household A, a directed edge from B to A is connected between nodes A and B. The total number of learning edges is 117, and the number of teaching edges is 53.[4] We found that 14 edges are duplicated, emerging in both the set of *learning edges* and the set of *teaching edges* as some households nominated each other, and these 14 duplicated edges are counted only once when constructing the e-commerce diffusion network. Therefore, there are 156 (=117 + 53-14) directed edges in the final constructed e-commerce diffusion network, and the density of this network is 0.0102. Thirteen isolated e-commerce households have neither learned from other people in their village nor taught others how to operate e-shops. The largest connected component contains 105 nodes, accounting for 85% of all the nodes.

In the survey, we asked households to nominate names of learning and teaching and also asked them about the time when learning or teaching happened, which was recorded in the form of the year. Therefore, we can obtain a "snapshot" of the e-commerce diffusion network in 2019 and a "snapshot" set containing eleven networks that reflect the state of e-commerce diffusion in each year from 2009 to 2019. These eleven networks are put together and form retrospective network panel data, which can approximately reflect the dynamic process of the e-commerce diffusion network evaluation in Dinglou Village over more than ten years. Some visualizations of these network "snapshots" are selected and presented in Fig. 2.

3.3. Rural social network

Three types of relationships were selected for the existing rural social networks: family networks, neighborhood networks reflecting spatial proximity, and peer-group networks. In the survey, in addition to asking respondents to nominate the ties reflecting e-commerce diffusion, we also asked them to nominate the edges of relationships mentioned above.

Family network. We defined parents, children, siblings, and grandparents as family relationships.[5] These relationships construct the family network of the village. This network is undirected, with 48 edges among 124 nodes, which indicates that the density of the family network is small. The average degree of this network is 0.774, which is also the

[4] The number of teaching edges is significantly less than that of learning edges because there are also biases when the respondents nominate the teaching edges. They were almost reluctant to tell interviewers whom they had taught. This is related to some native soil cultures in rural China. Native villagers would consider talking about whom they had taught akin to flaunting themselves. If other villagers learned such bragging behaviors, unfortunately, it would hurt the "face" of the flaunter.

[5] Admittedly, it is also essential to examine these relationships between households; in rural China, children will live in separate households from their parents when they reach adulthood. At this point, parents and children become two households, and their relationship is called a family relationship by our definition.

smallest among all three existing social networks in the village, but the average cluster coefficient is 0.794, the largest among these networks.

Neighborhood network. We detailedly recorded the spatial proximity among households in this village. The neighborhood network is constructed based on these records. If two households live close, connect an edge between the two nodes representing these households. The neighborhood network has 160 undirected edges with an average degree of 2.581, and its average cluster coefficient is 0.204.

Peer-group network. The relationships included in this network are siblings, respondent-nominated cousins, and respondent-nominated close friends. We also set it as an undirected network, meaning that two households will be considered closer friends so long as one of the respondents nominated another. The network has 342 edges, and its density is the largest among the three networks. Its average degree and average cluster coefficient are 5.516 and 0.231, respectively.

3.4. Model, variables, and analysis strategy

Temporal exponential random graph model (TERGM) is an extension of the exponential random graph model, which is suitable for modeling inter-temporal dependence in longitudinally observed networks (Desmarais & Cranmer, 2012a). TERGM can be written as the general form of ERGM (Robins et al., 2007; Harris, 2014) by the following equation.

$$P(y_t|y_{t-m},\dots,y_{t-1}) = \left(\frac{1}{c}\right) exp\left\{\sum_{k=1}^{k}\theta_k z_k(y_t, y_{t-1},\dots,y_{t-m})\right\} \tag{1}$$

Where y_t represents the observed network at time *t*, and $m \in \{0,1,\dots,t\text{-}1\}$, which is used to specify the previous networks, which y_t is conditional on the previous networks. z_k represents network statistic corresponding to special configuration *k*. θ_k is the parameter, and *c* is a normalization constant.

Equation (1) only specifies TERGM for the observed network at a single time, i.e., y_t. It is possible to model the joint probability of observing networks between time points $m+1$ and *t*. The joint probability is equal to the product of the generation probabilities of each network [as shown in Equation (2)]. TERGM deals with the time dependence over a time-series network sequence in this way.

$$P(y_{m+1},\dots,y_t|y_1,\dots,y_m) = \prod_{t=m+1}^{t} P\left(y_t|y_{t-m},\dots,y_{t-1}\right) \tag{2}$$

Desmarais and Cranmer (2012a) proposed a bootstrapped maximum pseudolikelihood estimation method (bootstrap MPLE) to estimate the parameters of TERGM. Leifeld et al. (2018) developed a software package to implement it. This study estimated the TERGM by applying the method they provided. In addition, Krivitsky and Harcourt also proposed another way to specify the temporal exponential random graph model - the separable temporal exponential random graph model (STERGM). It distinguishes the dynamic evolution process of the network into two processes, i.e., tie formation and tie dissolution, and can deal with both processes simultaneously (Krivitsky and Handcock, 2014; Handcock et al., 2019). Their parameter estimation method also differs from Desmarais and Cranmer's.[6] In this study, we do not use the STERGM approach.

Stochastic actor-oriented model (SAOM) is another model used to analyze network dynamics in this paper. The inventors of this model, Snijders and his colleagues have presented the major underlying principles of SAOM, such as basic assumptions of the model, model specification, model selection, and parameter estimation tests, in a highly accessible and straightforward way (Snijders et al., 2010).

Although SAOM and TERGM are similar in form, both are tools for empirical analysis models of network dynamics. However, much of the literature argues that there are significant differences in their philosophy of modeling network dynamics (Snijders, 2011b; Desmarais and Cranmer, 2012b; Block et al., 2019; Lusher et al., 2013), Section 2.3 has mentioned these briefly: mainly TERGM is a "tie-oriented" model, while SAOM is an "actor-oriented" model. The "tie-oriented" model means that the model's primary element is "tie." It focuses on the probability that ties generate or change given the rest of the network. On the other hand, the "actor-oriented" model assumes network evolution as the result of actors' series of purposeful actions. In this process, individual actors (nodes) will control the outgoing ties, i.e., creating, maintaining, or terminating relationships with other actors. ERGM focuses on the probability of edge given other parts of the network, while SAOM focuses on the choices made by nodes with regard to their outgoing edges.

The SAOM is also regarded as an empirical agent-based model (ABM). However, it differs from traditional ABM, which is used initially as a theoretical analysis tool, where researchers implement theoretical experiments through computational simulations to investigate the conditions and causal mechanisms that lead to the emergence of social phenomena (Edmonds and Hales, 2005; Macy and Flache, 2009). SAOM combines computational simulation models with statistical models. It conducts an empirical ABM analysis for network dynamics and can be used for model parameter estimation and statistical inference (Snijders et al., 2010). In brief, SAOM starts from actors (nodes in the network), and its modeling is based on local situations of actions while combining elements of generalized linear model statistical analysis. SAOM aims to provide a realistic and detailed representation of network dynamic processes in an empirical data set.

The Necessity of Simultaneously Applying TERGM and SAOM. In this study, we have employed TERGM and SAOM to analyze longitudinal network panel data on e-commerce diffusion in Dinglou Village. While these models are typically classified as "tie-oriented" and "actor-oriented," we argue that using both to examine the phenomenon of e-commerce diffusion in rural areas and address the research questions posed in this article is necessary.

This study aims to explore whether social capital transforms to support e-commerce diffusion, which can be operationalized by examining the formation process of ties indicating diffusion paths. Essentially, we want to know whether these ties are entrained with the existing rural social networks in the village. TERGM, a "tie-oriented" model, should be analytically sufficient. While SAOM is an "actor-oriented" model that assumes nodes' agency, and its developers consider this basic assumption to have a social science flavor (Snijders, 2017), in our study, it may not be the most appropriate choice.

Following a thorough discussion of the differences between ERGMs and SAOM, Block et al. (2019) provided some advice on model selection, including two highly relevant points to this study. Firstly, they suggested that actors typically choose ties in a manner that can be expressed using rewards and costs. If it is reasonable to assume that actors compare all potential ties with respect to these rewards and costs one by one, then SAOM would be an appropriate choice. On the other hand, if actors consider the rewards and costs of each tie separately, without any mutual comparison, then ERGM would be the more suitable option. Secondly, Block et al. (2019) suggested that it is important to consider whether the nodes sending outgoing ties have critical theoretical importance and should be considered as the actors with 'control' over the tie. This is referred to as the asymmetric transition dependence assumption, and they proposed that this assumption is impossible for ERGMs. They also pointed out that "tie-oriented" and "actor-oriented" are vague terms since ERGMs also could be interpreted as actors, or pairs of actors, myopically optimizing their ties one by one.

Analyzing the situation faced by this study in detail, firstly, from a

[6] The STERGM proposed by Krivitsky and Handcock mainly computes the method-of-moments estimator or the conditional maximum likelihood estimator. These estimation procedures are effective when the network size is not large or the number of observation time points is small. However, these two estimation methods are not as advantageous as bootstrap MPLE when facing voluminous data.

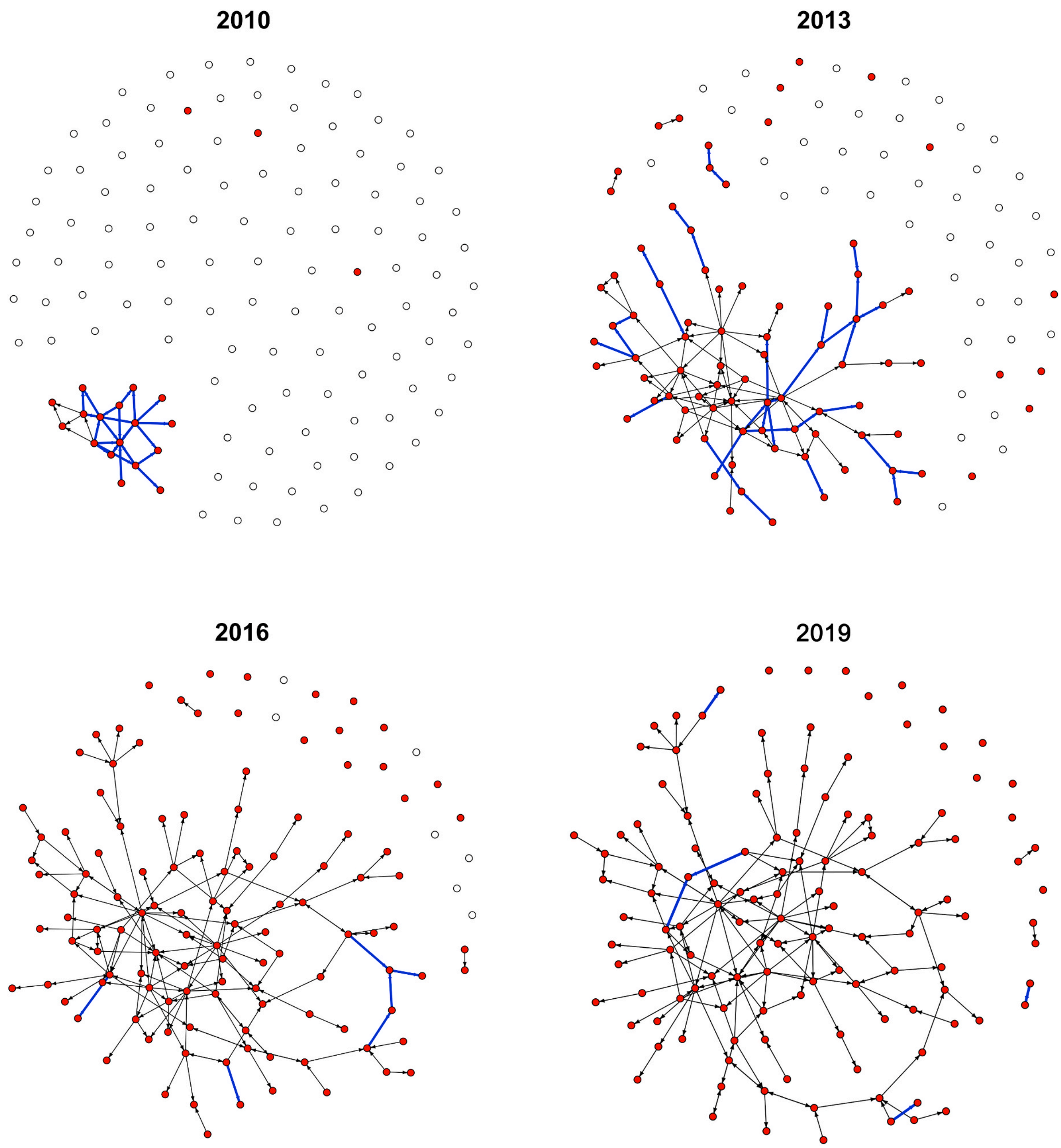

Fig. 2. Snapshots of the e-commerce diffusion network dynamic for four years (2010, 2013, 2016, and 2019).

selection perspective, it is nearly impossible for actors to compare all potential ties in terms of rewards and costs individually and select the optimal tie based on that comparison. It seems more reasonable to assume that the costs and rewards of each tie are considered separately in this scenario. Secondly, from a control perspective, households with mastered e-commerce skills can decide whom they want to teach, implying that sending nodes "control" the outgoing ties. However, this is not the whole premise for the formation of ties in the e-commerce diffusion network—the formation of edges in the e-commerce diffusion network results from both households' interaction and joint efforts. Therefore, learners as receiving nodes also play a crucial role, and their willingness to learn e-commerce skills cannot be entirely "controlled" by the sending actors. From this perspective, TERGM appears more suitable for analyzing the questions studied in this research than SAOM.

However, SAOM can offer some analytical capabilities that TERGM currently lacks. For instance, as we will demonstrate later, SAOM can help us identify which network among the three most influences on the e-commerce diffusion network dynamics. SAOM analysis enables us to compare the relative importance of effects within the same model, which is not yet possible in TERGM.

To summarize, SAOM analysis assumes that the actors sending outgoing ties have agency and control over those ties, which implies a more explicit actor-oriented assumption than TERGM. However, this does not necessarily mean that SAOM's "actor-oriented" assumption is more suitable for this study. TERGM's assumption seems to be more comprehensive. Nonetheless, SAOM analysis can still complement TERGM analysis, and the two models can mutually validate the robustness of the results obtained from each other. This is particularly important in ensuring the overall validity of the analysis.

3.4.1. Variables and analysis strategy

According to the ERGM conceptual framework for the explanation of tie formation in social networks (Lusher et al., 2013), we will mainly examine three types of factors that may influence the emergence of e-commerce diffusion networks: endogenous network structural effects, node attribute factors, and exogenous covariate network effects. Based on the recommendations of Lusher et al., we fit the model including seven network structural effects: *Edges*, *Reciprocity, Two-path*, *Isolates, Popularity*, *Activity*, and *Transitive Triplets*. The geometrically weighted degree (GWD) statistics are employed to measure *Popularity* and *Activity*. Nodal attribute effects include education (*Education*), age (*Age*), clans and production teams they affiliate with (*Clans* and *Production Teams*), whether they engage in costume production (*Production*), and the number of household laborers (*Labor Force*).[7] Exogenous covariate network effects include three types of rural social networks. In the TERGM analysis, all the network structural effects, nodal attribute effects, and covariate network effects mentioned above will be included in the model simultaneously.

The way of model specification and model selection of SAOM differs from TERGM. The SAOM is more likely to face non-convergence problems when specifying more complicated models because of its estimation algorithm, so it is hard to get the estimation results. The developers of SAOM suggest the following approach for model specification. First, start with a relatively simple model that only incorporates the major endogenous structural effects. Then, use the strategy of combining forward steps with backward steps to select a good SAOM model. Snijders and his colleagues consider this ad hoc stepwise strategy the best possibility for providing a series of procedures for model selection. They also give researchers a list of considerations in their article (Snijders et al., 2010).

The model we first specify incorporates the endogenous structural effects, which should be included according to the hints of Snijders et al. Then the actor covariates similar to node effects in TERGM, and three network covariates are also included.[8] We use the strategies mentioned above to construct the SAOM, and the final parameter estimation results are presented in this paper. Due to this model specification strategy, the effects included in SAOM will be somewhat different from those of TERGM.

Both TERGM and SAOM analyses assume that the underlying model reveals a uniform network dynamic process. That is, the parameters are constant across different periods of network formation. In order to reveal the process of social capital transformation in more detail, we will further diagnose the temporal heterogeneity of parameters, namely focusing on how the effects change across different periods of the e-commerce village growth.

4. Results

4.1. Results of TERGM

4.1.1. Network structural effects

Table 1 presents the results of TERGM analysis for e-commerce diffusion networks. Model I contains a *Memory Term* to capture the monotonic growth process of the e-commerce diffusion network. According to the suggestion by (Leifeld et al., 2018), the *Memory Term* is specified as a “positive autoregression” form. The parameter of this effect is considerable and significant. This estimate does not give us any additional information but only reflects how the dynamic e-commerce diffusion network is defined.

For network structural effects, besides the *Edges* effect being significant, another three effects, namely *Isolates*, *Two-paths*, and *Activity (Out-degree)*, are statistically significant in the TERGM. The parameter of *Activity (Out-degree)* effects is negative, which indicates the e-commerce diffusion network is not centralized on out-degrees. It means that the variance of contribution to the e-commerce diffusion network among households is slight.

The positive effect of *Isolates* indicates that some households never participated in teaching or learning. This effect might change during different stages of the ECV evolution process. At the early stage of ECV, the vast majority of households in the village must be isolated nodes. With more willingness to adopt e-commerce operations, more and more households would seek to learn from others, so they connected to the network, and the number of isolated nodes would decrease in this process. In the temporal heterogeneity analysis of effects presented later, it is found that the impact of isolates is not always significantly positive.

4.1.2. Node attributes effects

Education levels seem to not impact the evolution of e-commerce diffusion network. The differences in probability of ties formation among groups with different education levels were not significant. The nodal *Homophily (Education)* effect was also insignificant.

The *Receiver (Age)* effect was significantly positive, indicating that the elderly were more likely to be learners in the e-commerce diffusion process. In contrast, the estimation of the *Sender (Age)* effect was not significant. We got a significantly negative *Heterophily (Age)* effect (−0.029, with 95%CI [−0.036, −0.008]). With the age gap between two nodes increasing, the probability of formation of diffusion ties would decrease. Namely, villagers are more likely to share e-commerce know-how with people of similar ages.

Clans and production teams are the organizational attributes of households that we focus on in this study. We found that different groups did make different contributions to the e-commerce diffusion to some extent in this village. Nodes belonging to some clans (or production teams) were more likely to form diffusion ties. E-commerce diffusion is more likely between farmers in the same rural organization. The results of the nodal *Homophily (Production team)* effect show that villagers affiliated with the same production teams are more likely to share e-commerce know-how (0.472, with 95% CI [0.178, 0.742]). However, we noticed that the *Homophily (Clan)* effect was not significant in Model 1 (0.239, with 95% CI [−0.45, 0.556]). We considered that including the *Family Network* effect in this model led to such a result because the dyads with the same clans overlapped significantly with dyads in this exogenous covariate network. After controlling for the *Family Network*, the *Homophily (Clans)* effect is no longer significant, suggesting that the homophily of clans did not have an additional impact on e-commerce diffusion network formation.

4.1.3. Effects of the three rural social networks

The effects of three rural social networks, namely *Neighborhood Network*, *Family Network*, and *Peer-group Network*, were all significantly positive (1.097, 1.109, and 2.323, with 95% CI [0.338, 1.772], [0.497, 3.82], and [1.587, 2.82] respectively). Each significant and positive parameter meant that the ties indicating diffusion trajectories and ties within the corresponding network were entrained. These results revealed that all three are essential to contribute to the formation and evolution of e-commerce diffusion networks.

[7] In this study, we collected network data in the villages by household. Therefore, we also measured the nodal attributes by household. However, some attributes should be measured by the individual in general cases—age and education level. We measured the nodal age attribute with the age of the household’s youngest member over 16. We measured the nodal education level with the highest education level of the household members. We included the nodal attribute of *Production*, which indicates whether households had engaged in costume production. Because those households involved in costume production may have had earlier exposure to e-commerce and, therefore, were more likely to become e-commerce knowledge exporters.

[8] The endogenous structural effects include the following—first, the basic effects, i.e., the reciprocity effect; second, the triadic effects such as the transitive triplets; third, the degree-related effects, including the *Popularity (Indegree)*, *Activity (Outdegree)*, and *Popularity (Outdegree)* (or *Activity (Indegree)*) effects. These are slightly different from the endogenous structural effects specified in TERGM. We will show this in detail in Section 4.

Table 1
TERGM analysis of e-commerce diffusion network.

Effects	Model I (2009–2019)		Model II (2009–2012)		Model III (2012–2019)	
	p.e.	**95% CI**	**p.e.**	**95% CI**	**p.e.**	**95% CI**
Network Structural Effects						
Edges	**−10.004**	**[−13.187, −6.857]**	**−7.154**	**[−10.033, −4.275]**	**−7.106**	**[−12.382, −1.83]**
Reciprocity	0.663	[-1.678, 1.982]	−1.028	[−2.416, 0.360]	0.308	[−1.260, 1.876]
Two-path	**−0.355**	**[-0.617, -0.227]**	**−0.365**	**[-0.586, -0.144]**	−0.183	[-0.373, 0.007]
Isolates	**0.993**	**[0.255, 2.280]**	**2.942**	**[2.095, 3.789]**	−0.105	[-0.803, 0.593]
Popularity (In-degree)	0.399	[-0.368, 1.508]	**1.552**	**[0.121, 2.983]**	1.084	[-0.247, 2.415]
Activity (Out-degree)	**−1.873**	**[-2.509, -1.173]**	**−1.662**	**[-2.544, -0.78]**	**−2.251**	**[-3.145, -1.357]**
Transitive Triplets	0.388	[-0.216, 1.124]	0.326	[-0.335, 0.987]	−1.086	[-2.487, 0.315]
Nodal attribute: Education						
Sender (Junior Middle School)	0.443	[-0.186, 0.995]	0.552	[-0.126, 1.230]	0.206	[-0.876, 1.288]
Sender (High School)	0.470	[-0.286, 1.048]	0.194	[-0.486, 0.874]	0.593	[-0.491, 1.677]
Sender (University and above)	0.450	[-0.358, 1.057]	0.074	[-0.645, 0.793]	0.776	[-0.355, 1.907]
Receiver (Junior Middle School)	−0.086	[-0.393, 0.27]	−0.438	[-1.132, 0.256]	−0.001	[-0.905, 0.903]
Receiver (High School)	0.165	[-0.269, 0.629]	0.191	[-0.362, 0.744]	0.218	[-0.791, 1.227]
Receiver (University and above)	0.246	[-0.692, 0.755]	0.167	[-0.523, 0.857]	0.086	[-0.951, 1.123]
Sender (Age)	−0.028	[-0.049, 0.002]	−0.006	[-0.033, 0.021]	**−0.046**	**[-0.087, -0.005]**
Receiver (Age)	**0.032**	**[0.018, 0.046]**	**0.037**	**[0.008, 0.066]**	**0.048**	**[0.009, 0.087]**
Sender (Production)	0.486	[-0.177, 1.048]	0.342	[-0.332, 1.016]	0.582	[-0.312, 1.476]
Receiver (Production)	−0.630	[-5.367, 0.114]	−0.045	[-1.027, 0.937]	−1.133	[-2.826, 0.56]
Sender (Labor Force)	−0.196	[-0.528, 0.362]	0.117	[-0.191, 0.425]	−0.375	[-0.834, 0.084]
Receiver (Labor Force)	0.127	[-0.188, 0.347]	0.254	[-0.167, 0.675]	0.292	[-0.149, 0.733]
Nodal attribute: Clans						
Clan 2	**0.998**	**[0.402, 1.500]**	0.597	[-0.348, 1.542]	0.963	[-1.032, 2.958]
Clan 3	−0.648	[-1.468, 0.006]	**−0.799**	**[-1.577, -0.021]**	0.374	[-0.982, 1.730]
Clan 4	0.375	[-0.436, 0.778]	−0.228	[-0.894, 0.438]	0.741	[-0.472, 1.954]
Clan 5	0.024	[-0.384, 0.415]	−0.130	[-0.777, 0.517]	0.116	[-0.942, 1.174]
Clan 6	0.475	[-0.192, 1.053]	0.224	[-0.462, 0.91]	0.789	[-0.542, 2.12]
Nodal attribute: Production teams						
Team 2	**1.630**	**[0.731, 3.015]**	**1.376**	**[0.161, 2.591]**	0.576	[-1.749, 2.901]
Team 3	0.788	[-0.463, 1.214]	**0.919**	**[0.121, 1.717]**	0.183	[-1.557, 1.923]
Team 4	**1.147**	**[0.406, 1.974]**	0.913	[-0.053, 1.879]	1.031	[-0.972, 3.034]
Team 5	**1.579**	**[0.767, 2.579]**	0.890	[-0.100, 1.880]	1.317	[-0.663, 3.297]
Heterophily (Age)	**−0.029**	**[-0.036, -0.008]**	−0.008	[-0.039, 0.023]	**−0.043**	**[-0.082, -0.004]**
Homophily (Production Team)	**0.472**	**[0.178, 0.742]**	0.424	[-0.184, 1.032]	0.394	[-0.380, 1.168]
Homophily (Clan)	0.239	[-0.45, 0.556]	0.255	[-0.364, 0.874]	0.443	[-0.376, 1.262]
Homophily (Education)	−0.194	[-0.693, 0.334]	−0.065	[-0.600, 0.470]	−0.130	[-0.745, 0.485]
Network Covariates						
Neighborhood Network	**1.097**	**[0.338, 1.772]**	**1.812**	**[1.130, 2.494]**	**1.375**	**[0.538, 2.212]**
Family Network	**1.109**	**[0.497, 3.82]**	**1.212**	**[0.199, 2.225]**	**1.579**	**[0.652, 2.506]**
Peer-group Network	**2.323**	**[1.587, 2.82]**	**1.831**	**[1.151, 2.511]**	**2.478**	**[1.714, 3.242]**
TERGM –Memory Term	**27.233**	**[25.247, 28.838]**	–	–	–	–
TERGM - Time Covariate	**0.101**	**[0.062, 0.265]**	**−0.210**	**[-0.361, -0.059]**	**−0.487**	**[-0.673, -0.301]**

Note: (1) The bold parameters are significant and worth noting; (2) For *Education*, we set "Primary school and below" as the reference group; for Clans and Production teams, we set the first group of both two as the reference groups.

4.2. Result of SAOM

In this section, we will report the results of the SAOM analysis. According to (Snijders et al., 2010), SAOM has some requirements for dynamic network data. Before reporting the parameters estimation result of the model, we report the results of checking data requirements first.

Check data requirements. SAOM analysis requires a certain amount of actors in the network and observations ("panel waves") because the amount of information to be used in estimating the model depends on them. There are some rules of thumb: (1) the number of actors should be greater than 20; (2) the number of observations should be at least 2, but usually much less than 10. The former is easily satisfied in our case. As for the second, the network panel we constructed in this study contains 11 e-commerce diffusion network snapshots from 2009 to 2019. It seems not to meet the second requirement above. However, it is suggested that there are no problems with analyzing a larger number of time points. It is necessary to check whether the parameters remain constant over time or whether the temporal heterogeneity of effects should not be ignored.

SAOM requires that the dynamic network data provides sufficient information for estimating the model parameters, while the observed dynamic network should satisfy the requirement of gradual change, which is another basic assumption of this model. The thumb rules for checking these assumptions include the following. First, the total number of network changes should be large enough, and a total of 40 changes during all periods is the low side requirement. Second, the Jaccard index is used to judge whether the change process of a dynamic network is gradual. For a growing dynamic network, the Jaccard index should preferably be higher than 0.6 for each period; between 0.3 and 0.6 would be low but may still be acceptable. But if the Jaccard index is less than 0.2, the assumption of gradual changes may be violated. In our case, the total number of changes is 151, and the Jaccard indexes are all more than 0.6 for every wave (except the first wave).[9] (See Table S2 in Supplementary Materials).

Model goodness-of-fit, convergence check and collinearity check. We specified SAOM using the strategy of combining forward and backward steps as described in 3.4. The goodness-of-fit of the final model we selected is acceptable, and the algorithm's convergence also meets the requirements. The overall maximum convergence ratio is 0.130, less than the required 0.25, and the largest absolute value of the t-ratio for convergence is 0.064, which is less than the required 0.1 (the t-

[9] This requirement can be relaxed for the first wave since the graph density is usually low in the initial stage of the dynamic network evolution.

ratios of all individual parameters are given in Table 2). We also checked whether the estimated model had trouble with collinearity. The covariance matrix of the estimates was calculated. The correlations between parameter estimates presented in the covariance matrix all meet the requirement of the thumb rule, so the collinearity should not be worried (Section 4 of Supplementary Materials offers the details).

4.2.1. Interpretation of SAOM parameters

Regarding the SAOM parameters, we prioritize interpreting the impacts of three types of rural social networks, as they are relevant to the core research question of social capital transformation addressed in this paper. The results from the SAOM align with those from the TERGM for the parameters indicating the effects of three social networks. *Neighborhood Network*, *Family Network,* and *Peer-group Network* parameters in the SAOM are 1.337, 1.580, and 2.315, respectively, with p-values all less than 0.001. These results suggest that all three networks significantly contribute to the formation of the e-commerce diffusion network. Further, the SAOM analysis enables us to compare the relative importance of effects within the same model. For obtaining the relative importance of the networks' effects, this study applies the method provided by the literature (Indlekofer and Brandes, 2013), which shows that the peer-group network has the most significant influence on the e-commerce diffusion network dynamics, with a value of 0.034, while the values of neighborhood network and family network are 0.013 and 0.010, respectively.

The TERGM and SAOM presented in Tables 1 and 2 included different network structural effects and node attribute effects due to differences in their model specification and selection methods, as introduced in Section 3.4. Based on the respective model specification and selection methods, some network structure effects were included in SAOM but not in TERGM, for instance, *Popularity (Out-degree)* and *Balance*. Snijders et al. (2010) required that both of them should be included in the SAOM as a primary triad effect. In fact, the model including them does have a better SAOM goodness-of-fit performance. The parameter of the *Popularity (Out-degree)* effect is significantly negative (-6.746, $p < 0.001$), indicating that households with more outgoing edges are less likely to receive ingoing edges simultaneously. It is coherent with the actors' logic of technology diffusion. Actors who could export more must be skilled masters and naturally do not need to consult others. The significant negative parameter of the *Balance* effect (-6.584, $p < 0.001$) implies that households with similar learning sources are less likely to share their e-commerce experience with each other.

The parameter estimates for most node attribute effects in SAOM analysis are similar to their counterparts in TERGM. The age effects are very stable in both two models. The *Alter (Age)* effect, similar to the *Receiver (Age)* effect in TERGM, is significantly positive (0.033, $p = 0.007$), indicating that the elderly are more likely to consult others; the *Ego (Age)* effect is not significant in SAOM (-0.074, $p = 0.127$),[10] like the *Sender (Age)* effect in TERGM. The *Difference (Age)* effect is significantly negative (-0.036, $p = 0.032$), indicating that people of similar ages tend to share e-commerce know-how with each other. The parameter of *Homophily (Production Team)* effect revealed by SAOM is also consistent with the TERGM. Households are more inclined to select other households from the same production team as the recipients of their outgoing edges. In other words, they were more likely to impart the skills of operating e-commerce to fellow production team members.

Additionally, some findings of the network structure effects and node attribute effects identified by SAOM analysis are not aligned with those obtained from TERGM analysis. For instance, in the SAOM analysis, the *Transitive Triplets* and *Popularity (In-degree)* effects are significantly positive, whereas they appear insignificant in the TERGM analysis. Similarly, the *Alter (Production)* effect is significantly negative only in the SAOM analysis, but its counterpart in TERGM (*Receiver (Production)* effect) is not found to be significant. Regarding these contrasting results, we tend to rely on the findings yielded by TERGM, as discussed in Section 3.4. Although SAOM assumes nodes' agency, this assumption may be somewhat limited. In contrast, the assumptions of TERGM might be more comprehensive and applicable to this study.

4.3. Temporal heterogeneity of effects

The analysis using TERGM and SAOM above assumed that parameters are constant across different periods of network formation, i.e., the network dynamic evolution is driven by a uniform underlying model instead of different models of several periods. As mentioned earlier, for SAOM, it is necessary to check whether the parameters change over time when the number of observations grows larger. For the empirical case in this study, besides identifying rural networks' contributions to e-commerce diffusion, we also want to know whether the roles played by the three networks would change over time. In other words, we are also interested in the temporal heterogeneity of the effects.

More specifically, we hope to answer such an empirical question of whether social capital would transform more effectively in the earlier stage of ECV development. As discussed in Section 2.2, during the development process of many ECVs in China, various types of social actors were triggered to enter and provide support after e-commerce had diffused to some extent in villages, including Dinglou Village. Once the local government discovered that some farmers were already engaging in e-commerce spontaneously, it began allocating resources to support them. For instance, the government ordered local banks to provide convenient loans to households interested in e-commerce operations, allocated land for e-commerce households to help them expand their business, and even reduced or remitted taxes for villagers who had just started their businesses. The local government also organized various types of e-commerce training sessions to help beginners master the skills necessary for operating e-shops. These actions could create a favorable environment for villagers' e-commerce entrepreneurship (Qiu and Qiao, 2021). Moreover, investigating whether the social network effect reduces as more external supportive forces become involved in the development process of ECV also constitutes an essential part of our study of social capital transformation from a dynamic perspective. An analysis of the temporal heterogeneity of effects will help us answer this question.

For TERGM, we first used the approach proposed in the literature (Cranmer et al., 2012, 2014) to estimate the separated model for different periods. Related results are presented as Model II and Model III in Table 1. The year 2012 was the crucial watershed time-point for the development of Dinglou Village (Qiu and Qiao, 2021). Therefore, we divided 2009–2019 into two periods, with 2012 as the cut-point. The results showed that the effects of all three social networks were statistically significant at the 0.05 level in both two periods. In terms of effect size, only the neighborhood network effect decreases after 2012 compared to the earlier period, while the other two even increase to some extent after 2012. In order to test whether these effect size changes are statistically significant, we estimated the interaction terms of these three network variables and the time covariate. It is found that the effect size changes of the neighborhood network and the family network are not significant. The parameter of the interaction term of the peer-group network and the time covariate is significantly positive (0.759 with 95% CI [1.034, 1.666]).

We obtained similar results using SAOM (Model V and Model VI). The effect size changes of the *Neighborhood Network* and *Family Network* are insignificant (p-values are 0.243 and 0.762, respectively) using the

[10] Although the *Ego (Age)* effect is insignificant, we still included it in the model due to the significance of the *Alter (Age)* effect and *Difference (Age)* effect at the 0.05 level, following Snijders et al. (2010). Doing so allows us to test the overall effect of the nodal age attribute. The Wald test results show the chi-square equal to 8.66 with $df = 3$, $p = 0.034$. This evidence expresses that the e-commerce diffusion network dynamic depends on age.

Table 2
SAOM analysis of e-commerce diffusion network.

	Model IV (2009–2019)				Model V (2009–2012)				Model VI (2012–2019)			
	p.e.	s.e.	p-value	t-ratio	p.e.	s.e.	p-value	t-ratio	p.e.	s.e.	p-value	t-ratio
Reciprocity	8.334	0.941	0.000	−0.009	25.529	3.072	0.000	−0.017	6.038	1.277	0.000	−0.131
Transitive triplets	13.277	0.976	0.000	−0.041	47.589	2.991	0.000	0.012	7.251	3.084	0.019	0.011
Balance	−6.584	0.426	0.000	0.064	−23.508	1.488	0.000	−0.095	−4.590	0.613	0.000	−0.009
Popularity (In-degree)	0.242	0.090	0.007	−0.029	0.505	0.156	0.001	0.023	−0.089	0.173	0.608	−0.048
Popularity (Out-degree)	−6.746	0.492	0.000	−0.023	−23.934	2.020	0.000	0.013	−4.610	0.701	0.000	−0.027
Homophily (Production Team)	0.543	0.209	0.009	−0.013	0.515	0.312	0.098	−0.025	0.573	0.301	0.057	−0.065
Alter (Age)	0.033	0.012	0.007	−0.016	0.037	0.017	0.024	−0.005	0.027	0.017	0.117	0.011
Ego (Age)	−0.074	0.049	0.127	−0.046	−0.018	0.042	0.668	−0.074	−0.161	0.109	0.138	−0.034
Difference (Age)	−0.036	0.017	0.032	0.051	−0.021	0.023	0.346	−0.051	−0.045	0.023	0.051	−0.024
Alter (Production)	−0.887	0.374	0.018	0.024	−0.245	0.680	0.719	−0.069	−1.321	0.498	0.008	−0.112
Alter (Duration)	−0.963	0.204	0.000	0.024	−2.090	1.003	0.037	0.050	−0.790	0.208	0.000	−0.091
Neighborhood Network	1.337	0.289	0.000	0.032	1.765	0.383	0.000	−0.104	1.057	0.471	0.025	−0.077
Family Network	1.580	0.364	0.000	0.060	1.475	0.547	0.007	−0.057	1.709	0.543	0.002	−0.044
Peer-group Network	2.315	0.248	0.000	0.014	1.736	0.352	0.000	0.009	2.847	0.336	0.000	−0.066
Period 1	1.0671	0.2359			2.0892	0.4751			0.5798	0.1006		
Period 2	0.7598	0.1823			1.1461	0.2817			0.4366	0.0828		
Period 3	0.8952	0.1832			1.2347	0.2497			0.1529	0.047		
Period 4	0.8628	0.1503							0.096	0.0381		
Period 5	0.5551	0.1055							0.032	0.0226		
Period 6	0.1757	0.0537							0.0164	0.0166		
Period 7	0.1053	0.0428							0.0856	0.0399		
Period 8	0.0344	0.0239										
Period 9	0.0162	0.0159										
Period 10	0.0839	0.0371										

Notes: The variable *Duration* measured a nodal attribute which indicates how long a household had been involved in e-commerce operation. The homologous counterpart did not be included in TERGM. However, we found that including *Alter (Duration)* in SAOM would improve model goodness-of-fit significantly, and the result that the parameter estimation of *Alter (Duration)* revealed also conforms to reality and our empirical expectation.

method provided by (Ripley et al., 2019). The effect size of the *Peer--group Network* increased significantly after 2012 ($p = 0.022$).[11] Thus, there is no evidence suggesting that the contributions of three social networks to e-commerce diffusion were depleted after 2012, along with more social actors, especially local government, involved. That is to say, social capital does not transform more effectively only in the earlier stage of ECV, and the contribution of peer-group network even became more extraordinary in the post-period of ECV development.

5. Conclusion and discussion

With the widespread usage of ICT, e-commerce has become increasingly popular in rural China over the past decade. E-commerce with Chinese characteristics, such as e-commerce village (ECV), has emerged as a unique rural development phenomenon in China. Many studies have sought to explain the emergence of ECV, which is also concerned in this study. The emergence of ECV is regarded as a result of the diffusion of e-commerce as an innovation, and we hope to understand this phenomenon by examining the formation of an e-commerce diffusion network in a typical rural community. We have analyzed whether rural social networks contribute to the diffusion of e-commerce in China's ECV. The results provide empirical evidence for the assertion that the transformation of existing social capital in a rural community supports the e-commerce diffusion and facilitates the rural community development of ECV. By introducing the measurement of interpersonal networks, we can avoid the individual-blame bias often associated with Ryan's innovation diffusion research approach. We collect data on the e-commerce diffusion network dynamics in a typical ECV by tracing the trajectories of e-commerce diffusion. With the development of generative network statistical models such as ERGMs, we are able to infer the process and mechanism of e-commerce diffusion network formation by analyzing the network dynamic data we collected using these models. Furthermore, this allowed us to examine the dynamic process of existing social capital transformation within the village.

This study uses two network statistical models, TERGM and SAOM, to analyze the e-commerce diffusion network data collected in the Dinglou Village of Cao County, located in Shandong Province of China. We use these data to restore the dynamic process of e-commerce diffusion network formation from 2009 to 2019. We have found that the existing rural social capital did transform and positively influence the development of ECV. The neighborhood, family, and peer-group networks all contributed to the formation of the e-commerce diffusion network.

In addition, our analysis of temporal heterogeneity of effects reveals that social capital did not transform more effectively in the earlier spontaneous growth stage of ECV than later. Factually, social capital transformation occurred throughout the pre-period and post-period of ECV. The contributions of three social networks to the e-commerce diffusion network dynamic were not depleted even with external intervention. The effect of the peer-group network became even greater after the year 2012.

The findings about the effects of the three rural networks above are robust in both network statistical models. The other findings on the network structural effects and the node attribute effects are also illuminating, but some of them are not consistent in two types of models. The conclusions regarding nodes' age attribute effect are relatively consistent and clear. The elderly are more likely to consult others about how to operate e-commerce, but the tendency of the younger to become senders seems not to be noticeable. The heterophily effects of age are significant in both two models. Especially after 2012, people of similar age tended to share e-commerce know-how, which might be crucial for

[11] The literature (Ripley et al., 2019) tests it in this way: if $\widehat{\beta_1}$ is the estimated parameter of one effect in period 1, and $\widehat{\beta_2}$ is the estimated parameter of the same effect in period 2. se_1 and se_2 present standard error of these two estimations, respectively. Then the difference between these two parameters can be tested with the following statistic.

$$\frac{\widehat{\beta_1} - \widehat{\beta_2}}{\sqrt{se_1^2 + se_2^2}}$$

which has an approximating standard normal distribution, and the null hypothesis is $\beta_1 = \beta_2$.

ECV development.

However, this study still has many limitations. First, the study is based on a single case, so all the conclusions drawn from this study are specific to Dinglou Village. As a common problem in almost all holistic network studies, we also face the problem of generalizing the conclusions. One possible path to address this problem is to construct a representative sample of rural communities and then collect network data for every village in this sample. Researchers can apply the same model to analyze each network and synthesize the results using meta-analysis or other statistical techniques like the multilevel model (Smith et al., 2016; Lazega and Snijders, 2016). Using this approach does have the potential to yield conclusions with more generalizability, but the difficulty lies in the high survey costs.

The second limitation of this study is that we used retrospective network panel data to track network dynamics. The major problem with that is the respondents' memory bias. Especially, capturing network dynamics through a retrospective approach is challenging for certain relationship types. For example, the peer-group network in reality would also change over time in reality. People would make new friends and also might alienate some of their friends. This study treated the peer-group network as a static snapshot, i.e., we assumed that the peer-group network had not changed for over ten years, which was considered reasonable in rural Chinese acquaintance society, where termination of social ties would rarely happen. Admittedly, it is the second-best option. Solving this problem might depend on improving survey implement in the future.

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Data availability

The authors do not have permission to share data.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jrurstud.2023.103101.

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