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Social influences in network and households' e-commerce entrepreneurship in rural China

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ABSTRACT

This paper aims to understand the actions of farmers in adopting e-commerce technology for entrepreneurship in China's "Taobao Village" from the perspective of social influence. Drawing on first-hand data collected through field surveys in Dinglou, a typical Taobao Village in Northern China, the study employs the network autocorrelation model to investigate how social influences in network shape farmers' engagement in e-commerce entrepreneurial activities. Our findings reveal that a farmer's decision to participate in e-commerce is influenced not only by their directly connected friends in social network but also by other people occupying similar structural positions. However, the influence between structurally equivalent households is characterized by negative suppression, contrasting with previous research findings. By leveraging longitudinal data on household e-commerce entrepreneurship along with the temporal network autocorrelation model, we analyze the evolving dynamics of social influences throughout the different development stages of Taobao Village. Finally, we discuss the theoretical implications of these results.

1. Introduction

The rapid growth of e-commerce platforms has significantly changed how people make everyday purchases and created new business opportunities. Over the past decade in rural China, utilizing digital technology through these platforms has become essential for many households to benefit from technological advancements and share the development dividends in the digital era (Qiu and Qiao, 2021; Li et al., 2023; Peng et al., 2024). The number of 'Taobao Villages'[1] – rural areas with thriving e-commerce businesses – has increased dramatically (Luo and Sheng, 2018; Alibaba Research Institute, 2019). These villages have brought about a comprehensive rural transformation encompassing farmers' daily lives and livelihoods, rural industrial development, and urban–rural integration (Lin et al., 2016; Wang et al., 2021; Phelps et al., 2022; Zhang et al., 2023). Many previously economically disadvantaged rural regions have achieved poverty reduction and economic growth through e-commerce (World Bank and Alibaba Group, 2019).

The development of Taobao Villages originated from individual rural households adopting e-commerce technologies to pursue entrepreneurship. Studies also show that e-commerce entrepreneurship among farmers positively influences their income and sense of achievement (Zeng et al., 2018; Luo and Niu, 2019). Through in-depth field studies across various Taobao Villages, a significant social fact has been observed: despite being exposed to the same technology application environment, farmers exhibit diverse reactions to the opportunities arising from technological change. Some embrace e-commerce and initiate their businesses promptly, while others take a more cautious approach, delaying their involvement. Additionally, some decide to refrain from participating in these opportunities.

An individualistic theoretical perspective is often adopted to explore why farmers adopt e-commerce technology and engage in entrepreneurial activities. This approach posits whether adopting technology is a function of individual farmers' or households' specific endowment factors (van Dijk, 2012; Ma, 2017; Liu et al., 2019, 2021).

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[1] Among China's many popular e-commerce platforms, Alibaba Group's *Taobao.com* remains one of the most influential. Others include *jd.com*, *Pinduoduo* and so on. The concept of 'Taobao Villages' was initially established by Alibaba Research Institute in 2013 to identify rural e-commerce clusters based on data from various e-commerce platforms under Alibaba Group. Although the term originally referred specifically to Taobao-based commerce, it has evolved to encompass rural e-commerce clusters regardless of the platforms used by merchants. These villages serve as valuable case studies for assessing rural e-commerce development more generally. According to Alibaba Research Institute's annual report since 2013, 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) (Alibaba Research Institute, 2019).

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Sociologists typically argue that this understanding needs to be revised, primarily because it fails to account for the broader social context (Granovetter, 1985; Rogers, 2003). Network analysis offers practical tools from a relational perspective. It allows for a more comprehensive examination of the social context and the social influences within it. The theory of social embeddedness of economic action in New Economic Sociology provides the theoretical foundation for this perspective. Granovetter (1985) emphasized that economic actions are embedded in social relations and networks. Therefore, by investigating the social interactions and influences in networks, we can better understand the social forces that shape individual technology adoption decisions, addressing the explanatory gaps left by the individualistic perspective. Beyond sociology, many researchers in industrial economics have also recognized the importance of social relations and similarly paid attention to the issue of the social embeddedness of entrepreneurial activities. Nevertheless, within the entrepreneurship literature, substantial room remains for further investigation into the relationship between social networks and entrepreneurship. Previous studies on entrepreneurship have largely drawn on the sociological concept of social capital to analyze the linkages between relational networks and entrepreneurial outcomes. However, the diverse interpretations of social capital require a precise conceptual clarification. The instrumentalist interpretation conceptualizes social capital as "relations as resources" (Lin, 2002), essentially reducing it to an individual endowment, thereby aligning with the individualistic perspective. Alternatively, the macro-level approach treats social capital as a community characteristic (Putnam, 2000; Portes, 1998). While this perspective is widely discussed, related studies tend to be overly general, and there remains considerable debate over whether the network features conceptualized under this approach actually promote or hinder entrepreneurship (Westlund and Bolton, 2003).

Examining social embeddedness of entrepreneurship through the lens of social capital fails to address specific modes of social influence. This study uses first-hand data collected from a field survey in a prominent Taobao Village in China. Based on a measurement of the rural community's whole social network structure, this study examines the social embeddedness of entrepreneurship at the meso-level of social relations, rather than focusing on micro- or macro-level social capital. It aims to understand how the households' actions of adopting e-commerce technology and engaging in e-commerce entrepreneurship in Taobao Village are mutually influenced in their rural social network. Furthermore, given the diversity of social influence mechanisms and the ongoing scholarly debate concerning their relative explanatory power (Burt, 1987; Galaskiewicz and Burt, 1991; Mizruchi, 1993; Huang et al., 2011; Fujimoto and Valente, 2012), this study will closely examine these mechanisms in the context of rural e-commerce entrepreneurship. Additionally, we will consider the emergence of social influence as a process, analyzing how these mechanisms change dynamically over time. This study will provide an empirical case for examining the social embeddedness of entrepreneurship.

The subsequent sections of this paper are organized as follows: Section 2 begins with an overview of the two existing theoretical perspectives on technology adoption, reviews the literature on social influence mechanisms, and concludes by presenting four research hypotheses central to this study. Section 3 introduces the data and analytical methods used, focusing on the Network Autocorrelation Model and a detailed explanation of detecting social influences by setting the weight matrices in the Network Autocorrelation Model. Section 4 presents the analytical results. Section 5 discusses the theoretical implications of these results and some methodological considerations. Section 6 provides the conclusions of this study.

2. Literature review

2.1. Two theoretical perspectives on technology adoption

Individualistic perspective. This perspective focuses on the individual attributes of those who adopt new technologies, a framework extensively utilized by economists and management scholars in technology adoption research. Individual attributes encompass both objective endowment factors and subjective perceptual factors. Early studies on innovation diffusion and the digital divide emphasized the role of objective resource endowments. For instance, van Dijk proposed the "resources and appropriation theory" to explain the acceptance and adoption of new technologies. This theory posits that individuals adopt new technologies based on the resources they are allocated and possess, which in turn are highly correlated with their social status. Consequently, traditional measures of individual status can be employed to account for the variance in technology acceptance and adoption (van Dijk, 2012, 2005). The Technology Acceptance Model, prominent in information systems management, concentrates on subjective perceptions such as perceived usefulness and ease of use. Initially applied in the context of organizational technology adoption, recent research has extended this model to individual e-commerce adoption, examining personal perceptions from an individualistic perspective (Akasarakul et al., 2017).

In research on e-commerce technology adoption and e-commerce entrepreneurial activities among households in rural China, the individualistic perspective has been frequently utilized. Researchers use individual farmers' objective endowment factors or subjective perceptual factors to explain their e-commerce technology adoption behaviors. For instance, empirical studies have examined how age, education level, and household labor force size impact their decision to adopt e-commerce (Liu et al., 2019, 2021). Zeng et al. (2019) found that prior entrepreneurial endeavors positively influence farmers' likelihood of adopting e-commerce. With a similar perspective, Luo and Niu (2019) analyzed a World Bank survey of "Taobao Villages" to highlight that e-commerce participation is higher among households with younger household heads, with secondary education (particularly those with technical and vocational education), urban work experience, and e-commerce knowledge (Luo and Niu, 2019). Some studies concentrate on farmers' subjective intent to engage in e-commerce entrepreneurship, diverging from directly examining their technology adoption behaviors yet still adhering to the logic of the individualistic perspective (Ma, 2017).

The limitation of the individualistic perspective is its pronounced disregard for the social dimensions inherent in technology adoption processes. This perspective suggests that entrepreneurial use of new technology depends solely on individual factors, whether objective endowment factors or subjective perceptual factors. It is believed that this perspective implies an "atomized" assumption of individuals treating households as independent units making autonomous decisions about e-commerce adoption and entrepreneurship. It pays little attention to interactions between households or, at the very least, does not prioritize these interactions as the central focus of its analysis.

Everett M. Rogers, the master of diffusion of innovations theory, pointed out a similar problem: "the individual-blame bias" (Rogers, 2003). He argues that this is one of the main flaws in the traditional innovation diffusion research paradigm, where researchers tend to rely on individual-level factors to explain the innovation adoption and neglect the broader social systems. Rogers attributed this individual-blame bias partly to research methods. The convenience of collecting data from individuals and the ease of measuring individual-level variables have led to a reliance on individual-based sampling surveys. He references Barton (1968) to highlight the challenge of avoiding the "individual-blame bias" inherent in such surveys: *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.* The studies mentioned earlier, which adopt the individualistic perspective, typically collect data through sampling survey methods, potentially perpetuating the individual-blame bias.

Social influence perspective. Sociologists emphasize that human actions are deeply embedded within social contexts, and they criticize research from the individualistic perspective as insufficiently socialized, echoing Rogers' critique of the "individual-blame bias". Granovetter

(1985) asserted that individual actions are embedded in the structures of social relations, necessitating the examination of specific relationships and the network structures they form. Viewing e-commerce entrepreneurship as a socially embedded action (Liu and Zheng, 2011; Leong et al., 2016; Qiu and Huang, 2021), particularly examining how networks influenced farmers' adoption of e-commerce, can address the omission of social context from an individualistic perspective. Moreover, considering that an acquaintance society typically characterizes rural Chinese communities, the influences through interpersonal interactions should not be disregarded.

However, not all studies investigating or analyzing social networks adhere to the social influence perspective. Many studies on rural e-commerce entrepreneurship in China follow an instrumental approach to social network research (Lin, 2002). These studies concentrated on the supportive impact of network relations on farmers' e-commerce entrepreneurship activities (Zeng et al., 2019; Ma and Yang, 2011; Jiang et al., 2014; Tang and Zhou, 2018). Researchers posit that networks can be leveraged to access social resources, with more extensive and diverse networks indicating more affluent social capital, which can provide farmers with the necessary resources and emotional support to engage in e-commerce entrepreneurship or enhance their confidence in entrepreneurial success. Nevertheless, this instrumental approach of network research leans more towards the individualistic perspective, treating social capital obtained through networks as an individual asset and viewing farmers' entrepreneurial actions as a function of social capital factors. Furthermore, such research fails to examine the mutual influences among actors through networks directly, but considers potential mutual influences as "nuisances" in statistical analysis (Mouw, 2003, 2006) rather than as integral components of social context.

Numerous studies extend beyond viewing farmers' social networks merely as social capital to delve into the interactions within these networks, particularly focusing on social influences that occur. For instance, research has shown that in rural China, characterized by the nature of an acquaintance society, e-commerce entrepreneurship becomes highly visible among peasant households through social networks. Dense networks significantly enhance the likelihood of entrepreneurial opportunities being recognized and discovered by others in the community, thereby increasing the potential for imitation and replication. This mechanism may be central to the digital empowerment that has led to the emergence of Taobao Villages (Leong et al., 2016; Yu et al., 2018). Qiu and Huang (2021) further highlights the importance of network density within villages. However, such studies lack concrete and precise measurements of the networks among farmers and their whole structure. Consequently, these studies often rely on intuitive judgments derived from observations and case interviews, which, while insightful, face challenges for validation and hinder more nuanced, in-depth analyses of the specific mechanisms of social influence within the network.

This study aims to deepen understanding of the social influences that have shaped the adoption of e-commerce in rural China by quantitatively evaluating the social network in a specific Taobao Village. Our measurement of the social network extends beyond the size of individual networks to encompass the whole network structure of the community. Note that the social network measured here consists of place-based relations, rather than non-place-based relations formed via social media. The former primarily reflect direct face-to-face interactions, and we deliberately exclude online social connections for now, as their inclusion would further complicate the analysis. Evidence suggests that the role of physical proximity remains important for e-commerce development in China (Zhang et al., 2026). In the context of traditional rural China, investigating such place-based social relations is particularly vital. In the latter part of this literature review and subsequent method section, we explore various mechanisms of social influence and demonstrate how network analysis models can be used to investigate them.

2.2. Mechanisms of social influence

Influence between adjacent households. The influence between adjacent households might be a straightforward hypothesis that posits that the actions of others (B) directly connected to farmer A (ego) affect A's decision-making. Prevailing research on Chinese rural e-commerce often emphasizes this type of influence. Evaluating adjacent influence is akin to assessing how the number of peers who have embraced a specific action in one's network impacts the likelihood of an individual adopting the same action. For instance, studies have shown that the more entrepreneurial role models a farmer has in his/her network, the more likely he/she will make an entrepreneurial decision (Jiang et al., 2014). While this focus on the influence through direct connections within rural networks is valuable, social network scholars have expanded their investigations beyond adjacent influence. They also explore mutual influence between non-adjacent actors — individuals who are not directly connected but may still impact each other's decisions. This perspective has led to competitive theoretical and empirical hypotheses in research (Burt, 1987; Galaskiewicz and Burt, 1991; Podolny et al., 1996).

Influence between non-adjacent households. In her early research on the "invisible college", American sociologist Crane highlighted the significance of non-adjacent connections in social networks (Crane, 1972). However, she did not provide extensive empirical analysis on the potential impacts of such connections. Burt (1987) revisited Coleman and his colleagues' classic study on tetracycline antibiotics adoption (Coleman et al., 1957). He distinguished two models of innovation diffusion: the Cohesion Model and the Structural Equivalence Model. These models correspond to two competing hypotheses regarding physicians' adoption of tetracycline antibiotics. The Cohesion Model aligns with the concept of adjacent influence, suggesting that social influence occurs between directly connected individuals. The closer and more frequent the interactions between ego and alter, the more likely it is that the alter's adoption of innovation will trigger changes in ego. This model follows the approach of Coleman's original research. In contrast, Burt's Structural Equivalence Model suggests that ego and a specific alter, though not necessarily close friends or able to communicate directly (i.e., not directly connected in the social network), can still exert mutual influence. One theoretical explanation for this is that ego and specific alters are positioned similarly within the social structure, a concept sociologists refer to as the reference group. Individuals may adjust their actions based on their perception of others in similar structural positions, even without direct communication.

Structural equivalence, a concept first defined by Harrison White and his colleague (Lorrain and White, 1971), has become a pivotal concept in social network analysis (Wasserman and Faust, 1994) and is integrated into network science as a critical method for assessing node similarity based on network structure information (Newman, 2010). It refers to the similarity between actors (or nodes) based on their positions within a network structure rather than direct connections. Obviously, the Structural Equivalence Model encompasses examining non-adjacency influences. In Fig. 1(left), actors A and B lack direct connections, as do actors A and B, and C and D in Fig. 1(right). Nevertheless, they are structurally equivalent as defined by the concept based on their overall positions in the network. Burt's research found that the Structural Equivalence Model better explained physicians' adoption of new drugs than the Cohesion Model, which only considers direct interactions. He concluded that social influence is more likely to manifest between structurally equivalent actors than solely between those directly connected. A subsequent study by Galaskiewicz and Burt (1991) on the dissemination of evaluative criteria across organizations further supported this assertion.

Within the scope of e-commerce adoption in rural Chinese communities, the question of whether the Structural Equivalence Model provides better explanatory power than the Cohesion Model, which focuses on direct interactions, merits further exploration.

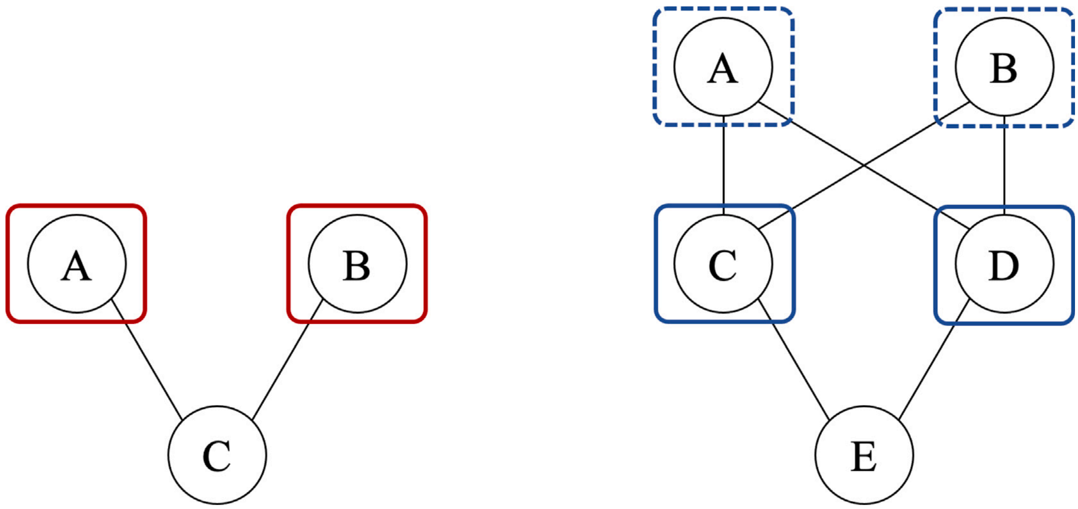

Fig. 1. Structural equivalence.
Note: In the left figure, A and B, enclosed by the red solid line, are structurally equivalent; The right figure illustrates two pairs of structurally equivalent nodes: Nodes A and B, enclosed by a blue dotted line, and nodes C and D, enclosed by a blue solid line. It is important to note that these structurally equivalent nodes are not directly connected in both cases.

Equal social influence. The two scenarios discussed above pertain to differential social influence mechanisms, with a similar assumption that the influences exerted by alters on a particular household within the community are distinct — some specific alters exert influences on egos' decisions (in the case of adjacent influence, specific alters are the alters directly connected to egos; in the structural equivalence model, specific alters are those who are structurally equivalent with egos), while other alters in the community do not. Conversely, an alternative hypothesis proposes that social influence in a community might be more evenly distributed. This concept of equal social influence suggests that every community member exerts a similar level of influence on a household's actions and decisions.

Equal social influence constitutes an extreme case, yet it is theoretically justifiable and empirically conceivable, warranting further examination. Studies on farmers' entrepreneurial behavior often invoke the concept of "entrepreneurial atmosphere" to explain the rise of such behavior. It suggests that a vibrant entrepreneurial atmosphere in a community can enhance farmers' inclination towards entrepreneurship (Jiang and Guo, 2012), and a favorable rural entrepreneurial atmosphere can also foster conducive conditions for entrepreneurial activities (Qiu and Qiao, 2021). Echoing this, literature on Taobao Village's e-commerce initiatives has also put forth analogous views. Sun (2018) based on fieldwork in a famous Taobao Village, noted that in the acquaintance society of rural China, where daily interactions among people are too frequent — captured by the proverb "You cannot avoid seeing each other even if you lower your head" (Chinese 低头不见抬头见) — it is challenging to pinpoint the influence from a specific alter (or some specific alters). Sun proposed "learning within the community" to illustrate how households are influenced by a broad range of community members rather than specific individuals (those who are directly connected or structural equivalence). Similar findings also emerged from our fieldwork in Taobao Villages. We found that villagers often could not identify specific individuals as key influences on their e-commerce engagement. When inquired about the key influences, they frequently said, "It seems that everyone in the village has taken part". Nonetheless, these insights are predominantly qualitative and lack quantitative supporting evidence. Moreover, defining and measuring the entrepreneurial atmosphere in a community also remains challenging. This paper tries to address this gap by measuring the impact of entrepreneurial atmosphere through the lens of equal social influence and to test whether equal social influence indeed occurs in real-world contexts.

The dynamics of social influence. The discussion above has outlined three typical modes of social influence, each with distinct theoretical implications. In the evolution of a Taobao Village, these forms of social influences may not remain constant. Instead, the dominant form of influence could shift across various periods, and more crucially, the underlying mechanisms of social influence may also change. Previous studies have revealed that the initial phase of many Taobao Villages was characterized by positive peer effect, stemming from mutual emulation and knowledge dissemination among households within the community, fostering a climate of reciprocal enhancement. However, as Taobao Village evolved, the proliferation of e-commerce households often led to increased competitive pressures. For instance, a study by Zeng and colleagues (Zeng et al., 2015) on Dongfeng Taobao Village in Suining County, Jiangsu Province, discerned that the rapid expansion of online stores resulted in product homogenization, intensifying intra-community rivalries. This burgeoning competition suggests a potential shift towards negative social influence, indicative of mutual constraint among households.

The population ecology of organizational theory offers insights into similar dynamic shifts in social influence. It emphasizes that competition within an organizational field depends upon the concentration of organizations with similar forms. In the nascent stage of a novel organizational form, a lower density catalyzes a pronounced inclination toward isomorphism in various aspects. Conversely, as the concentration of similar organizations increases, competition intensifies, leading to decreased creation rates and increased mortality rates for organizations (Hannan and Freeman, 1989). These theoretical assertions, known as density dependence hypotheses, have been tested by numerous empirical studies (Baum and Powell, 1995). If e-commerce entrepreneurship in villages also adheres to this density dependence logic, we can expect that the positive mutual influence among households will not remain constant. As competition intensifies, this positive mutual influence may diminish, potentially giving way to the negative mutual influence brought about by competition, particularly in the later stages of Taobao Village.

Based on the review and discussion of the relevant literature and theories, we propose four hypotheses regarding social influence in Taobao Village. These hypotheses will guide the subsequent research presented in this article.

H1: Households' decision to adopt e-commerce technology for entrepreneurial activity is significantly influenced by their adjacent households in the rural network.

H2: Households occupying similar structural positions in the rural network significantly influence each other's decisions to adopt e-commerce technology for entrepreneurial activity.

H3: Nearly every household within the rural community exerts an equal influence on a given household's decision to adopt e-commerce technology for entrepreneurial activity, regardless of specific relationships or network positions.

H4: The ways in which households influence each other within a Taobao Village change significantly across different stages of its development.

3. Method

3.1. Data

This study is based on first-hand data collected through a field survey in Dinglou Village, located in Cao County, southwest Shandong Province, China. Dinglou Village is one of the initial 14 Taobao Villages identified by the Ali Research Institute in 2013 and is among the earliest Taobao Villages in Shandong Province.

Our goal was to conduct a general survey of all the permanent households in this village. Of the 245 permanent households, we successfully interviewed 210. The remaining 35 were not included due to refusal (three cases), health issues (eight cases), or temporary absence during the survey period (24 cases). Nearly 86% of the total target households were successfully interviewed. For a more detailed account of the field survey location and the survey implementation process, kindly refer to the literature (Qiao and Qiu, 2024). As of 2019, more than half of the village households had engaged in e-commerce entrepreneurial activities. After excluding households with members aged 70 or above, our final analysis sample consisted of 184 households. We collected data on households' engagement in e-commerce entrepreneurship, including the timeline of their participation and, where applicable, their exit from the sector. Utilizing the nomination method, we inquired about various types of inter-household relationships. Based on these relational ties, we constructed the rural social network, which forms the core of this study.

3.2. Model

The primary analytical tool employed in this paper is the Network Autocorrelation Model (NAM). This model helps us identify interpersonal social influences occurring through direct or indirect network ties. Notably, Burt (1987) used this method to reanalyze Coleman's data on physicians adopting tetracycline. Leenders (2002) has provided a comprehensive explanation of this model. The NAM can be represented as follow:

$$\boldsymbol{y} = \rho \boldsymbol{W} \boldsymbol{y} + \beta \boldsymbol{X} + \epsilon \tag{1}$$

In this equation, the outcome variable $\boldsymbol{y}$ denotes the action attribute of nodes (actors) within network $\boldsymbol{G}$. For a network $\boldsymbol{G}$ with n nodes, $\boldsymbol{y}$ is an $n \times 1$ vector. In our study, y_i is a binary variable (0 or 1) indicating whether a household has adopted e-commerce for entrepreneurship.

$\boldsymbol{W}$ signifies the weight matrix of mutual influence between nodes in network $\boldsymbol{G}$. Each element w_{ij} of $\boldsymbol{W}$ denotes the influence that actor j has on actor i, with larger values indicating greater influence. By varying this weight matrix, researchers can test different hypotheses regarding different ways of influence, and we will elaborate it in a dedicated section later.

$\boldsymbol{W} \boldsymbol{y}$, the product of the $n \times n$ matrix and the $n \times 1$ vector, results in an $n \times 1$ vector that can be interpreted as a lagged term of the outcome variable $\boldsymbol{y}$. $\boldsymbol{X}$ represents several attributes of the nodes in network $\boldsymbol{G}$, such as the age and educational attainment of households. For k actor attributes, $\boldsymbol{X}$ is an $n \times k$ matrix. This allows us to control for individual characteristics that may affect e-commerce adoption. ρ and β are the key parameters of the model. ρ is the coefficient for the lagged term $\boldsymbol{W} \boldsymbol{y}$, also referred to as the network autocorrelation parameter. It measures the effect that the focal attribute of other individuals (alters) exert on the primary actors (egos). A positive ρ suggests positive social influences through the network, while a negative ρ might indicate negative suppression among their actions. βs represent the correlations between the actor attribute variables in $\boldsymbol{X}$ and the outcome variable $\boldsymbol{y}$. ϵ is the error term, which is normally distributed with a mean of 0 and variance $\epsilon \sim N\left(0, \sigma^2 \boldsymbol{I}\right)$.

We will analyze the retrospective panel data of e-commerce entrepreneurship dynamics using Temporal Network Autocorrelation Models (TNAM). TNAM is an expanded approach of NAM in panel data of complete networks. It can be represented similarly to Eq. (1), in which y_{it} is an attribute measured on actor i at time t, and $\boldsymbol{W}$ can be a time-varying weight matrix containing the repeated network measures (Duxbury, 2022). We estimate NAM using the R package "sna" by Butts (2008) and estimate TNAM using the "tnam" package provided by Leifeld and Cranmer (2017).

3.3. Variables

Outcome variable. In this study, the outcome variable ($\boldsymbol{y}$) is the adoption of e-commerce for entrepreneurial activities by rural households. Households currently engaged in e-commerce entrepreneurship or with experience are coded as '1', while those without experience in e-commerce are coded as '0'. From a network analysis perspective, the decision to adopt e-commerce for entrepreneurial purposes is treated as a distinct node attribute. Our survey reveals a significant adoption rate within the network: 124 households, representing over two-thirds (67.4%) of the total nodes, have adopted e-commerce entrepreneurship.

Other household attribute variables. In our model, represented by Eq. (1), the matrix $\boldsymbol{X}$ includes several key household attributes that may influence e-commerce adoption. Research indicates that education and age significantly correlate with the likelihood of engaging in e-commerce entrepreneurship, relationships that have been emphasized in numerous studies. Specifically, younger individuals with higher education are generally more likely to participate in e-commerce activities (World Bank and Alibaba Group, 2019; Luo and Niu, 2019). To assess the households' educational attainment and age profile, we consider the highest level of education achieved by any household member and the age of the youngest household member who is over 16 years old.

The early producers in Dinglou Village, engaged in production before the advent of e-commerce, had a significant advantage in sourcing and costs during the initial phase of Taobao Village development. This advantage likely made them more inclined to adopt e-commerce technologies for product sales compared to other households. While e-commerce operation by individual households is not typically labor-intensive, having a larger labor force within the family may increase a household's propensity to engage in e-commerce entrepreneurship because they can operate without hiring external employees, conferring a cost-efficiency advantage.

Consequently, our model incorporates four independent variables in addition to the rural social network: household education, age, whether an early producer or not, and labor force size. These variables, like the outcome variable — e-commerce adoption, reflect the attributes of nodes within the network.

Rural social network. In addition to the node attributes mentioned above, the social network within the village emerges as the most crucial independent variable of this study. We focus specifically on the peer group network within the village, represented as an undirected graph. This network is constructed based on nominations of brothers, cousins, and intimate friends with whom the interviewees frequently interact. Fig. 2 provides a visualization of this rural social network. The network comprises 331 relational ties in total, with its largest connected component consisting of 139 nodes (76% of all nodes) and 315 ties. The network exhibits an average degree of 3.6, a global clustering coefficient of 0.23, a diameter of 10 within its largest connected component, and an average shortest path length of 3.87.

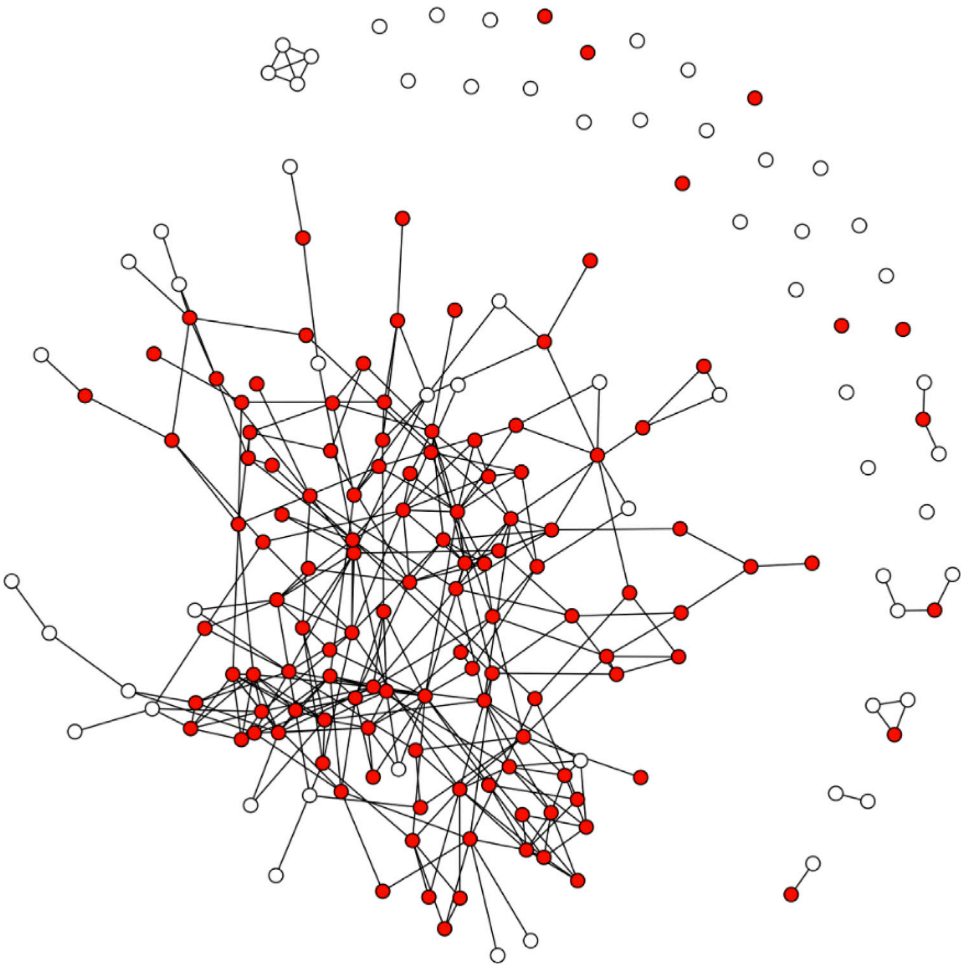

Fig. 2. Rural social network of Dinglou village.

3.4. Analytic strategies

Fig. 3 presents a schematic overview of the analytic strategies used in this study. Our investigation begins with an analysis of cross-sectional data on e-commerce entrepreneurship in Dinglou Village, which captures a snapshot of the activities at the time of the survey. We employ several NAMs for the dependent variable, incorporating the previously mentioned node attribute variables and weight matrices derived from the rural social network to identify social influences.

To identify social influence and explore the distinct mechanisms of social influence, we have defined five weight matrices: (1) the original adjacency matrix, (2) row normalization of adjacency matrix, (3) column normalization of adjacency matrix, (4) structural equivalence proximity matrix, and (5) equal influence weight matrix. Should the network autocorrelation parameter (ρ) estimated using any of (1) to (3) be statistically significant and the model including it fit well, this would confirm the influence between adjacent households (to test **H1**); (4) is used to capture the influences among households with similarly structural positions in social network (i.e., structural equivalent households) (to test **H2**); and (5) is used to test **H3**.

Following the cross-sectional analysis, we will expand our investigation to longitudinal data, tracking households' engagement in and withdrawal from e-commerce entrepreneurship over a decade. This extended analysis will employ TNAMs. These models will not only corroborate the findings from the cross-sectional analysis but also allow us to explore the evolution of network autocorrelation parameters over time. This examination aims to test **H4**, which elucidates the dynamic changes in social influence related to the progression of e-commerce development.

The following sections will introduce the theoretical and empirical implications of these five weight matrices used in NAMs. Following the introduction, we will present the results of our model estimations.

3.5. Specify the weight matrices for social influence analysis

3.5.1. The original adjacency matrix

Incorporating the original adjacency matrix of a relationship network (denoted as $\boldsymbol{A}$) as the influence weight matrix into an NAM is the most straightforward and fundamental method for estimating the influence between directly connected nodes. Utilizing the original adjacency matrix yields an absolute (not relative) measure of influence between nodes. Each element of the adjacency matrix $\boldsymbol{A}$, represented as a_{ij}, signifies the presence of a connection between nodes i and j.

3.5.2. Row/column normalization of adjacency matrix

Leenders (2002) suggested normalizing adjacency matrix to specify $\boldsymbol{W}$ when considering theoretically specific network autocorrelation processes. The most common way to specify $\boldsymbol{W}$ is to set the row normalization of $\boldsymbol{A}$.

$$w_{ij} = \frac{a_{ij}}{a_{i.}}$$

with $a_{i.} = \sum_i a_{ij}$, the ith row sum of $\boldsymbol{A}$. So $a_{i.}$ denotes the number of actors to whom i has a tie.

Leenders also proposed another way to specify normalized matrix, that is column normalization of $\boldsymbol{A}$, but it is less commonly used:

$$w_{ij} = \frac{a_{ij}}{a_{.j}}$$

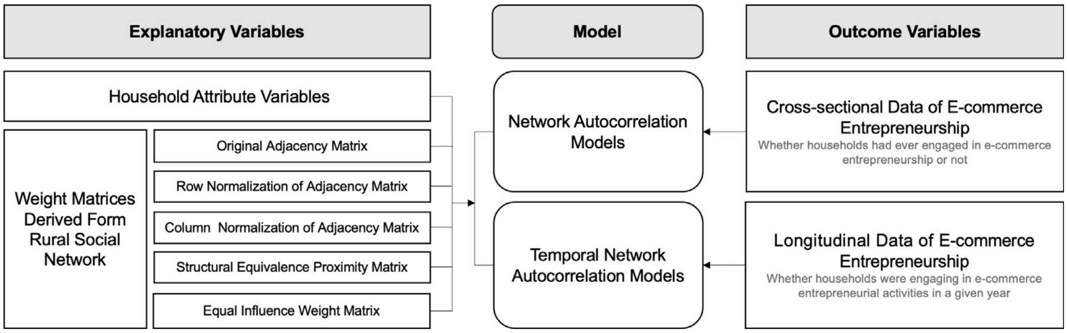

Fig. 3. Analytic strategies.

with $a_{.j} = \sum_j a_{ij}$, the jth column sum of $\boldsymbol{A}$.

These two normalization methods reflect distinct theoretical assumptions regarding the influence accepted or exerted. Row normalization assumes that each actor receives the same total amount of influence from all actors. Consequently, the influence accepted by i from j decreases as the number of actors influencing i increases. Conversely, column normalization posits that each actor exerts the same total amount of influence on all actors. Thus, the influence exerted by j on i decreases as the number of actors that j influences increases. We will compare the models' goodness-of-fit to determine which assumption more closely aligns with reality.

3.5.3. Structural equivalence proximity matrix and equal influence weight matrix

Burt and Doreian (1982) introduced a method for constructing a structural equivalence proximity matrix based on the structural distance (d_{ij})[2] between two nodes. A small structural distance indicates that two actors are structurally equivalent, suggesting a high degree of similarity in their network positions. The elements of the structural equivalence proximity matrix can be expressed as

$$w_{ij} = \frac{l_{ji}}{1 - l_{ii}}$$

where,

$$l_{ij} = \frac{(d_j - d_{ij})^{\upsilon}}{\sum_{q=1}^{g} (d_j - d_{qj})^{\upsilon}} \qquad (2)$$

The term l_{ij} is referred to as the structural-proximity coefficient, where $d_j = \max_i(d_{ij})$ represents the maximum structural distance for actor i across all nodes. The structural-proximity coefficient l_{ij} measures the perceived structural similarity between actor i and actor j, with values ranging from 0 to 1. The coefficient increases as the structural distance between two nodes decreases; conversely, it decreases as the distance increases. The elements w_{ij} in the constructed weight matrix $\boldsymbol{W}$ represent the influence that node i accepts from node j, depending on the perceived structural proximity between i and j. Furthermore, the elements on the main diagonal of matrix $\boldsymbol{W}$ are all zero, that is, $w_{ii} = 0$.

The exponent parameter υ in Eq. (2) is a constant that determines the weight of structural distance when constructing the structural-proximity coefficient, thereby controlling the scope of social influence. A higher υ value emphasizes structural similarity between nodes, indicating that node i primarily perceives and is influenced by alters who are structurally similar to them. A value of υ much larger than 1 indicates that the ego considers only the interests of their closest alters. Conversely, υ approaching zero suggests that node i is influenced by nearly everyone in the network (Leenders, 2002). To test our hypotheses, we construct two influence matrices using different υ values: a structural equivalence proximity matrix ($\upsilon = 2$)[3] and an equal influence weight matrix ($\upsilon = 0.0001$, a value near 0). These matrices are used to examine the structural equivalence influence hypothesis (**H2**) and the equal influence hypothesis (**H3**), respectively.

4. Results

4.1. Household attributes that affect e-commerce adoption

We developed a Linear Probability Model (LPM) incorporating four key household attribute variables listed in Table 1, selected for their potential influence on e-commerce adoption likelihood. We estimated the model parameters using OLS, with results presented in the second column of Table 3. This analysis adopts an individualistic perspective, focusing on how individual household endowments contribute to their e-commerce entrepreneurship.

Our findings reveal a correlation between farmers' educational attainment and e-commerce entrepreneurship behavior. We included educational attainment in the regression as three dummy variables, using primary school or below as the reference category. Households with high school education are significantly more likely to engage in e-commerce entrepreneurship compared to those with only primary school education ($\beta = 0.190$, $p = 0.032$). However, there was no significant difference in e-commerce entrepreneurship likelihood between households with junior high school education and those with primary school education or below ($\beta = 0.039$, $p = 0.606$). Similarly, no significant difference was observed between households with a college education or above and those with a primary school education or below ($\beta = 0.056$, $p = 0.570$).

Among the remaining three household attribute variables, age emerged as the only factor with a significant negative correlation to e-commerce entrepreneurship. This finding indicates that older individuals are less likely to engage in e-commerce entrepreneurial activities ($\beta = -0.017$, $p < 0.001$). While households that had engaged in product production before 2010 showed a higher likelihood of operating e-commerce businesses, this result did not achieve statistical significance

[2] Structural distance (d_{ij}) is defined using Euclidean distance as a measure of structural equivalence. Let x_{ik} be the value of the tie from node i to node k on a single relation. We define a distance measure of structural similarity for actors i and j as Euclidean distance between the ties to and from these nodes. For nodes i and j, $d_{ij} = \sqrt{\sum_{k=1}^{g}[(x_{ik} - x_{jk})^2 + (x_{ki} - x_{kj})^2]}$, $(i \neq k, j \neq k)$. If two nodes are more structurally similar, the structural distance between them will be smaller; if two nodes are structurally equivalent, their structural distance will be equal to zero.

[3] To identify the most appropriate value of the parameter υ for the structural equivalence proximity matrix, we estimate models with integer values of υ ranging from 1 to 10. Our analysis revealed that the model achieved the best goodness-of-fit when $\upsilon = 2$. Consequently, $\upsilon = 2$ is adopted here for computing l_{ij}. We list the goodness-of-fit results for different υ values from 1 to 10 in Appendix A (see Supplementary Materials).

Table 1
Descriptive Analysis of Variables (N = 184).

Variables	Mean	S.D.	Variables	Mean	S.D.
E-commerce adoption	0.674	0.470	Primary school and below	0.277	0.449
Age	36.772	15.899	Junior Middle School	0.337	0.474
Early producer	0.038	0.192	High School	0.228	0.421
Labor Force Size	2.321	0.761	University and above	0.158	0.365

Table 2
Goodness-of-fit of NAMs.

	Weight Matrix	R^2	AIC	Order
Model 1		0.351	179.952	5
Model 2	(I) The original adjacency matrix	0.442	152.035	2
Model 2a	(Ia) Row normalization of adjacency matrix	0.357	172.992	4
Model 2b	(Ib) Column normalization of adjacency matrix	0.399	159.914	3
Model 3[§]	(II) Structural equivalence proximity matrix	0.475	141.706	1
Model 4	(III) Equal influence weight matrix	0.352	181.336	6

Note: § denotes the best-fitting model.

($\beta = 0.160$, $p = 0.286$). Similarly, the correlation between households' labor force size and participation in e-commerce operations was also not statistically significant ($\beta = -0.069$, $p = 0.143$).

The LPM demonstrated a substantial explanatory power, with an R^2 of 0.351, indicating that the model accounts for about 35% of the variation in e-commerce adoption, which is considered a reasonable fit for a linear regression model. However, it is essential to note that the individualistic perspective has inherent limitations that cannot be overcome using this model. A fundamental assumption underlying the validity of OLS estimation is that the observations are independent, which implies that each household makes its e-commerce entrepreneurship decisions independently. However, in reality, each household does not make e-commerce entrepreneurship decisions independently, especially within a rural community of acquaintances. The attributes of households alone are insufficient to explain their adoption of e-commerce. The decision to adopt e-commerce likely involves mutual influence among households, an influence that is shaped by the social network within the village.

4.2. Social influences in network

4.2.1. Analysis based on Moran's *I* index

Before applying NAM to analyze e-commerce adoption among Dinglou Village households, we preliminarily establish the existence of social influences within the network by calculating Moran's ***I*** index.

Moran's ***I***, introduced by Australian statistician Patrick Alfred Pierce Moran in the 20th century, is a comprehensive index measuring the degree of spatial autocorrelation. Initially, it was employed to assess the correlation among spatially proximate entities. The Moran's ***I*** index can be expressed in the following form:

$$\boldsymbol{I} = \frac{n}{S_0} \cdot \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} z_i z_j}{\sum_{i=1}^{n} {z_i}^2} \tag{3}$$

In Eq. (3), z_i represents the deviation of the actor's attribute from its mean $(y_i - \bar{y})$, w_{ij} is the spatial weight between actors i and j (i.e., the extent to which actors i and j influence each other), n denotes the total number of actors in the space, and S_0 is the sum of all spatial weights. Moran's ***I*** index ranges from −1 to 1, where a value greater than 0 indicates positive spatial autocorrelation among the actors, with larger values signifying stronger correlation.

While initially developed for spatial analysis, Moran's ***I*** index can be readily adapted to network analysis. This adaptation is possible because spatial configuration represents a specific form of network (i.e., a regular network). To apply this index to our social network, we substitute w_{ij} with the adjacency matrix of the network. The e-commerce entrepreneurial actions of the farmers in Dinglou Village exhibit significant positive autocorrelation (Moran's $\boldsymbol{I} = 0.246$, $p < 0.001$), preliminarily confirming social influences within the rural network.

4.2.2. Analysis based on NAM

Following the analytical strategy outlined earlier, we specify LPM (**Model 1**) and five NAMs with different weight matrices. We compare the goodness-of-fit for all these models, with the results in Table 2.

Initially, when examining the R^2, all five network autocorrelation models with weight matrices perform better than the non-autocorrelation model (**Model 1**). This result indicates that models accounting for social influence provide better explanatory power than those reflecting only the individualistic perspective. However, Leenders (2002) suggests that the traditional R^2 may not be the most appropriate measure for assessing the goodness-of-fit for NAMs. Instead, the Akaike Information Criterion (AIC), derived from the model log-likelihood, should be considered for comparison.

Therefore, we calculated the AIC for five NAMs (**Model 2** to **Model 4** in Table 2). Among them, **Model 3**, which uses the structural equivalence proximity matrix, exhibits the highest R^2 (0.475) and the lowest AIC (141.706). **Model 2**, which employs the original adjacency matrix, ranks second ($R^2 = 0.442$, AIC = 152.035). Models using row normalization and column normalization of the adjacency matrix (**Model 2a** and **Model 2b**) fit less well, with higher AIC. This result suggests that neither the assumption of equal total accepted influence across all actors nor the assumption of equal total exerted influence is as appropriate as directly assessing the absolute influence levels. **Model 4**, with equal influence weight matrix, has the lowest R^2 (0.352) and the highest AIC (181.336), indicating that the hypothesis concerning the impact of the community's entrepreneurial atmosphere is the least supported by empirical findings.

We will only report the estimations of models including the original adjacency matrix, the structural equivalence proximity matrix, and the equal influence weight matrix, as detailed in columns 3 to 5 of Table 3 (**Model 2** to **Model 4**).

The focus of this analysis here is on the parameter estimation results of ρ. In these three network autocorrelation models, the first two ρ estimations are statistically significant ($p < 0.001$). It is evident that households engaged in e-commerce entrepreneurial activities are influenced by other households with adjacent connections within their network, as well as by those occupying similar structural positions within the network. However, the directions of these two modes of social influence are different.

The autocorrelation parameter obtained from the original adjacency matrix model (**Model 2**) is significantly positive ($\rho = 0.056$, $p < 0.001$), indicating positive mutual influence among adjacent households. Essentially, an increase in the number of friends within a household's network who are involved in e-commerce entrepreneurship raises the probability that the household will also participate, suggesting a demonstration effect. In contrast, the network autocorrelation parameter obtained from the structural equivalence model (**Model 3**) is significantly negative ($\rho = -0.015$, $p < 0.001$), indicating a negative mutual influence among households occupying similar structural positions. Here, the more individuals in similar structural positions engaged in e-commerce entrepreneurship, the less likely it is for focal households to engage, suggesting an inhibitory effect.

4.3. The dynamic of social influences in network

The analysis above provides a snapshot of e-commerce entrepreneurship among households in the village using cross-sectional data. Actually, social influence is a dynamic process rather than a static one. Villagers are not merely passive observers at a single moment; they

Table 3
Estimates of LPM and NAMs.

	Model 1	Model 2	Model 3§	Model 4
Weight Matrix	–	(I)	(II)	(III)
ρ		0.056***	−0.015***	−0.002
		(0.010)	(0.002)	(0.003)
Education (Primary school and below = 0)				
Junior Middle School	0.039	0.021	−0.002	0.040
	(0.076)	(0.068)	(0.067)	(0.074)
High School	0.190*	0.134+	0.120	0.184*
	(0.088)	(0.080)	(0.078)	(0.087)
University and above	0.056	0.031	0.003	0.051
	(0.098)	(0.088)	(0.086)	(0.096)
Age	−0.017***	−0.012***	−0.010***	−0.017***
	(0.002)	(0.002)	(0.002)	(0.002)
Early Producer	0.160	0.069	0.107	0.161
	(0.150)	(0.136)	(0.132)	(0.147)
Labor Force Size	−0.069	−0.035	−0.030	−0.068
	(0.047)	(0.043)	(0.042)	(0.046)
Constant	0.763***	0.534***	0.989***	1.014**
	(0.121)	(0.116)	(0.112)	(0.345)

Note: (1) *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, + $p < 0.1$; (2) Standard errors in parentheses; (3) § denotes the best-fitting model.

experience the entire development process of the Taobao Village. The decision to engage in e-commerce entrepreneurship at any given time is shaped by the concurrent status of other villagers, as well as by the historical actions of both themselves and their peers. Furthermore, the mechanisms of social influence are likely to evolve through different phases of Taobao Village's development (as posited in **H4** of this study). To investigate this temporal heterogeneity of effects, we will estimate the network autocorrelation model for different periods, focusing on how the network autocorrelation parameters change over time.

To capture these dynamic aspects, we employ longitudinal data and analyze them using TNAM (Leifeld and Cranmer, 2017), which has been widely applied in the studies investigating the dynamics of social influences within a network (Metz and Ingold, 2017; Schaefer et al., 2021). In TNAM, except for the early producer variable, which is a time-invariant attribute for households, all other variables mentioned in Table 1 are incorporated in the analytical model with their corresponding time-varying forms.

First, the nodes' action attribute we focus on — household e-commerce entrepreneurship — that is, dependent variable $\boldsymbol{y}$ in the network autocorrelation model, is time-varying. Given its potential for annual variation (captured by y_{it}), $\boldsymbol{y}$ is represented in TNAM as an $nt \times 1$ vector of cross-sections stacked by periods (i.e., observations for n households across t time periods). During our field survey, we recorded not only the year in which households started engaging in e-commerce entrepreneurship but also if and when they ceased operations. From these records, we construct y_{it}, which indicates whether household i was engaged in e-commerce entrepreneurship in the specific year t. Fig. 4 illustrates the evolution of e-commerce entrepreneurial households. The red line represents the total count, including those who have exited, while the blue line represents the count exclusive of exits. The lines were indistinguishable from each other before 2012. However, beginning in 2013, a divergence emerged, indicating an annual attrition of e-commerce households. The blue curve peaked less prominently in 2016 and has since followed a gently declining trend. From 2017 to 2019, the annual count of households discontinuing e-commerce operations surpassed the number of new entrants in the village. By the time of our field survey in 2019, the cumulative number of households that had participated in e-commerce entrepreneurship reached 124, as detailed in Section 3.3. After accounting for those who exited, 95 households remained active in e-commerce. Since 2013, 29 households, roughly a quarter of the total, have ceased their e-commerce endeavors.

Second, because $\boldsymbol{y}$ (household e-commerce entrepreneurship) is time-varying, the product $\boldsymbol{W}\boldsymbol{y}$, which is used to estimate the network autocorrelation parameter ρ, also varies over time. In TNAM, the influence weight matrix $\boldsymbol{W}$ is an $nt \times nt$ block-diagonal weight matrix, and thus $\boldsymbol{W}\boldsymbol{y}$, referred to as the weighted spatial lag, is an $nt \times 1$ vector. For each y_{it}, $\boldsymbol{W}\boldsymbol{y}$ gives a weighted sum of the y_{jt}, with weights $w_{ij,t}$.

Third, all other control variables in TNAM, including household education level, age, and the labor force size, are time-varying. We have incorporated annual observations of these variables for each household into the dataset for modeling and analysis.

Fourth, to capture the temporal dynamics in the number of households engaged in e-commerce — the blue line in Fig. 4 depicts a significant rise followed by a slight decline in household e-commerce participation — we include time covariates and their squared terms in all models.[4]

Finally, before examining the temporal heterogeneity of the effects, we first fit two sets of TNAMs. The first set includes **Model 5** to **Model 7** presented in Table 3. These models sequentially incorporate distinct influence weight matrices: the original adjacency matrix (**Model 5**), the structural equivalence proximity matrix (**Model 6**), and the equal influence weight matrix (**Model 7**). The other variables included here are the same as those in **Model 2** to **Model 4**. Naturally, as previously noted, these covariates are all measured annually and thus treated as time-varying. The second set includes **Model 8** to **Model 10**. These models extend **Model 5** to **Model 7** by including two additional variables: (1) the lagged dependent variable $\boldsymbol{y}_{t-1}$, representing the household's e-commerce entrepreneurship status at the prior time point, and (2) the interaction term between the lagged dependent variable $\boldsymbol{y}_{t-1}$ and the influence weight matrix $\boldsymbol{W}$. This interaction term captures the potential influence of others' prior status on the current decision-making of the focal household. Notably, due to the inclusion of lagged dependent variables, the first round of observations is omitted from these models, and Appendix C provides a detailed explanation of this (see Supplementary Materials).

4.3.1. Result of TNAMs

Utilizing the TNAM yielded principal findings consistent with those from previous cross-sectional analyses. **Model 5** to **Model 10** presented in Table 3 show the results of estimating TNAMs.

The estimations of network autocorrelation parameters in **Model 5** to **Model 7**, which hold our major interest, align with the results from **Model 2** to **Model 4** in both the direction of the effects and statistical significance. This consistency further substantiates the robustness of the previous analytical findings. The node attribute effects derived from these three models are also consistent with the principal findings from our prior cross-sectional analysis.

Based on **Model 5** to **Model 7**, we further refine the analysis in **Model 8** to **Model 10** by including two additional variables. Including these variables significantly improves the model's goodness-of-fit compared to the previous three models. Within these three models, the regression coefficients for the lagged dependent variable are positive and statistically significant, reflecting the substantial influence of a household's prior e-commerce entrepreneurship status on its subsequent choices. Regarding network autocorrelation parameters, the estimate derived from the original adjacency matrix exhibits a modest decline (from 0.089 to 0.056), yet its significance remains unchanged. The autocorrelation parameter derived from the structural equivalence proximity matrix sustains a negative value ($\rho = -0.006$), but there is a notable reduction in both the magnitude and the statistical significance compared to **Model 6**. The possible reasons for this reduction lie in the strong temporal dependence in farmers' e-commerce entrepreneurial activities and the inherent correlation between the independent variable $\boldsymbol{W}\boldsymbol{y}_t$ (used to capture social influence among structurally similar

[4] The parameters estimated for these temporal terms are all statistically significant at least at the $p < 0.01$ level (see Table 4).

Table 4
Estimates of TNAMs.

	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Weight Matrix	(I)	(II)	(III)	(I)	(II)	(III)
ρ	0.089***	−0.024***	0.002	0.056***	−0.006+	0.002
	(0.005)	(0.002)	(0.001)	(0.009)	(0.004)	(0.001)
Education (Primary school and below = 0)						
Junior Middle School	0.023	−0.003	0.034	0.009	0.002	0.013
	(0.052)	(0.052)	(0.060)	(0.020)	(0.021)	(0.021)
High School	0.129*	0.136*	0.194**	0.057*	0.062*	0.070**
	(0.061)	(0.061)	(0.070)	(0.023)	(0.024)	(0.024)
University and above	0.153*	0.143*	0.187*	0.059*	0.060*	0.063*
	(0.067)	(0.067)	(0.077)	(0.026)	(0.027)	(0.027)
Age	−0.003*	−0.002	−0.007***	−0.002**	−0.001*	−0.003***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Early Producer	0.131	0.201+	0.241*	0.066+	0.093*	0.096*
	(0.103)	(0.103)	(0.119)	(0.040)	(0.041)	(0.042)
Labor Force Size	0.015	0.011	0.004	0.002	0.000	−0.005
	(0.021)	(0.021)	(0.023)	(0.011)	(0.012)	(0.012)
Time Covariate	0.094***	0.271***	0.124***	0.039***	0.106***	0.102**
	(0.010)	(0.011)	(0.031)	(0.011)	(0.013)	(0.034)
Square of Time Covariate	−0.005***	−0.015***	−0.007***	−0.003***	−0.007***	−0.006**
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001	(0.002)
Lagged dependent variable				0.714***	0.696***	0.747***
				(0.017)	(0.017)	(0.016)
Lagged weight matrix				−0.032***	−0.002	−0.003**
				(0.010)	(0.004)	(0.001)
Constant	−0.222***	−0.373***	−0.298***	−0.050	−0.122**	−0.168**
	(0.058)	(0.058)	(0.070)	(0.041)	(0.043)	(0.063)
AIC	1203.633	1232.247	1457.405	336.413	360.113	401.664
Log Likelihood	−589.816	−604.124	−716.702	−154.206	−166.056	−186.832

Note: (1) *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, + $p < 0.1$; (2) Standard errors in parentheses.

actors) and the lagged dependent variable $\boldsymbol{y}_{t-1}$. Consequently, compared with the coefficient of −0.024 from the model without including the lagged dependent variable, the estimate of −0.006 can be interpreted as reflecting a relatively "cleaner", albeit weaker and only marginally significant, effect. However, it should be noted that this estimate only reveals an average level of influence among structurally similar farmers throughout the entire development process. In the following analysis, we will further investigate whether the structural equivalence effect remains consistently weak or varies across different phases of Taobao Village's growth. Lastly, the autocorrelation parameter for the equal influence weight matrix remains insignificant (ρ = 0.002, t = 1.380). The interaction effects exhibit negative trends across all three models but are statistically significant only in **Model 8** and **Model 10**. This result suggests that the impact of the entrepreneurial atmosphere may be subject to a temporal delay (see Table 4).

4.3.2. Temporal heterogeneity of network autocorrelation

While the previous analysis employed longitudinal data to model the dynamics of households' e-commerce entrepreneurship, it assumed a single temporal homogeneity model underpinning the entire dynamic process. This assumption means that social influences, captured by autocorrelation parameters from these models, remain constant throughout different phases of Taobao Village's growth. To test **H4**, we will now examine the temporal heterogeneity of these influences.

Defining the growth stages of Taobao Village is a complex challenge. In the early years of e-commerce in Dinglou Village, participation was relatively modest. As illustrated in Fig. 4, fewer than 40 households were engaged in e-commerce by the end of 2011. We employed Bayesian analysis of change point problems — a technique designed to identify change points — to analyze the dynamic expansion of the number of e-commerce households, as indicated by the red line. This data-driven approach initially divided Dinglou Village's e-commerce development into two phases: 2009–2012 and 2012–2019.

Indeed, the phases identified through the data-driven approach align well with the observed realities of Taobao Village's growth, as documented in our field research. Before 2012, e-commerce in this village grew spontaneously without any external intervention. In April 2013, the local government discovered the burgeoning e-commerce activities in Dinglou Village. Subsequently, county and town governments began to intensively promote rural e-commerce, introducing numerous preferential policies to encourage and support local villagers to engage in e-commerce entrepreneurship. This effort led to the spread of e-commerce from Dinglou to neighboring villages in the same township, resulting in a surge of new entrants and heightened competition post-2013. We further divided the period from 2012 to 2019 into two phases, with 2016 as the threshold. Fig. 4 illustrates that by 2016, the number of households that had ever engaged in e-commerce entrepreneurship had doubled since 2012. More importantly, after 2016, the number of active e-commerce households began to decline gradually, as indicated by the blue line in the figure.

In our analysis, we fit TNAM to investigate the dynamics of social influences during the periods 2009–2012, 2012–2016, and 2016–2019 respectively. Fig. 5 presents the findings from this period-specific analysis, which also utilizes the original adjacency matrix, structural equivalence proximity matrix, and equal influence weight matrix to quantify the social influences. We marked the effect size of the network autocorrelation parameter estimates with dots in the figure and represented the 95% confidence intervals of these estimates with error bars. If the error bar crosses 0, the estimate is not statistically significant at a 0.05 significance level.

The analysis results here support **H4**, which posits that the ways households influence each other within Taobao Village vary significantly at different stages of its development. During the initial phase (2009–2012), a significant effect was only found in the network autocorrelation parameter ρ derived from the original adjacency matrix, which was positive (ρ = 0.060, 95% CI = [0.029, 0.091]). This result suggests that social influence at this stage was primarily driven by positive reinforcement through mutual learning and imitation among intimate peers. In contrast, the ρ estimates derived from the structural equivalence proximity matrix and equal influence weight matrix were

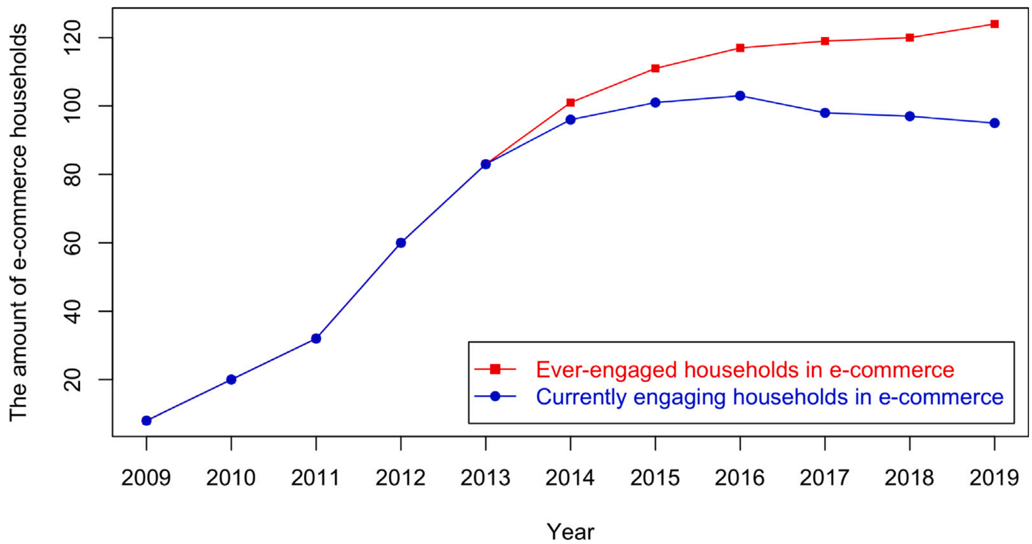

Fig. 4. The evolution of amount of e-commerce households.

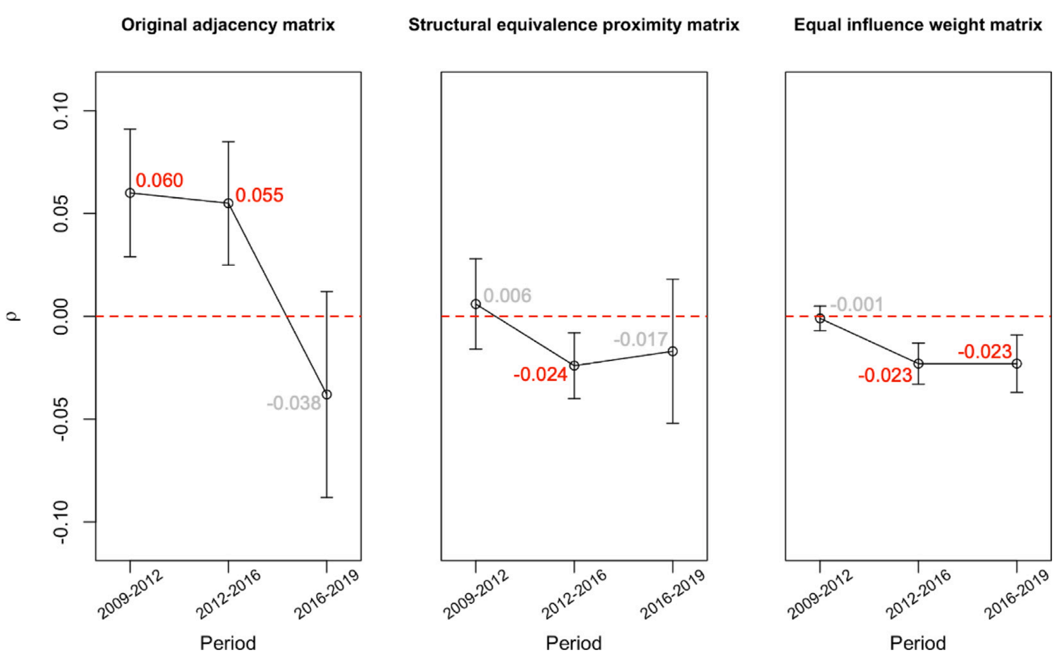

Fig. 5. ρs for different periods derived from three types of weight matrices and corresponding confidence intervals.
Note: The numbers next to the dots are the estimated values of the respective ρ coefficients. Red numbers indicate statistical significance at the 95% level, while gray numbers denote results that are not statistically significant.

not significant. In the 2012–2016 period, the three forms of social influences we examined coexisted, but the directions of effects differed. The ρ estimate derived from the original adjacency matrix remained positive, indicating that positive mutual influence among intimate peers through learning and imitation is still ongoing. However, the ρ estimates derived from the structural equivalence proximity matrix and the equal influence weight matrix were significantly negative (−0.024 and −0.023, respectively). This result reflects the heightened competition within the village during this period, suggesting a complex interplay between competition and cooperation among households. By 2016–2019, the previously observed positive influence among intimate peers had dissipated, as evidenced by a negative and non-significant ρ estimate (ρ = −0.038, 95% CI = [−0.088, 0.012]). The ρ estimate derived from the structural equivalence proximity matrix also lost significance (ρ = −0.017, 95% CI = [−0.052, 0.018]). In contrast, the ρ estimate derived from the equal influence weight matrix remained significant, underscoring the dominance of competitive pressures within the community during this stage.

There are several possible explanations for the disappearance of the significant positive adjacent influence during 2016–2019. One possible explanation also stems from the logic of competitive pressure. For households that had not yet engaged in e-commerce entrepreneurship by 2016–2019, their decision-making process may have been influenced by potential market saturation. As the density of e-commerce households increases, the relationship between closely connected households could shift from "cooperative learning" to "potential competition". The negative (though statistically non-significant) network autocorrelation coefficient in this period offers a hint of this "crowding-out effect". Another possible explanation is that, by 2016–2019 e-commerce expertise in this village had likely transitioned from "niche expertise" to "community common knowledge". Consequently, a household seeking operational knowledge could readily acquire it from the broader community environment without relying on households to whom it was directly connected, thereby rendering the adjacent influence less salient. These two explanations reflect motivational and informational perspectives, respectively. Although we cannot currently disentangle these mechanisms quantitatively or determine which one dominates, we believe they are both plausible and likely complementary.

5. Discussion

5.1. Contributions

Sociology consistently prioritizes the social context of action, and this principle extends to the study of technology adoption. Our research focuses on the rural e-commerce transformation in China over the past decade, advocating for a perspective that transcends the individualistic approach, which views e-commerce adoption merely as a function of farmers' inherent attributes. The social influence of rural households' e-commerce adoption behaviors should be examined within the context of their social interactions. Additionally, more than merely discussing social influence is needed. As sociologists, we aim to distinguish and analyze the varied mechanisms of social influence.

The primary contribution of this paper lies in the following aspects. First, we measure the social networks within Taobao Village. Although prior studies recognize the critical role of social networks in the development of Taobao Village, they lack precise and appropriate measures of social ties between households and of the whole network structure, and therefore face challenges in validating and conducting in-depth analyses of the specific mechanisms of social influence within the network. Network analysis provides powerful tools from a relational perspective for examining the "field" in which actors interact (Bourdieu and Wacquant, 1992; DiMaggio and Powell, 1983; DiMaggio, 1986). Second, by collecting whole network data in Taobao Village, we quantify the social influence of e-commerce adoption among households in the social network and also explore three distinct mechanisms of social influence. Third, we investigate the dynamics of social influence in the network by integrating longitudinal data on households' e-commerce adoption behaviors.

5.2. Theoretical tensions in empirical findings

Within the context of social influence on e-commerce adoption in Taobao Villages, this paper extends the focus of sociologists to two key mechanisms of influence: influence between adjacent households and influence between structurally equivalent households. These mechanisms correspond to **H1** and **H2** of this paper, respectively. Our empirical evidence supports both of these hypotheses. Our findings align with those of Burt and other scholars across multiple studies (Burt, 1987; Galaskiewicz and Burt, 1991), indicating that the structural equivalence model offers greater explanatory power (better model fit) than the other, suggesting that **H2** more closely reflects social reality in our context. However, it is essential to note that the direction of the structural equivalence effect in our study differs from most previous research. Regarding e-commerce adoption, we observe a clear and robust negative suppression effect among structurally equivalent actors.

Burt theoretically posits that influence among structurally equivalent actors reflects a competitive logic. In his study of physician drug adoption, he found that when deciding whether to adopt a new technological innovation, the "ego" perceived pressure from structurally similar "alters", leading to similar choices. In the context of e-commerce adoption we examined in this study, we believe that the theoretical argument — that influence among structurally similar actors reflects competitive logic within a competitive field — still holds. However, the response to competitive pressure leads the "ego" to make contrary choices (i.e., either not adopting e-commerce or withdrawing from e-commerce entrepreneurship). This divergence from previous findings is particularly intriguing and warrants further discussion.

Our preliminary explanation for this divergence is that the nature of the adoption behavior examined in this study inherently differs from those in prior studies, such as physicians adopting new drugs or nonprofit organizations seeking philanthropic donations. In this study, although e-commerce adoption is examined as a form of technology adoption behavior, it must be acknowledged that it is considerably more complex compared to the behaviors studied in previous literature. E-commerce adoption is inherently intertwined with market-oriented entrepreneurial action. Competition among rural households naturally carries the implication of market competition and can, in a sense, be regarded as zero-sum: any gain by one directly entails a loss for another, as they mutually constrain each other's opportunity space — implying a relationship of direct exclusion. In contexts such as physicians adopting new drugs or nonprofit organizations seeking philanthropic donations, an increase in adopters does not necessarily compress the opportunity space for others to adopt similar behaviors. Although the actors are positioned as competitors, the competition is non-zero-sum. In these cases, adoption by one actor can enhance behavioral legitimacy or reduce perceived risks for others. Consequently, it provides positive motivation for potential adopters when they compare themselves to their competitive reference group. While these issues merit further attention, the core focus of this paper remains empirical rather than theoretical. We hope these empirical findings and preliminary discussions can offer a useful point of departure for more in-depth theoretical inquiry in the future.

5.3. Methodological considerations

In the model selection for analysis, we will discuss this in more detail. It is noteworthy that the majority of our analyses are based on the network autocorrelation model framework. Specifically, the form of the network autocorrelation model we employ in this study is commonly referred to as the network effect model. However, there is another variant of the network autocorrelation model known as the network disturbances model. Like the network effect model, the network disturbances model also posits that the attributes of individual nodes within a network are correlated. The key difference is that the network disturbances model attributes this correlation to the residuals or "disturbances" in the model. The fundamental form of this model is as follows:

$$\boldsymbol{y} = \beta \boldsymbol{X} + \epsilon,$$

$$\epsilon = \rho \boldsymbol{W} \epsilon + \boldsymbol{\eta}$$

The network effect model and the network disturbance model have substantial differences in their theoretical implications. As previously discussed, the network effect model seems more suitable for capturing mutual learning, observation, and imitation, which are the direct or indirect interactions between nodes through communication or comparison. However, the network disturbance model posits that autocorrelation stems from omitted variables, namely, some other features not included in the model that are correlated among households within a village. This form of autocorrelation diverges from the mutual influence of technology adoption among households and distinctly strays from the essence of our theoretical focus.

Nonetheless, we specified and estimated the corresponding network disturbance models. These models exhibit poorer fit than the previously presented network effect models, suggesting that their assumed interaction mechanisms may not align with empirical reality. The results of the network disturbance models are detailed in Appendix B (see Supplementary Materials).

5.4. Limitations

The limitations of this study should be acknowledged. First, this research is based on a single-case design. Although the selected Taobao Village is representative in terms of rural e-commerce development, the external validity of our findings remains limited and requires further validation through additional studies. While farmers' e-commerce entrepreneurship can indeed be viewed as a form of technology adoption, it is considerably more complex than the types typically examined in the innovation diffusion literature (as discussed in Section 5.2). Specifically, it represents a form of technology adoption under conditions of constrained market opportunities, especially in potentially highly homogeneous markets, where the exclusivity of opportunities may become more pronounced. The findings of this study may be specific to the market context of Dinglou Village, which exhibits high product homogeneity. Notably, many other Taobao Villages in China share similar market characteristics, suggesting they may represent a common category. Future research could extend similar investigations to other Taobao Villages to further assess the external validity of our conclusions. Second, this research examines only one type of social ties — relations among intimate peers, which are place-based, as previously noted. However, social ties formed in non-place-based online spaces may also influence farmers' adoption of e-commerce. The picture of social relations is even more complex than a simple binary between place-based and non-place-based relations. To capture these complexities requires collecting and analyzing data on more complex, multiple networks (Lomi et al., 2016; Dickison et al., 2016). Third, the theoretical discussion of competitive logic warrants further empirical testing. This would need additional data, such as detailed metrics on profit erosion by new entrants or product overlap among households. As these market indicators were not directly measured in this study, this limitation remains unaddressed.

6. Conclusion

This paper uses first-hand survey data to explore the adoption of e-commerce technology in Dinglou Taobao Village, Cao County, Shandong Province. It reveals that the individualistic perspective, which focuses solely on the factor endowments of individuals, needs to be revised to explain e-commerce adoption in rural China. In acquaintance communities characterized by frequent communication and mutual observation, the visibility of e-commerce entrepreneurial activities is significantly amplified, underscoring the importance of social influence that should not be ignored.

To capture this social dimension, we collected data on relational ties reflecting intimate interaction among households, allowing us to construct a comprehensive rural social network. We employed NAMs to explore the social influences within this network. By applying various types of weight matrices in our model, we could compare different social influence mechanisms, providing a nuanced understanding of how social relationships shape e-commerce adoption. Furthermore, we utilized longitudinal data on household e-commerce entrepreneurship along with the TNAM model. This approach allowed us to analyze the evolving dynamics of social influences throughout the different development stages of Taobao Village.

We discover that farmers' adoption of e-commerce is influenced not only by their directly connected friends in social networks but also by other people occupying similar structural positions. The structural equivalence influence model demonstrates greater explanatory power compared to the cohesion model, which focuses on direct interactions. This finding aligns with most related previous studies. However, our study diverges from prior research in a significant way. The influence between structurally equivalent households is characterized by negative suppression rather than the positive facilitation of innovation adoption suggested by earlier studies. We have preliminarily discussed the reasons for these divergences in Section 5. The model assuming equal influence across the community yields the poorest fit for our observed data in cross-sectional analysis. The corresponding network autocorrelation parameters are also insignificant, which suggests that the hypothesis of a general entrepreneurial atmosphere fostering households' e-commerce adoption is not supported.

Utilizing longitudinal data on households' e-commerce adoption, this study conducts a dynamic analysis to capture how the social influences within the network vary over time. Such an approach is rare in technology adoption literature but essential for uncovering how mechanisms of social influence within the network evolve dynamically. Our findings reveal a temporal trend: as Taobao Villages evolve, the social influence among households shifts from initial positive facilitation to negative suppression. This transition can be explained through a competitive logic. Additionally, different mechanisms of social influence we examined showed varying specific manifestations in their results. During the initial spontaneous growth stage of e-commerce in Dinglou Village, we observe positive peer effects among close friends and negative suppression effects between structurally equivalent households, although the latter does not reach statistical significance. As the number of e-commerce households in the village rapidly increased post-2012, the positive peer effects among close friends persisted, while a significant negative suppression effect emerged between structurally equivalent households, likely driven by competitive pressures. After 2016, however, the positive peer effects among close friends vanished, and the competitive logic can also explain this result. Furthermore, our analysis of the community's entrepreneurial atmosphere also reveals a shifting temporal trend. The results show that during the earliest stage of Taobao Village development, the network autocorrelation parameter estimated via the equal influence weight matrix was not significantly different from zero. However, in the middle and later stages of Taobao Villages' development from 2012 to our survey in 2019, we observed a negative suppressive atmosphere emerging among households. We believe that this is caused by competitive pressure perceived by households as more villagers engage in e-commerce entrepreneurship.

This study highlights the complex relationship between social networks and e-commerce development in rural China. The results show that the ways in which households influence each other within a Taobao Village indeed change significantly across different stages of its development. Our findings further confirm that rural social networks are crucial for the development of Taobao Villages in China. Farmers' actions are embedded in the rural social network, and farmers' actions in adopting e-commerce technology for entrepreneurship influence each other through networks in Taobao Village. Therefore, when examining rural households' e-commerce entrepreneurship and rural e-commerce industry development, we cannot ignore the social embeddedness. In the future, besides collecting similar research data from a broader range of Taobao Villages to verify external validity and directly examining the competitive logic based on the measurement of relevant market indicators, it is perhaps even more important to aggregate existing related empirical findings to further synthesize key theoretical issues. For instance, the inconsistency found in this study regarding the structural equivalence effect, compared to previous findings, highlights the need for new theoretical frameworks. Understanding how actors in similar structural positions influence each other draws on classic sociological theories, such as role theory, reference group theory, innovation diffusion, and social network theory. A key priority is to clarify the conditions under which specific forms of social influence occur. The findings in this study suggest that whether the structural equivalence effect manifests as positive facilitation or negative suppression depends on the inherent nature of the action itself. The case study and conclusions provided here offer new clues for exploring the boundaries of related theory.

CRediT authorship contribution statement

Tianyu Qiao: Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Zeqi Qiu:** Supervision, Funding acquisition, Conceptualization.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used Claude and Kimi Chat in order to improve readability and language of the work. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

Declaration of competing interest

The authors declare that there is no conflict of interest.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.socnet.2026.04.001.

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