Computers in Human Behavior 172 (2025) 108746

Contents lists available at ScienceDirect

Computers in Human Behavior

journal homepage: www.elsevier.com/locate/comphumbeh

How dormant ties are reactivated through social media during major life events

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ARTICLE INFO

Handling editor: Marianna Sigala

Keywords:
Dormant tie
Major life events
Social media
Node centrality
Network density

ABSTRACT

Dormant ties comprise a significant portion of our social networks, carrying latent yet inactive social capital. In the era of social media, reactivating dormant ties becomes more convenient during major life events, offering crucial informational and emotional support in times of uncertainty or emergencies. However, little is known about who is more likely to reactivate dormant ties, which types of networks facilitate such reactivation, and how these ties evolve after trigger events in the digital age. Based on the social media records of a nationally representative sample of a Generation Z cohort in China spanning three whole years, which comprises approximately 2.1 million online posts and interactions, we show large-scale evidence on the reactivation of dormant ties during major life events. Our findings indicate that during life transitions or events such as the COVID-19 pandemic, dormant ties are more likely to be reactivated around central nodes in the network, further enhancing their centrality. However, this polarisation trend is mitigated in networks with higher density, where the reactivation of dormant ties is more evenly distributed. In addition, following trigger events, interactions with reactivated contacts tend to decline but remain active for at least six months on social media. Overall, this study deepens our understanding of how social media facilitates the mobilisation of latent social capital in navigating major life events.

1. Introduction

In the face of major life events, such as starting a new phase of life, changing jobs, relationship breakups, or a global health crisis that affects the majority of the population, individuals may need to mobilise all sorts of resources to deal with increased uncertainties and stress (Lazarus & Folkman, 1984; Luhmann et al., 2021; Moffatt & Heaven, 2017; Suls & Mullen, 1981; Tedeschi et al., 1998; Van Ingen & Wright, 2016). In these scenarios, social networks serve as an important source of information and emotional support (Bedaso et al., 2021; Cohen & McKay, 2020; Granovetter, 2018; Mickelson & Kubzansky, 2003; Rajkumar et al., 2022; Szkody et al., 2021). In addition to members of the core network with whom individuals have maintained frequent contact and strong attachment (Hurlbert et al., 2000; Lin et al., 2013; Perry & Pescosolido, 2015; Thomas & Dommermuth, 2020), the dormant part of the network may also be reactivated and provide crucial support (Wu et al., 2021; Yang et al., 2021). Dormant ties – connections that existed in the past but have remained inactive for an extended period – constitute a substantial portion of individual networks (Levin et al., 2011; Rondi et al., 2024). In fact, existing studies have shown that the dormant ties may be more helpful than the existing active ones because they are more likely to carry non-redundant information (Levin et al., 2011; Walter et al., 2015).

Considering the crucial role of dormant ties at these significant junctures in life, as well as the large share they occupy in personal networks, insufficient attention has been paid by researchers and individuals to this ‘silent majority’. While pioneering research in this vein has expounded upon the types of reactivated dormant ties (Levin et al., 2011) and the support they provide (Levin et al., 2011; Walter et al., 2015; Yang et al., 2021), several fundamental questions remain

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https://doi.org/10.1016/j.chb.2025.108746
Received 15 March 2025; Received in revised form 9 June 2025; Accepted 28 June 2025
Available online 4 July 2025
0747-5632/

unanswered: When individuals face major life events, what types of networks are more likely to facilitate the reactivation of dormant ties? Within each network, who is more likely to reactivate dormant ties? Once reactivated, what forms do these ties take? Addressing these questions offers essential insights into the dynamics of social networks and how people mobilise latent social capital for support during pivotal moments in life.

In the era of digital technologies and social media, research on dormant ties becomes even more critical and brings about yet more challenges. Instant yet asynchronous communication enables friends to connect with each other more easily by lifting time and space barriers (Quinn, 2013; Sumner et al., 2021). For many people, especially the young, online communications almost certainly exceed those taking place in an offline, face-to-face scenario (Lewis, 2021). Especially for those who are not residing in the same community, many connections between friends may be maintained entirely online. Therefore, to examine how major life events reactivate dormant ties in the digital age, it is necessary not only to understand the relationships between respondents and their contacts in real life but also to comprehend their online interactions.

To answer the above questions in the digital era, we require data on both whole and personal networks, as well as long-term data to track the dynamics at both levels on social media. However, data on personal networks is common, but data on whole networks, especially large-scale whole networks on social media, is rare; information on static networks is common, but on dynamic networks, especially including both active and dormant ties, it is also rare. Given the scarcity of large-scale, long-term data for detecting, monitoring, and tracing dormant ties, answering these questions can be a daunting task for researchers.

To overcome these obstacles, we constructed a database that compiles social media records from a nationally representative sample of Grade 7 students ($N = 8495$) over a three-year period, which has three significant advantages. First, tracing the network changes of a nationally representative sample, rather than capturing a self-selected and inevitably biased sample from social media (Golder & Macy, 2014) allows for a more accurate understanding of the issues under investigation. Second, this nationally representative sample was taken from 221 middle school classes nationwide. This not only enabled us to monitor the changes in the egocentric networks of specific individuals but also provided insights into the evolution of whole networks of these 221 classes over time, thereby allowing us to examine determinants of both individual nodes and whole networks. Third, considering that interactions were mainly conducted online after the cohort graduated from middle school, we tracked their actions on the largest Chinese social media platform and collected millions of online posts and within-class interactions. The digital footprints provided us with a more accurate way to detect dormant ties and their reactivation in response to major life events, thereby surmounting to a significant degree the difficulties in studying the non-active part of networks and their dynamics.

In this study, we focus on the impact of two major life events on reactivating dormant ties: high school graduation and the COVID-19 pandemic. High school graduation is a milestone life event for adolescents transitioning into adulthood, after which the majority will either enter college or join the workforce, and many will leave their hometowns to embark on new chapters in life (Horowitz & Entwisle, 2021; McDaniel & Kuehn, 2013). The COVID-19 pandemic stands as one of the most impactful global events in recent years, exerting significant effects on various aspects of personal life, including income (Josephson et al., 2021), learning outcomes (Betthäuser et al., 2023; Parolin & Lee, 2021), physical and mental health (Blomberg et al., 2021; Danielsen et al., 2023; Tanaka & Okamoto, 2021), safety and security (Huang et al., 2023; Nivette et al., 2021; Ravindran & Shah, 2023), as well as life expectancy (Andrasfay & Goldman, 2021; Schöley et al., 2022). Using these two events as examples, we examined how major life events reactivate dormant ties. Specifically, we investigated (1) which types of social networks (e.g. dense or sparse networks) are more conducive to the reactivation of dormant ties; (2) within each network, which individuals (nodes) are more likely to initiate such reactivations; and (3) once reactivated, how these ties evolve over time. Overall, this study provides new insights into the 'silent majority' of social networks and how people mobilise latent social capital to navigate major life events in the digital era.

2. Literature review

2.1. Dormant ties in social networks

Dormant ties, also known as inactive connections, are relationships between individuals who have not communicated for an extended period (Levin et al., 2011). In today's highly mobile society, losing touch has become increasingly common (Burt, 2002), as people can only maintain a limited number of active relationships (Dunbar, 1998; Hill & Dunbar, 2003). Current research suggests that, due to time and cognitive constraints, the average number of contacts with whom we have a reciprocal and relatively stable relationship accounts for only 10 % of all known contacts, while those with whom we maintain frequent contact account for less than 5 % (Bzdok & Dunbar, 2022; Dunbar, 2020). Apart from our closest family and friends, 90–95 % of contacts may fall into dormancy.

Recent research has revealed important insights about this 'silent majority'. For instance, dormant ties can be both strong and weak ties (Levin et al., 2011), and while they are inactive, they should not necessarily be considered lost. A recent study found that a substantial portion of 'newly added ties' recorded in longitudinal egocentric network data were, in fact, reactivated dormant ties. The proportion of reactivated dormant ties was nearly half among young adults and exceeded two-thirds among older adults (Offer & Fischer, 2022). Since these connections are built on prior relationships, reactivating them often requires less effort than forming new ties (Levin et al., 2011). However, reconnecting is not always straightforward, as the prospect of reactivation can also bring about anxiety and discomfort (Rondi et al., 2024; Walter et al., 2015).

In most cases, because these relationships have shared histories, they can serve as a source of social capital that can potentially be mobilised (Rondi et al., 2024). Existing studies have shown that dormant ties can be a valuable source of information, knowledge, and emotional support. For example, reactivating dormant ties can benefit knowledge seekers by offering novel insights and information (Levin et al., 2011). Beyond work-related advice and expertise, reactivating these ties can also provide emotional support in coping with work- and family-related stressors (Yang et al., 2021). In entrepreneurial settings, reactivating dormant ties is an effective networking strategy, as the experiences an individual's former contacts gain while the tie remains dormant can become valuable assets when the connection is re-established (Wu et al., 2021).

Research on dormant ties and their reactivation highlights the dynamic nature of social networks and offers new insights into the abundant yet inactive social capital within personal networks. However, despite the growing body of research in this vein, several fundamental questions remain underexplored: how do overall network structures and individual node characteristics influence the reactivation of dormant ties? How do these ties evolve over time after reactivation? In particular, the widespread adoption of digital technologies has made it easier to reactivate dormant ties, allowing individuals to seek support more conveniently when needed and further highlighting the importance of answering these questions. Accordingly, this study aims to contribute to the existing literature by exploring these issues.

2.2. Major life events and social networks

When major life events occur, social networks are essential sources of instrumental and emotional support, helping individuals navigate unfamiliar situations or cope with significant changes (Bedaso et al., 2021; Mickelson & Kubzansky, 2003; Szkody et al., 2021). People may receive vital support from both their core network members, with whom they maintain strong bonds (Hurlbert et al., 2000; Lin et al., 2013; Perry & Pescosolido, 2015; Thomas & Dommermuth, 2020), and from rekindled connections within the dormant parts of their network, with whom they have not interacted for a long time (Wu et al., 2021; Yang et al., 2021). For instance, women experiencing widowhood found support by intensifying existing ties as well as by reconnecting with former friends, relatives, or community members (Zettel & Rook, 2004). Similarly, during the COVID-19 pandemic, maintaining contact with existing strong bonds and reactivating dormant ties both emerged as effective coping strategies (Perry et al., 2023; Yang et al., 2021).

While social networks provide support during major life events, these events also have a complex and multifaceted impact on social networks themselves, influencing both their structures and functions. When faced with major life events, such as marriage or starting a new job, individuals must adopt new identities and social roles, often prompting them to reassess and adjust their social connections in response to changing circumstances. Following major life events, some active ties may become dormant (Small et al., 2015; Terhell et al., 2004), while some previously dormant ties may be reactivated. For example, the transition to parenthood may lead to a reconfiguration of social networks, particularly with an increased emphasis on kin connections (Hammer et al., 1982). Likewise, during a global health crisis such as the COVID-19 pandemic, individuals may require various forms of support – informational, medical, or emotional – leading to the reactivation or strengthening of relationships that can offer such assistance (Tindle et al., 2022; Yang et al., 2021).

In the digital era, the rise of social media has significantly influenced social networks by enabling individuals to maintain and expand their connections more conveniently (Manago et al., 2012). Social media allows people to connect with a broader audience, fostering relationships that transcend geographical boundaries and extend beyond traditional social circles. Existing research suggests that social media use is linked to broader social connections (Moshkovitz & Hayat, 2021) and more frequent contact with core network members (Vriens & Van Ingen, 2018). In addition to facilitating the formation of new ties and the maintenance of existing ones, the widespread use of social media may also contribute to the reactivation of dormant ties, resulting in a more dynamic network structure, particularly in response to major life events.

Understanding how social networks change during major life events would offer valuable insights into how individuals leverage their network potential to navigate uncertainty and stress (Wrzus et al., 2013). In particular, the 'silent majority' of social networks – that is, dormant ties – are more likely to be reactivated during major life events, thus substantially impacting network dynamics. In the digital age, studying changes in social networks, especially the dynamics of dormant ties, requires close attention to people's online interactions on social media, which is the key objective of this paper.

3. Data and methods

3.1. Data

To examine the dynamics of dormant ties on social media, we constructed a database of social media records from a nationally representative sample of a Generation Z cohort in China. In 2013, we employed a probability proportional to size sampling method and randomly selected 10,279 Grade 7 students (mostly aged 12–13) from 221 classes across 112 schools nationwide. The smallest sampling unit was the class, and all students in the sampled classes were enrolled in the baseline survey in 2013, with follow-up rounds conducted in 2014, 2015, 2017, and 2019.

In 2018, when the majority of respondents were aged 17–18, we sought their permission for the research team to access their online posts and interactions with their middle school classmates on WeChat, which is the largest social media platform in China with over one billion monthly active users. A total of 8636 respondents granted us permission. From May 2018 to April 2021, we collected 1,048,999 public online posts and 1,030,710 interactions that occurred beneath these posts among respondents who were mutually verified friends on WeChat. Of these interactions, 75.13 % were between former classmates, 86.13 % between individuals from the same middle school, and 99.17 % between those from the same county. During the period examined in this study, which extends from May 2018 (the starting point of data collection) to July 2020 (six months after the outbreak of the COVID-19 pandemic), 8495 respondents actively engaged in updating posts or giving likes or comments and were therefore included in our analysis. Statistical tests show that the subsample of 8495 respondents has similar distributions on core sociodemographic variables to those of the overall sample (see Supplementary Table 1). The public online posts and associated interactions of the 8495 respondents formed our analytical sample.

3.2. Measures

The existing literature does not offer a clear definition of dormant ties or their reactivation. In our study, dormant ties were defined as relationships with no observed interactions for at least one year – specifically, from the start of online data collection in May 2018 to the occurrence of a major life event, either high school graduation in June 2019 or the outbreak of the COVID-19 pandemic in January 2020. A tie was considered reactivated if at least one interaction (either a like or a comment) was observed within six months following a trigger event.

3.3. Methods

3.3.1. Dormant tie reactivation and heterogeneities across different networks and nodes

We first examined how major life events trigger the reactivation of dormant ties before analysing how pre-event network density and the degree centrality of individual nodes affect the post-event likelihood of dormant tie reactivation. Network density refers to the proportion of existing connections in a network relative to the total possible connections, while degree centrality reflects a node's importance by measuring its direct connections relative to the total number of nodes in the network. Using these measures, we calculated how network density correlates with the proportion of reactivated nodes in each county and with the average number of reactivated ties per node. We also calculated Pearson correlation coefficients between node centrality and the number of reactivated ties in each county and examined how this correlation relates to network density.

3.3.2. Propensity score matching

Given the potential heterogeneity in the personal attributes of nodes with high and low centrality scores that could influence both their centrality and the likelihood of reactivating dormant ties after major life events, we used propensity score matching to reduce potential bias. The treatment variable was degree centrality, which was categorised into two groups based on the median value prior to the major life events, which served as the cutoff point. The outcome variable was the number of reactivated ties, measured by incoming and outgoing edges after high school graduation and the COVID-19 pandemic.

We estimated propensity scores using eight covariates: gender (male vs female), educational level (attended university vs not), family background (low vs high parental socioeconomic status), and the Big Five personality traits (lower 50 % vs upper 50 % for each dimension). We then used the predicted propensity scores to create a balanced sample of nodes with high and low centrality, for which the nearest-neighbour matching algorithm was applied. After matching, the covariate distributions for the two groups were similar, with standardised mean differences for all covariates below 0.05 (see Supplementary Table 2), indicating good balance between the two groups. While this approach accounts only for observed covariates and cannot eliminate hidden bias from unobserved confounders, it reduces potential bias and increases precision in estimation (Austin, 2011).

3.3.3. Agent-based model

We employed agent-based models to explore the potential mechanisms underlying the heterogeneities in tie reactivation across different networks and nodes. As more than 99 % of dormant ties were reactivated within the 26 counties, the simulation process was conducted separately for each county. The simulation followed these steps.

Step 1 – Network initialisation: The initial network structure of each county was configured based on the real network structure prior to the event.

Step 2 – Increased demand for social interaction: Following a major life event, each agent's demand for social interaction increased as defined by:

$$N = \alpha L, \tag{1}$$

where N is the total demand for social interaction following a major life event, L is the number of contacts the agent had before the event, and α (≥ 1) is a parameter that needs to be optimised during the simulation.

Step 3 – Reactivating dormant ties: Each agent performed $N - L$ trials to reactivate dormant ties. The probability of reactivation in each trial was determined by:

$$F = \left(1 - \left(\frac{L}{E}\right)^{w}\right)\left(\beta + (1-\beta)\left(\frac{1}{d}\right)^{\gamma}\right)^{m}, \tag{2}$$

where F is the reactivation probability, E is the maximum number of contacts an agent can manage among their middle school peers, d is the online distance between two agents, β is the minimum probability of tie reactivation when the distance between two agents is infinite, and w, β, γ, and m are global parameters for each county that need to be optimised during the simulation.

The difference between the simulated and real county networks was quantified using the difference in their degree distributions:

$$\Delta D = \sqrt{\sum_{i=1}^{N}\left(k_i^{(sim)} - k_i^{(real)}\right)^2}, \tag{3}$$

where ΔD is the degree distribution difference, N is the total number of nodes in each county, and $k_i^{(sim)}$ and $k_i^{(real)}$ represent the degrees of the i-th node in the simulated and real county networks, respectively, after sorting all node degrees in ascending order. Finally, we used the Kolmogorov–Smirnov test to assess whether significant differences existed between the degree distributions of real and simulated networks in each of the 26 counties.

3.3.4. Dynamics of reactivated ties

To depict the dynamics of reactivated ties following the two life events, we used Sankey flow diagrams to visualise personal network changes. The Sankey diagram for the event of high school graduation covers the period from May 2018 to June 2020, and the diagram for the COVID-19 pandemic shows changes from May 2018 to January 2021.

We also calculated the average frequency of interactions between an individual and each of their contacts every week, which is based on the following equation:

$$\mu_j = \frac{\sum_{x\in Y_j}\left(\frac{\sum_{i\in Q_{xj}} x_i}{|Q_{xj}|}\right)}{|Y_j|}, \tag{4}$$

where μ_j represents the weekly average frequency of a specific type of online interaction with contacts whose interactions with our respondents were first observed during a given time period j. j takes values from 1 to 13. Specifically, $j = 1$ represents the period from May 1, 2018 to June 9, 2019; $j = 2, 3, \ldots, 7$ denotes each of the six months following high school graduation from June 10, 2019 to December 9, 2019, and $j = 8, 9, \ldots, 13$ signifies each of the six months following COVID-19 from January 20, 2020 to July 19, 2020. x denotes target respondents in the dataset. x_i is the frequency of interactions between a respondent x and one of their contacts i in a given week. Q_{xj} marks the set of core friends or reactivated contacts with whom a specific respondent x has interactions in the time period j. Y_j represents the set of respondents who had interactions with at least one contact from the specified category (core friends or reactivated contacts) during period j. To minimise the impact of holidays over the three-year period, each data point represents a moving average of the current week, the previous week, and the following week.

For the purpose of showing what role reactivated ties play in the overall network, we made a comparison between the cumulative frequency of interactions with core friends and with reactivated contacts, and we also compared the respective proportion of interactions with these two groups. The cumulative frequency for each week was calculated using Equation (5), while the proportion of interactions was derived from Equation (6):

$$\lambda_p = \sum_{x\in Y_p}\left(\sum_{i\in Q_{xp}} x_i\right), \tag{5}$$

$$\kappa_p = \sum_{x\in Y_p}\left(\sum_{i\in Q_{xp}} x_i\right)\Big/\sum_{p=1,2,3}\lambda_p, \tag{6}$$

In Equation (5), λ_p is the weekly frequency of online interactions with contacts whose interactions were first observed in a certain time period p. p takes values of 1, 2, and 3, which represents the period 1 May 2018–9 June 2019, 10 June 2019–9 December 2019, and 20 January 2020–19 July 2020, respectively. Accordingly, λ_1, λ_2 and λ_3 represent the weekly frequency of online interactions among core friends, among reactivated contacts following high school graduation, and among reactivated contacts following the outbreak of the COVID-19 pandemic, respectively. Y_p represents the set of respondents who had interactions with at least one core friend or reactivated contact in the time period p. Q_{xp} represents the set of contacts that a specific respondent x has interactions with in the time period p. In Equation (6), $\kappa_p (p = 1, 2, 3)$ denotes the proportion of online interactions among core friends, among reactivated contacts following high school graduation, and among reactivated contacts following the outbreak of the COVID-19 pandemic, respectively. All the other parameters have the same meanings as in Equation (4).

3.3.5. Robustness checks

Considering that 8495 out of 10,279 respondents shared their WeChat accounts, we conducted additional analyses to check whether there was selection bias regarding the analytical sample. We first implemented a series of comparisons between the analytical sample and the overall sample to examine whether they had systematic differences. We also generated a weight parameter to make further adjustments so that the sample we used for analysis was fully comparable to that of the overall sample. The weighted results are similar to the ones shown in the main text (see Supplementary Figs. 1–2 for more details).

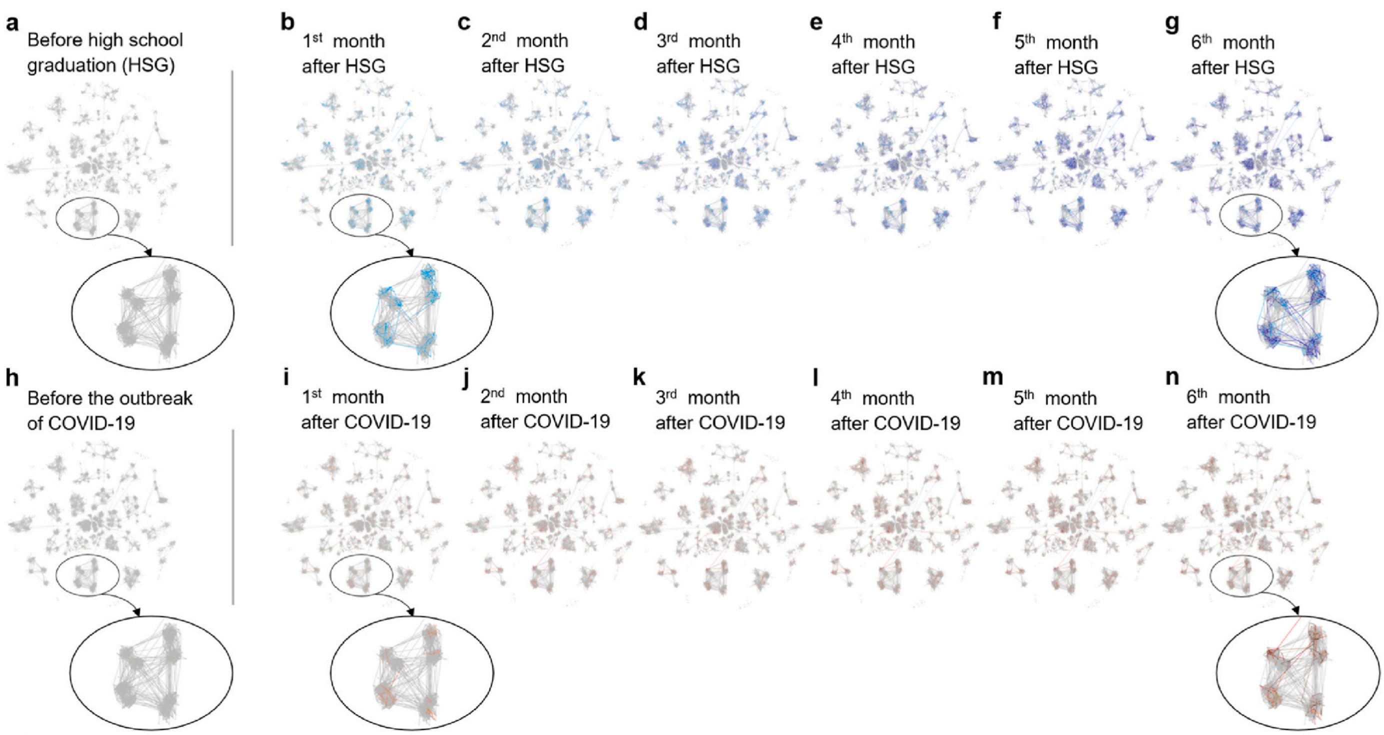
4. Results

4.1. How major life events reactivate dormant ties

We first examine how major life events reactivate dormant ties, as shown in Fig. 1. The upper row illustrates the configuration of the whole network before the cohort's high school graduation and the changes six months afterwards, while the lower row depicts the network changes before and after the COVID-19 pandemic. The entire network comprises 26 clusters, corresponding to the 26 counties covered by the offline survey. Each cluster contains multiple sub-clusters, corresponding to the schools and classes randomly drawn from these counties.

More specifically, Fig. 1a illustrates the network formed by the respondents' social media interactions with middle school friends before June 9, 2019 (the time of this cohort's college entrance examination, marking the end of their high school stage). Although the cohort had graduated from middle school during this period of time, connections with previous friends via social media persisted. Most interactions were found among former classmates, but ties across sub-clusters also existed, indicating connections beyond the original class boundaries. The cumulative average degree (the total number of friends that an individual directly interacts with on average) at this stage is 3.81 (see Methods for more details). Considering that during this period, most students were diligently preparing for their college entrance examination, the active ties they maintained despite this busy and stressful time are likely to be those with their close friends since middle school, who we refer to as the 'core friends' of their middle school years.

Figs. 1b–1g present the monthly changes in the whole network of this cohort after high school graduation, spanning the period from 10 June to December 9, 2019, a total of six months during which most respondents navigated through their first semester in college or the initial adaptation phase in the workplace. The cumulative average degree among newly



o

Time period	Accumulative average degree from 1 May 2018	95% Confidence Interval	Time period	Accumulative average degree from 1 May 2018	95% Confidence Interval
1 May 2018–10 Jun. 2019 (**a**)	3.81	[3.70, 3.92]	1 May 2018–19 Jan. 2020 (**h**)	6.04	[5.90, 6.18]
1 May 2018–9 Jul. 2019 (**b**)	4.20	[4.08, 4.31]	1 May 2018–19 Feb. 2020 (**i**)	6.23	[6.09, 6.38]
1 May 2018–9 Aug. 2019 (**c**)	4.49	[4.37, 4.61]	1 May 2018–19 Mar. 2020 (**j**)	6.34	[6.19, 6.48]
1 May 2018–9 Sept. 2019 (**d**)	4.85	[4.72, 4.98]	1 May 2018–19 Apr. 2020 (**k**)	6.46	[6.32, 6.61]
1 May 2018–9 Oct. 2019 (**e**)	5.19	[5.06, 5.33]	1 May 2018–19 May. 2020 (**l**)	6.57	[6.42, 6.72]
1 May 2018–9 Nov. 2019 (**f**)	5.45	[5.32, 5.59]	1 May 2018–19 Jun. 2020 (**m**)	6.67	[6.53, 6.82]
1 May 2018–9 Dec. 2019 (**g**)	5.71	[5.57, 5.85]	1 May 2018–19 Jul. 2020 (**n**)	6.79	[6.64, 6.94]

Fig. 1. Network changes before and after major life events. This is a cumulative undirected network diagram, in which each line indicates that online interactions exist between two individuals since May 1, 2018. **a**, The whole network configuration before the cohort's high school graduation (HSG), covering the period from May 1, 2018 to June 9, 2019. **b–g**, Monthly changes in the whole network following high school graduation from June 10, 2019 to December 10, 2019; first month (**b**), second month (**c**), third month (**d**), fourth month (**e**), fifth month (**f**) and sixth month (**g**). Blue lines highlight ties that were dormant in the previous stage but became active after high school graduation. **h**, The configuration of the whole network before the outbreak of the COVID-19 pandemic. **i–n**, Monthly changes in the whole network following the outbreak of COVID-19 from January 20, 2020 to July 19, 2020; first month (**i**), second month (**j**), third month (**k**), fourth month (**l**), fifth month (**m**) and sixth month (**n**). Red lines depict ties that were dormant before the pandemic but became active after this societal event. **o**, The cumulative average degree from May 1, 2018 onwards, with 95 % confidence intervals estimated using the *t*-distribution. $N = 8495$.

observed connections (depicted by blue lines) is 1.90, and that of the whole network increased from 3.81 to 5.71. Among the newly observed ties, the vast majority are found within the original class or school boundaries, signifying reconnection with previous classmates or schoolmates. This indicates that entering a new life stage prompted the reactivation of dormant ties on social media platforms.

Regarding the network changes before and after the COVID-19 pandemic, Fig. 1h shows the network before the event, formed by the respondents' interactions on social media before January 20, 2020. On January 20, 2020, it was announced that the novel coronavirus could be transmitted from person to person, and the Chinese authorities officially initiated actions to combat the epidemic. Figs. 1i–1n present the monthly changes in the whole network from 20 January to 19 July, spanning the same length of six months. During this period, nationwide social distancing measures were implemented, and most schools and universities transitioned to online teaching. Over the six months following the onset of the COVID-19 pandemic, the cumulative average degree among newly observed connections (depicted by red lines) is 0.75, and that of the whole network grows from 6.04 to 6.79.

Overall, these two major life events prompted around 71 % of respondents to reactivate dormant ties, demonstrating that this is a common phenomenon in the population. Notably, we can observe that the reactivation of dormant ties following major life events is not a one-time behaviour; instead, it can be seen for at least six months after the events take place. Furthermore, from May 1, 2018 to July 19, 2020, reactivated ties following the two trigger events account for around 39 % among all active ties for an average person, equivalent to around 2/3 the number of core friends from middle school stage, showing that reactivated dormant ties form an unignorable component of personal social networks in the face of major life events.

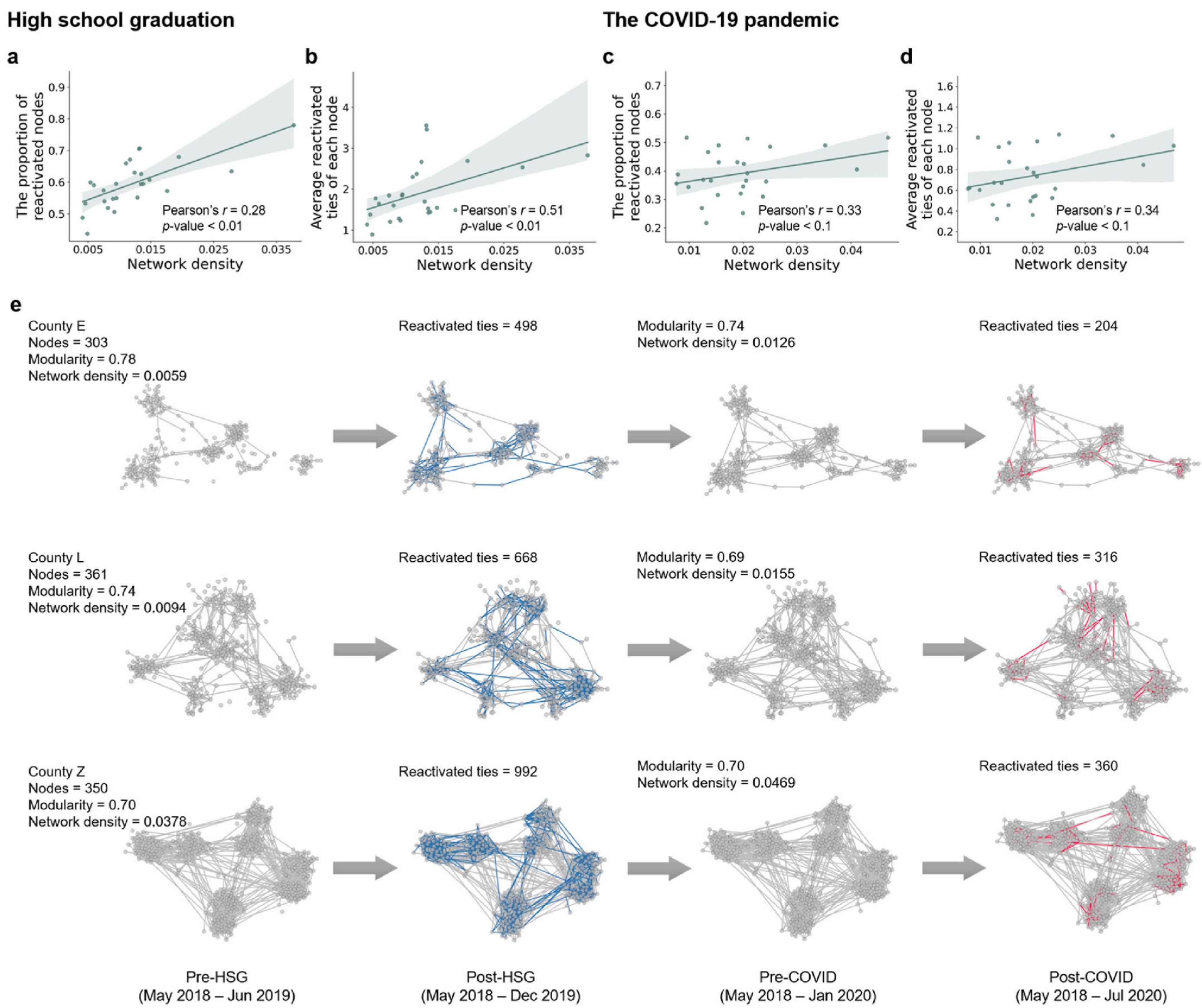


Fig. 2. The correlation between pre-event network density and post-event reactivation of dormant ties. **a–b**, The correlation between the network density of the 26 counties before high school graduation and the proportion of reactivated ties (**a**) or the average reactivated ties of each node (**b**) within each county over the six months following the event. Shaded areas represent 95% confidence intervals estimated using the *t*-distribution. **c–d**, The correlation between the network density of the 26 counties before the COVID-19 pandemic and the proportion of reactivated ties (**c**) or the average reactivated ties of each node (**d**) within each county over the six months following the event. Shaded areas represent 95% confidence intervals estimated using the *t*-distribution. **e**, The network characteristics of Counties E, L and Z and the respective number of reactivated ties of each county after the two life events. Blue and red lines highlight ties that were dormant in the previous stage but became reactivated after the two life events, respectively.

4.2. Heterogeneities across different networks and nodes

Despite the frequency with which dormant ties are reactivated in response to major life events, the likelihood of tie reactivation as well as the actual number of ties reactivated vary in the population. Who is more likely to reactivate dormant ties and to reactivate more ties? We first examine the effect of network characteristics and explore what types of networks cultivate such reactivation. Then we examine characteristics of individual nodes within different networks and identify which nodes are more likely to reactivate dormant ties in response to major life events.

Regarding network characteristics, Fig. 2 shows how network density correlates with tie reactivation. As shown in Fig. 2a, the network density in each county before high school graduation is positively correlated with the proportion of reactivated nodes within six months following the trigger event ($r = 0.28$, $p < 0.01$). It also has a positive correlation with the average reactivated ties of each node ($r = 0.51$, $p < 0.01$), as displayed in Fig. 2b. Similarly, a higher network density before the COVID-19 pandemic also predicts a higher proportion of reactivated nodes ($r = 0.33$, $p < 0.1$) and more reactivated ties of each node on average ($r = 0.34$, $p < 0.1$), as can be seen in Figs. 2c and 2d.

Using three counties as examples, Fig. 2e illustrates the effect of network density on dormant ties reactivation. Counties E, L, and Z have similar network structures, numbers of nodes and levels of modularity, but differ in network density. County E has the lowest network density before high school graduation and the lowest number of reactivated ties after the event. Compared to County E, the network density of County L before the event and the number of reactivated ties afterwards are both higher. County Z has the highest pre-event network density and the most dormant ties reactivated afterwards. The same pattern applies to the scenarios before and after the COVID-19 pandemic.

Turning to characteristics of individual nodes, we find node centrality before a certain life event has a positive effect on dormant tie reactivation in response to the event. Fig. 3 shows the effect of pre-event node centrality on post-event tie reactivation and how it varies across different networks. Taking County V as an example, dormant ties are more likely to get reactivated around nodes with higher degree centrality, in terms of both incoming edges ($r = 0.26$, $p < 0.01$) and outgoing edges ($r = 0.25$, $p < 0.01$), as shown in Fig. 3a. The same pattern applies to the post-COVID scenario (Fig. 3b).

We then broadened our scope from a single county to all 26 counties. Fig. 3a displays the correlation coefficients between pre-graduation node centrality and post-graduation reactivated ties of all counties in descending order. For incoming edges, 23 out of 26 counties have a

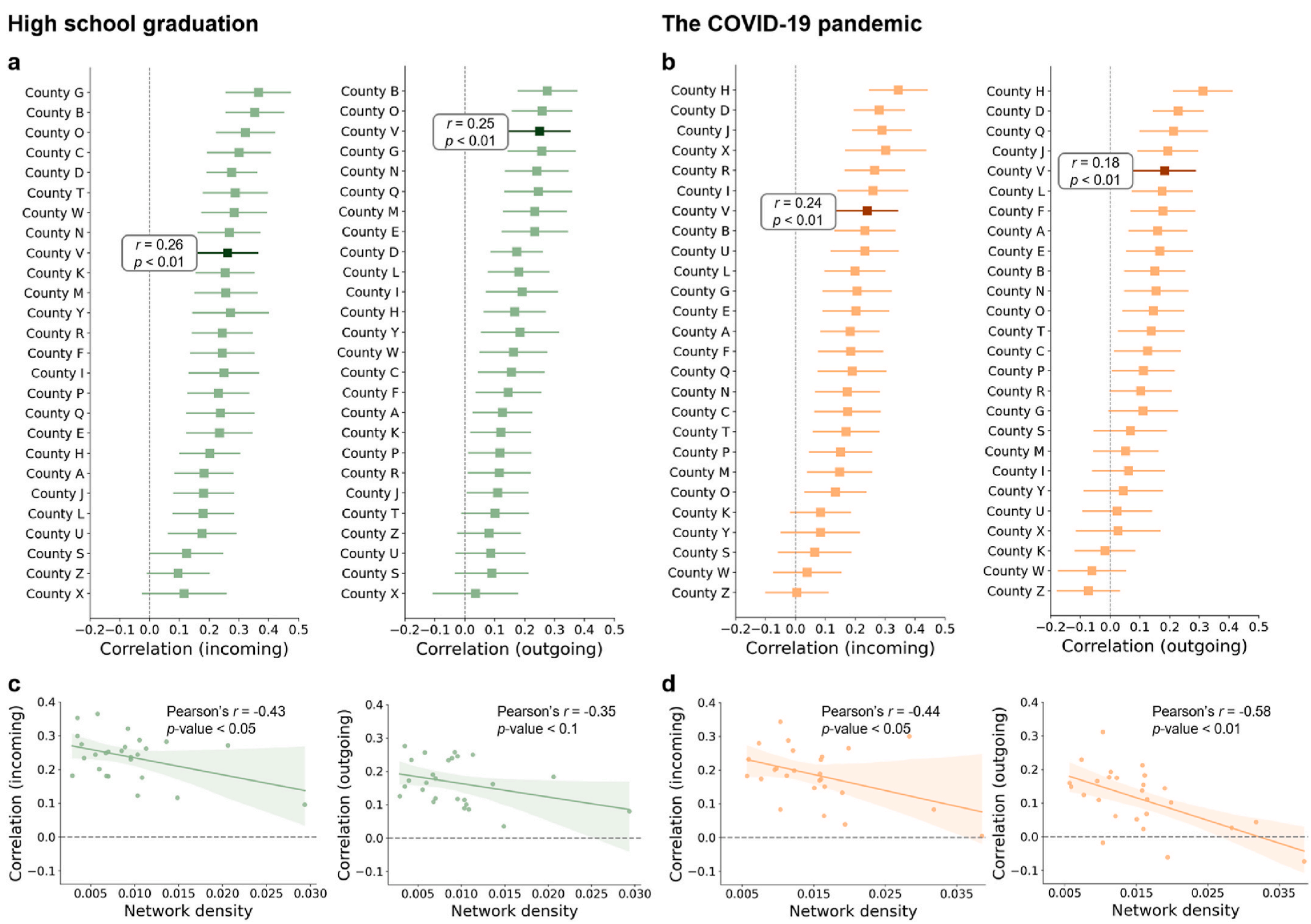


Fig. 3. How pre-event node centrality affects post-event dormant tie reactivation as well as the variations among different networks. **a**, Correlation coefficients between pre-graduation node centrality and post-graduation reactivated ties in 26 counties with 95 % confidence intervals, for incoming edges and outgoing edges, respectively, sorted in descending order by coefficient size. **b**, Correlation coefficients between pre-COVID node centrality and post-COVID reactivated ties in 26 counties with 95 % confidence intervals, for incoming edges and outgoing edges, respectively, sorted in descending order by coefficient size. **a**–**b**, 95 % confidence intervals calculated using Fisher's z-transformation. **c**, The variation of the correlation coefficients across 26 counties and how it is associated with pre-graduation network density, with 95% confidence interval shaded, for incoming edges and outgoing edges, respectively. **d**, The variation of the correlation coefficients across 26 counties and how it is associated with pre-COVID network density, with 95% confidence interval shaded, for incoming edges and outgoing edges, respectively. **c**–**d**, 95 % confidence intervals calculated using the t-distribution. $N = 8495$.

significant positive correlation ($p < 0.05$). For outgoing edges, the coefficients are found to be significantly larger than zero ($p < 0.05$) in 21 out of 26 counties. The findings are similar for the event of the COVID-19 pandemic (Fig. 3b). This suggests that, for most networks in our sample, not only do central nodes tend to reactivate more dormant ties in the face of major life events, but they are also more likely to be reactivated by their dormant friends. To reduce potential heterogeneity in personal attributes between nodes with high and low centrality scores, a robustness analysis using propensity scores was conducted, yielding similar results (see the Methods section and Supplementary Tables 2–3 for details).

We also analysed how the effect of node centrality is moderated by network density. As shown in Figs. 3c and 3d, for both life events and for both incoming and outgoing edges, the positive correlation between pre-event node centrality and post-event reactivated ties decreases as the network density increases. In other words, node centrality has a smaller effect on reactivating dormant ties in denser networks. Overall, denser networks not only foster a higher average number of tie reactivations following major life events but also result in a more equal distribution of these reactivated ties. This means that although major life events tend to reactivate dormant ties around central nodes in most networks, and therefore tend to make central nodes more central, network density has

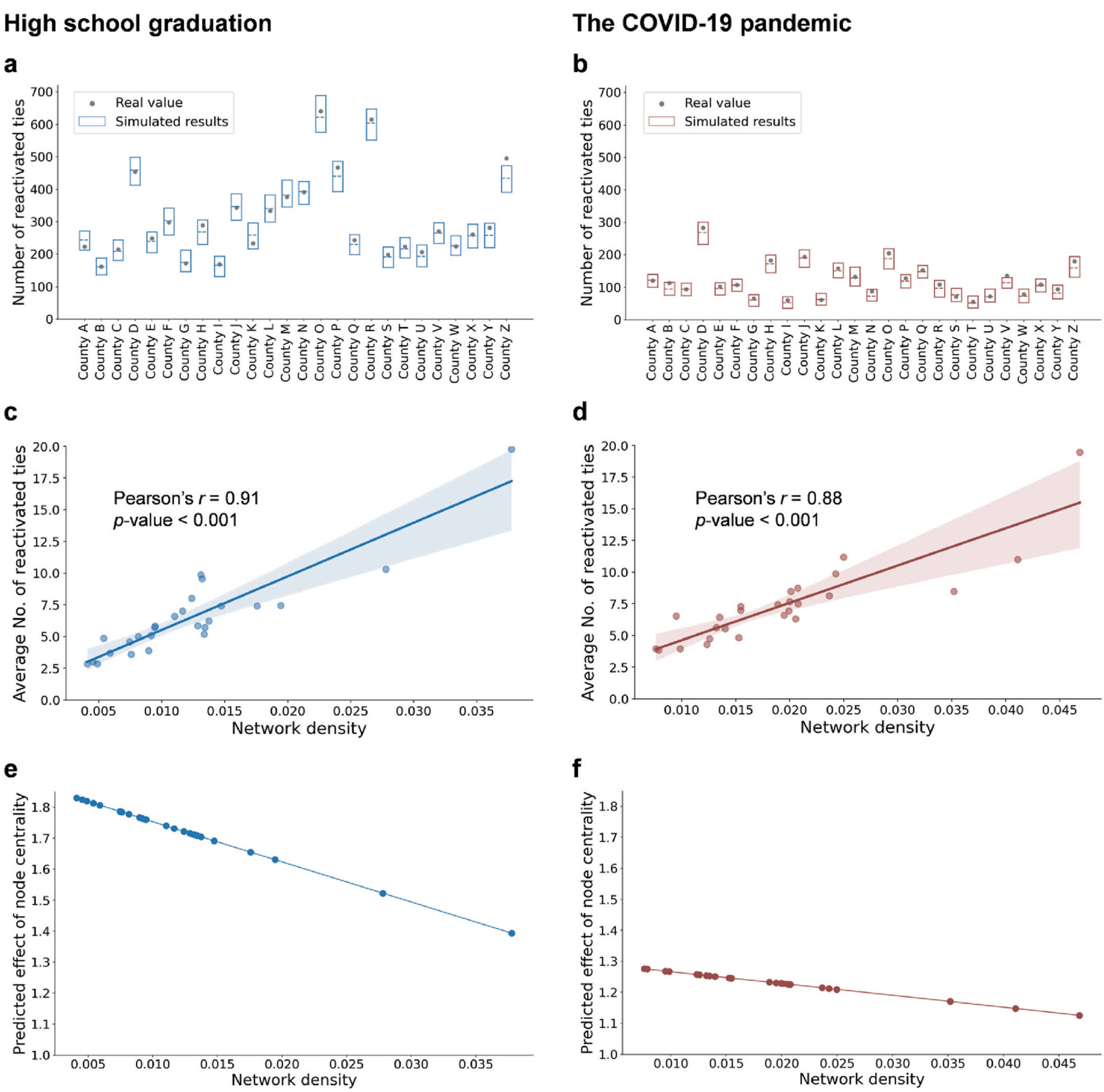


Fig. 4. Simulation results from agent-based models. **a–b**, Comparison of the real and simulated numbers of reactivated ties following high school graduation and the COVID-19 pandemic, respectively. Dots represent the real values for each county, while boxes indicate the range of results from 500 simulations, with the dashed line showing the mean of the simulated results. **c–d**, Effect of pre-event network density on the average number of reactivated ties per node following the two major life events. Shaded areas represent 95% confidence intervals estimated using the *t*-distribution. **e–f**, Predicted effect of pre-event node centrality, conditioned on different network densities following the two major life events. $N = 8495$.

a positive effect on mitigating this trend of polarisation.

Furthermore, we employed agent-based models (ABMs) to simulate the tie reactivation process. The pre-event network structure was used for model initialisation, with two behavioural rules assigned to each agent. First, agents maintaining more active ties before a major life event are presumed to have a higher level of trust in network members, and are thus more likely to reactivate dormant ties within that network. Second, due to limited cognitive capacity, the probability of reactivating a dormant tie is constrained by the number of relationships an agent can monitor simultaneously and the actual social distance between the agent and a specific contact (Dunbar, 1998; Hill & Dunbar, 2003). Detailed model specifications and simulation processes based on these rules are presented in the Methods section.

As shown in Figs. 4a and 4b, the number of reactivated ties generated by the simulation closely matched the real data. Regarding degree distributions, Kolmogorov–Smirnov tests indicated no significant differences between the real and simulated networks across all 26 counties, with all p-values exceeding 0.05 (see Supplementary Table 4 for details). Furthermore, the simulations replicated the observed result: pre-event network density positively influences the average number of reactivated ties per node (Figs. 4c and 4d) and mitigates the role of node centrality (Figs. 4e and 4f).

However, as the dataset encompasses only 26 counties with a limited range of network densities, the relationship between dormant tie reactivation and network density beyond this range cannot be observed. Simulations based on ABMs suggest that, on average, the effect of pre-event node centrality on tie reactivation would diminish to null if network density increased to 0.068 and 0.080 for the two life events, respectively. Under such conditions, existing central nodes would no longer become more central during major life events.

4.3. Dynamics of reactivated ties following trigger events

Once dormant ties are reactivated following a major life event, what forms do they take afterwards? We further delve into the dynamics of reactivated ties from three aspects: the retention rate of reactivated ties, the changing frequency of interactions between individuals and reactivated friends, and the contribution of reactivated ties in the overall online interactions following major life events. Additional analysis showed that although network density and node centrality affect the likelihood of dormant tie reactivation, they have no effect on the dynamics of reactivated ties (see Supplementary Tables 5–6 and Fig. 3 for more details), and therefore we conducted the following analysis based on the overall sample.

Fig. 5 depicts the retention rates of reactivated ties following the two life events. Fig. 5a shows that 60 % of the cohort reactivated at least one dormant tie within six months after high school graduation. By following the reactivated ties for another six months, we can see that among individuals who had reactivated dormant ties, 75 % retained connection with at least one reactivated friend. There are similar findings in the COVID-19 scenario, as displayed in Fig. 5b. Among those who had reactivated at least one dormant tie within six months after the COVID-19 pandemic, 65 % maintained active interactions with at least one reconnected friend for another six months, that is, one year after the outbreak of the pandemic.

Regarding the frequency of interactions, Fig. 6 depicts the average frequency of online interactions between respondents and each of their core friends (grey lines) as well as each of their reactivated contacts (blue and red lines) on a weekly basis. The calculations were based on Equation (4). Previous research indicates that on social media, commenting behaviour between two individuals has a higher correlation with their tie strength than liking (Arnaboldi et al., 2013), which suggests subtle differences between these two types of online interactions. Therefore, to analyse the dynamics of reactivated ties, we examined separately four different types of online interaction behaviours: liking in outgoing and incoming directions (giving and receiving likes) and commenting in outgoing and incoming directions (giving and receiving comments).

As shown in Figs. 6a–6d, a common pattern reveals itself across all four types of online behaviours among reactivated ties: the average frequency of interactions reaches its peak in the month of reactivation, when it surpasses the frequency of interactions among core friends, and then declines significantly after the peak and maintains a level that is more or less similar to that of core friends. After July 20, 2020, around one year after high school graduation and six months after the outbreak of the COVID-19 pandemic, the blue and red lines have largely merged with the grey one, suggesting that reactivated ties tend not to fall dormant after reactivation, but to maintain a level that is roughly similar to that of core friends.

We further examine below the contribution of reactivated ties in the online interactions following major life events by comparing the distribution of online interactions among core friends and that among reactivated contacts. Due to the fact that we are tracing a closed network, every like or comment sent out by one respondent is received by another within the network. Therefore, from a collective perspective, the cumulative frequency of likes or comments given equals that of likes or comments received. For this reason, we combine receiving and giving likes into one graph, and combine receiving and giving comments into

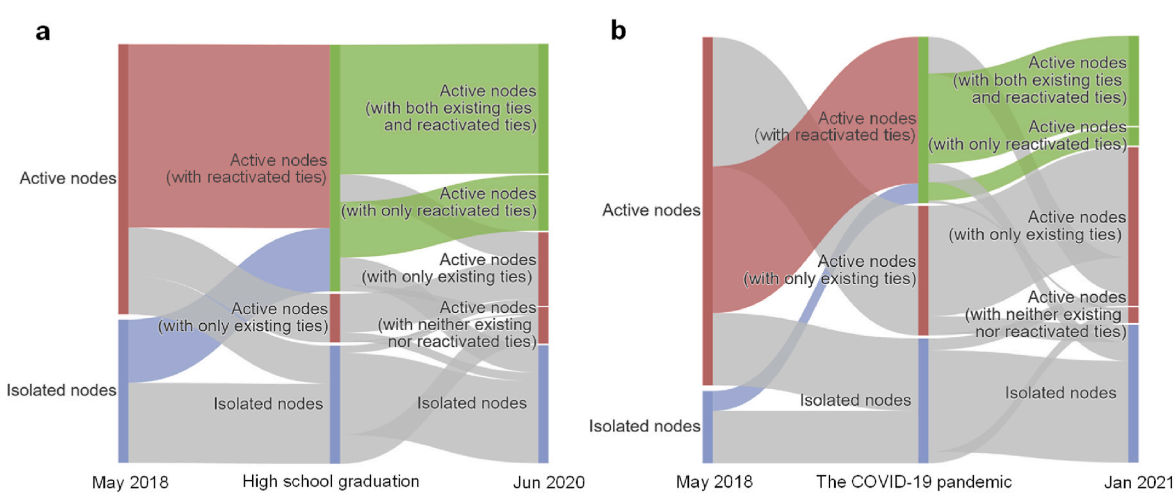


Fig. 5. Personal network changes of different nodes at three time points before and after each major life event. **a**, Changes in personal networks for different nodes in response to high school graduation. **b**, Changes in personal networks for different nodes in response to the COVID-19 pandemic. **a–b**, The total height of the diagram indicates the overall sample, and the height of each arc represents the percentage of the overall sample transitioning from one category to another. $N = 8495$.

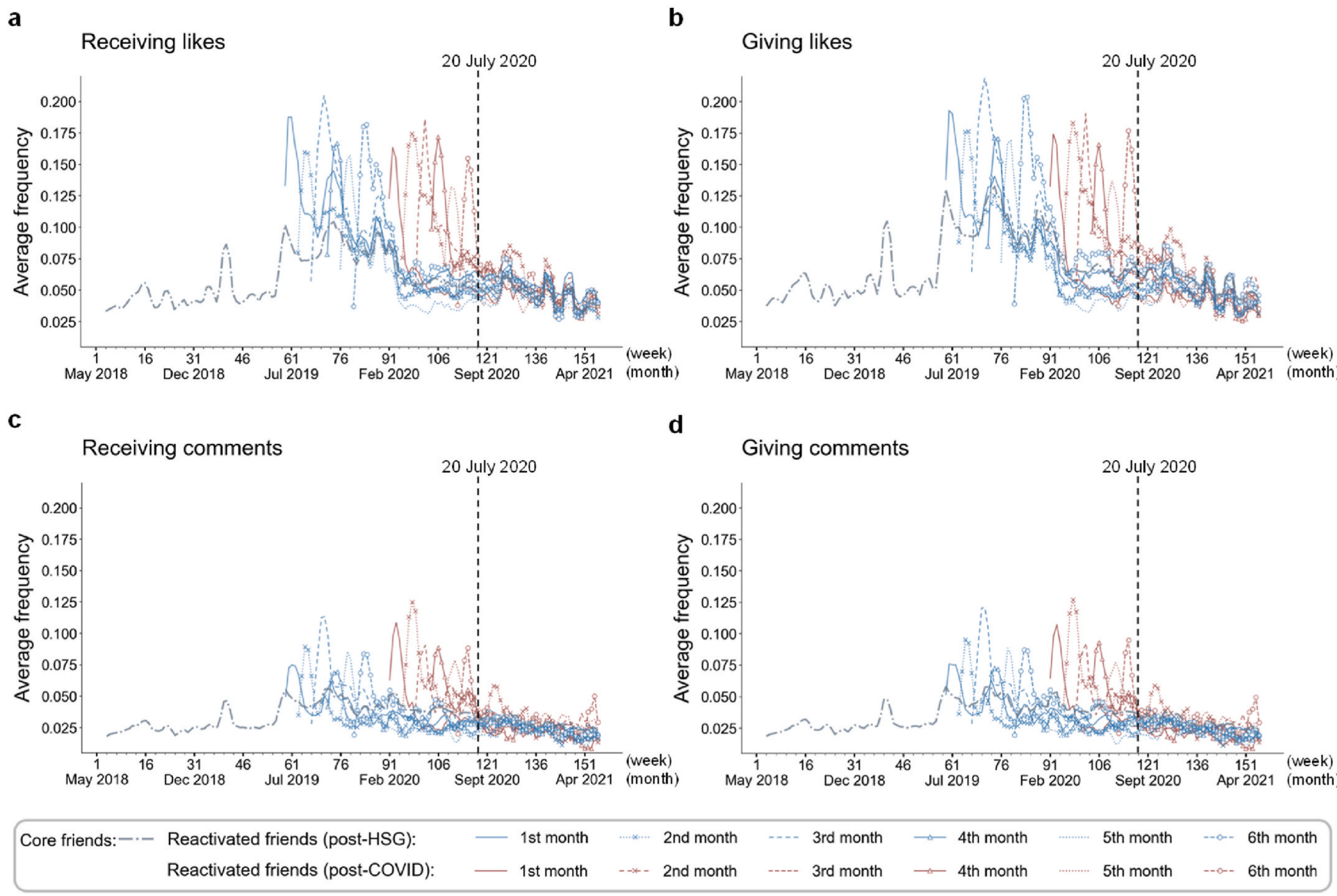


Fig. 6. Dynamics of respondents' online interactions with core friends and reactivated contacts on a weekly basis. **a–d**, Weekly average frequency of online interactions between respondents and each of their contacts, calculated among those who interacted with at least one contact from the specified category (core friends or reactivated contacts) during the given period. Grey lines show interactions with core friends, calculated among respondents who interacted with at least one core friend between May 1, 2018 to June 9, 2019. Blue lines show interactions with reactivated contacts in each of the six months following high school graduation, calculated among respondents who interacted with at least one reactivated contact in the corresponding month. Red lines show interactions with reactivated contacts in each of the six months following the COVID-19 outbreak, calculated among those who interacted with at least one reactivated contact in the corresponding month. Panels represent: **a**, receiving likes; **b**, giving likes; **c**, receiving comments; and **d**, giving comments. $N = 8495$.

another, as shown in Fig. 7.

As Figs. 7a and 7c illustrate, in the social media data we collected, the weekly frequencies of likes are significantly higher than those of comments. When it comes to their distributions among core friends and reactivated contacts, however, these two types of online interaction behaviours exhibit a high degree of similarity. This is more evident on the proportion charts (Figs. 7b and 7d). After July 20, 2020, interactions with reactivated contacts account for an average 37.73% and 35.38% in liking and commenting behaviours respectively, a substantial proportion that remains roughly stable until the end of our observation window (see Supplementary Table 7 for more details). The calculations in Figs. 7a and 7c were based on Equation (5) and those in Figs. 7b and 7d on Equation (6). Overall, following the two major life events, reactivated contacts not only account for more than 1/3 of all contacts, but contribute more than 1/3 of online interactions, with no sign of declining at least one year after trigger events take place.

5. Discussion

Facing major life events, most people resort to their personal social networks for various resources and support, during which dormant ties, the silent majority of our social network, are very likely to get reactivated and to exert an important role (Wu et al., 2021; Yang et al., 2021). However, research on dormant ties remains limited and our knowledge about network evolution confronting major life events remains scarce. In an effort to address this knowledge gap, we constructed a comprehensive database for a nationally representative sample of a Generation Z cohort from 221 middle school classes in China, which integrates their offline relationships and their online interactions on Chinese largest social media platform over a three-year period. Based on this large-scale and nationally representative database, we first showed to what extent and in what timescale major life events revive dormant ties, then explored heterogeneities across different networks and nodes, and finally investigated the general dynamics of the reactivated ties following trigger events, in what forms they exist and how long they persist.

This study makes three main contributions to the existing literature. First, due to the lack of appropriate data, we have long had insufficient insight into whether and how the majority of social capital – carried by dormant ties in social networks – can be mobilised. Unlike previous studies that have relied primarily on small and self-selected samples (Levin et al., 2011; Quinn, 2013; Rondi et al., 2024; Walter et al., 2015; Yang et al., 2021), this study provides large-scale evidence, based on nationally representative data, that reactivating dormant ties is a common phenomenon when people experience major life events. Following high school graduation and the COVID-19 pandemic, over 70 % of respondents in our sample reactivated at least one dormant tie on social media. In addition, the size of reactivated dormant ties is not a trivial

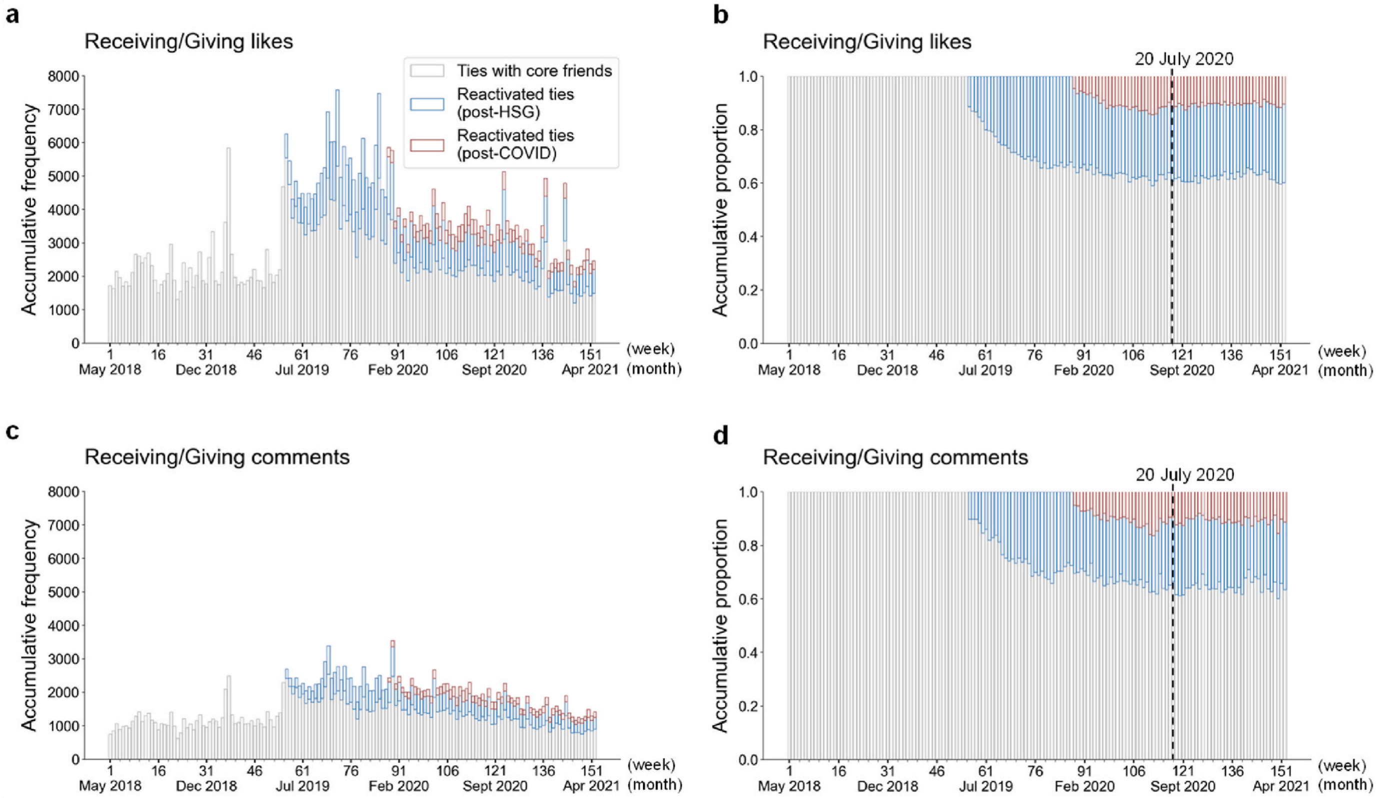


Fig. 7. Distribution of online interactions among core friends and reactivated contacts on a weekly basis. **a**, Cumulative frequency of likes received from (given to) core friends and reactivated contacts of all respondents. **b**, Proportion of likes received from (given to) core friends and reactivated contacts of all respondents. **c**, Cumulative frequency of comments received from (given to) core friends and reactivated contacts of all respondents. **d**, Proportion of comments received from (given to) core friends and reactivated contacts of all respondents. **a–d**, grey bars denote interactions among core friends; blue bars indicate interactions among reactivated contacts following high school graduation, and red bars represent interactions among reactivated contacts following the outbreak of the COVID-19 pandemic. *N* = 8495.

number. On average, the number of reactivated friends prompted by the two trigger events is equivalent to more than 2/3 the number of core friends and more than 1/3 of all active contacts from middle school stage for each individual, which is a considerable component of their personal network. Previous research on social networks and social capital has primarily focused on active ties (Brass, 2022), which represent only the tip of the iceberg in people's network relationships (Bzdok & Dunbar, 2022; Dunbar, 2020). This study helps clarify how dormant ties are reactivated during major life events, thereby deepening our comprehension of the resources and functions embedded in social networks. In particular, in the digital era, the widespread adoption of digital devices and social media has facilitated the reactivation of dormant ties. Research in this vein is thus increasingly relevant to understanding how individuals cope with uncertainty and stress, as well as the varying forms of social capital in the digital age.

Second, this study goes further and reveals significant heterogeneities across different networks and nodes. Our findings demonstrate that both network density and node centrality increase the likelihood of tie reactivation. During major life events, central nodes in a network are more likely to mobilise inactive social capital from dormant ties and are more frequently contacted by former acquaintances. Consequently, these nodes tend to become more central during such events, regardless of their personal attributes. However, this trend is less pronounced in dense networks. In these networks, not only are more dormant ties reactivated on average by each node, but the distribution of reactivations is also more equitable, suggesting that dense networks offer advantages for mobilising latent social capital during critical moments. This study extends earlier research by showing that, although network density is not a significant predictor of tie dormancy (Marin & Hampton, 2019), it is significantly associated with tie reactivation in the context of major life events. The findings highlight the significance of network structural characteristics, shedding new light on how network features shape individuals' access to social support at critical junctures.

The analysis using ABMs uncovered potential mechanisms underlying the effects of network density. The results indicate that higher network density moderates the influence of node centrality by fostering greater trust among members. Furthermore, in denser networks, central nodes are more likely to approach the upper limit of relationships they can monitor simultaneously. As a result, peripheral nodes have a higher likelihood of reactivating dormant ties, while the activation capacity of central nodes is somewhat constrained. This dynamic leads to a more balanced distribution of social capital in response to major life events. Overall, the mechanisms uncovered provide psychological and cognitive explanations for why structural features of networks matter, thereby advancing theoretical understanding by establishing micro-level foundations for macro-level observations.

Third, despite the heterogeneities in the likelihood of reactivation, once revived, the dynamics of reconnected ties tends to follow a similar route. We find that the average interaction frequency peaks at the time of reactivation, then declines to a level roughly equivalent to that of core friends, and most of these ties remain active six months later instead of retreating into dormancy. The overall interactions with reactivated ties contribute to more than 1/3 of both liking and commenting behaviours, which remain stable until the end of our observation window. The evidence reveals the mid-to long-term statuses of reactivated dormant ties following major life events. It also underscores the significant role that maintaining these ties plays in shaping the configuration and evolution of social networks. While previous research has highlighted the potential value of dormant ties as a source of latent social capital (Levin et al., 2011; Rondi et al., 2024), our findings suggest that, once reactivated, these ties can continue to play a meaningful role over time. These findings highlight the growing importance of including dormant ties in research on network dynamics in the digital era.

This study also contains several practical implications for network building in digital societies and support provision during major life events. Regarding network building, our findings demonstrate the advantages of denser networks in mobilising latent social capital at critical moments, even when these networks primarily exist on social media. In an era characterised by increasing screen time and with many networks maintained online, network building should still be encouraged, as these connections may serve as vital sources of support during major life events. In terms of support provision, social media platforms could design algorithms to recommend contacts with whom users have had prior interactions, particularly during emergencies such as public health crises. Similarly, administrative sectors and mental health intervention programs could encourage individuals to actively reconnect with past contacts. The informational and emotional support provided by reactivated dormant ties can help individuals better cope with stress and uncertainty (Perry et al., 2023; Yang et al., 2021). Particular attention should be given to communities with sparse networks, where information and resources tend to concentrate around central nodes, potentially leaving marginalised individuals without essential support. In such cases, additional external support may be necessary.

This study is subject to a few limitations, which point towards potential directions for future research. First, in the empirical analysis of this study, we rely on behavioural data to monitor tie reactivation and persistence. While active interaction represents a milestone in the development of interpersonal attachments (Friedkin, 1990), interaction frequency does not in itself reflect the closeness or commitment of the reactivated relationships (Marsden & Campbell, 2012). Future research could incorporate additional dimensions of interaction, such as the closeness and commitment of reactivated relationships, and further explore whether these factors influence the longevity of such connections. Second, in this study, dormant ties were defined as those with no observed interactions for at least one year, and the reactivation of a dormant tie was defined as the occurrence of at least one interaction. Compared to more traditional forms of tie reactivation, such as a face-to-face reunion or a phone call, interactions on social media are more lightweight, and some may be transient or superficial. If traditional forms of reactivation are used as the benchmark, reactivation via social media represents a lower threshold and may therefore lead to an overestimation of reactivation rates. Further research could examine the specific roles reactivated ties via social media play following major life events, the extent to which they provide instrumental or emotional support, and how this differs from support offered by ties reactivated through more traditional means. Moreover, as this study is based on a nationally representative sample of a Generation Z cohort, the findings may have been influenced by specific cohort characteristics. Future research could assess the generalisability of these results to other cohorts when suitable datasets become available.

In conclusion, the dynamics of dormant ties in the face of major life events is a crucial yet often overlooked patch in the landscape of network research. Based on longitudinal data of a nationally representative sample on social media, this study examines the reactivation and persistence of dormant ties following two major life events, making a step forward to better understanding the 'silent majority' in our social networks. We demonstrate that the 'silent majority' are not always silent; on the contrary, their revival takes place on a substantial scale at critical moments on social media and tends to persist beyond the trigger events. While central nodes are more likely to revive the inactive social capital, denser networks allow more nodes to get reconnected. We argue that only by further opening the black box of dormant ties can we draw a more comprehensive and accurate picture of how social networks evolve and function at critical life junctures in the digital age.

CRediT authorship contribution statement

Yizhang Zhao: Conceptualization, Formal analysis, Writing. **Wei Bai:** Formal analysis. **Tianyu Qiao:** Conceptualization, Formal analysis. **Weidong Wang:** Data curation, Conceptualization.

Ethics statement

Ethical approval was granted by the Ethics Committee of the National Survey Research Center at Renmin University of China on April 11, 2018 (RN2018041101), confirming that the study complied with ethical review requirements for scientific research and authorising its conduct following the approved research protocol. The study was conducted in accordance with the relevant guidelines of the Declaration of Helsinki. Participants were informed of the purpose of the research, potential risks, data protection measures, and their right to withdraw at any time. Informed consent was obtained from all participants. As all survey participants were aged 16 or above at the time of invitation, their individual consent was sufficient for participation per the current legal framework in China.

Declaration of competing interest

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

Acknowledgements

This study is supported by the National Social Science Fund of China [No. 23CSH006].

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.chb.2025.108746.

Data availability

Data will be made available on request.

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