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Collapse of an online social network: Burning social capital to create it?

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ABSTRACT

The last decade has shown that sometimes even the largest online social networks (OSNs) collapse. Significant cascading mechanisms have been identified in the pattern of abandoning the OSN iWiW at its peak of popularity and after. We set out to examine the key actors who were the first to leave their networks by contrasting explanations based on the structural position of users in the network. Using heterogeneous choice models, we found that a higher number of connections as well as less clustered ego-networks hindered early abandonment while early adoption was only a secondary factor.

Introduction

The rise and popularity of online social networks (OSNs) in the new millennium overshadows even the success of the Internet itself. The sociological reasons behind the phenomenon are relatively well studied (e.g., Boyd, 2008; 2014). Explanations concentrate on different aspects and motives of social capital that include emotional (e.g., sense of belonging) as well as practical reasons (e.g., access to information) of participation (Burke et al., 2010, 2011; Brooks et al., 2014; Ellison et al., 2011, 2014). Today, when Twitter and Facebook are so ubiquitous and users spend many hours every day interacting through these sites, it is difficult to fathom how OSNs could collapse at all.

What makes the collapse of online social networks interesting is the prominent role network effects play in their growth and functionality. OSN users connect with people they already know offline (Boyd, 2008). Thus, without a critical mass of known contacts on a particular OSN, its functions have a very limited utility. This means that a popular OSN is unlikely to collapse, but once a collapse has started, a cascade mechanism can accelerate the abandonment of the site, prompting many people to choose a rival OSN.

Although the collapse of popular OSNs is not frequent, there have been examples of abandonment of early OSNs for new and more adaptive ones in the past years. Perceptions and functionalities of the old and new sites can be used to explain these changes (Boyd, 2008; Wilkinson and Thelwall, 2010; Robards, 2012). Such system-level explanations, however, do not provide us with a deeper understanding of user behavior that is typically independent of or precedes provider decisions. It is more insightful to search for explanations at the individual and micro-structural level. In this study, we analyze individual and structural mechanisms that triggered users to abandon a site. We know from related research that cascade mechanisms are present in abandoning the OSNs (Török and Kertész, 2017). It is important to know, however, form a scientific perspective, and also, for the managers of the sites from a business perspective, where these cascades start. Is it the central, old, hardcore users, who are tempted to "innovate" and change for a newer, better site? Or is it the peripheral users, who do not profit so much from the current platform?

Previous studies found that OSNs are important means of maintaining and enriching social capital (Burke et al., 2010, 2011; Brooks et al., 2014; Ellison et al., 2011, 2014). Similarly, explanations related to social capital could be potentially useful also for understanding their abandonment. Specifically we will test, whether users in structural positions that are less favorable in terms of social capital are the ones who are more likely to leave the network. In the following, we provide a brief description of iWIW, the OSN we focus on. Next, we give an overview of previous studies on the collapse of OSNs, followed by theoretical considerations, which may help us in understanding the underlying micro motives behind the collapse. Finally, we formulate our hypotheses.

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iWiW: an abandoned OSN

We investigate the sociological and structural mechanisms explaining the abandonment of OSNs using the example of a once highly popular Hungarian site iWiW. iWiW (*international who is who*, originally WiW) was founded in 2002. It was one of the first online social networks in the world and the most popular online social network in Hungary until October 2010, when its popularity was exceeded by that of Facebook (Webisztan blog, 2010). iWiW started as a small innovative non-profit project and it was exclusively based on invitations in its emerging stage. The site grew and was subsequently acquired by Hungarian Telekom in 2006. Afterwards, it gradually took up a less personal, more corporate identity. Facebook was launched in Hungary in October 2008 and was available in Hungarian from April 2009. Although often criticized for its inadequate speed and many bugs, at the time of Facebook's arrival, iWiW had almost 3.5 million active users (in a country with a population of 10 million this meant two-third of all Internet users). To maintain its market position, iWiW went through several redesigns. Redesigns were improvements of service, but also reactions to the proliferation of user generated advertisements and viral marketing. Despite the innovations, the OSN gradually lost its popularity; after experiencing a striking decline in user activity, iWiW was finally shut down by the provider in 2014, becoming a part of social and Internet history.

Previous research on collapse of OSNs

Shifts in the popularity of different online social networks cannot be explained by a single motivational factor. Previous research points to a complex set of reasons and mechanisms that underlie the decision to leave one site for another. Among reconfigurations of the online social network landscape, Facebook's overtake of MySpace was probably the one to receive the most attention.

The first explanation relates to the contextual effects of human life. People's social network and also online social network are clustered along different contexts, such as changing school or starting a new job (Boyd 2014; Fischer, 1977; Feld, 1981). From this aspect, Facebook was considered to more likely involve familial and other 'adult' relationships and evoked a desire for a more conscious digital trace management (Robards, 2012; Wilkinson and Thelwall, 2010). The second explanation is built on individual preferences for different features on the sites. Facebook, for instance, is viewed as more mature, sterile, and boring than MySpace, this induces a stronger preference by more educated users (Lenhart et al., 2010). Concerns about the type of information presented and questions of privacy could have also made Facebook more attractive to certain users (Patchin and Hinduja, 2010).

In 2008, the world map of the leading OSN services was quite colorful, yet today, in most countries Facebook dominates. Facebook replaced dominant global and local OSNs in several countries between 2009 and 2011. Global ones include Orkut in India and Brazil, Hi5 in Mexico, Portugal and Romania, while local ones are, for example Hyves in the Netherlands, NK in Poland, and Cyworld in South Korea (Yin et al., 2013; Heidemann et al., 2012). These transitions, however, are much less documented in the scientific literature. Studies have been conducted, for instance, on Hyves (Corten, 2012), on a U.S university network (Panzarasa et al., 2009), on Cyworld (Ahn et al., 2007), or on the Hungarian iWiW network (Lengyel et al., 2015), but none of these attempted to explain the collapse of these networks.

Cascade dynamics

We argue that we know little about the micro mechanisms explaining the collapse of OSNs. An important characteristic of online social networks also from this perspective is the presence of network effects. The key feature of OSNs is that it enables users to connect and communicate with each other. Without a critical mass of known contacts on a particular OSN, its functions have a very limited utility, and the utility of a platform to a user depends on the number of platform users among the user's connections. The literature in economics refers to this phenomenon as network externalities (Katz and Shapiro, 1992). Network externalities create a switching cost for customers and an entry barrier for alternative providers (Economides, 1996). On the one hand, this implies that initially the new platform has to provide far superior services for a critical mass of users to switch. On the other hand, if users start to switch, the new platform becomes more attractive to their connections and a cascade mechanism can occur.

In line with this, it was found that the more acquaintances of a user leave a mobile service provider, the higher the probability of their churn is(Dasgupta et al., 2008). Similarly, a study of an OSN found that a higher number and share of inactive connections increases, while a higher number of active ones decreases the probability of leaving the site in the subsequent period (Wu et al., 2013). Leaving the network, however, is not necessary for a cascade to start: the network can also collapse due to the high proportion of inactive users. This cascade mechanism may progress through the entire network, or alternatively, it may stop at boundaries between closely connected subnetworks. The model of Garcia et al., (2013, 2017) suggests that in the presence of network externalities given the number of connections, a locally dense structure (high *k*-coreness) increases the resilience of the network (cf. also Bruggeman, 2018). When examining five online social networks empirically, however, they found that currently successful OSNs have relatively *low k*-coreness compared to failed or declining ones. Using the data of the iWiW network, Török and Kertész (2017) modelled cascade dynamics of abandonment. They compared iWiW data with a generalized threshold model of churning, in which the probability of leaving the network was uniform over users and depended only on a network threshold effect.

To understand how the structural position of users contributes to leaving the old platform, and to the beginning of a cascade of abandonment, we link our explanation to research on social capital and embeddedness.

Social capital and OSNs

According to the most general definition, social capital is *investment in social relations with expected returns* (Lin, 1999). Previous research analyzed the relationship between perceived social capital and different aspects of OSN use. Despite the difficulties in measuring the extent of social capital in OSNs, authors agree that social capital benefits generally characterize the use of online social networks. There is disagreement, however, about the structural properties that correlate with larger expected returns of social capital.

Burke et al. (2010) found a positive impact of the number of Facebook friends on social capital. Ellison et al. (2011) also found a positive, but diminishing effect of the number of friends. This is in line with van der Gaag and Snijders (2002), who suggested that adding new alters yields not a proportional, but instead, a diminishing returns on social capital; as help, provided by multiple alters can be unnecessary or even inconvenient. Additionally, Tong et al. (2008) argued that over a certain limit, sociometric popularity may turn into a hindrance rather than an asset on an OSN, as it creates the impression of friending others superficially beyond the plausible extent.

For the analysis of the relationship between OSNs and social capital, a distinction between *bridging* and *bonding* social capital is important (Putnam, 2001; Ellison et al., 2014; Williams, 2006). Bridging social capital summarizes those aspects that are correlated with access to information, resources, and opportunities through social ties (Burt, 1992). Bonding social capital summarizes the benefits from trust, intimacy, and cooperation in dense, close, and stronger relationships. It has also been shown that direct person-to-person communication on Facebook is associated with bridging social capital (Burke et al., 2011). Brooks et al. (2014) found that transitivity on Facebook is negatively correlated with perceived bonding social capital measured subjectively in a questionnaire. They operationalized transitivity within ego's friendship network, excluding ego; thus they argued that high transitivity indicates closed and unconnected clusters within ego's network – which goes together with low bonding social capital. They also found no positive impact of Louvain modularity or transitivity on bridging social capital.

Social embeddedness and network decay

The duality of perspectives on social capital is also reflected in the rich literature on embeddedness (Granovetter, 1985; Uzzi, 1997). Following Granovetter (1985; 1992), Nahapiet and Ghoshal (1998) described structural embeddedness as the network of relations as a whole that constitutes an important dimension of social capital. In contrast, by relational embeddedness they described the kind of personal relationships that have developed through the history of interactions, and could include trust, emotional attachment, and "actor bonds" (Hakansson and Snehota, 1995; Nahapiet and Ghoshal, 1998; Gulati, 1998; van den Hooff et al, 2010).

Structural and relational embeddedness also influences the exit from networks. Polidoro et al. (2011) argued that structural embeddedness creates a shadow of others, that is, a sanction potential of common partners (see Coleman, 1990), which ensures cooperation – although this configuration is associated with increased competitive tension. They find support for this argument in the analysis of strategic alliances. An opposite result was found by Greve et al. (2010) about withdrawal from interfirm alliances showing that alliances with more closed triads were more likely to collapse.

Considering organizational networks, Burt (1992, 2000, 2002) emphasized the information and control opportunities of people bridging structural holes in the network. In the analysis of networks of employees, Burt (2002) found that bridging links were disappearing in a very high rate from the networks of business contacts, at a significantly higher rate than non-bridges. However, what is more directly related to our question is not the dissolution of links, but the withdrawal of persons from the network. In connection with this, he found that bankers with a high number of bridges were somewhat less likely to exit the company; however, this relationship disappeared after controlling for peer evaluation (which was positively correlated with the number of bridges). Kratzer and Takács (2007) found that the prospects of staying in an R&D team are enhanced by social closure, but the expectation to stay in the organization was enlarged by the efficiency and effectivity of the individual social network, indicating that different structural dimensions of social capital might be important for different types of career choices. In contrast, Krackhardt (1999) argued that a position between two mutually exclusive cliques creates ambiguous role expectations, which contributes to negative feelings; therefore we would expect higher exit rates for employees in bridge positions. This question was empirically examined by Flap and Völker (2001), who analyzed job satisfaction separately for its social and instrumental aspects. They found that openness of the strategic network increased satisfaction with the instrumental aspect of the job, and closeness improved the aspect of solidarity.

The costs and benefits associated with these different networks, however, can be different from each other. In case of OSNs, these are also specific to the structure and functionalities of the service. Therefore, we need to review the costs and benefits associated with OSNs generally and the peculiarities of the examined network.

Uses and functionalities of iWiW and contemporary OSNs

For understanding whether mechanisms related to social capital played an important role in abandoning the site or not, it is essential to go through the key functionalities of iWiW and contemporary OSNs. On OSNs, technical affordances, social norms, and practices that guide user engagement are in a fluid interplay contributing to a constantly shifting, evolving environment (Ellison and Boyd, 2013).

Most OSNs today are organized around a stream of recently updated content (e.g. Facebook's News Feed). They are able to fulfil the function of social grooming in an entertaining way between people who feel attachment or belonging to each other (Ellison et al., 2014). Earlier OSNs were much more profile-centric. Prior to 2007, the three defining features that constituted the core of OSN functionality were the profile, the connection lists, and the ability to traverse those connections (Ellison and Boyd, 2013). Profiles, as on iWiW, were designed to be static portraits, constructed and updated through text and images by the profile owner. iWiW was generally regarded as a useful digital phonebook (by default, the email address of every member was visible), and was criticized for its lack of dynamic content. The visibility and the possibility of the exploration of connections were the most luring features of iWiW. For many years, the site offered a visualization of the user's social network with the possibility of showing the shortest path to any member. Connections of anyone could be displayed, which was highly useful for building new ties, partnerships, and finding new job opportunities. The newsfeed function was only added to the system in 2009, and it did not have a filtering mechanism, or a function enabling interaction (like the "like" button introduced later on Facebook).

These functionalities are important when analyzing the costs and benefits for different users of iWiW. As the main functionalities facilitated efficiently collecting contact data and creating a communication platform, in essence, the platform made maintaining social capital easier by decreasing the costs of social grooming. As this efficiency was true for each contact, we assume - although we do not observe social capital directly - that the more connections one had the more gains one could reach in terms of social capital. Costs associated with staying on the OSN included logging in regularly, keeping the profile up-to-date, and answering requests, which were low due to the efficiency of the OSN compared to maintaining offline relationships. Yet, if users were not compensated by the benefits in terms of social capital, thely could choose to leave the network.

Therefore, **we assume that users with a higher degree**[1] **were less willing to leave the site (H1a).** This may follow from that they could lose more in terms of maintaining their social capital online.

Furthermore, the literature on social capital suggests that new contacts have a diminishing return on social capital (van der Gaag and Snijders, 2002), which was also found for OSNs (Ellison et al., 2011). Accordingly, **we expect that the number of connections has a negative, but diminishing effect on exiting the network (H1b).**

Less straightforward is the prediction considering the structural position, whether it is closed (clustered) or open (bridging). Burt (2002) argues that bridging position in the network creates information and control advantages, and also finds that employees in bridging positions are less likely to exit. We believe that this information advantage of bridge positions is also an asset considering OSNs: people communicate with their strong ties in several contexts, and information can be exchanged with them using several mutual connections. This is not true for weak ties, as in this case the OSN can transmit information that otherwise would not reach the user; therefore the gain in social capital is higher for users with many weak ties. Consequently, we **assume that people in closed (clustered) network positions were more likely, while ones in more open (bridging) positions were less likely to leave the network unilaterally (H2).**

Note, however, that based on structural embeddedness arguments, we could reach the opposite prediction. That literature suggests that dense, locally closed networks provide sanction potential, which prevents opportunistic, norm-breaking behavior (Coleman, 1988, 1990; Takács et al., 2008). This norm-breaking may correspond to the

[1] Here we do not differentiate indegree from outdegree, and consider the OSN as an undirected network.

unilateral exit from the network in our case. The decision on the validity of these arguments depends on how we imagine the underlying strategic interaction. The embeddedness arguments assume a social dilemma situation, where parties are tempted to take advantage of their partners. In contrast, changing a communication platform is usually not interpreted as a social dilemma, but as a coordination game, where the optimum is to be on the same platform, and unilaterally changing to the new platform is not profitable, even if it is somewhat superior to the old one (Katz and Saphiro 1992). In line with this favored interpretation, partners cannot sanction the exiting member directly by acting similarly (exiting and changing to the new platform), as this would benefit the exiting party. Still, in case of locally clustered networks, the sanctioning potential argument could be relevant considering that clustered ego-networks indicate strong and multiplex ties, where members interact frequently in further (non-OSN) contexts.

Adoption of innovations

In addition to the literature on social capital, research on the diffusion of innovations has implications for the life cycles of OSNs. It has been long recognized that users with specific attributes and demographic characteristics (e.g., higher education or social status) are more likely to adopt innovations earlier (Rogers, 1983). Psychological characteristics related to adoption of innovations were measured by concepts of consumer creativity (Hirschman, 1980) or technological readiness (Parasuraman, 2000). Evidence for the effect of consumer attitudes and personal innovativeness has been found by technological adoption models of information technologies and online services (Dickerson and Gentry, 1983; Agarwal and Prasad, 1998; O'Cass and Fenech, 2003; Lu et al., 2005).

The relevance of personal characteristics lies in that we expect more innovative users to join innovations, such as new OSNs in their early stages. Taking into consideration the constraints of available time to spend on OSNs – the simultaneous use of multiple sites is costly – and their increased engagement with the new platforms, these innovative users could leave old OSNs earlier for joining newer ones.

Although we cannot observe relevant personal traits directly, we can assume that the same traits of innovativeness that influenced users to adopt iWiW early drives them to switch to a more sophisticated service some years later. Hence, we use the relative arrival of users as a proxy for personal innovativeness. **We expect that users, who were relatively early in joining iWiW will be also more willing to leave the site relatively early (H3).**

Interactions and temporal dependencies

Network diffusion studies highlighted the importance of actors with a high degree in the adoption of innovations (Coleman et al., 1966; Becker, 1970; Valente, 1996). This suggests that people in more central network positions are more likely to be opinion leaders, who start using new services first, and consequently leave the old ones. On the other hand, these innovative people have a longer history on iWiW, therefore they also had more time to expand their connections. From the point of view of social capital accumulated on the old site, however, we expect that the old site has the highest value for users with a high degree, thus the collapse of the network is expected to start from the periphery.

Another complication is that small networks typically include strong ties, while weak ties appear when one has more friends. Therefore we expect a negative correlation between the number of connections in the network and the clustering of these ego-networks (Ravasz and Barabási, 2003; Opsahl and Panzarasa, 2009). The predictions here point in the same direction, as both large and open ego-networks are supposed to hinder early leaving. The size and openness of the ego-network, however, might have an interaction effect on exiting the OSN. For example, one may assume that with only a few connections, the composition of the network really matters. To sort out these predictions, our basic strategy is to apply multivariate models, where net effects can be computed.

A further point must be added about the impact of network clustering on leaving the site. Previously we relied on the argument that joining a new network automatically goes together with leaving the old one. This is apparently true as a general tendency, as it is usually inefficient to manage one's social network using several sites. A dual practice, however, might be maintained in specific situations. In many social network sites, users engage with different audiences with distinct norms and expectations, a phenomenon that is described as *context collapse* (Marwick and Boyd, 2011; Vitak, 2012; Boyd, 2014). As a consequence of context collapse and of the stress of self-representation in large and diverse networks, users are unwilling to share their information or content with all their connections (Hogan, 2010). In these cases using separate OSNs to interact with the different groups of people may emerge as a strategy (Boyd, 2014). Therefore, users with diverse networks are expected to join the new platform relatively early; however, they may also stay on the old platform longer.

Most of our arguments about who starts a cascade might be sensitive to the actual popularity of the OSN. Personal motivations change over time and they are different at the stage of rising popularity and at the stage of decline. The determinants of who abandons the site early are expected to depend on the availability of outside alternatives. Early adoption, in particular, is expected to be influential in prompting early leave before and around the peak of popularity, but not later. As existing studies typically assume constant effects over time, we cannot form expectations on sound theoretical bases. Because of the above-mentioned reasons, however, assuming these mechanisms to be similar over the life cycle of the network could hide important differences. To uncover these differences we explore our hypotheses across three different stages of the life cycle (rising popularity, peak of popularity, and decline) of the OSN. **We expect H1a H1b, H2 and H3 to be valid to varying degrees in the rising popularity, the peak popularity and the declining phase of iWiW (Research Question RQ1).**

Data

The entire iWiW network, along with a few individual level variables, was archived in 2013 and an anonymized dataset was compiled by the provider. This dataset was purchased and has been made available for scientific analysis. The whole dataset contains a central table of users, where one row represents one user and its attributes. Attributes include users' first and last login dates, the inviter's ID, self-declared place of residence and age (N = 4,610,996). The second table used in our analysis contains information on all network connections. Here, one row identifies a connection between two users and contains the date of its creation (N = 924,247,707 directed ties).

As the vast majority of users left the site without deleting their profiles, the dynamics of abandoning the site can be analyzed using the last login date. This is also an appropriate choice because users could see the last login date of anyone on iWiW, therefore their perception of the viability of the OSN was influenced by this information.

The analysis focuses on the period between 2007 and 2012. We did not analyze the years of growing popularity prior to 2007, as there were very few exits. We also excluded the final year of 2013, when the network became essentially abandoned (see details in Fig. 1). We divided the analysis into three periods: the initial years (2007–2008), the first years following the entry of Facebook (2009–2010), and the years of decline (2011–2012). Our main reason for this categorization was related to the appearance of Facebook in the Hungarian online sphere (end of 2008), as it was the first real competitor for iWiW. This classification overlaps with three important stages of the life cycle of iWiW inferred from daily page downloads: rising popularity, peak of popularity, and decline. Users were excluded from the analysis if they registered on the site but never used it, if their last login date was missing, if they had zero connections or had more than 2000 connections. The

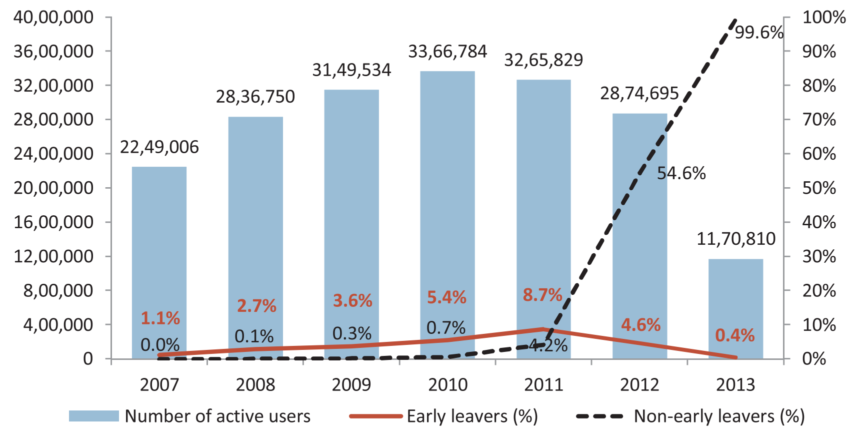

Fig. 1. Dynamics of abandoning the network.
Note: The number of active users in a year indicates users registered before 31st December and with last login later than 1st of January of the respective year.

upper limit was used to exclude celebrities, politicians, and users with commercial interests. These conditions altogether resulted in the exclusion of 7.6% of cases. In addition, users under the age of 14 were deleted (10.8% of cases). The resulting dataset includes 3,762,529 individuals and 796,810,090 directed connections.

The average number of connections was 210, and only a very few of them (1.77) were unreciprocated (Table 1). This is a fairly low rate (0.8%) compared to what is observed in real social networks, but a high reciprocity is common in online social networks. Mislove et al. (2007) report that the fraction of symmetric links is 100% on Orkut, 79%, on Youtube, and 62% on Flickr. Kumar et al. (2010) find 84% ties to be symmetric on Yahoo! 360. Scellato et al. (2010) report 100% reciprocal ties on BrightKite and FourSquare, 79% on Twitter, and 69% on LiveJournal. The reason for high reciprocity observed on iWiW (and on similar sites) is partly caused by design: the requested person can decide whether to accept the connection or not. If the request is declined it disappears from the database. If it is accepted, it becomes a reciprocated connection. Furthermore, if someone sends a request and it stays unanswered for a while, the sender can also withdraw it, and it again disappears from our database. Additionally, leaving a connection request unanswered for a long time may be perceived as rudeness, therefore it may be associated with a higher social cost in contrast to simply accepting or declining the request.

Measures

As we already mentioned, the vast majority of users left the site without deleting their profiles. We can estimate the share of the actually deleted profiles from the invitation data, as we see the inviter's ID in the data of the invited users. Twenty-two percent of all inviter IDs do not have a profile in our data, therefore, our estimate is that our database contains 78% of the users. No further data (such as the date of registration and deletion) is available for deleted users, therefore our analysis is based on the assumption that the remaining 78% of the users

Table 1
Descriptive statistics of the iWiW users.

Variable	Mean	S.D.	Valid N
Age at registration	32.62	12.93	2,495,067
Registration day	30 Oct. 2007	569.5 days	3,762,529
Last login day	22 Apr. 2012	424.7 days	3,762,529
N of confirmed connections	210.0	203.4	3,762,529
N of unreciprocated connections	1.77	5.82	3,762,529
	Women	Men	Valid N
Gender	55%	45%	3,762,529
	Hungary	Other	Valid N
Country	88%	12%	3,762,529

provide important insights about the dynamics of leaving the network.

Our dependent variable is whether users left the OSN 'relatively early' compared to their contacts or not. Hence, the construction of the variable is based on the classification of users. Users who abandoned the site when most of their connections were still active are called 'early leavers' and their last login date is labeled as 'early abandonment'. 'Non-early leavers' for a given year are those, whose last login took place in the given year, but a significant share of their connections was already inactive then. 'Stayers' are those whose last login was later than the actual year. As there is no apparent cut-point in the probability distribution of abandoning the network depending on the number of active contacts, we present results for the threshold of 90% as a definition of 'most of user connections'. To check the robustness of the results, we also run models with alternative thresholds of 95% and 80%. These alternative specifications yielded very similar results and did not alter our substantive conclusions.

The key independent variable related to H1a and H1b was degree, which was defined by the number of confirmed connections. The definition of early abandonment is not completely independent from degree. Users with less than ten connections are counted as early leavers if they abandoned the OSN earlier than any of their contacts. However, only by chance, one has higher probability to be the first in the group of two than in the group of ten. Therefore, early abandonment is by construction negatively correlated with degree for very low degrees. To overcome this spurious correlation, we also checked the validity of our results excluding users with less than ten connections (see details later, in the section Alternative specifications and robustness checks), which did not change the substantial conclusions.

As a measurement of openness for testing H2, we used the local clustering coefficient of the ego's network (Watts and Strogatz 1998; Holme and Kim 2002; Jackson 2008; Opsahl 2013):

$$LCC_i(g) = \frac{\sum_{j\neq i;k\neq j;k\neq i} g_{ij}g_{ik}g_{jk}}{\sum_{j\neq i;k\neq j;k\neq i} g_{ij}g_{ik}},$$

where i, j, k represent nodes of the network g, and g_{ij} denotes an edge between i and j. LCC is therefore distributed between zero and one, and describes the extent to which ties (g_{jk}) are present in the ego-network (of node i) among its alters (j and k). As an alternative, we also tested the robustness of our results using the constraint measure (Burt, 2000), and the transitivity (clustering) measure excluding ego used by Brooks et al. (2014). We opted for these measures instead of other candidates, e.g., betweenness centrality, because they are less computation-intensive, so their calculation for a huge network was feasible.

Early adoption regarding H3 was measured with the difference (in years) between the date when one joined iWiW and the average date when users of the same age joined. Thus, its positive values signify a more innovative behavior meaning that these users joined the network earlier than others of the same age. We expect that those, who are defined as earlier adopters in this sense, will leave the OSN quickly for a newer one. Therefore, the time of joining the network can be an important predictor of leaving. However, in addition to innovativeness, joining iWiW early may also be correlated with the user's (unobserved) interest in the site. Furthermore, innovativeness may change (decrease) with aging, so individuals acted innovatively a long time ago might not show innovative behavior when leaving the OSN later. Note that these latter mechanisms work against our prediction; therefore if we still find a significant effect of the time of joining, then it would certainly favor our hypothesis. In order to check the validity of our conclusions about the role of early adoption, alternative operationalizations have also been used (see the section on alternative specifications). In the case of alternative specifications, we used a random sample of 10% of users for robustness checks, as the computations are time-consuming.

Method

Social network studies often use social influence models (Robins et al., 2001) to analyze how social networks predict the changes in individual behavior (see de Nooy, 2011 for an overview). This approach – following Marsden and Podolny (1990) – uses event history models (also called survival models or hazard models) for predicting the timing of an event depending on the characteristics and network position of the individual.

The use of proportional hazard models, however, is not fully appropriate for our case, as these models assume that the coefficients of the independent variables are constant over time (Allison, 1982). We think that assuming the effects of our key independent variables to be time-invariant is too strong. This is because we examine very different stages of the network: the take-up, the time of competing with Facebook, and the decline. The change in the patterns of leaving the network in fact might be the sign of an (upcoming) collapse.

A second option is to use binary logistic regression with interaction terms over time, or separate models for each time-periods. This method is also problematic because the coefficients of the logit models (and their standard errors) depend on the residual variation, so they are not comparable across models or in between interactions (Allison, 1999). There are potential solutions to this problem (Allison, 1999), but they have their own drawbacks (Williams, 2009).

Therefore, we opted for the more flexible heterogeneous choice model approach for representing the discrete individual choice of early leave (Williams, 2009). Based on Keele and Park (2006) and Williams (2009), the heterogeneous choice model with a binary outcome variable of early abandonment (y_i) is defined as:

$$\Pr(y_i) = g\left(\frac{x_i\beta}{\exp(z_i\gamma)}\right) = g\left(\frac{x_i\beta}{\exp(ln(\sigma_i))}\right) = g\left(\frac{x_i\beta}{\sigma_i}\right),$$

where g is the logit link function (that can also be probit). In the numerator, x_i is the vector of independent variables for observation i, and β is the vector of coefficients. This part of the model is called the choice equation (and it also contains a constant term). In the denominator, z_i is the variable, by which values we assume that there is different residual variation (in our cases, time) and γ is its coefficient on the variance. This part of the formula is called the variance equation. Variables in the variance equation model can be dummy or continuous variables, but in both cases we have to assume a linear effect on the error variances (e.g., as time passing by, error variances decrease). As we assume that error variances do not change linearly, we included time-periods as dummy variables in the variance equation and used the same variables as interaction terms in the choice equation. We used the STATA oglm program for the analysis (Williams, 2010).

Given the large and complete data, traditional significance tests should not be considered as in sampling based surveys. Small effect sizes indicate differences, but misguide the interpretations of the results for core explanations (Golder and Macy, 2014). Therefore, in addition to the analysis of odds ratios, marginal effects were also considered to judge the presence of a relevant mechanism (Bartus, 2003).

The dependent variable in the multivariate model was if users left the site early (relatively to their network). Independent variables were age at registration, early adoption, degree (and the logarithm of degree to test H1b, as a negative coefficient for the logarithm of degree would indicate a diminishing negative effect), the number of non-reciprocated ties, LCC, and period (initial years [2007–2008], the first years following the entry of Facebook [2009–2010], and the years of decline [2011–2012]).

Four alternative specifications regarding the dependent variable of this model were used to check the robustness of the results. In the first one, we ran a model with only those person-years where the user still had the possibility to be an early leaver (as more than 90% of their connections were still active). In the second and third one, we varied the 10% threshold of inactive friends for early leaving and used 5% and 20%. In the fourth one, we excluded from the model those users who had less than 10 connections (Tables A-1, A-2 in the Supplementary Material).

Five further alternatively specified models considered the robustness of our independent variables. In model 5 and 6 we considered alternative measures for early adoption, in model 7 we added the interaction between the degree and our clustering measure (LCC), and finally in models 8 and 9 we tested the robustness of the results using the alternative clustering measures (Table A-2, A-3 in the Supplementay Material)

Results

Basic dynamics

Fig. 1 shows that iWiW reached a saturation point in 2010, two years after the appearance of Facebook in Hungary. A gradually increasing rate of leaving can be observed. In 2010, 6% of the users abandoned the site. Before 2011, we do not see a proliferation of this behavior: less than one percent of users can be categorized as non-early leavers in these years. The turning point was 2011; this is when the avalanche started. The rate of abandonment reached 13% and most users lost at least 10% of their connections. Hence, there was a boom in the share of non-early leavers in 2012.

Analyzing the probability of becoming an early leaver by the number of connections it is visible that peripheral users were more likely to be early leavers than users with many connections (Fig. 2). The monotonic tendency is violated only for superhubs: except for the year 2012, users with more than 600 contacts were more likely to leave their

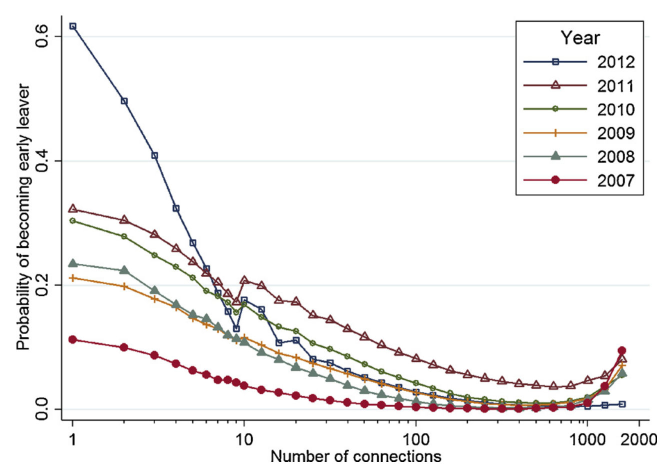

Fig. 2. Probability of being early leaver by the number of connections.

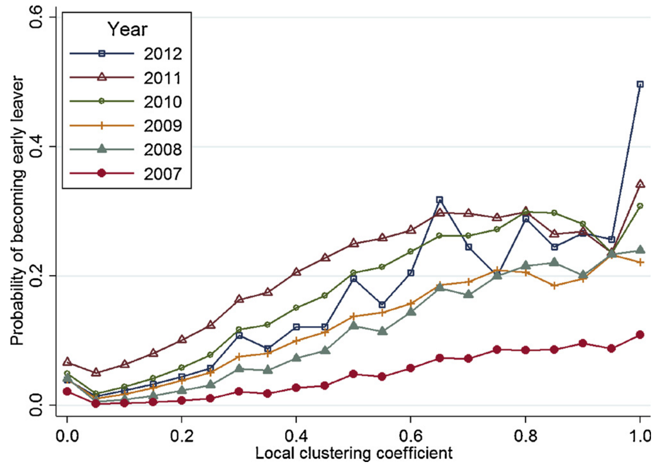

Fig. 3. Probability of becoming early leaver by local clustering and year.
Note: Cases are grouped by Local clustering coefficient (LCC) value precision of 0.05

network early than people with somewhat less connections.

Fig. 3 displays the probability of early leave by the clustering of one's network in the different years. Since the lines are ascending, we can conclude that users with locally closed (more clustered) networks are more likely to be early leavers. As all lines show the same tendency, the relationship is preserved in all periods. Meanwhile, the probability of early abandonment is gradually increasing from 2007 to 2011, indicated by steeper lines in Fig. 3.

A non-linear relationship can be observed between early adoption and early abandonment (Fig. 4). Early adoption is measured as the difference in years between the date of registration of the user and the average date of registration of the same aged users. Users who joined later than the average user of their age have negative values of early adoption. Fig. 4 is broken down by years. As early adopters naturally joined in the early period of iWiW, we can observe that the lines representing the earlier years start more from the right side of Fig. 4.

The increasing tails of each line represent that the likelihood of leaving the site increases with time after registration for about 1–2 years. The right tales of the lines indicate that users, who joined relatively early, spent a long time in the network, and built an extensive network are less likely to abandon the OSN early.

We should not draw far-reaching conclusions; however, based on bivariate analyses as the variables of interest are strongly correlated

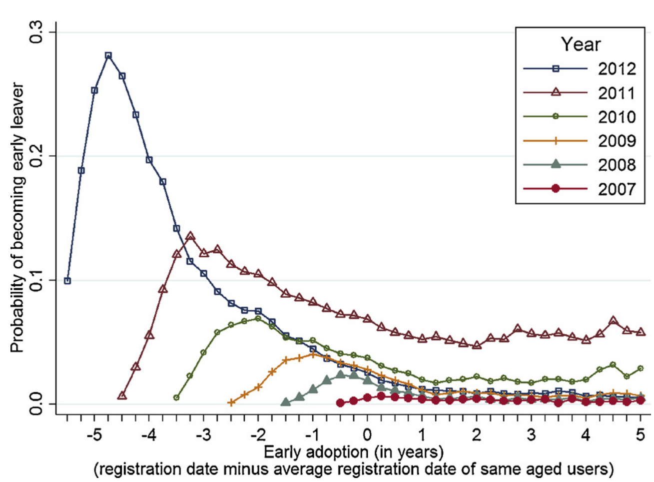

Fig. 4. Probability of becoming early leaver by early adoption and year.
Notes: Early adoption is measured by the difference in years of joining iWiW between the user and the average user of the same age. Early adopters are displayed on the right side of the Figure.

Table 2
Pairwise correlations between the key independent variables.

	Degree	LCC
LCC	−0.377	
Early adoption	0.400	−0.374

(Table 2). The negative relationship between degree and local clustering indicates that people start building their network with strong ties, connecting with people who typically know each other. As the ego-network grows, more and more people are included from different social circles. The positive correlation between degree and early adoption represent that the users, who joined the network relatively early, also tend to have a larger network on iWiW.

Multivariate analysis

To separate these factors in the prediction of early leaving, we apply multivariate models. We used heterogeneous choice models for assessing the effects of user characteristics and local clustering on abandoning the network early and for comparing the change of their magnitude across years. This was expressed by adding time variables and interactions with time variables to the choice model.

The dependent binary variable of our multivariate models was early leave: if the user could be characterized as an early leaver in the given year or not. Our key independent variables were age, early adoption, the number of non-reciprocated ties, and local clustering (LCC). Degree was included in the model in both its linear and logarithmic form, as we aimed to test whether the effect of degree on being an early leaver is nonlinear, corresponding to H1b. For easier readability of the tables, we included the linear term of degree in 100 connections.

The main effects in the heterogeneous choice models correspond to the baseline years 2009–2010. Interactions of the independent variables with 'year = 2007–2008' and 'year = 2011–2012' test whether the effects are different in the preceding or in the subsequent years (Table 3).

Table 3 summarizes the results. Individual degree decreases the chance of abandoning the OSN early. This means that the information aspect of social capital played a very important role in keeping key actors on iWiW, which confirms hypothesis H1a.

We also see that the effect of degree on abandoning the network is nonlinear, the significant and negative coefficient of the logarithmic term indicates a diminishing negative effect, supporting H1b. However, in contrast to the two-way analysis (Fig. 2), we do not see that after a tipping point, the sign of the effect related to degree would change. (This could be apparent, if the logarithmic effect of degree had the opposite sign as that of the main effect.) We checked this result also with alternative specifications (not shown here) and arrived at the same conclusions.

The positive impact of locally open networks is confirmed: a high local clustering coefficient increases probability of leaving the network early (H2). Those who have a highly clustered, redundant network were more likely to abandon the site early. From the effect size of the local clustering coefficient one can conclude that the explanation related to structural holes and bridging social capital is central for detecting who would (not) start the avalanche.

Considering our research question (RQ1) about the validity of these effects across the life cycle of the network, interactions suggest that the effect of connectedness decreases in the period of decline, while the effect of local clustering did not change significantly across the examined periods. Considering the main effects and the interactions, we can conclude that mechanisms related to social capital are valid in each phase.

Furthermore, early adoption increases the chance of abandoning the site early (H3). This effect is small in magnitude, and hence its importance lags behind the mechanisms related to social capital.

Table 3
Predictors of early abandonment.

Variables	Coefficient	S.E.	Marginal effect
Main effects			
Age at registration	0.002***	0.000	0.000
Early adoption	0.138***	0.003	0.002
Degree (100 connections)	−0.183***	0.004	−0.002
Log_{10}(degree)	−0.981***	0.010	−0.121
Non- reciprocated ties	5.734***	0.087	0.071
LCC	1.314***	0.018	0.016
year = 2007-2008	−0.679	4.103	0.015
year = 2011-2012	0.484	2.373	0.005
Interactions with year = 2007–2008			
Age at registration	−0.017	0.026	−0.000
Early adoption	0.067	0.364	0.001
Degree (100 connections)	−0.184	0.654	−0.002
Log_{10}(degree)	−1.114	3.724	−0.014
Non- reciprocated ties	10.14	28.23	0.125
LCC	−0.468	1.506	−0.006
Interactions with year = 2011–2012			
Age at registration	0.001	0.006	0.000
Early adoption	−0.145***	0.015	−0.002
Degree (100 connections)	0.168***	0.032	0.002
Log_{10}(degree)	−0.008	2.018	−0.000
Non- reciprocated ties	−5.177***	1.159	−0.064
LCC	0.101	2.933	0.001
Variance (lnsigma)			
year = 2007-2008	0.360	1.778	
year = 2011-2012	-0.021	2.073	
Thresholds			
Cutpoint 1	1.629***	0.0190	
N (user-years)	12,486,426		
Pseudo R^2	0.113		

Notes: Heterogeneous choice (oglm) models. ***: $p < 0.001$, **: $p < 0.01$, *: $p < 0.05$.

Furthermore, it is valid only in the period of Facebook's arrival (2009–2010); in the collapsing years an interaction effect with the opposite sign and approximately the same magnitude is found. Added to the main effect, we see that early adoption does not exert any effect in this period.

Considering the control variables, it is visible that older users are more likely to leave the network early. Not surprisingly, users with more non-reciprocated ties are more likely early leavers.

Odds ratios from the above estimates indicate substantial differences. For example, increasing the number of connections from 100 to 200 decreases the chance of early abandonment by 39%. Similarly, a decrease in the local clustering coefficient from 0.2 to 0.1 is associated with a 28% decrease in the probability of early abandonment. Average marginal effects corresponding to the estimates (Table 3) are much smaller. This is due to the fact that we predict a relatively rare occurrence: early abandonment appears only for 22.2% of all users. We examine this throughout the users' life cycle, therefore in a given year, early abandonment has a probability of 0.046 only. The average marginal effects predict that increasing the size of one's network from 100 to 200 is associated with a 0.67 percentage point decrease of early abandonment. This number seems to be small, but it is sizable compared to the 4.6% baseline chance of early leave.

Alternative specifications and robustness checks

In this section, we test whether our results are robust to alternative specifications. A key decision was how to operationalize our dependent variable of early abandonment. In the baseline models we defined early leave if two conditions were met: the user abandoned the site in the examined period and more than 90% of their ties were still active in the given year. As a first alternative, we examined uniquely those situations, when the user was still able to leave early, and excluded those person-years, when more than 10% of the user's social connections have already left. In contrast to the baseline model, which is more related to the differences between early leavers and other user groups, this analysis represents user choices more directly (Table A-1 in Supplementary material, Model 1).

We also examined alternatives, in which the 10% threshold value for early abandonment was varied. Models 2 and 3 in Table A-1 of Supplementary material report results from the alternative specifications based on 5% and 20% threshold values for early leave. In addition, we have also run models without users with less than ten connections, in order to overcome the spurious correlation mentioned earlier in the section of Measures (Table A-2 in Supplementary material, Model 4).

The results from these four alternative model specifications are only slightly different from the baseline model: all main effects are similar to the ones we found in the baseline specification, only the tendencies of how they changed over time are different. Therefore, the substantive conclusions about our main hypotheses are mostly unaltered.

We found deviations affecting the validity of our hypotheses only in the case of alternative measurements of early adoption. A problem is that with early adoption, as a proxy for innovativeness, it is impossible to separate the contextual effects of the time of registration and the time spent on the network, as any one of these and the time of leave determines the other. Substantively, however, early registration is a good proxy of innovativeness, while the time spent on the network is not. Furthermore, as we have argued, we have reasons to believe that social mechanisms, triggering early abandonment, change over time: they are different in the period of a mature network, when the major competitor enters, and in the declining phase. The models presented earlier have confirmed the presence of these differences. Further complication arises from the likely presence of a life-cycle effect. As the bivariate analysis shows, new users have an increasing likelihood of early abandonment, which peaks 1–2 years after registration. If they stay after this critical period, they become more committed.

We tried to mitigate this problem in the following two ways. First, we created an alternative, network-based measure of early adoption. This alternative measure was defined as the difference between the date of registration of users and the average date of registration in their network. Also for this alternative measure, higher numbers indicate more innovative behavior. Second, we simply used the date of registration compared to its average value (where again, the higher number indicates more innovative behavior). On the one hand, we see that the network-based measure of early adoption has an opposite effect compared to the original one, indicating that in 2009–2010 those users were more likely to leave early, who registered later than their social ties (Table A-2 in Supplementary material, Model 5). This result casts doubt on the validity of H3, while the baseline specification supported this hypothesis. On the other hand, if we use the registration date as a measure, we get the same results as in the baseline model: people, who registered earlier, tend to leave early (Table A-2 in Supplementary material, Model 6).

As we mentioned above, we also tested, whether the effect of the size of the ego-network and the clustering coefficient are interdependent by including their interaction in the model (Table A-2 in Supplementary material, Model 7). We did not find this interaction significant in the (baseline) peak period, neither in the subsequent declining phase, but in the early period a negative interaction shows that clustering is less important when users have many connections.

Results from models including the alternative measures of network openness, are presented in Table A-3 in Supplementary material. Coefficients of the constraint measure support H2, just as LCC supported it. (Note that interpretation of the constraint measure is the opposite of LCC's one, as positive values here indicate bridging positions, therefore here the negative coefficients correspond to H2). When excluding ego from the transitivity measure, which was found to be negatively correlated with bonding social capital on Facebook by

Brooks et al. (2014), we find its negative effects on leaving the network.

Discussion

Since the early years of the millennium, online social networks (OSNs) have a salient impact on our lives. Today, a good portion of humanity is connected through ONSs; active monthly Facebook users worldwide reached 2.2 billion by the end of March 2018 with an increase of 13% year-over-year (Facebook, 2018). The burst of popularity of OSNs highlighted that technical advancements become highly valuable when they serve fundamental human needs – and the need of belonging, and being an integral part of groups and communities in particular (e.g., Lindenberg, 1989; Ormel et al., 1997; Wellman, 1999; Ellison and Boyd, 2013). These online platforms are governed not just by their technological underpinnings, but also by the principles of human social interaction and the interplay between the two (Agarwal et al., 2008). OSNs impact how people connect to and communicate with one another both for entertainment and efficiency purposes; they inform ways of self-presentation (Tifferet and Vilnai-Yavetz, 2014; Bareket-Bojmel et al., 2016; Lincoln and Robards, 2017; Crabtree and Pillow, 2017); they continually reshape how information is created, disseminated, and consumed (Winter et al., 2015; Anspach, 2017); how companies, organizations or political entities engage with and gauge their consumers and supporters (Sørensen, 2016; Sitta et al., 2018). OSNs have also been lauded or criticized for facilitating large-scale national political and social transformations (Howard et al., 2011; Gustafsson, 2012; Hall et al., 2018; Rennick, 2013).

In addition to their abovementioned functions, OSNs have become important sources of social capital, where user investments are rewarded with a higher potential of future returns (Brooks et al., 2014; Bohn et al., 2014; Ellison et al., 2014). For this reason, the growth of OSNs can be understood easily. At the same time, it is much more challenging to understand how social capital influences the collapse of an OSN. Naturally, the role of social capital might be different in the process, as social capital might have a changing value over the life cycle of an OSN. In other contexts, for instance, in the case of right positioning in an interfirm network, Walker et al. (2000) found that structural holes are valuable in the early stage of network formation, while more densely connected ties that foster a higher amount of cooperation are beneficial in the stage of stable functioning of the organization. Very little research, however, examined the role of social capital at the end of a life cycle.

In this paper, we were primarily interested in how structural position of individuals explain the withdrawal of individuals from the network, which – by causing a subsequent cascading mechanism – contributes to the *collapse* of an OSN. We analyzed these structural positions from the point of view of social capital and network embeddedness. By studying different stages of the life cycle of an OSN, we also attempted to compare the impact of social capital related and other mechanisms over time. With these accounts of micro-level mechanisms, we also hoped to highlight important determinants of apparent shifts in the popularity of online social networks.

We examined the Hungarian network, iWiW, which was one of the first OSNs in the world and the most popular one in Hungary until 2010, after which it lost its significance and was subsequently shut down. Our analysis of the anonymized database concentrated on users who left the OSN early and played a pivotal role in starting the cascade. We classified users as 'early leavers' if they left the site when more than 90% of their social connections were still active on the OSN.

The extent of relations corresponds to the quantity of accumulated social capital. As connections contain strong as well as weak ties, degree related effects could potentially be related to both bridging and the bonding types of social capital. **We found that the less degree one has, the more likely early abandonment is (H1a)**. Our results, which are robust across various specifications, indicate that the size of the ego-network prevents users from leaving the OSN early. Users with many connections still considered iWiW as an important "phone-book source" of social network information that is not available otherwise and hence could have been lost by leaving the site. **Our results also confirmed that the effect of degree on leaving the network is nonlinear; more connections prevented users from leaving the network in a diminishing manner (H1b).**

We also investigated whether closed or open structures are relevant aspects of social capital for hindering early abandonment. **We found that the higher the local clustering coefficient (the less open the network),the more likely early abandonment is (H2)**. Hence we confirmed that actors who have benefited from structural holes in their network on iWiW were less likely to abandon the site early. This observation has a theoretical consequence considering the resilience of the network. For example, Garcia et al. (2013) suggest that higher *k*-coreness of the network increases resilience. We found, however, that a highly clustered structure associated with higher *k*-coreness is less valuable from the individual's perspective and therefore increases the risk of a collapse cascade.

It is clear that multiple mechanisms are responsible for the decline of the OSN. As we discussed, the appearance and rising popularity of new OSNs are largely responsible for the decline of user activity. Benefits of social capital from joining a new site could also determine the collapse of an old one. As long as weak ties were accessible on iWiW, they constituted a significant resource of bridging social capital. As long as friends were active on iWiW, they satisfied user need for bonding social capital. On the one hand, new technological features of recent OSNs allowed better access to novel information and hence elevated access to bridging social capital (Burke et al., 2011; Ellison et al. 2010; Ellison et al., 2014). For instance, friends of friends are now connected on Facebook by having access to messages and comments on common friends' walls. On the other hand, the possibility of posting and checking unlimited amounts of information to and from friends created an efficient tool for social grooming (Ellison et al., 2014; Donath, 2007; Tufekci, 2008; Thelwall and Wilkinson, 2010) and made the maintenance of bonding social capital easier. Our results about the significant impact of the local clustering coefficient underline the particular importance of *bridging* social capital in this transformation. Note again that in this paper we used structural indices as proxies of social capital, and did not measure the actual use of these resources. Note furthermore, that the result about the local clustering did not support the alternative hypothesis, which we could have made based on the withholding effect of social embeddedness on exiting the network.

We also tested whether early adoption contributes to the early abandonment of the network. Based on the network literature on the diffusion of innovations, we predicted that the early adopters, who boosted the popularity of the OSN were also responsible for the cascades of early abandonment when they switched to new alternatives. **We indeed found that the more early adopter the user is, the more likely early abandonment is (H3).** We measured this relative timing of adoption by joining iWiW earlier than a typical member of the age group. This mechanism, however, is only of secondary importance compared to explanations based on structural positions. We found smaller effect sizes, and the result was also not robust across measurements: The result turned to the opposite when the user's time of registration was compared to the average time of registration in the user's ego-network.

There might be different explanations behind finding the impact of early adoption weaker and not robust across measurements. One is that innovative early adopters use the old and a new network simultaneously for a longer period, therefore, they do actually join the alternative network first, but many of them also keep the old network for maintaining the connection to a distinct group of their contacts. The second is that early adoption may have been correlated to the user's preferences toward the network. Due to this fact, an alternative exogenous innovativeness value could probably have given us different results.

We argued that the mechanisms explaining leaving the network can be qualitatively different, depending on the life-cycle of the network (RQ1). We found that early adoption was not relevant any more in the declining phase of iWiW, and the importance of structural positions also differed in the examined phases. The size of the ego-network network became a weaker predictor in the declining phase of the network after the peak of popularity.

Nevertheless, we have to note that this study described only one particular context of social life. The relationship between different contexts is, so far, not clear, but we know that people enter many contexts in their daily life and that there is quite some interdependence between contexts. All ego-networks are fragmented by contexts and we experience radical changes in our social network when going through certain life phases and events (Brooks et al., 2014). A list of such defining events could include: going to secondary school or college, changing of the workplace, moving to another city, adopting a new hobby, joining a voluntary association, a breakup or divorce, a new romantic partner, or having children. Our social networks as well as our online social networks are clustered locally along these different contexts (Fischer, 1977; Feld, 1981; Boyd, 2014). Just like with adapting to a new software environment at our new workplace, we might easily adapt to a different OSN that is popular in our new community context.

All things considered, we were able to draw important conclusions about social capital related mechanisms behind the collapse of an OSN. We have to note, however, that while our conclusions are based on a complete set of data with regard to connections, the data is not rich in depth: we do not have more information on individual background variables, the strength of ties, on actual returns to social capital, or even more importantly, on the exclusive or parallel use of alternative OSNs. A possible known limitation of the analysis is that we miss those users, who deleted their profiles completely. Fortunately, such cases were extremely rare before 2013. We do not have data on the intensity of user activity either, for example, on the frequency of logins and interactions with others. Only the very last login date to the network is saved. A simple login is a low cost activity and the results might be different for activities requiring higher intensity.

Moreover, conclusions from analyzing a complete Hungarian OSN could not potentially be generalized to other national or international OSNs that lost their popularity. Further research could investigate this or could justify our claims by studying other radical shifts in the OSN world. The idea that users can be members of the old and a new network at the same time could also be used in extending previous models of network externalities.

It is important to emphasize though that despite the limitations, we found a general support for our social capital based explanation. This is a robust result supporting the relevance of social capital for user behavior on OSNs.

Our study has implications not just for the study of online social networks, but also for the analysis of leaving social groups and social contexts in general. Other studies, particularly in the organizational context, identified social capital and structural embeddedness related explanations for leaving intention or for leaving (Dess and Shaw, 2001; Burt, 2002; Kratzer and Takács, 2007; Soltis et al., 2013; Greve et al., 2010; Polidoro et al., 2011). They also highlighted, however, that leaving an organization or an organizational unit cannot be analyzed independently from the availability of outside options.

The results are relevant also for networks operators. While nobody could predict such a dramatic cascade of collapse when it happened at iWiW, ex post we could identify the users who could trigger a cascade of abandonment. In this sense our conclusion is clear: in the case of iWiW, the avalanche did not start from the core. Degree has a negative effect on early abandonment, and being an early member is associated with a somewhat higher probability of leaving the network before one's contacts only after controlling for the size of the user's network.

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Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.socnet.2018.11.004.

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