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Do diversity and context collapse kill an online social network?

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Abstract

Our social lives consist of various circles, such as family, friends, and colleagues. Differences in norms and expectations among these circles can create tension in large online social networks (OSNs) due to blurred boundaries. It is unclear whether this phenomenon, known as context collapse, outweighs the convenience of having diverse communities in one place for OSN users. To explore this trade-off, we examined if ego network characteristics indicating context collapse could explain users' decisions to leave iWiW, a defunct Hungarian OSN with over 3.5 million active users at its peak. We assessed context collapse based on two conditions: the absence of overlapping communities measured by network modularity and social differences between those communities. We find that users with fragmented social networks indeed leave the platform earlier if these distinct communities differ significantly in their age profiles and urban-rural composition. However, the highest probability of leaving was among those with non-fragmented networks and similar communities. These seemingly contradicting results are caused by the process that network fragmentation itself decreases the probability of leaving. Thus, our results demonstrate simultaneously how brokerage can be valuable and context collapse stressful for users of OSNs.

Keywords Online social networks, Diversity, Context collapse, Ego networks, Social capital, Modularity

Introduction

People have contact with diverse groups. One's family members, old-school friends, colleagues, and neighbors can have very different interests, attitudes, or political preferences. In the offline world, these differences rarely conflict as most of the time these groups are not present at the same place and same time. In online social networks (OSNs), however, these groups are not so easily kept apart. Such situations can create tension and stress for individuals, especially when their different social circles have diverse norms and expect them to follow incompatible roles (Binder et al. 2012). This situation is known in the literature as context collapse: when diverse audiences are all present on the same platform (Marwick and Boyd 2011; Davis and Jurgenson 2014) and evaluate the same social performance of an individual. Offline, individuals would usually

adjust their behavior and presentation to the group they are interacting with; online, one cannot make these adjustments so easily. For example, one's social media post can be liked by university friends and acquaintances but met with disapproval by family members.

Context collapse is known to influence behavior online significantly (Marwick and Boyd 2011; Beam et al. 2018; Gil-Lopez et al. 2018). While in some instances—described as context collusion (Davis and Jurgenson 2014; Loh and Walsh 2021)—individuals intentionally blur contexts, context collapse typically happens unintentionally due to the collision of different social environments and difficulties of separating them at the platform. It is very much understudied how this type of context collapse (context collision) can have such a huge unintended impact that users decide to exit specific platforms. In this paper, we operationalize context collapse in terms of the divergence of characteristics of connected users and investigate whether context collapse could contribute to the likelihood that a user abandons an online social network. To start, in line with the description by Marwick and Boyd (2011), we characterize context collapse as a social and spatial collapse, in which individuals must face expectations of diverse audiences and therefore have internal conflicts of determining which actions are appropriate and contribute to self-performance and identity (cf. Brandtzaeg and Lüders 2018). Our first indicator is based on the extent to which one's connections are segregated into ego network communities that convey diverging expectations and social norms due to their dissimilarity in users' age. Our second indicator measures the extent to which ego-network communities differ due to the urbanization of users' locations. Then, we study the relationship between these indicators and the likelihood that the user leaves the OSN, defined either by the time of the last login or the time of the last new friendship creation. We use the anonymized dataset of iWiW (international Who is Who), a once large but now defunct Hungarian OSN.

Our work adds the potentially crucial aspect of context collapse to the scholarship on why individuals stay on or leave OSNs. Previous research highlighted that social capital benefits can explain when and whether people abandon an online social network (Lőrincz et al. 2019). Other studies concentrated on the effects of interaction overload and unwanted relationships (Hwang et al. 2019). Furthermore, empirical studies have demonstrated that using attributes computed from the local network community around the user allows building a robust statistical model to predict exit (Garcia et al. 2013; Lengyel et al. 2020; Ngonmang et al. 2012; Török and Kertész 2017). Our study contributes to this literature by scrutinizing the role of context collapse in the abandonment of an online social network and closely examining how age and urbanization divergence of ego network communities can particularly be important in this process.

Clashing expectations of diverse groups

The perspectives we encounter in the different contexts of our lives can be highly diverse. As suggested by Simmel, we live at the intersection of these social circles (Simmel 1908/2009; Alba and Kadushin 1976). New circles are added with new stages of life: starting secondary school or university, changing workplaces, moving to another city, taking up a new hobby, joining a voluntary association, breaking up or divorcing with a partner, or bringing children to kindergartens and schools (Alwin et al. 2018). Our social life is divided between different circles and our ego networks are significantly clustered

by these contexts, though the extent of this clustering varies significantly from person to person (Feld 1981; Fischer 1977).

Cultural codes, meanings, and values often vary between these groups: opinions and norms that are acceptable in one group can be disliked or condemned in another. Sometimes these groups overlap and intersect; in a traditional village community, neighbors might also be co-workers and relatives. More typically, however, members of the different groups do not meet often, and one can play different roles in these contexts. Individuals avoid conflict between incompatible roles and expectations of these circles as these groups are more or less separable from each other. Individuals behave according to the actual role, which meets the expectations of the group they are currently present in (Goffman 1978). Breaking up the boundaries between these groups already started with mass media (Meyrowitz 1986), and intensified by the universal diffusion of social media.

This natural hypocrisy that eases our lives is more difficult to perform in online social networks. OSNs break down the boundaries between the diverse groups the ego belongs. Individual posts on social media can be observed by different social circles of the individual, with their different norms and expectations. This context collapse constrains online behavior and activity differently than clearly separable face-to-face audiences do (Marwick and Boyd 2011; Vitak 2012).

Context collapse consists of two core ingredients, both of which must be present. One is to have several distinct groups in the ego network of the individual. We measure it using the modularity (Newman and Girvan 2004) of the ego networks, a measure of the tendency that links are within rather than between distinct groups of alters. The lack of modularity indicates the absence of distinct groups in a user's social network. The other is that the composition of these groups must be different in some way that is salient to the formation of norms and expectations toward online behavior. This is described by the dissimilarity of the communities. If the communities are similar to each other, it is more likely that they share similar norms and social meaning, thus it is also more likely that they have similar expectations towards the individual, which decreases potential tension. Differences by certain socio-demographic characteristics between groups may be more likely to create clashes online. There are dimensions that traditionally contribute to cultural and attitudinal differences. Among them, socio-economic status (e.g., Hargittai 2007), age (Blank 2022), and the urban–rural character of residence are factors that contribute to the digital divide (e.g., Salemik et al. 2017; Thonipara et al. 2023), and explain differences in online behavior (Talukdar and Gauri 2011), thus resulting in potential misunderstandings in the online space.

The presence of context collapse in online social networks, its relationship with user behavior, and privacy strategies have been widely studied (see e.g., Marwick and Boyd 2014) on different platforms like Facebook (Brandtzaeg and Lüders 2018; Vitak et al. 2012; Costa 2018; Beam et al. 2018), Twitter (Marwick and Boyd 2011), and YouTube (Wesch 2009). Context collapse creates a kind of stress of self-representation that is stronger in highly diverse networks (Hogan 2010; Binder et al. 2012). Additionally, context collapse could also be relevant in a temporal dimension in the sense that older content can affect the interactions of the present (Brandtzaeg and Lüders 2018). The presence of context collapse may also cause the feeling of a loss of privacy (Marwick and Boyd 2014).

However, exposure to context collapse depends on the platforms' algorithms. Current social media sites have adopted measures, such as content filtering algorithms, customization, and personalization of information access, to mitigate these problems—but at the same time, they have created new ones of filter bubbles and echo chambers (e.g., Auxier and Vitak 2019) that pose other kinds of problems for the user like boredom and redundancy (e.g., Flaxman et al. 2016).

Strategies for managing context collapse

In online social networks, if tension from context collapse is experienced, it could be suppressed in multiple ways. Users may manage their networks by not confirming the friend requests of those who are not part of their inner circle or creating a separate account for wider audiences (Vitak et al. 2012). It can be avoided by proper privacy settings (Costa 2018) if the platform allows it. Individuals might constrain their self-representation in large and diverse networks (Burkell and Fortier 2016), and they evaluate the relative importance of their different audience segments (Marder et al. 2016). They may shift to an observational mode of behavior by reducing their sharing activity (Hogan 2010). Alternatively, others may take up the role of exhibitionists and broadcast their true opinions without any filtering and sensitivity to their reception in the network (Boyd 2008). Observers and exhibitionists are at the two extremes of activity. Most users develop strategies to cope with the tension of diversity by balancing their diverse audience (Vitak et al. 2015). They might resolve the tension by being present at different OSNs with different social circles (Boyd 2014), or ultimately, they could abandon their presence at the OSN.

Social network positions and the utility of OSNs

In addition to considerations related to context collapse, individual network positions may also influence the utility of staying on the OSN through several mechanisms.

An additional important characteristic of ego networks is the extent of interconnection between alters. Being a member of an interconnected network may increase the potential for mobilizing and preserving social resources (Lin 1999), which in online social networks is correlated with engagement and perception of community (bonding social capital) (Brooks et al. 2014; Tian 2016). However, high interconnection is also an indication of strong, high-bandwidth ties (Aral and Van Alstyne 2011); having a higher frequency and more types of interactions (Granovetter 1973; Burt 1995); therefore, for users having mostly strong ties, staying on the OSN may be less essential, as they possibly have several further means of communication. Networks containing more weak ties, which tend to bridge distinct groups, often serve more practical purposes (Uzzi 1997). For those who have many weak ties, the diverse information they receive from the OSN may be quite valuable. Bridging positions are associated with access to diverse and novel information, which creates social capital for the individual (Burt 2005). Such positions allow the individual to exchange favors across groups (Jackson 2020; Jackson et al. 2012).

To control for these mechanisms, we introduce the local clustering coefficient to the models, which measures the chance that two of ego's random friends know each other.

Concerning the diversity of alters, there are two opposing arguments. On the one hand, having connections to a diverse set of others is associated with higher exposure to a wider range of ideas and stimuli, which can contribute to the individual's social

capital (Borgatti et al. 1998). Pang (2022) also found that a more diverse network structure is positively correlated with involvement in online social networks. On the other hand, people prefer to interact with those, who are similar to themselves (Lazarsfeld and Merton 1954; McPherson et al. 2001), consequently, they also discuss important matters with these persons (Marsden 1988).

To better understand the balance of these forces, we study the relationship between ego network structure and continued use of iWiW (international Who is Who), a once large but now defunct Hungarian OSN. iWiW was an early OSN primarily used to maintain social ties and contained much less dynamic content than platforms widely used today. With Facebook having gained worldwide popularity, national and local OSNs could not keep up, and most shut down between 2008 and 2013 (see Lőrincz et al. 2019). The study of an early OSN like iWiW is especially appropriate for our substantive questions because at that time, content filtering algorithms and the possibility of sophisticated content management and privacy settings that suppress context collapse were not available.

While Facebook users could also experience context collapse, we argue that the introduction of Facebook in Hungary offered an escape from an increasingly heterogeneous environment of iWiW. During the decline of iWiW, early adopters of Facebook in Hungary were likely to encounter a more exclusive group of users of typically young early adopters on the new platform without less potential tension from context collapse.

Research questions and hypotheses

Could context collapse be stressful enough to push users to leave an OSN? This is an important problem both from the above-mentioned theoretical perspectives, but also from a practical perspective of OSN providers who do their best to tailor their sites to commit their users. Implying from the conceptual foundations of context collapse (e.g., Hogan 2010; Marwick and Boyd 2011, 2014; Vitak 2012; Davis and Jurgenson 2014), we argue that tensions from context collapse are larger if the user has a fragmented ego network with highly different communities regarding their expectations towards the user.

We operationalize these concepts in terms of individual ego network characteristics. Following Brooks et al. (2014), Norbutas and Corten (2018), and Wachs et al. (2019), we use the modularity of ego networks as a measure of their structural fragmentation. High values of modularity indicate that an ego's communities are distinct and disconnected. We argue that diverse expectations can arise if ego network communities are very different in terms of relevant socio-demographic characteristics. From the earlier mentioned dimensions affecting online behavior and expectations towards the user, we have reliable information about age and the urban–rural character of residence—and not about socio-economic status. Thus, we consider differences along these dimensions that likely imply differences in expectations and norms of online behavior.

As we assume that both high modularity and large differences between communities in the ego network are necessary conditions for context collapse, we assume that the positive interaction of modularity and dissimilarity of communities in one's ego network has a positive effect on leaving the OSN. Accordingly, our hypotheses are the following.

H1: We expect that the high modularity of the ego network together with large age differences between ego network communities increases the likelihood of leaving the OSN; and.

H2: We expect that the high modularity of the ego network together with large urban–rural differences between ego network communities increases the likelihood of leaving the OSN.

Materials and methods

Data

We analyze the network and user data of an OSN that has been offline for several years. iWiW was founded in 2002 and was one of the first widespread online social networks in the world. At its peak, with more than 3.5 million users, it was the biggest OSN in Hungary with a population of 10 million, where this meant two-thirds of all Internet users. After 2010, with the appearance of Facebook, iWiW began to lose users. After a decline in user activity, it was shut down by the provider in 2014. We analyze the archived and anonymized database of iWiW provided by its former owners. From the original dataset we deleted users who registered on the site, but never logged in; users with zero connections, and ones with more than 2000 connections, to exclude celebrities and those with commercial interests. We also excluded users, who reported registration age under 14. With these criteria, we removed 18% of users. The 3.8 million remaining users were not necessarily active across the full lifecycle of the platform. For computational reasons, we carry out our analyses on a random sample of approximately 10,000 users. Note that the analysis of ego networks of such a large sample is valid both from the statistical as well as from the substantive point of view to draw conclusions about the entire population. The descriptive statistics of the sample and the entire iWIW data are presented in Table 1. The composition of the sample and the whole iWIW are similar to each other.

For the analysis, we use the interval between January 2007 and December 2012. Less than 1% of users left the site before 2007, and only 30% remained after 2012 when our observation period ended.

Data structure

To analyses the relationship between context collapse and leaving the network, we consider the monthly snapshots of the ego networks of each user in our sample throughout the 72 months observation period. Our observations are at the level of user-month, which means that each of the 10,000 users is present in the dataset as many times as many months they spent in the network within the observed period, and their ego networks are created from the whole database for each month. For example, the first row shows the data of the first user in their first month, the second row shows the data of the same user in the second month, etc. Altogether we have 559,179 observations (rows) in the dataset. The user appears the first time in the dataset in the month they joined the

Table 1 Descriptive statistics of users in the sample

	Sample for the analysis			Entire iWIW data		
	Mean	**SD**	**N**	**Mean**	**SD**	**N**
Age	36.54	13.88	6,837	36.49	13.83	2,495,067
Gender	Male: 45%	Female: 55%	10,311	Male: 45%	Female: 55%	3,762,529
Registration date	08/Nov/ 2007	534.8 days	10,311	30/Oct/ 2007	569.5 days	3,762,529
Last login date	27/Apr/ 2012	393.8 days	10,311	22/Apr/ 2012	424.7 days	3,762,529

social network and their last appearance is the month when they left the network. For each user, we flag the last month they spent in the network creating the 'leave' variable with the value 1 for the last month of the user, and the value 0 for each preceding month. Characteristics of users in each month are recorded in different variables (columns). For each user, there are time-invariant variables (e.g., gender) and time-varying variables (e.g., number of connections). Table 2. illustrate the data structure, where User1 joins the network in January 2007 and stays for four months, while User2 joins in February 2008 and leaves three months later. Additionally, User10,000 joins in January 2008 and stays during the whole period, until December 2012.

Measures

Our binary dependent variable is leaving the site in a given month. We use the label 'leaving the site' for the time when the last login occurred. (As an alternative measure, serving as a robustness test, we also use the date of the last friendship creation.) The average probability of leaving the network in a random month was 1.2%. Its high standard deviation (11.1%) is due to the increased likelihood of leaving in 2012 (Fig. 1).

Our hypotheses suggest that users having ego networks with high modularity and large differences between communities in terms of age and urbanization are more likely to leave the OSN. To quantify modularity of an ego network, we first used the Louvain community detection algorithm (Blondel et al. 2008) to obtain a mutually exclusive classification of individuals in the ego network for each month. We then measured the modularity of the ego network as it quantifies the tendency of edges to concentrate within modules rather than between them (Newman and Girvan 2004):

$$mod\,(\ell) = \sum_{k=1}^{K} \left[f_{kk}\,(\ell) - f_{kk}^{*} \right]^2 \tag{1}$$

where ℓ is a partition of the network to K modules, $f_{kk}\,(\ell)$ is the fraction of links within the kth module compared to the whole network, and f_{kk}^{*} is the same fraction under random assignment of vertices to modules. Thus, the higher the modularity score is, the more links are concentrated within the modules compared to random assignment. The Louvain method searches for the partitioning of a social network into modules that attain the highest value of modularity. The algorithm explores the space of possible

Table 2 Structure of the dataset

	Months spent in the network	Date	Leave	Gender	N of contacts	(…)	Modularity
User1	1	2007_01	0	Male	20		0.21
User1	2	2007_02	0	Male	32		0.23
User1	3	2007_03	0	Male	34		0.23
User1	4	2007_04	1	Male	51		0.25
User2	1	2008_02	0	Female	12		0.20
User2	2	2008_03	0	Female	43		0.21
User2	3	2008_04	1	Female	67		0.25
(…)							
User10,000	1	2008_01	0	Female	21		0.21
User10,000	2	2008_02	0	Female	45		0.23
User10,000	3	2008_03	0	Female	55		0.23
(…)							
User10,000	72	2012_12	1	Female	233		0.32

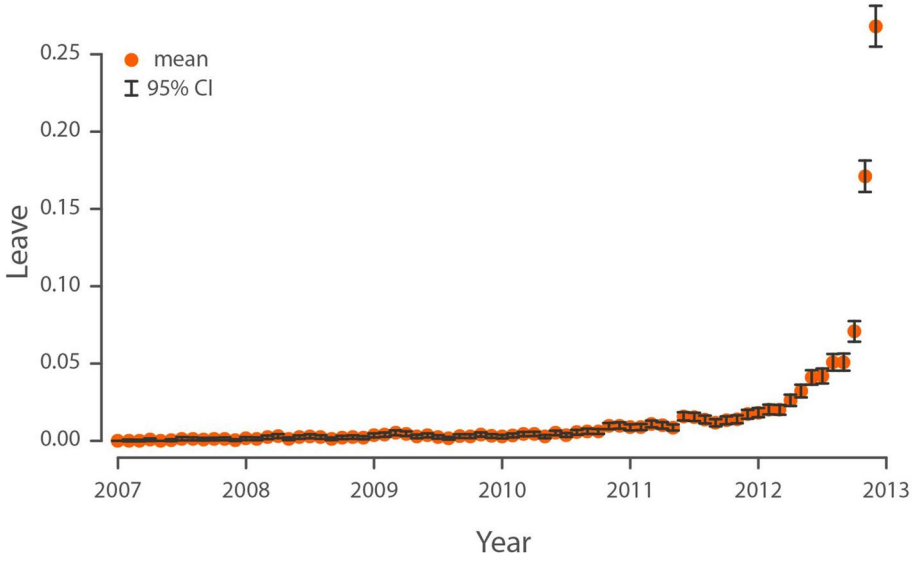

Fig. 1 Probability of leaving by month in the analysis. The horizontal axis illustrates the month, and the vertical axis denotes the probability of leaving measured by the last login date. Probabilities were calculated by the ratio of those left in the given month and the number of those haven't left the network yet. Standard errors for the confidence intervals were calculated for these ratios

partitions in a greedy optimization. The modularity calculation compares the actual partition against a null model known as the configuration model, which fixes the degree of each node and randomizes edges. Note that by considering the actual structure of the network, we control for ego network dynamics that are not introduced by the ego (e.g., transitive closure over time), and also take into account the contact changes of the ego (e.g., new and deleted ties). Furthermore, as Brooks et al. (2014) note, although it is generally unreasonable to allow any node to connect to any other node, in the context of ego networks that contain only the focal individual and their direct social contexts, this null model is actually quite apt, as any two nodes in the ego network have at least the ego as a friend in common. We calculated a modularity score (in the [−1, 1] interval, though typically between [0, 1]) for each individual and each month (for the 557,705 observations), indicating how distinct identified communities are in the sense of having high network density within, and low density between them.

We measure dissimilarities between different communities corresponding to H1 and H2 in two dimensions. We consider self-reported user variables of age, and domicile as dimensions for these measures. Examples of four actual ego networks with different modularity (panel A and B) and dissimilarity (panel C and D) are illustrated on Fig. 2. Panel A shows an ego network with low modularity, while network B's modularity is high, representing the first and the third quartiles of the modularity distribution, respectively. Panel C and D show two networks with around the same value of modularity, but with different levels of dissimilarity in urbanization between communities. Panel C shows an ego network, where the communities are similarly heterogeneous from the urbanization perspective, while panel D visualizes a network, where different communities have different compositions according to urbanization.

To obtain measures of dissimilarity, we first calculated the average values of each community of a user. As the definition context collapse requires the presence of diverse audiences on the same platform, we assume that even one outstanding community is enough

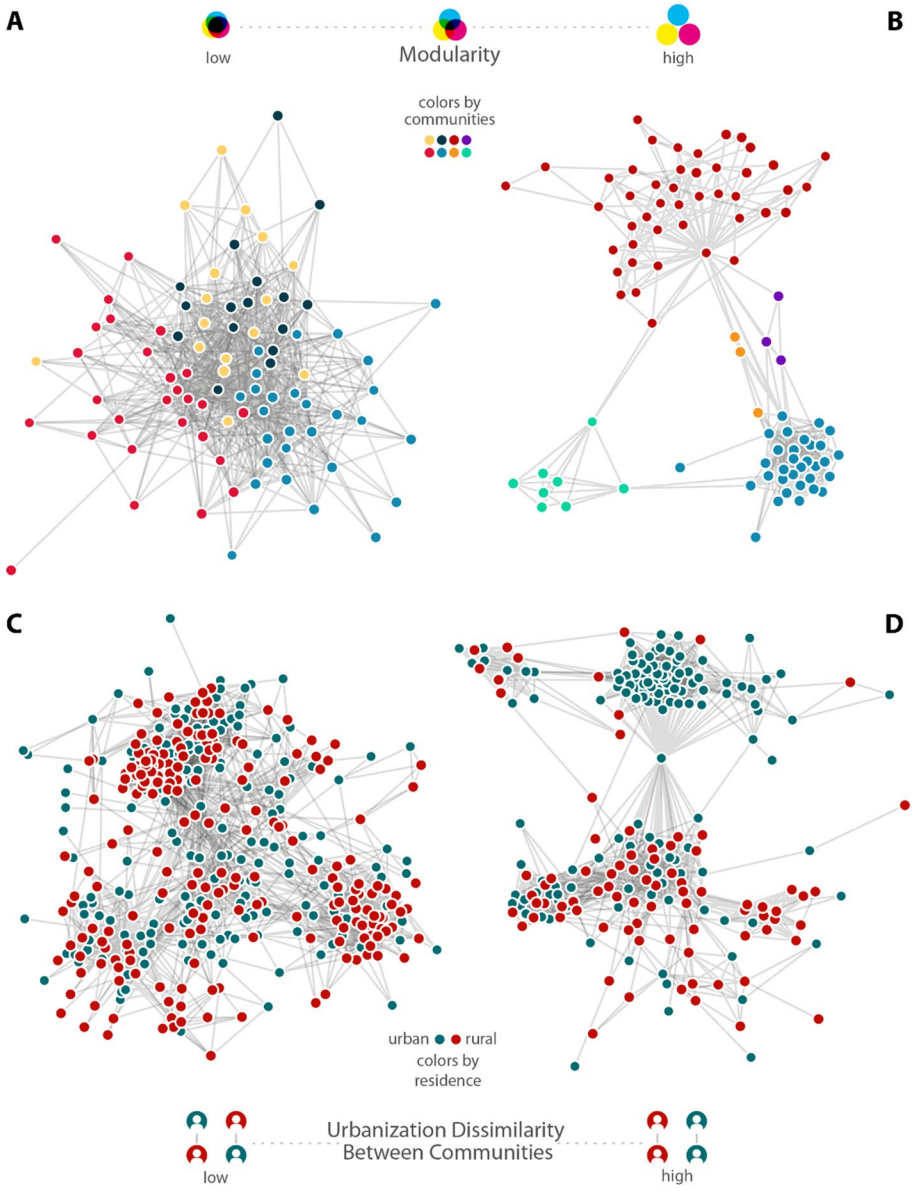

Fig. 2 Ego networks with different levels of modularity and dissimilarity in urbanization

for its emergence. Thus, we calculated the pairwise differences between these averages within the ego network, and took the maximum of these. To only focus on meaningful communities, we excluded the ones that are very small either in absolute size (smaller than 5 persons) or in comparison with the ego network (smaller than 10%) from the calculation of the maximum difference. Accordingly, the formula for the calculation of the age dissimilarity is as follows:

$$\begin{aligned} &age\ dissimilarity = \max\left(\left|avg_{age_k} - avg_{age_l}\right|\right), \\ &for\ each\ k \neq l, N_k \geq 5, N_l \geq 5, \frac{N_k}{N} \geq 0.1, \frac{N_l}{N} \geq 0.1 \end{aligned} \tag{2}$$

where N_k and N_l represents the sizes of *kth* and *lth* communities, N shows the number of alters in the ego network and avg_{age} denotes the average age of individuals in the given community.

Considering urbanization, we classified users' domiciles to two categories. If the user lived in the capital or a major city, we labeled them as urban, otherwise, they were classified as rural. Community urbanization dissimilarity corresponds to the maximum difference between the share of urban domicile between two communities within the ego network Thus, the calculation is similar to the one of age dissimilarity if we substitute the average age with the share of urban domicile within the community. It has a zero value if all communities have the same urbanizational composition, and one if ego has one community with only rural, and another with only urban friends. Thus the corresponding formula is the following:

$$\begin{aligned} &urbanization\ dissimilarity = \max\left(\left|\frac{N_{kurban}}{N_k} - \frac{N_{lurban}}{N_l}\right|\right), \\ &for\ each\ k \neq l, N_k \geq 5, N_l \geq 5, \frac{N_k}{N} \geq 0.1, \frac{N_l}{N} \geq 0.1 \end{aligned} \tag{3}$$

where N_k and N_l represents the sizes of k^{th} and l^{th} communities, N shows the number of alters in the ego network and N_{kurban} denotes the number of individuals living in a city in the given community.

To control for the social capital, the OSN provides to its users by connecting them to geographically distant friends, we included the geographic distance of the ego from their friends in the model. The corresponding measure was:

$$average\ distance\ from\ friends = \sum_{i=1}^{N} \frac{d_{ego,i}}{N}, \tag{4}$$

where d is the geographic distance in kilometers between the residence of the ego and his or her alter i, and N represents the number of ego's alters. Thus, geographical distinction shows the average geographical distance between ego and his or her alters.

Means and standard deviations of these key variables are shown in Table 3. We observe some missing values across the variables, which causes some variations in the number of observations.

Table 3 Descriptive statistics of the main and control variables for our hypotheses

	Mean	SD	N
Leave	0.012	0.111	559,179
Modularity	0.343	0.150	557,705
Community dissimilarity			
Age	9.572	5.966	527,715
Urbanization	0.314	0.197	528,100
Social capital control variables			
N of communities	3.624	1.131	553,760
N of connections (100)	2.072	1.824	559,179
Clustering (local)	0.161	0.128	553,843
Avg. distance from friends (km)	44.548	41.396	557,690
Individual control variables			
Age	36.693	13.200	396,969
Gender (1 = F, 2 = M)	1.442	0.497	559,179

Statistical methodology

To predict leaving the OSN, we use discrete-time survival models (Allison 2014). We choose a non-parametric baseline hazard function as we do not have a priori assumptions about its form, and because our main research interest lies in the regression parameters, namely in the interpretation of the effects of the independent variables on leaving (Cox 1972). Independent variables include both time-invariant and time-varying variables. The first group of independent variables include characteristics of users, namely age and gender. The second group of independent variables are related to users' connections and contain the number of connections they have, the number of different communities (detected by Louvain community detection), the modularity score, and the local clustering coefficient. The third group of independent variables is built up by the above-described community dissimilarity measures according to age, location and gender. The fourth group of independent variables we include in the models are the ones, which measure the distinction of ego from the ego network communities, from the perspective of age, location and gender. Statistical calculations were executed by STATA's logit and margins commands including dummy variables for each month.

Results

We analyse the impact of context collapse indicators in a stepwise manner. First, we consider context collapse regarding urbanization, for which we test the corresponding main effects as a baseline (Table 4 Model 1), and then add the interaction term corresponding to context collapse (Table 4 Model 2). Second, we test the effect of context collapse with respect to age in a similar manner, by first adding only the main effects (Table 4 Model 3), and then the interaction term that measures context collapse (Table 4 Model 4). In a final model (Table 4 Model 5) we include both types of context collapse together to check the robustness of the results.

Our dependent variable is leaving the site; thus positive coefficients indicate characteristics that are associated with leaving. Considering separately the two factors that build up the context collapse measure by urbanization, we observe that modularity has a negative effect on leaving, while difference between communities by urbanization facilitates leaving (Table 4 Model 1). The variable measuring context collapse by urbanization has a positive and significant coefficient, which is in line with H1 suggesting that high modularity with large urbanization difference between communities increases the likelihood of leaving the OSN (Table 4 Model 2).

We observe similar tendencies in the case of context collapse by age. Focusing on the main effects, modularity decreases, but large age difference between communities increases the likelihood of leaving (Table 4 Model 3). The coefficient of the interaction term measuring context collapse by age is again positive and significant supporting H2. This shows that people having communities that are diverse by age, and structurally distinct are more likely to leave the social network (Table 4 Model 4). These results remain unchanged in the final model, where we include both measures of context collapse (Table 4 Model 5).

Our user-level controls show that older users tend to stay longer on the site in contrast to younger users. We can also see that gender does not have a significant effect on leaving the site. Coefficients of the network indicators suggest that having more friends and having more communities are associated with staying longer on the site, but a more

Table 4 Discrete-time survival models on leaving the OSN (coefficients)

	Dependent variable: leaving the OSN				
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Age	-0.0120***	-0.0121***	-0.0131***	-0.0132***	-0.0132***
	(0.00137)	(0.00137)	(0.00136)	(0.00136)	(0.00136)
Gender	-0.00844	-0.00444	0.000307	-0.000124	0.00588
	(0.0378)	(0.0378)	(0.0378)	(0.0378)	(0.0379)
N of communities	-0.119***	-0.122***	-0.144***	-0.144***	-0.157***
	(0.0237)	(0.0237)	(0.0239)	(0.0239)	(0.0245)
N of friends (100)	-0.382***	-0.389***	-0.382***	-0.371***	-0.376***
	(0.0165)	(0.0165)	(0.0163)	(0.0165)	(0.0166)
Local clustering	1.387***	0.998***	1.246***	1.429***	1.057***
	(0.310)	(0.320)	(0.312)	(0.314)	(0.325)
Modularity	-2.913***	-4.261***	-2.675***	-3.516***	-4.792***
	(0.225)	(0.356)	(0.228)	(0.322)	(0.418)
Average distance from friends (km)	-0.00211***	-0.00211***	-0.00164***	-0.00161***	-0.00184***
	(0.000555)	(0.000556)	(0.000536)	(0.000536)	(0.000555)
Urbanization					
Difference between communities	0.215**	-1.035***			-1.014***
	(0.106)	(0.275)			(0.276)
Difference between communities x modularity (context collapse)		3.651***			3.510***
		(0.731)			(0.734)
Age					
Difference between communities			0.0206***	-0.00672	-0.00523
			(0.00329)	(0.00798)	(0.00795)
Difference between communities x modularity (context collapse)				0.0904***	0.0844***
				(0.0239)	(0.0237)
Pseudo-R^2	0.121	0.122	0.122	0.122	0.123
Observations	360,645	360,645	360,609	360,609	360,609

Time is included in nonparametric form including dummy variables for each month. Standard errors in parentheses

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

clustered local network is related to a higher likelihood of leaving (cf. Lőrincz et al. 2019). In line with our previous assumption, the larger the geographical distance between the ego and their friends is, the less likely that they will leave the social network.

Nevertheless, in case of logistic models interaction terms should not be interpreted by the coefficients. As the size of the coefficients in logistic models do not only depend on the size of the effect, but also on the explained variance of the model, the comparison of two coefficients between different subgroups of the sample can be misleading. As interaction terms reflect differences between subgroups, they should be interpreted by average marginal effects instead of the coefficients themselves (Mood 2010). Therefore, to check the validity of the results, we calculated the average marginal effects for the same models. These are displayed in Table 5 in the appendix. It shows that results remained identical in terms of direction and significance of the effects of the independent variables.

Interactions

It must be considered that the variables measuring context collapse were calculated as the interactions of two variables; modularity and difference between communities. Although the directions of these interactions correspond to our hypotheses (that high

modularity together with large differences between communities predict leaving the site), the main effects of its compounds were not fully in line with our previous assumptions. Namely, we observed that high modularity in itself is associated with lower likelihood of leaving. Thus, to get a deeper understanding of these effects together, we plotted the predicted probability of exit based on our models by modularity and difference between communities.

We visualize these interactions with respect to the average marginal effects in Fig. 3. For both the maximum difference between communities and for modularity we display the values belonging to the 1st, 25th, 50th, 75th and 99th percentiles of the data. Looking at the lines on the figure, we observe that depending on the level of modularity, they tend towards different directions. When modularity is high, they increase, thus, higher differences between communities are associated with higher probability of leaving, which is in line with our hypotheses. However, we see that the probability of leaving is the highest in case both modularity and differences between communities are low, and not when they are both high, which contradicts the hypotheses. In other words, we assumed that the rightmost point of the line denoting the highest modularity is higher than the leftmost point of the line with the lowest modularity, which is not the case. Therefore, we can conclude that although the tendencies support the hypothesized patterns, the range of the data does not allow us to observe the expected peaks, i.e. if we had data with higher modularity, or differences between communities, we might have observed such points. We can also observe, that the reason for it is the main effect of modularity, which is sizeable and negative, reflected by the fact that lines with low modularity are associated with higher probability of leaving in both panels of Fig. 3.

Alternative specifications

To check the robustness of our findings, we ran models with two alternative specifications. First, as logging in to the network is a very low-effort activity, we examined our hypotheses using an alternative measurement of leaving, defining it by the last time of creating a new tie; an act that indicates higher commitment. Thus, we run models with

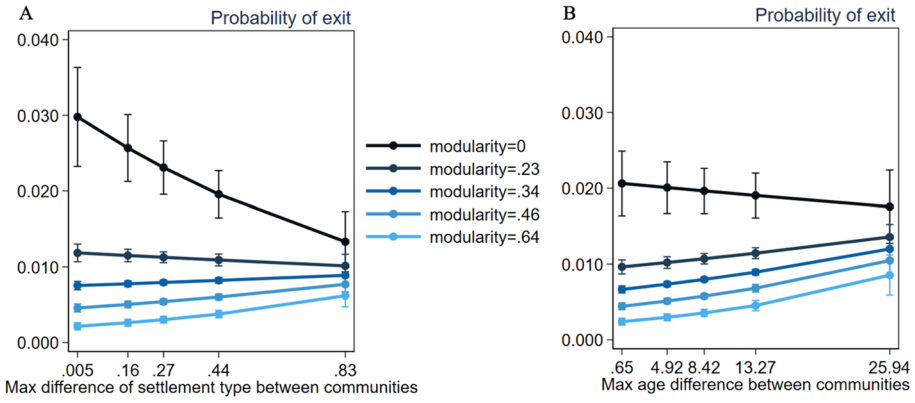

Fig. 3 The interaction effect of modularity with urbanization- and age-related community dissimilarities on leaving the OSN. Panel A: Vertical axis denotes the probability of leaving according to the predicted probability of Model 2, Table 4. Horizontal axis denotes the maximum difference between communities by urbanization, calculated by Formula (3), using the values of the 1st, 25th, 50th, 75th and 99th percentiles. Panel B: Vertical axis denotes the probability of leaving according to the predicted probability of Model 4, Table 4. Horizontal axis denotes the maximum difference between communities by age, calculated by Formula (2), using the values of the 1st, 25th, 50th, 75th, and 99th percentiles. Legends present different values of modularity belonging to the 1st, 25th, 50th, 75th, and 99th percentiles of the data

the dependent variable of leaving measured by the date of the user's last tie creation. The results are shown in Appendix Table 6. In these alternatively specified models, the significance, magnitude, and direction of the coefficients related to our hypotheses are the same as in our primary specification.

Second, as previous studies (Török and Kertész 2017) showed that leaving the network is heavily influenced by the proportion of inactive friends—which can even lead to the cascading collapse of the network–, we created alternative models, in which we controlled for the share of friends who became inactive until the previous month (see Table 7. in the Appendix). The fact that this factor is indeed important is illustrated in the pseudo-R^2 of the models, which approximately increased from 12 to 19%. With the inclusion of this new control variable, the magnitudes of the coefficients corresponding to our hypotheses have somewhat weakened, nevertheless, their directions and the related conclusions have not changed. The direction of the effects of the urbanization difference between communities did not change (although they became non-significant). Nevertheless, the interaction between modularity and urbanization differences between communities kept being significant and positive, such as in the original model. The effect of the age difference between communities as well as the interaction between age difference and modularity remained significant and the direction of the effects did not change either—compared to the original model. The only difference observable is in the model, which includes all variables (Model 5), where after controlling for other community differences, the interaction of age dissimilarity and modularity became non-significant, while the magnitude of the effect only slightly decreased. Nevertheless, as we have presented previously, to get a complete picture of the effects, interaction terms are important to be interpreted together with the main effects. In this respect, we can say that both at urbanization- and age-related community differences, the interactions show the same patterns as in the original model: although the positive coefficients of the interactions support our hypotheses, interpreting them together with the negative main effect of modularity, the positive effect of the interaction never compensate the strong negative influence of modularity on leaving.

Discussion

Understanding why some online social networks survive for a long time and why others are getting abandoned and replaced by new services, is not only important for the service providers but also for researchers wanting to understand online lived experience. Multiple factors affect such a process. Among these, we focused on the role of the joint presence of diversity and fragmentation that may provide stress and tension to the users.

Originally, we hypothesized that high fragmentation (modularity) of the users' networks together with diverse communities having diverging expectations towards the users, namely the presence of context collapse, would predict that users leave the site. We measured community differences by age (H1) and urbanization (H2). Based on our analysis of a large but now defunct online social network (iWiW), we reject this hypothesis. Although we found evidence for the hypothesized tendencies, that in the case of highly fragmented ego networks, larger differences between communities increase the likelihood of leaving; the highest probability for leaving was present among those with non-fragmented networks including similar communities. These results were present both in the case of age- and urbanization differences, as well as after controlling for

social influence in leaving the platform. These seemingly contradicting results are caused by the process that network fragmentation itself decreases the probability of leaving.

There are several possible explanations for this result. One is that being a member of different communities can be an asset in OSNs. Thus, fragmented networks indicated by high modularity offer social capital benefits, because of bridging positions, so being the intersection between diverse communities is associated with greater social capital (Burt 2005; Jackson 2020), a benefit that keeps users on the platform as they do not want to give it up. Our additional related control variable corresponds to this explanation. We have found that having an ego network with high local clustering coefficient increases the probability of leaving. High local clustering is an indication of the lack of bridging position, and it also supports the assumption that the network is built up by strong, high-bandwidth ties, which means that keeping the connection with them on the OSN is not that important for the ego as they can connect and meet them at other channels and places. Furthermore, we found that living far away from friends and/or family members predicts staying on iWiW longer. This result also supports the interpretation that online social networks are used to manage and maintain social ties, especially if keeping contact with these connections would take more effort otherwise—like in the case of geographically distant friends.

In addition, the observed pattern that users with more fragmented networks did not leave iWiW can also be explained by another phenomenon. At the peak of the iWiW's life cycle, Facebook appeared in Hungary as a viable substitute for the platform—and that is the time when the collapse of the network started. It is likely that users who go to new platforms relatively early do not entirely abandon the old ones, preserving the benefits of belonging to the current OSN too. Moreover, pragmatic users facing context collapse on iWiW may have adopted a strategy of managing identities on different networks (Boyd 2014) and using them selectively for some of their social circles. In these cases, different OSNs will be actively used for different communities or different purposes. Thus, for users having fragmented ego networks, maintaining their presence on iWIW for a longer time—even after the majority of the users left—can provide a special benefit, which can explain why they are less likely to leave the site. This strategy might explain the contradicting results we observed in the data. To elaborate on this potential explanation, a qualitative approach or data on the joint activity on the sites would be needed.

Our study cannot address every aspect of the potential tradeoff between diversity and tension in social networks. We miss user information on ethnicity, religious belief, political opinion, interests, and socio-economic status. Even for the attributes we do observe, there are likely complex social interactions relating to context collapse—for instance between gender and age (cf. Sivak and Smirnov 2019)—that our models do not capture. Another dimension of behavior we cannot observe in our data is whether a user partially withdraws from the site by censoring their profile or limiting their posts. Such strategies seem to be optimal responses to context collapse, especially for individuals who still gain significant value from their network. Our alternative specification, predicting the time of a user's last new connection, is an attempt to proxy for a shift from active to passive use of the platform.

Our study has been the first to provide a comprehensive empirical account of a serious potential systemic consequence of context collapse: exit from an online social network. Our results can therefore be of vital relevance for OSN providers. These results, however,

came from an early social network. On iWiW, there was no option for filtering posts for selected audiences. Nevertheless, nowadays multiple online social networks have this feature, which changed the options for avoiding context collapse a lot. Additionally, algorithms also affect the content we see on social media (Kim 2017; Swart 2021). Consequently, even if there is disturbing content on the feed of the user, it is not evident that they see it. Literature on OSNs highlights how users self-segregate their activity into echo chambers along the dimensions that interest them the most (Del Vicario et al. 2016; Flaxman et al. 2016), or by people with whom they agree. Therefore, our arguments have more limited validity on platforms that actively filter content according to the preferences of users, thus suppressing context collapse.

Despite these limitations, we also provide new illustrative support for the theoretical literature that emphasizes the benefits of ego network diversity compared to its disadvantages.

Appendix

See Tables 5, 6, 7.

Table 5 Discrete-time survival models on leaving the OSN (average marginal effects)

	Dependent variable: leaving the OSN				
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Age	-9.54e-05***	-9.55e-05***	-0.000104***	-0.000105***	-0.000105***
	(1.10e-05)	(1.10e-05)	(1.09e-05)	(1.09e-05)	(1.09e-05)
Gender	-6.68e-05	-3.52e-05	2.43e-06	-9.78e-07	4.65e-05
	(0.000299)	(0.000299)	(0.000299)	(0.000299)	(0.000300)
N of communities	-0.000940***	-0.000970***	-0.00114***	-0.00114***	-0.00124***
	(0.000188)	(0.000188)	(0.000190)	(0.000190)	(0.000195)
N of friends (100)	-0.00303***	-0.00308***	-0.00302***	-0.00293***	-0.00297***
	(0.000140)	(0.000141)	(0.000139)	(0.000140)	(0.000141)
Local clustering	0.0110***	0.00791**	0.00986***	0.0113***	0.00836**
	(0.00246)	(0.00254)	(0.00248)	(0.00249)	(0.00257)
Modularity	-0.0231***	-0.0337***	-0.0212***	-0.0278***	-0.0379***
	(0.00183)	(0.00288)	(0.00184)	(0.00259)	(0.00337)
Average distance from friends (km)	-1.67e-05***	-1.67e-05***	-1.30e-05**	-1.28e-05**	-1.46e-05***
	(4.40e-06)	(4.41e-06)	(4.25e-06)	(4.25e-06)	(4.40e-06)
Urbanization					
Difference between communities	0.00171*	-0.00820***			-0.00802***
	(0.000841)	(0.00218)			(0.00218)
Difference between communities x modularity (context collapse)		0.0289***			0.0278***
		(0.00581)			(0.00582)
Age					
Difference between communities			0.000163***	-5.32e-05	-4.14e-05
			(2.61e-05)	(6.31e-05)	(6.29e-05)
Difference between communities x modularity (context collapse)				0.000715***	0.000667***
				(0.000189)	(0.000188)
Pseudo-R^2	0.121	0.122	0.122	0.122	0.123
Observations	360,645	360,645	360,609	360,609	360,609

Time is included in nonparametric form. Standard errors in parentheses

*** $p < 0.001$, ** $p < 0.001$, * $p < 0.05$

Table 6 Alternative specification: the date of last friendship as the dependent variable

	Dependent variable: leaving the OSN				
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Age	-0.00276**	-0.00281***	-0.00459***	-0.00486***	-0.00483***
	(0.00107)	(0.00107)	(0.00108)	(0.00108)	(0.00108)
Gender	0.0311	0.0364	0.0410	0.0411	0.0479*
	(0.0279)	(0.0279)	(0.0279)	(0.0279)	(0.0280)
N of communities	-0.0490***	-0.0522***	-0.0766***	-0.0758***	-0.0846***
	(0.0172)	(0.0172)	(0.0175)	(0.0175)	(0.0179)
N of friends (100)	-0.317***	-0.323***	-0.320***	-0.310***	-0.315***
	(0.0110)	(0.0111)	(0.0110)	(0.0111)	(0.0112)
Local clustering	1.088***	0.747***	0.924***	1.148***	0.812***
	(0.260)	(0.266)	(0.263)	(0.264)	(0.270)
Modularity	-2.149***	-3.312***	-1.920***	-2.765***	-3.879***
	(0.162)	(0.252)	(0.164)	(0.232)	(0.299)
Average distance from friends (km)	-0.00203***	-0.00203***	-0.00169***	-0.00166***	-0.00181***
	(0.000389)	(0.000390)	(0.000377)	(0.000378)	(0.000390)
Urbanization					
Difference between communities	0.164**	-1.043***			-1.045***
	(0.0771)	(0.213)			(0.214)
Difference between communities x modularity (context collapse)		3.230***			3.133***
		(0.528)			(0.530)
Age					
Difference between communities			0.0197***	-0.0105*	-0.00949
			(0.00258)	(0.00635)	(0.00633)
Difference between communities x modularity (context collapse)				0.0920***	0.0877***
				(0.0175)	(0.0175)
Pseudo-R^2	0.139	0.140	0.140	0.141	0.142
Observations	317,720	317,720	317,706	317,706	317,706

Time is included in nonparametric form. Standard errors in parentheses: *** $p<0.001$, ** $p<0.01$, * $p<0.05$

Table 7 Alternative specification: including the percentage of inactive friends as a control variable to control for cascading collapse

	Dependent variable: leaving the OSN				
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Age	-0.00373***	-0.00377***	-0.00441***	-0.00448***	-0.00451***
	(0.00136)	(0.00136)	(0.00136)	(0.00136)	(0.00136)
Gender	0.0295	0.0313	0.0347	0.0332	0.0381
	(0.0389)	(0.0389)	(0.0389)	(0.0390)	(0.0390)
N of communities	-0.0415*	-0.0434*	-0.0566**	-0.0569**	-0.0665***
	(0.0242)	(0.0243)	(0.0245)	(0.0245)	(0.0251)
N of friends (100)	-0.215***	-0.219***	-0.217***	-0.213***	-0.215***
	(0.0158)	(0.0159)	(0.0157)	(0.0159)	(0.0161)
Local clustering	3.175***	3.001***	3.097***	3.157***	2.998***
	(0.306)	(0.319)	(0.308)	(0.309)	(0.322)
Modularity	-1.183***	-1.752***	-1.025***	-1.431***	-2.000***
	(0.231)	(0.366)	(0.232)	(0.338)	(0.437)
Average distance from friends (km)	-0.00319***	-0.00320***	-0.00284***	-0.00283***	-0.00305***
	(0.000601)	(0.000601)	(0.000581)	(0.000581)	(0.000600)
Share of inactive friends	7.382***	7.361***	7.366***	7.353***	7.330***
	(0.138)	(0.139)	(0.139)	(0.139)	(0.139)
Urbanization					
Difference between communities	0.179	-0.344			-0.331
	(0.109)	(0.282)			(0.282)
Difference between communities x modularity (context collapse)		1.523**			1.457*
		(0.754)			(0.755)
Age					
Difference between communities			0.0126***	0.000256	0.000657
			(0.00340)	(0.00818)	(0.00817)
Difference between communities x modularity (context collapse)				0.0411*	0.0392
				(0.0246)	(0.0246)
Pseudo-R^2	0.193	0.193	0.193	0.193	0.194
Observations	356,861	356,861	356,825	356,825	356,825

Time is included in nonparametric form. Standard errors in parentheses: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

Author contributions
JK and LL conceptualized and performed statistical modelling and created visualizations (Figs. 1, 3). JW calculated network measures and created visualizations (Fig. 2). KT developed theoretical framework. All authors contributed to writing the manuscript and reviewing its final version.

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Data availability
The analysis uses individual records of the archived data of the iWIW social networking site. Due to privacy law, the database of individual records is only available for research in a restricted environment, which is provided by the Databank of HUN-REN Centre for Economic and Regional Studies, on-site only in Budapest, Hungary. Inquires and further information: https://adatbank.krtk.mta.hu/en/, adatbank@krtk.hu.

Declarations

Competing interests
The authors declare no competing interests.

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References

Alba RD, Kadushin C (1976) The intersection of social circles: a new measure of social proximity in networks. Sociol Methods Res 5(1):77–102
Allison PD (2014) Event history and survival analysis: regression for longitudinal event data. SAGE Publications, Thousand Oaks
Alwin DF, Felmlee DH, Kreager DA (eds) (2018) Social networks and the life course: integrating the development of human lives and social relational network. Springer, Berlin
Aral S, Van Alstyne M (2011) The diversity-bandwidth trade-off. Am J Sociol 117(1):90–171
Auxier BE, Vitak J (2019) Factors motivating customization and echo chamber creation within digital news environments. Soc Media Soc 5(2):2056305119847506
Beam MA, Child JT, Hutchens MJ, Hmielowski JD (2018) Context collapse and privacy management: diversity in Facebook friends increases online news reading and sharing. New Media Soc 20(7):2296–2314
Binder JF, Howes A, Smart D (2012) Harmony and tension on social network sites: side-effects of increasing online interconnectivity. Inf Commun Soc 15(9):1279–1297
Blank G (2022) Who uses social media? The SAGE handbook of social media research methods, vol 67
Blondel VD, Guillaume J-L, Lambiotte R, Lefebvre E (2008) Fast unfolding of communities in large networks. J Stat MechTheory Exp 5(10):P10008
Borgatti SP, Jones C, Everett MG (1998) Network measures of social capital. Connections 21(2):27–36
Boyd DM (2008) Taken out of context: American teen sociality in networked publics. ProQuest, Ann Arbor
Boyd DM (2014) It's complicated: the social lives of networked teens. Yale University Press, New Haven
Brandtzaeg PB, Lüders M (2018) Time collapse in social media: extending the context collapse. Soc Media Soc 4(1):1–10
Brooks B, Hogan B, Ellison N, Lampe C, Vitak J (2014) Assessing structural correlates to social capital in Facebook ego networks. Soc Netw 37(3):1–15
Burkell J, Fortier A (2016) Display and control in online social spaces: toward a typology of users. New Media Soc 20(3):845–861
Burt RS (1995) Structural holes. Harvard University Press, Cambridge
Burt RS (2005) Brokerage and closure: an introduction to social capital. Oxford University Press, Oxford
Costa E (2018) Affordances-in-practice: An ethnographic critique of social media logic and context collapse. New Media Soc 20(10):3641–3656
Cox DR (1972) Regression models and life-tables. J Roy Stat Soc Ser B (Methodol) 34(2):187–202
Davis JL, Jurgenson N (2014) Context collapse: theorizing context collusions and collisions. Inf Commun Soc 17(4):476–485
Del Vicario M, Vivaldo G, Bessi A, Zollo F, Scala A, Caldarelli G, Quattrociocchi W (2016) Echo chambers: emotional contagion and group polarization on Facebook. Sci Rep 6:37825
Feld SL (1981) The focused organization of social ties. Am J Sociol 86(5):1015–1035
Fischer CS (1977) Networks and places: social relations in the urban setting. Free Press, New York
Flaxman S, Goel S, Rao JM (2016) Filter bubbles, echo chambers, and online news consumption. Public Opin Q 80(S1):298–320
Garcia D, Mavrodiev P, Schweitzer F (2013) Social resilience in online communities: the autopsy of friendster. In: COSN'13: proceedings of the first ACM conference on online social networks, pp 39–50. Association for Computer Machinery
Gil-Lopez T, Shen C, Benefield GA, Palomares NA, Kosinski M, Stillwell D (2018) One size fits all: context collapse, self-presentation strategies and language styles on Facebook. J Comput-Mediat Commun 23(3):127–145
Goffman E (1978) The presentation of self in everyday life. Harmondsworth London
Granovetter M (1973) The strength of weak ties. Am J Sociol 78(6):1360–1380
Hargittai E (2007) Whose space? Differences among users and non-users of social network sites. J Comput-Mediat Commun 13(1):276–297
Hogan B (2010) The presentation of self in the age of social media: distinguishing performances and exhibitions online. Bull Sci Technol Soc 30(6):377–386
Hwang HS, Shim JW, Park SB (2019) Why we migrate in the virtual world: factors affecting switching intentions in SNS. Inf Commun Soc 22(14):2127–2137
Jackson MO (2020) A typology of social capital and associated network measures. Soc Choice Welfare 54(2–3):311–336
Jackson MO, Rodriguez-Barraquer T, Tan X (2012) Social capital and social quilts: Network patterns of favor exchange. Am Econ Rev 102(5):1857–1897
Kim SA (2017) Social media algorithms: why you see what you see. Georgetown Law Technol Rev 2:147
Lazarsfeld P, Merton RK (1954) Friendship as a social process: a substantive and methodological analysis. In: Berger M, Abel T, Charles H (eds) Freedom and control in modern society. Van Nostrand, New York, pp 18–66
Lengyel B, Bokányi E, Di Clemente R, Kertész J, González MC (2020) The role of geography in the complex diffusion of innovations. Sci Rep 10(15065)
Lin N (1999) Building a network theory of social capital. Connections 22(1):28–51
Loh J, Walsh MJ (2021) Social media context collapse: the consequential differences between context collusion versus context collision. Soc Media Soc 7(3):20563051211041650

Lőrincz L, Koltai J, Győr AF, Takács K (2019) Collapse of an online social network: burning social capital to create it? Soc Netw 57:43–53
Marder B, Joinson A, Shankar A, Thirlaway K (2016) Strength matters: Self-presentation to the strongest audience rather than lowest common denominator when faced with multiple audiences in social network sites. Comput Hum Behav 61:56–62
Marsden PV (1988) Homogeneity in confiding relations. Soc Netw 10(1):57–76
Marwick AE, Boyd D (2011) I tweet honestly, I tweet passionately: Twitter users, context collapse, and the imagined audience. New Media Soc 13(1):114–133
Marwick A, Boyd D (2014) 'It's just drama': teen perspectives on conflict and aggression in a networked era. J Youth Stud 17(9):1187–1204
McPherson M, Smith-Lovin L, Cook JM (2001) Birds of a feather: homophily in social networks. Ann Rev Sociol 27(1):415–444
Meyrowitz J (1986) No sense of place: the impact of electronic media on social behavior. Oxford University Press, Oxford
Mood C (2010) Logistic regression: Why we cannot do what we think we can do, and what we can do about it. Eur Sociol Rev 26(1):67–82
Newman MEJ, Girvan M (2004) Finding and evaluating community structure in networks. Phys Rev E 69(2):026113
Ngonmang B, Viennet E, Tchuente M (2012) Churn prediction in a real online social network using local community analysis. In: ASONAM'12: proceedings of the 2012 international conference on advances in social networks analysis and mining, pp 282–288. IEEE Computer Society
Norbutas L, Corten R (2018) Network structure and economic prosperity in municipalities: a large-scale test of social capital theory using social media data. Soc Netw 52:120–134
Pang H (2022) Connecting mobile social media with psychosocial well-being: understanding relationship between WeChat involvement, network characteristics, online capital and life satisfaction. Soc Netw 68:256–263
Salemink K, Strijker D, Bosworth G (2017) Rural development in the digital age: a systematic literature review on unequal ICT availability, adoption, and use in rural areas. J Rural Stud 54:360–371
Simmel G (2009) Sociology: investigations on the Forms of Sociation. Brill. (Original work published 1908)
Sivak E, Smirnov I (2019) Parents mention sons more often than daughters on social media. Proc Natl Acad Sci 116(6):2039–2041
Swart J (2021) Experiencing algorithms: How young people understand, feel about, and engage with algorithmic news selection on social media. Soc Media Soc 7(2):20563051211008828
Talukdar D, Gauri DK (2011) Home Internet access and usage in the USA: trends in the socio-economic digital divide. Commun Assoc Inf Syst 28(1):7
Thonipara A, Sternberg R, Proeger T, Haefner L (2023) Digital divide, craft firms' websites and urban-rural disparities—empirical evidence from a web-scraping approach. Rev Region Res 43(1):69–99
Tian X (2016) Network domains in social networking sites: expectations, meanings, and social capital. Inf Commun Soc 19(2):188–202
Török J, Kertész J (2017) Cascading collapse of online social networks. Sci Rep 7(1):16743
Uzzi B (1997) Social structure and competition in interfirm networks: the paradox of embeddedness. Adm Sci Q 42(1):35–67
Vitak J (2012) The impact of context collapse and privacy on social network site disclosures. J Broadcast Electron Media 56(4):451–470
Vitak J, Blasiola S, Patil S, Litt E (2015) Balancing audience and privacy tensions on social network sites: Strategies of highly engaged users. Int J Commun 9(1):1485–1504
Vitak J, Lampe C, Gray R, Ellison NB (2012) Why won't you be my Facebook friend?": strategies for managing context collapse in the workplace. In: iConference'12: proceedings of the 2012 iConference, pp 555–557. Association for Computing Machinery
Wachs J, Yasseri T, Lengyel B, Kertész J (2019) Social capital predicts corruption risk in towns. R Soc Open Sci 6(4):182103
Wesch M (2009) Youtube and you: Experiences of self-awareness in the context collapse of the recording webcam. Explor Media Ecol 8(2):19–34

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