The Role of Followers and Followees in the Adoption of Innovations

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Abstract

An online social network is a key platform through which innovation diffuses. To learn about innovativeness, we simultaneously investigate two Twitter networks, the relationships network, following-follower relationships, and the activity network, the flow of tweets. Specifically, the innovativeness relations to the networks' indegree and outdegree, the volume of platform use, and the profile's age. The more active and central the user, the earlier the adoption. Innovativeness increases with the number of followers only when at least several of them adopt the innovation. Surprisingly, having more followees is linked to later engagement with the innovation. This association is mediated by the number of adopters' followees. Those who created a Twitter profile later are also more likely to adopt innovations later. This study is novel in distinguishing between the two networks and analyzing their interactions. Its contribution lies in identifying the innovativeness of users in an online social network platform diffusion.

Keywords: Online Social Networks; Relationships Graphs; Centrality Measures; Adoption; Innovativeness.

1. Introduction

An innovation such as product usage, behavior, or idea can spread through a social network (Rogers, 2010). Adopting new behavior is a complex phenomenon that has been the focal point of research since 1943 (Ryan & Gross, 1943). Social media has become more influential in the adoption of innovations (Danowski et al., 2011). Valente (1996) pointed out the importance of mass media in the transfer of information. However, today social networks have similar functions and should be treated with the same degree of importance. Much of the research in this area focuses on the influence of the information to which a social network user is exposed (Goldenberg et al., 2009; Valente, 1996) and the exposure message strength (Berger & Milkman, 2012). We focus on how well the users' attributes in the network associate with their innovativeness.

To accomplish our goal, we examine two different networks that co-exist on Twitter simultaneity. One is the *relationships network* which constitute the users' relationships with other users on Twitter, or the connections between followers and followees. The other network is *the activity (adopters) network*, which focuses only on the users who are active in the flow of information about the innovation. The connections in the activity network are a subset of the relationship network connections between the activity network's users, meaning their Twitter platform relationships. Using Twitter as a diffusion platform for ideas, this study expands our understanding of adoption behavior. It adds new perspectives to the social networks co-existing on the platform and how their users' attributes affect users' innovativeness. In particular, it focuses on the relation between followees and followers in both networks, a relationship that has not been examined previously.

Section 2 reviews the relevant literature. Section 3 describes our method of collecting a year's worth of activities about mindfulness on Twitter in the greater London area. Section 4 presents the results, followed by a discussion and the contributions and limitations in Section 5.

2. Related work

Innovativeness is the reaction to an encounter with an innovation (Goldsmith & Foxall, 2003). The measure of the behavioral concept of innovativeness relies on the time of adoption of a novel idea, meaning how fast people adopt the innovation. The time involved can range from immediate adoption to gradually accepting and adopting it or to rejecting it altogether.

Innovativeness is a people trait; hence, one has a similar tendency to different innovations (Li et al., 2018a), while innovativeness differs between people (Rogers, 2010). The first users to adopt are not necessarily the most influential users (Hasson &

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Akeel, 2019), however, their position within the network is known to influence the adoption rate of a new product (Barbuto et al., 2019).

Adoption is an active action such as using an innovation. Diffusion of innovation (Rogers, 2010) includes ideas and therefore it is common to include information diffusion in it (Barnett & Vishwanath, 2017). It is possible to use the concept of adoption to describe the spread of a novel idea from an information diffusion perspective (Li et al., 2018). Social networks promote this diffusion by spreading information and persuading people to adopt an innovation (Muller & Peres, 2019).

There are various ways of measuring the point at which innovations are adopted on online social networks. Examples include hashtag use (Fink et al., 2016; González-Bailón et al., 2011; Li et al., 2018; Liu et al., 2016), reposting or retweets (Stieglitz & Dang-Xuan, 2013; Zhang et al., 2020), or the posting of URLs (Goel et al., 2016). Regardless of the method, the first time it is used is regarded as the moment of its adoption.

Twitter is a leading online social network platform used for disseminating information (Antonakaki et al., 2021). Given this ability, Twitter is ideal for diffusion of innovation studies (Chang, 2010). For example, researchers have investigated information diffusion on Twitter predicting retweets (Hoang & Mothe, 2018).

Mindfulness is a process of bringing attention to the present moment using meditation techniques from Buddhism (Bishop et al., 2004). This topic was discussed and researched throughout the years and due to its benefits (Dane & Brummel, 2014; Kabat-Zinn, Jon, 1982; Tang et al., 2015) became more popular and widespread. Therefore, this trending idea is suitable for multi-year temporal research on the diffusion of innovations.

2.1 Centrality measures

A user's social neighborhood is a key factor in the innovation and diffusion process (Coleman et al., 1966; Lazarsfeld et al., 1968; Levy & Nail, 1993). The exchange of ideas and the behavior of those who have already adopted the innovation create an environment that expedites adoption. We can represent the social neighborhood using nodes to denote a network of users and edges to denote their social connections.

The centrality of a node can be measured according to the realization of the centrality concept. The local structure-based centrality measure is the degree, a count (or sum) of the node's connections. PageRank ranks users based on the importance of those who connect with them (Brin & Page, 1998). Transitivity or the clustering coefficient measures how prone the nodes are to form triangles (Battiston et al., 2014; Watts & Strogatz, 1998). Betweenness measures how much a user falls on the shortest path between other pairs of users (Bavelas, 1948; Freeman, 1978). In the case of a directed network, we can define in- and out-measures to represent the in-bound and out-bound connections to a node.

Many social networks are scale-free networks (Barabassi, 2013). In such networks, very few nodes have many connections. Such hubs are very influential (Van den Bulte & Wuyts, 2007). The two-step flow theory (Menzel & Katz, 1955) maintains that hubs are more exposed to media and therefore adopt innovations first. The influential theory (Watts & Dodds, 2007) claims that the early adoption of an innovation by hubs is key to the diffusion process. One explanation for this association is that the early adoption of an innovation by influential members is due to its exposure to more people in their network and therefore having higher and earlier exposure to an innovation spreading (Goldenberg et al., 2009). These studies looked at the hubs' number of followees because they measure exposure to knowledge or recommendations. The centrality indicators also correlate with the users' influence on innovation diffusing processes (Hinz et al., 2011; Iyengar, R. et al., 2011). However, it is still unclear whether the innovativeness is related to the directional edges of the relationships network or of the activity network. Moreover, there are no studies to our knowledge that explore these networks' interactions.

Following more users on an online social network has a two-fold impact. On one hand, the users are exposed to wider sources of information, and therefore learn about innovations sooner (Borgatti & Foster, 2003). On the other hand, they might be overwhelmed by this massive influx of information, prompting them to avoid any innovations described (Iyengar, S. S. & Lepper, 2000).

2.2 Research questions

Given the association between a social network's structural attributes and innovativeness of people (Goldenberg et al., 2009; Katz, 1957), we expect that as the number of followers or following increases, the likelihood that the user will adopt the innovation sooner increases. However, other studies have documented an opposite exposure effect (Iyengar & Lepper, 2000). Therefore, we investigated which is the case in the relationship network regardless of the connections with the activity network. Meaning, is the relationships network itself related to the adoption process and in what way? We explored the following research questions:

RQ1: *What are the associations between the structure of the relationships network and the users' adoption times?*

RQ1 examines the impact of the connections in social networks regardless of whether there is a real flow of knowledge through these connections. In the Twitter network, RQ1 translates into the question of the impact of followers and following on the adoption time without referring to the tweets themselves or whether these connections are active and prone to eventual adoption.

RQ2 considers the role of activity influences by examining only the connections to users who adopted (or will adopt) the innovation. In other words, what do the users' connections in the activity network indicate on the users' innovativeness. Here we would expect a stronger reverse correlation of the activity network centrality measures with the time of adoption. Assuming that as people tend to be similar to their environment (Cardol et al., 2006; Manski, 1993), users who have many connections that eventually adopt should be more susceptible to adoption and therefore adopt sooner. Therefore, we asked:

RQ2: *What are the associations between the structure of the activity network and the users' adoption times?*

Since the structure of the activity network is a subset of the whole network, the interaction between the two networks can refine the connections and the understanding of the adoption's time frame. We investigated whether all of the effects of the centralities originate in the exposure to more and prompt information (Goldenberg et al., 2009). If that is the case, any effect of the relationships network would be eliminated when controlling for the activity network. Another possibility is that there is an interaction between these co-existing networks. Thus, we asked:

RQ3: *How does the interaction between the relationships network and the activity network affect the users' adoption time frame?*

Finally, since the platform itself was once a diffusing innovation adopted by the same users at some point, did these users maintain their innovativeness of the platform with adopting innovations diffusing on that same platform? Previous research has suggested that this might be the case (Li et al., 2018). Therefore, our final research question is:

RQ4: *Does the user's innovativeness in adopting the use of the social network platform also translate into innovativeness in adopting an idea?*

3. Methodology

3.1 Data Collection

We used Twitter as the online social network and the idea of mindfulness as the subject of the adoption. The dataset was built by searching Twitter (via the API) for the word "mindfulness" for one year: March 1, 2019-February 29, 2020. We ended the data collection on March 1, 2020 to free the research from any influences of Covid-19, which might change attitudes toward mindfulness. We limited our data to tweets from the greater London area (a 200 km radius) to ensure that most of our information would be in English. We chose mindfulness as the subject because this idea was at the peak of growth at the United Kingdom during this time period (Google Trends, 2022). In addition, the term "mindfulness" does not have other usages, meaning that any mention of this word has the same meaning. For users who tweeted (or retweeted) about mindfulness, we collected all of their tweets or retweets about mindfulness since the launch of Twitter (March 1, 2006). We also enriched the data with profile metadata, including the date when the profile was created, the number of tweets, the number of followers, and the number of Twitter users the participants were following. Finally, we collected the followings'/followers' connections between all users in our network. Of the users, 18.1% had a Botometer (Yang et al., 2019) score above 0.37 or had a username containing 'mindful', 'mediated', or 'mind' filtered out from the research.

Overall, we collected 42,124 adopters with more than 2.3 million links connecting them. The procedures were programmed in Python with a tweepy module (Roesslein, 2009) and a full archive search endpoint. Data were stored and later consolidated using MS-SQL servers and analyzed with R.

3.2 Definitions of the variables

This paper studies the adoption of a behavior. On social network sites, adoption can have many representations. Most of them are limited to the "virtual space" (Morozov, 2011). Hence, we defined the *time of adoption* as the first time someone tweeted or retweeted about the mindfulness subject. This moment represents the assimilation of the idea into ones' mindset. We were interested in the spread of the notion of mindfulness, not necessarily the actual practice. Meaning the statement and intention action of tweeting on the mindfulness subject to which original tweets and retweets answer the need; therefore, both are included. In our context, novel idea to a person, the innovation, is an idea to which the user on the social network has not yet referred through either a tweet or a retweet. The activity network is a snapshot of all the adopters until the end of the data collection. All the information on the innovation passes through the activity network's users. Since the users are only those who were active regarding the innovation, by definition, all of the users on this network are eventually adopters of the innovation. *In degree, out degree, page rank, betweenness, and transitivity* are in the activity networks when the connection represents a following/follower relationship between adopters. The centrality values of isolated nodes and leaves were set to accepted values. For isolated nodes, betweenness and transitivity were set to zero (Buechel & Buskens, 2013; Kaiser, 2008). Page rank was set to the value of the inverse number of vertices (Nykl et al., 2014). Leafs' transitivity was also set to zero (Kaiser, 2008). Time measures were converted to days since Twitter's launch day.

4. Results

4.1 Descriptive statistics

All variables except the profile creation date have high levels of skewness (10.9>skewness>1.8) and kurtosis (167.8>kurtosis>8.3). Log transformation scaled them. Of the records, 3.4% have more than five standard deviations from the mean of the transformed variable. We flagged them as outliers and did not include them in the analysis.

Descriptive statistics for all variables of the remaining 33,306 adopters are presented in Table 1, and the correlation matrix is presented in Table 2.

The correlation matrix provides an overview of the connections between the different attributes' bivariate relationships.

The centrality measures show that in the activity network, indegree and outdegree are strongly correlated (0.8). Additionally, they correlate with the PageRank and betweenness measures. Thus, we concluded that a user's centrality is aligned across different aspects of his/her centrality.

The number of followings, followers, and tweets are strongly correlated between themselves. These measures are also reverse correlated with the number of days the Twitter account has been active. Thus, as expected, users who have been on Twitter longer have more connections and tweets.

Not surprisingly, there is a strong relationship (r=o.65) between the number of followings in the relationships network and the indegree in the activity network. Similarly, the number of followers in the relationships network and the outdegree in the activity network are strongly correlated (0.7).

Finally, older accounts correlate with more connections both in the relationships and the activity networks. Moreover, they have more volume history of tweets and are more central.

Variable	Mean	Std. Dev	Median	Min.	Max.	Skewness	Kurtosis
AdoptionFrame	4278.4	795.6	4640	519	5113	-1.1	3.5
NumOfFollowing	1107.2	1464.2	568	1	14296	3	15.9
NumOfFollowers	1705.8	5213.1	471	1	125552	10.9	167.8
TotalTweets	12205.9	32528.3	2696	0	1249851	9.5	182
ProfileCreateFrame	2627.5	1184.1	2435	189	5109	0.3	1.9
Indegree	47.81	60.7	25	0	603	2.4	11
Outdegree	40.46	82.02	15	0	2867	7.9	132.1
Transitivity	0.12	0.1	0.1	0	1	1.8	8.3
PageRank	0	0	0	0	0	2.7	12.2
Betweenness	46270.5	131239.3	5081.42	0	4835611	9.5	172.7

Table 1 - Descriptive Statistics

1	AdoptionFrame	1	2	3	4	5	6	7	8	9
2	LogNumOfFollowing	-0.34								
3	LogNumOfFollowers	-0.38	0.73							
4	LogTotalTweets	-0.40	0.62	0.71						
5	ProfileCreateFrame	0.33	-0.39	-0.47	-0.52					
6	LogIndegree	-0.36	0.65	0.47	0.25	-0.12				
7	LogOutdegree	-0.37	0.52	0.70	0.34	-0.16	0.80			
8	LogPageRank	-0.28	0.54	0.41	0.24	-0.05	0.67	0.62		
9	LogBetweenness	-0.36	0.60	0.63	0.33	-0.18	0.84	0.88	0.57	
10	LogTransitivity	0.13	-0.31	-0.34	-0.32	0.16	-0.04	-0.20	-0.26	-0.22

Table 2 - Correlation Matrix

4.2 Regression method

The user's innovativeness, as reflected in the timing of adoption, depends on the user's centrality and other network attributes. We utilized six linear regression models to explore these relationships. Model 1 and Model 2 include the adopters' activity network centrality attributes. Model 1 contains the first-order elements, while Model 2 has additional selected interactions and square elements. Models 3 and 4 use the relationships network and the online social network attributes. Model 5 has all first-order elements. Lastly, Model 6 contains all of the aforementioned attributes and the interactions we are interested in exploring. The interactions are between the number of followings in the relationships network and those in the activity network and similarly between the number of followers in both networks.

We checked for multicollinearity using VIF. All variables had VIF<10. The backward stepwise regression method reduced the number of attributes so that only the most influential attributes remained. The regression assumptions were examined visually and were met. To avoid overfitting, we used a random training set of 70% of the data to create all of the models and tested them with the remaining 30%. We calculated the out of sample coefficient of determination (OOS adj. R^2) from the test set and compared it with the model calculated adj. coefficient of determination.

4.3 Regression Results

Table 3 reports the beta weights of the regressions.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Activity network centrality attributes						
LogIndegree	-0.21 ***	0.34 ***			-0.29 ***	-0.02
LogOutdegree	-0.18 ***	0.13 ***			-0.06 ***	0.04
LogTransitivity	0.08 ***	0.04 ***				
LogPageRank		0.59 ***			-0.06 ***	
LogBetweenness		-0.12 ***				
(LogIndegree)^2		-0.63 ***				
LogOutdegree:LogPageRank		-0.44 ***				
LogOutdegree:LogBetweenness		-0.23 ***				
Online social network attributes						
LogTotalTweets			-0.18 ***	0.06 *	-0.30 ***	-0.28 ***
LogNumOfFollowing			-0.08 ***	0.03	0.17 ***	0.29 ***
LogNumOfFollowers			-0.13 ***	0.29 ***		0.03
ProfileCreateFrame			0.14 ***	-0.21 ***	0.19 ***	
ProfileCreateFrame^2				0.37 ***		0.20 ***
LogTotalTweets:LogNumOfFollowers				-0.47 ***		
LogNumOfFollowing:LogNumOfFollowers				-0.23 ***		
Interaction						
LogNumOfFollowing:LogIndegree						-0.40 ***
LogNumOfFollowers:LogOutdegree						-0.13 ***
Adj. R^2	0.15	0.17	0.19	0.20	0.26	0.27
OOS adj. R^2	0.14	0.16	0.18	0.19	0.25	0.26

Table 3 -Regression results with standardized coefficients. ***p < 0.001; **p < 0.01; *p < 0.05

Model 1 and Model 2 contain the users' centrality attributes in the activity network, which explained up to 17% of the time-of-adoption variance. Model 3 and Model 4 contain only the users' attributes from the relationships network. They explained up to 20% of the time-of-adoption variance. Combining both networks' data in Model 5 and Model 6 explained up to 27% of the time-of-adoption variance. The models were not overfitted because all of the models showed similar out of sample coefficients of determination.

Models 1 and 2 regress the centrality measures in the activity network's associations with the users' innovativeness. In the first-order elements, the number of connections is the most influential centrality measure (-0.21 and -0.18 for LogIndegree and LogOutdegree, respectively). PageRank and Betweenness become imperative only when considering their interaction with the users' outdegree. In general, as the bivariate relationships showed, user centrality in the activity network is negatively correlated with the time of adoption. Betweenness negatively relates to the time of adoption, and the influence is stronger with a higher level of outdegree. In PageRank, the relationship is reversed when controlling for other centrality measures but is moderated by the outdegree.

Model 3 shows the relationship between the number of days until the users' adoption as a function of the four attributes from their Twitter profile and the relationships network. We see a negative relationship between the time of adoption and the number of tweets (-0.18), the number of followings in the relationships network (-0.08), the number of followers in the relationships network (-0.13) and the age of the profile (reversed to the profile creation frame of 0.14). In other words, a user who is active and has many connections adopts a diffusing innovation earlier on that online social network.

As Model 4 indicates, both the number of followings and the number of tweets are negatively linked to the time of adoption (see Figure 1). This trend is strengthened with the increased number of followers. The time at which the profile was created has a U-shaped relationship with the users' time of adoption. Up until about an average creation date (+0.2sd, April 2014), the later the user created the Twitter profile, the earlier the adoption time. From that point on, the later the profile creation, the later the adoption.

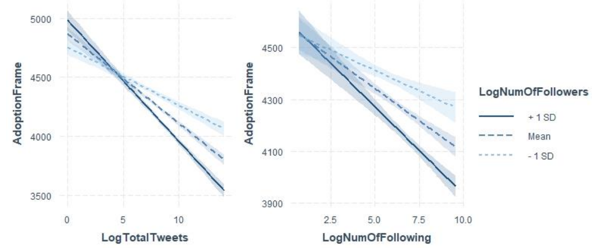

Figure 1. Adoption time frame as a function of Log(Total Tweets) and Log(Number of followings) with different levels of the number of followers.

Model 5 contains all of the online network's attributes and the activity network's centrality measures. The relationship between the time of adoption and the indegree (-0.29), outdegree (-0.06), and total tweets (-0.30) remains reversed, meaning, there is a positive relationship between them and the user's innovativeness. However, once the indegree and outdegree are introduced into the model, the number of followers becomes insignificant. In addition, the number of followings has a positive relationship with the time of adoption (0.17). This result suggests that a considerable portion of the effects of the number of followings is due to the number of followings in the activity network.

Model 6 incorporates all of the above measures with a second-order element of the profile's creation date. In addition, we examined two interactions: the number of followers/followings from the relationships network with the number of followers/followings from the activity network, respectively. The number of tweets maintains its negative relationship with the adoption time (-0.28), as was evident in all of the models. In addition, the profile's creation date has the same U-shaped relationship with the adoption time. Up until an average creation date (May 2013), the later the user created the Twitter profile, the earlier the adoption time and the opposite relationship afterward.

As the correlation matrix shows, the numbers of followings and followers are negatively correlated with the time of adoption. These attributes have a shared variance with the total number of tweets and the activity network's indegree and outdegree. A user with more followers is indicative of earlier adoption *only* when the user has more than -0.5sd than the average number of followers from the activity network (LogOutdegree > 1.88 or Outdegree > 6.5). Otherwise, the trend is not significant (Figure 2A). Users following more users adopt later, which is the opposite of the bivariate correlation signals. This negative trend between followings and time of adoption appears only when controlling for the number of tweets and indegree. Thus, we conclude that the negative bivariate correlation is due to these attributes' relationship with the number of followings. However, when users follow a large number of those in the activity network (indegree), the trend is mediated and becomes weaker (Figure 2B).

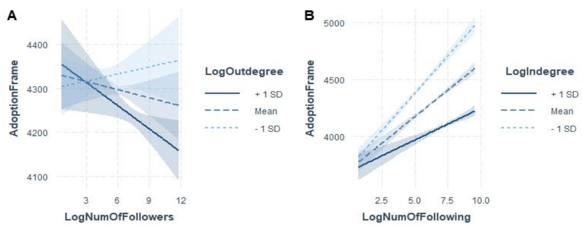

Figure 2. (A) The followers' relation with the adoption time and its interaction with outdegree. (B) The followings' relation with the adoption time and its interaction with indegree.

5 Discussion

We empirically tested the association between the time it takes an online social network's users to adopt an innovation and their activity network and relationships network centralities, in addition to the attributes of the users' use of the platform. We demonstrated that these attributes explain a significant portion of the user's innovativeness regardless of the content of the messages they read about the innovation or the amount of traffic on the subject to which they are exposed.

We identified four main online social network attributes as indicative of the users' innovativeness. The first is the degree to which the individual is an active user of the platform. The second and third are the number of the users' connections, meaning the number of followees and followers. The fourth is the date when the profile was created. In general, those who are active and central users adopt innovations earlier.

The tendency to adopt the use of the online platform can also indicate the tendency to adopt innovations discussed on it. There is a U-shaped relationship between creating a Twitter account and the adoption of an innovation. Older account users adopt innovations earlier the later they created accounts. Newer account users adopt later the later they created accounts. One explanation for these results is if platform usage has a Gaussian curve shape, an old account can indicate a less active user who has already passed the peak use of the platform. This explanation is supported by the increase seen in the median age of accounts sending out tweets, meaning that more tweets are from newer accounts (Leetaru, 2019). Therefore, the newer the account, the earlier the adoption. In newer accounts, a later creation can indicate the users' lagging behavior, which may translate into a later adoption time.

Users who have tweeted many times and those who are central in the activity network are prone to early adoption. The factors that are most likely to indicate early adoption time are the users' number of tweets and the users' indegree and outdegree in the activity network. In other words, the volume of the users' tweets and the position in the network of adopters are associated with the adoption time of innovations. It is possible that these early adopters have more exposure to information from other sources that provide them with content to share on Twitter (Katz, 1957), i.e., cosmopolitan (Valente, 1996) or boundary spanners (Long et al., 2013).

Previous studies discussed different explanations for the positive relationship observed between the number of users' connections and users' innovativeness. We also observed this correlation. However, controlling for the number of tweets and the number of connections in the activity network revealed different relationships. Moreover, the type of connection, number of followees and followers had other associations.

As users follow more users on an online social network, this increased exposure actually leads to a *later* adoption of an innovation. This is contrary to the findings that following many users increases the exposure to innovations and, therefore, leads to earlier adoption (Goldenberg et al., 2009). One explanation might be that, because these users are exposed to many stimulations, they might be less affected by each one. This trend is weaker when the users follow more users who do eventually adopt (indegree in the activity network). This mediating effect even strengthens the possibility that the variety of topics the user is exposed to might be the key to this behavior. The increase in the adopters' followees might point to an increase in exposure if some of the followees adopted prior to the user.

Another possible explanation is that the choice to follow those who eventually adopt the specific innovation points to a type of user who is more prone to adopting innovations. This explanation corresponds with the literature on homophily claiming that connected people are likely to have similar tendencies and preferences (Gaffney et al., 2012; Jeong & Bae, 2018; McPherson et al., 2001). Therefore, a user who follows more users who eventually adopt the innovation is likely to be more like them and therefore prone to adopt earlier.

If users adopt an innovation due to their exposure to information, the number of followers they have should have no effect on the timing of their adoption because it does not change the user's exposure. However, there are several explanations for the positive link found between this factor and innovativeness. First, we know that there is a reciprocal relationship between followers and followees. Therefore, we might be seeing the effect of this association. Second, the number of followers may affect the adoption time because users attract many followers because they provide content. Therefore, they are more likely to be active and hence more innovative, especially on the same platform. The number of tweets would reflect this association. Indeed, we see a strong correlation with the number of tweets. A user with many followers also tweets a lot. Therefore, in our method of adoption through tweets on the subject, they might be more prone to adopt earlier. Third, followers strongly correlate with the number of followers in the activity network (outdegree). As each follower has the chance to be an adopter, we see more adopters' followers with users who have more followers. Moreover, adopters of the specific innovation have personality traits corresponding with the decision to adopt it. These same followers' personality traits can also apply to the users’ preferences (Gaffney et al., 2012; Jeong & Bae, 2018; McPherson et al., 2001), which can increase the user innovativeness to the diffusing innovation.

These three effects account for the variety previously attributed to the number of followers. Indeed, the followers' effect is not significant when controlling for them. Moreover, the number of followers has a positive relationship with the users' innovativeness but only when there is at least a rudimentary number of adopters among them. Otherwise, there is no significant relationship between the adoption time and the number of followers. Thus, people with many followers are more active, but this is not necessarily associated with early adoption. The key factor involved is how many of these followers are users who will eventually adopt the innovation. In an environment that does promote adoption, the more followers there are, the earlier the adoption of the innovation that diffuses on the same platform.

5.1 Limitations

Future studies should consider other factors correlating peoples' innovativeness in the process of adopting a diffusing idea online. They can deepen the examination of the users' exposure by adding the magnitude of the exposure to the innovation. The adoption behavior connected to the messages themselves should also be explored. Specifically, we believe that future research needs to include the frequency of the messages and the intensity of the content to which the users are exposed. Finally, we examined these phenomena with regard to one innovation, 'Mindfulness' and one social network platform, 'Twitter'. One concern is that the results are not generalizable to all innovations. Even though other studies have used one microblogging platform and one topic to draw conclusions (Guan & Chen, 2014; Micu et al., 2017; Zhu et al., 2021), we believe that to ensure that these results are not unique to the topic or to the platform, future studies should reproduce our findings using other innovations and social networks.

5.2 Contribution

This paper advances our knowledge about the diffusion of innovation in an online social network and the users' innovativeness in several respects. First, it illuminates the possible path that explains the effects of the users’ followers on the network. The assumption that more followers equals a more innovative person is more complex and needs refinement. Other considerations are the user’s volume of tweets and the number of users who eventually adopt among the users' followees and followers. When practitioners use an online social network to promote a product and look for innovative individuals, the hubs are not always the users who are prone to early adoption. The key factor is whether they are in an environment of people who eventually adopt the innovation. We would suggest using the other three elements to determine the expected innovativeness. Still, having more followers indicates earlier adoption when the user has a few active users regarding the innovation in his/her followers' base.

Second, our study shows that users who follow more users adopt later. This result contradicts findings that many connections point to an early time of adoption (for example, Goldenberg et al., 2009; Katz, 1957). We demonstrate the importance of separating the followees from the followers to understand the different independent relationships on platforms that allow for one-sided following. This distinction deepens our understanding of the relationship between these users’ attributes (followers and followees) and the users' personality traits that point to innovativeness. We also demonstrate the mediating effect of an environment with more users who eventually adopt the specific innovation. The trend of later adoption as the number of followees increases is weaker as more followees are from the activity network. This finding directs researchers and practitioners to focus on both types of followees when dealing with diffusion and to identify the users' innovativeness predisposition.

Third, we offer an innovative view of the age of the user's account and suggest viewing users' lagger behavior of the platform adoption as indicative of the tendency to be a lagger adopter of other innovations. A user who adopted the platform later is more likely to adopt an innovation later as well. Practitioners can consider these users as such when planning their promotion activities.

Fourth, we demonstrate that active and central users are those with innovative tendencies. We also show that, as their volume of tweets and centrality increase, so does their innovativeness. We suggest these attributes as clues to identifying user adoption time propensity in the diffusion cycle.

Finally, our measure used for the adoption is novel. It relies on Morozov's 'The net delusion' (2011) notion that the tweet activity fulfills people's feeling of activism. Most of the literature on diffusion using online social network uses retweets (Stieglitz & Dang-Xuan, 2013; Zhang et al., 2020) or hashtags (Fink et al., 2016; González-Bailón et al., 2011; Li et al., 2018; Liu et al., 2016). Our approach will help future researchers focus on the use of specific words related to a trend as evidence of user engagement.

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