Discovering the Impact of Notifications on Social Network Addiction

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Abstract. Addiction is a complex phenomenon, coming from environmental, biological, and psychological causes. It is defined as a natural response of the body to external stimuli that become compulsive needs. From the biological point of view, the brain has the central role: many neural circuits and, above all, the Dopamine System, are involved in the addiction process. Over the last decade, social network communication has become an increasingly addictive activity, for which users appear to engage in social media excessively and/or compulsively. In this work, we show that the current online social networks' notifications system triggers addictive behaviors. We prove our hypothesis simulating the mathematical modeling of the Dopamine System on real interactions among members of a set of 18 Facebook groups. In line with recent psychological studies, we find that the addicted users show a high frequency of social interactions on the platform.

Keywords: Social networks · Computational model · Internet addiction · Facebook groups

1 Introduction

Addiction is a complex phenomenon that has had different interpretations over the years. In general, we can define it as the natural response of the body to external stimuli that become a compulsive need. This condition appears as a total loss of control and repetitions of the same actions periodically, arduous to break because they create an unreal feeling of wellness [22].

Since the 1960s, researchers of diverse fields (such as medicine, sociology, and psychology) started to analyze the addiction from various points of view, underlying how many factors contribute to its development, such as biological, psychological, and environmental aspects. From a biological perspective, the brain plays a central role [18]. The Dopamine System (DS) is a group of cells originating in the midbrain whose function is to anticipate the reward. The level of dopamine, a neurotransmitter, increases in reaching a stimulus, originating a sense of pleasure. However, in an addiction context, this mechanism breaks and induces to search for a higher or more frequent reward. Consequently, the

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effect of dopamine decreases, causing tolerance and withdrawal symptoms. As well as the biological aspects, the environmental factors, such as the impact of age, gender, and social background, have a crucial influence on the spread of addiction, as shown in [1]. Some particular habits are popular in social groups because people, especially the younger ones, tend to imitate reciprocally, and this behaviour is generally known as emulation.

In the last decade, the introduction of new technologies, like smartphones and 5G, and the advent of Social Media, are changing the way of how people communicate. In particular, Social Media are one of the most used Internet applications, with more than 3 billion of users, where people can create virtual contacts by increasing the number of connections and frequency of contact. Social Media completely changed the social life of people facilitating their interactions.

Indeed, as described in [8,16], platforms, such as Facebook, are popular communication tools, used for many activities as maintenance of online and offline relationships, oneself promotion, gaming and marketing. Over the last decade, the engagement between users and social networks has become pervasive to the point of being a problematic phenomenon, characterized by compulsive behaviours (loss of control, mood modification and so on). For this reason, researchers belonging to different fields have started to analyze these behaviours as a new kind of addiction.

In this context, we study Internet addiction, namely the excessive Internet (and technology) use that may interfere with daily life, and the way it spreads through the interaction on social networks.

We start our work simulating the mathematical model of Dopamine System [14,15] on a dataset extracted from Facebook containing the interactions of 18 real social groups. We associate the DS model to each member of the group; then, we use the real interactions to simulate the exchange of messages among the members. Thus the stimuli are the messages sent to and received from the other users. Consequently, each individual has his/her dopamine level, and by analyzing the intensity of interaction, we identify the users that are susceptible to become addicted.

Then, analysing the real communication data, we are able to show that there are intrinsic mechanisms, like notifications, which repeatedly engaging the users, may contribute to the development of social networks addiction.

The rest of this paper is organized as follows. In Sect. 2, we introduce the problem of the Internet addiction, mentioning the sociological aspects of this phenomenon, then we describe the network communication model, which we consider for our work, and the mathematical model of the Dopamine System. In Sects. 3 and 4 we describe, respectively, the characteristics of the dataset we collect and how we perform the simulations. Finally, in Sects. 5 and 6 we draw our conclusions and discuss future work.

2 The Internet Addiction

In few years, the impact of Internet and technology has fundamentally changed the way we relate and communicate with each other [23]. People, especially the younger ones, tend to prefer online communication, choosing text messages to communicate with their peers [7]. Moreover, social network platforms offer a great variety of services and apps that improve the engagement with the users, whose number will be approximately of 3 billion in 2021 as estimated in [20].

Adopting a computer-mediated communication has multiple consequences on users life, such as the loss of empathy and the increase of stress [13], and, as underlined in [3], there is growing scientific evidence suggesting that the excessive and compulsive use of social networking sites may result in symptoms traditionally associated with substance-related addictions, such as salience, mood modifications, tolerance, withdrawal, relapse, and conflict.

In order to bring more clarity to this phenomenon, researchers have started to investigate Internet addiction, trying to understand which mechanisms affect the user's behaviour. Indeed, users show different attitudes to this communication form, which mainly depends on their level of stress, sense of isolation and inadequacy [17].

As pointed out in [5], the Internet addiction can be analyzed according to biological, social and psychological factors. Recent research suggests that *age* influences particularly social media addiction [2]: younger users are more likely to engage in online activities. Among social factors, the authors in [5] propose: *gender*, *intensity of use*, *user's met needs*, and *social comparison*. Gender influences the nature of online activities; while intensity, met needs, and social comparison identify how social user needs an intense and frequent use of social networks to establish new relationships and compare themselves to other individuals. Finally, *stress*, *empathy*, *conscientiousness*, and *depression* are the most common psychological factors predicting the Internet addiction. In particular, as described in [11], the stress increment affects the social media use. In [12], instead, researchers study how users, who do not exhibit the ability to share and understand others' emotions, are more inclined to use social media rather than in-person contact for their social interactions.

These factors together can be used to predict a sort of susceptibility to Internet addiction. However, in this context, the main issue is represented by the objective difficulty to quantify accurately their effects on user behaviour. Indeed, parameters as stress or empathy cannot be measured quantitatively. Therefore, in this work, we proceed applying a novel approach, which studies the Internet addiction analyzing only the structure and the mechanisms at the basis of social network sites.

2.1 The Network Communication Model

Online Social Groups (OSGs) are becoming increasingly important social networks because they represent a new opportunity for user participation and engagement. Formally, a group is described as two or more individuals who are connected by and within social relationships [6]. In the online world, we can find several examples of OSG, such as the Facebook Groups, the hashtag communities of Twitter or Instagram, or the Steemit communities. The common factor of all these proposals is that these groups form around an interest or a topic, such as an artist, or a sport which is of interest among all the members of the group.

Inside an Online Social Group, users can write contents (generally called *post*) with which then other users can interact. Interactions happen in two forms: via written interactions (or *comments*), or via more immediate *reactions*. An immediate reaction is a quick way to express a feedback towards a specific post. Usually, they take the form of positive feelings, such as the "*Like*" button in Facebook, or the "*Heart*" buttons of Twitter and Instagram. This form of feedback is largely used by users because of the ease with which they can be expressed. Although common, immediate reactions are not always relevant, since sometimes they are expressed mindlessly by users. On the other hand, comments remain the most relevant because they require a non trivial intellectual effort to be produced, and therefore are perceived as more meaningful if compared to a single immediate reaction. Moreover, comments do not necessarily target a specific content, but they can be considered as additional considerations to a discussion, thus targeting all the people involved in the same conversation.

Users can express reactions to comments as well, and that comments can be further commented, creating an arbitrarily deep structure of comments which can be organised as a tree. Notifications in OSGs advise the members of a group that new content has been published (as a comment or a reaction). We identify three cases in which the notification system is triggered:

- **New content:** a new content is created, and all users of the group (except the creator of the content) receive a notification concerning the newly created content;
- **Reaction:** a user expressed a reaction towards a specific content or comment. Only the user that created the content or comment will receive a notification;
- **New comment:** a new comment was created, therefore all users participating to the discussion are notified;

In Fig. 1, we represent the scheme of the notification system, in which the user U_1 is the author of the original post, for which all the other members of the group ($m_1 ... m_n$) receive a notification. If the U_1's post receives a comment or a reaction, only U_1 receive a notification, while any replies to a previous comment (with a comment or a reaction) involves a notification for U_1 and the author of the comment (in the scheme represented as U_2).

2.2 The Mathematical Model of Dopamine System

From a biological point of view, the Dopamine System (DS) is one of the neurological circuits mainly involved in the addiction context. As shown in [21], the Dopamine System is part of the reward pathways in the brain, and so all the positive feelings obtained in response to positive reinforcement, which means achieving something when we perform an action.

In the case of addiction, there are different consequences affecting the brain, such as compulsion, loss of control, and negative emotional state, which depend

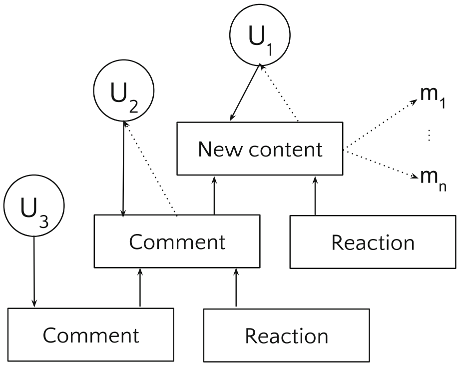

Fig. 1. The scheme of the notification system implemented in social networks. U_1 is the user that writes a new content, which implies a notification to all group's members $(m_1, ..., m_n)$. If another user (U_2) replies (with a comment or a reaction), only U_1 will receive a notification. If U_2 receives a comment or a reaction, the notifications will be sent to U_2 and U_1. In the scheme, the solid edges represent the act of express a comment or a reaction; the dotted edges the notification path.

on the increasing amount of dopamine. These effects are exactly the same regardless the kind of addiction. Then, in order to investigate this phenomenon, the authors in [14,15] extend and simplify the mathematical model of the Dopamine System, proposed by Gutkin et al. in [10] to analyze the nicotine addiction. Such a model describes the main neurological processes involved in addiction phenomena and it has been validated against experimental data [4].

The model in [14,15] describes, in an abstract way, the interaction between dopamine and neurological receptors that lead to persistent changes in brain structures (due to neuronal plasticity) that really occur in the case of addiction. The authors represent the "memorization" of the received stimuli, which can result in tolerance and withdrawal symptoms, implementing threshold-based switches, with simpler differential equations defined by cases. As a result, the model consists of two differential equations:

– *Dopamine concentration.* The following differential equation describes the dynamics of the variable D representing the dopamine concentration in the prefrontal cortex:

$$\frac{dD}{dt} = \alpha \left(-D + k + \begin{cases} 1, & if\ r - M \geq \theta_p \\ 0, & if\ \theta_n \leq r - M \leq \theta_p \\ -\frac{D*M}{2}, & if\ r - M \leq \theta_n \end{cases} \right)$$

The dynamics of D is calculated by considering the following parameters:
- k is the basal production rate of dopamine;
- r is the perceived stimulus;
- M is the memory of the stimulus, whose value is given by the second differential equation;

- θ_p is the positive threshold, in the simulation is set to 80;
- θ_n is the negative threshold, in the simulation is set to -30;
- $\alpha = 0.3$ is a unique time-scaling parameter.

Apart from standard decay and basal production, the differential equation describes the dynamics of the dopamine concentration by considering three cases given by the comparison of the current stimulus r with the memory M and the two thresholds (both chosen by performing simulations). When the stimulus is largely greater than the memory, the dopamine concentration increases. When the stimulus and the memory are comparable the dopamine concentration does not increase. Finally, when the stimulus is largely smaller than the memory, the dopamine concentration decreases with a rate that depends both on D and on M.

– *Memory.* The second differential equation describes, in an abstract way, the opponent process (in psychology defined as a contrary emotional reaction to a previous stimulus) that is modeled as a "memorization" process of previous stimuli.

$$\frac{dM}{dt} = \alpha \left(-M + \begin{cases} \frac{r-M}{2}, & if\ r > M \\ 0, & otherwise \end{cases} \right)$$

Dopamine and memory take different times to reach "high" values: Memory requires some time to reach values comparable to the stimulus r, but when it reaches such a level, it contrasts the increase of dopamine concentration in the brain.

In this work, we identify the notifications, described in details in Sect. 2.1, with the stimulus r that triggers the user in the visit of social network platforms. Indeed, these messages engage the users, notifying them that the discussions of the group were enriched by additional contents or that someone expressed a feedback. To better describe the communication model, we assign different intensities to each action we observe in the dataset (reported in details in Sect. 3):

- **Posting a new content**: when a user writes a new content, all the group's members (including the author of the content) receive a stimulus of intensity 100, that is comparable to the stimulus considered in the model presented in [14,15] in normal conditions;
- **Writing a comment**: when a user writes a new comment, she/he will receive a stimulus of intensity 100;
- **Receiving a comment**: since comments are the most exhaustive form of feedback, all the members receiving a comment will receive a stimulus of intensity 150;
- **Receiving a reaction**: all the users will receive a stimulus of intensity 15 for each obtained reaction;

To establish if a user shows a susceptible behaviour to addiction, we considered properly the memory level, because it represents the tolerance and so the phenomenon that better characterizes the addiction. In the model described in [14,15], the selected threshold is $M \geq 15$, because at that point in the performed simulations, the users showed peaks and consequently decreases in dopamine trend. In our work, we will run experiments in order to find the Memory threshold that better characterized our networks, as we will describe in details in Sect. 4.

3 Dataset

Table 1. General description of the Facebook groups.

Group	Category	Users	Days	Start	End	Posts	Comments	Reactions
Ed1	Education	2,668	388	01/01/17	24/01/18	3,555	63,350	60,463
Ed2		9,506	317	06/04/17	18/02/18	5,271	77,933	350,781
Ed3		4,156	393	25/01/17	22/02/18	5,060	41,480	144,764
Sp1	Sport	1,308	249	27/08/17	03/05/18	5,588	3,823	1,456
Sp2		1,065	370	04/02/17	09/02/18	708	3,421	106,622
Sp3		11,017	28	13/02/18	14/03/18	6,353	79,998	332,727
Sp4		8,585	249	27/08/17	03/05/18	5,588	162,283	340,676
Wo1	Work	3,107	406	02/01/17	12/02/18	1,444	19,007	47,492
Wo2		1,170	418	04/01/17	26/02/18	945	16,891	12,124
Wo3		2,134	318	13/06/17	27/04/18	4,809	3,296	6,479
Wo4		1,097	485	03/01/17	04/05/18	2,651	2,382	4,577
En1	Entertainment	2,133	130	30/09/17	08/02/18	5,009	65,205	182,315
En2		1,526	123	22/10/17	23/02/18	3,777	32,235	85,891
En3		7,300	120	02/01/18	03/05/18	4,904	72,631	266,666
En4		2,578	178	09/09/17	06/03/18	3,543	33,098	56,227
Ne1	News	2,022	111	07/10/17	26/01/18	155	9,777	66,668
Ne2		8,355	91	08/11/17	07/02/18	3,397	282,358	341,091
Ne3		795	406	02/01/17	12/02/18	1,133	5,476	2,675

The dataset we use for our simulations consist of the timestamped activity of 18 heterogeneous Facebook groups, which can be grouped in 5 categories, according to their description. The dataset consists of the 17 Facebook groups already described in [9], plus another group that falls under the Sport category. Table 1 contains the most relevant information of the groups contained in the dataset. The Table shows the label we use to identify the groups (`Group`) and their category (`Category`), the number of users that interacted during the observation (`Users`), the length of the observation in days (`Days`) along with the date of the start (`Start`) and end (`End`) of the observation, and lastly the total number of posts retrieved (`Posts`) and their comments (`Comments`) and reactions (`Reactions`). The dataset is relevant because it contains all the information needed for our model described in Sect. 2.1.

The users are unevenly distributed among the groups and range from 795 of Ne3 to $11,017$ of Sp3. The observations have different length as well, ranging

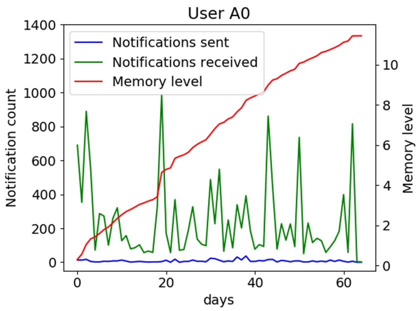

Fig. 2. Notification and memory level of user A0.

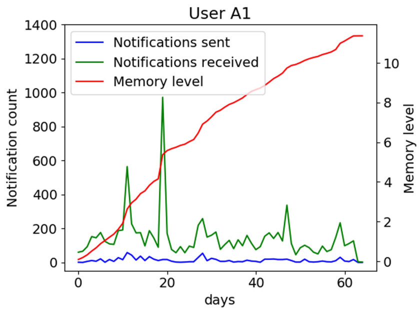

Fig. 3. Notification and memory level of user A1.

from 28 days of Sp3 to 485 days of Wo4. The different length of the observations is due to the activity of the groups, indeed in some groups (see Wo2) the activity was so low that we were able to read all the history of the group. On the other hand, in the case of Sp3 there was so much activity that we were able only to read the activity of about one month. We also report the number of posts, comments and reactions per group to give the reader an idea concerning the activity of each group. As expected, the number of posts is usually lower than the number of comments, which is, in turn, usually lower than the number of reactions. This is due to the fact that starting a conversation thread requires much intellectual effort, while reactions are more immediate and easy to express.

4 Simulations

The activity of the groups presented in Sect. 3 was retrieved, and the DS, presented in Sect. 2.2, was simulated according to the notifications defined in Sect. 2.1. Being aware that the original model was designed to detect addictive behaviours in a slightly different scenario, we needed a parameter tuning and validation session. We decided to run the simulations on a test group to select the correct parameters according to clearly addicted behaviours based on user activity.

The group chosen for the parameter tuning is En3 because it shows average properties. After a preliminary analysis of the activity of the users in the group, we decided to focus on users who showed an unusual (i.e. high) number of notifications per day to detect potentially addicted users. This choice was driven by the fact that users encouraged to check the status of the group multiple times per day are more likely to develop an addictive behaviour. Indeed, as described in [5], one of the factors detecting this kind of addiction is represented by the *intensity*, which is directly linked to the compulsory behaviour that usually characterized the addicted user.

At the end of this preliminary screening, two users were found that receive more than 100 notifications daily. The simulation of the DS of the two users can be found in Figs. 2 and 3. Their names and ids are replaced with arbitrary strings (*AO*, and *A1*) to prevent possible privacy disclosures. In both cases, we see that the notifications received are far more than the ones sent. Moreover, despite receiving a notification causes the DS to update the Memory level, simply counting the notifications does suffice to detect addictive behaviours. This is given by the fact that not all notifications produce the same stimulus, as described in Sect. 2.2.

To establish if a user became addicted, we considered properly the memory level, because it represents the tolerance and so the phenomenon that better characterizes the addiction. We decided to set to 10 the memory level to detect users that are in an addicted state, because at that point in the performed simulations, the users showed peaks and consequently decreases in dopamine trend.

5 Results

Figure 4 shows the distribution of notifications sent, notifications received, Memory and Dopamine at the end of the simulations for each user of the dataset at the end of the simulations. The histograms concerning the number of notifications sent and received show that most users are not greatly involved in the activities of the group. On the other hand, there are also few users with a very high involvement which managed to interact a lot with other users of the group, suggesting us that they may have developed addiction (see Table 2 for a more detailed view). Our supposition is confirmed by the distribution of the Memory of the users at the end of the simulation. Indeed, we see that tens of users achieved a Memory level of at least 10.

A more detailed view of the 84 addicted users, divided by groups, can be found in Table 2. The table shows, for each group, the number of users found to have developed addiction (Memory $\geq$10), and their average number of notifications (sent or received), Memory and Dopamine levels at the end of the simulations. The Table shows that in seven groups none of the users developed addiction, in eight groups up to 3 users developed addiction, and in the remaining groups En1, Sp4, and Ne2 respectively 9, 21 and 37 users were found addicted. Interestingly enough, in the Work category no users were found addicted, while in the categories Education and Entertainment at least one user per group was found addicted. This suggests us that social media addiction is not tied, or at least more common, in specific group categories rather than others.

We now explore more in detail the users who were found with highest number of notifications, Memory, and Dopamine (see Table 3). The user with the highest notification count (TN) is the addicted uses of Ne1 which exceeds $68,000$ notifications. Its Memory is almost three times the threshold we set for considering a user addicted. Interestingly enough, this user is not also the user with the most severe addiction. Indeed, the user with the highest Memory level (TM) belongs to the group Ne2 and has a Memory level of 39.50, more than 10 points higher. The number of notifications is of comparable magnitude, but lower of approximately 2000 units. Lastly, the user with the highest Dopamine (TD) belongs to

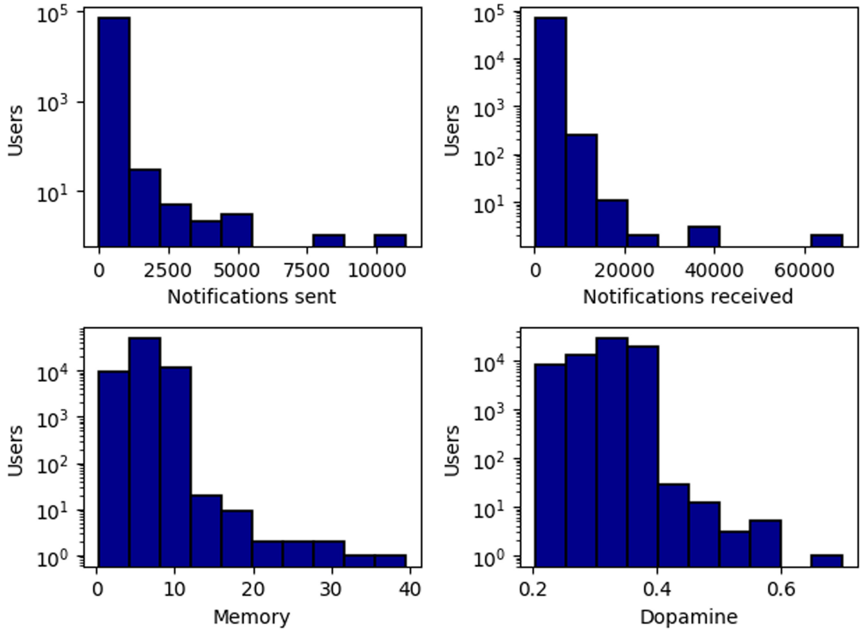

Fig. 4. Notification sent and received, Memory, and Dopamine distribution of all users in all groups.

the group Ne2 as well. While this user has a high Memory level, reaching 35, the number of notifications is much lower with respect to the other two users, barely reaching 40, 000. This is a clear sign that the number of notifications is not proportional to the Memory of the users. Indeed, comparing the plots in Figs. 8, 9 and 10, representing the number of notifications sent and received, and the levels of Dopamine of the users TN, TM and TD respectively, we can notice that the frequency and the peaks of the stimuli have the highest impact on the development of the addiction. Moreover, none of the three users shows withdrawal symptoms, since the level of Dopamine tends to increment, which means that they do not interrupt the use of the platform.

Figure 5 shows the bivariate distribution of the notifications sent and received by each user. Green dots mark users who belong to the *safe* groups (Ne3, Sp1, Sp2, Wo1, Wo2, Wo3, Wo4), i.e. where no users were found to be addicted. Yellow markers are users who belong to the *risky* groups (Ed1, Ed2, Ed3, Ne1, En2, En3, En4, Sp3), i.e. where only up to three users were found to be addicted. Orange dots mark users who belong to the *dangerous* groups (Ne2, En1, and Sp4), i.e. groups with more than 3 addicted users. Addicted users are highlighted with a red marker in the plot to make them easier to spot. The peculiar distribution is given by the fact that users belong to a set of 18 different groups and each “band” of points corresponds to the users of a group. The plot shows that close to 5, 000 notifications received groups from all the three categories can be found,

Table 2. Number of addicted users per group. The average number of notification, Memory and Dopamine levels of the addicted users divided in each group is also shown.

Group	Addicted	Avg		Group	Addicted	Avg	
Ed1	3	Nots	15,675.3	En4	1	Nots	9,722.0
		Mem	17.65			Mem	10.32
		Dop	0.50			Dop	0.38
Ed2	2	Nots	11,758.5	Sp1	0	Nots	-
		Mem	10.62			Mem	-
		Dop	0.39			Dop	-
Ed3	3	Nots	15,751.3	Sp2	0	Nots	-
		Mem	12.08			Mem	-
		Dop	0.40			Dop	-
Ne1	1	Nots	68,681.0	Sp3	3	Nots	13,515.3
		Mem	28.68			Mem	11.67
		Dop	0.45			Dop	0.41
Ne2	37	Nots	13,805.9	Sp4	21	Nots	11,131.61
		Mem	14.80			Mem	11.57
		Dop	0.43			Dop	0.41
Ne3	0	Nots	-	Wo1	0	Nots	-
		Mem	-			Mem	-
		Dop	-			Dop	-
En1	9	Nots	18,420.3	Wo2	0	Nots	-
		Mem	15.56			Mem	-
		Dop	0.45			Dop	-
En2	2	Nots	15,389.0	Wo3	0	Nots	-
		Mem	13.67			Mem	-
		Dop	0.42			Dop	-
En3	2	Nots	13,172.0	Wo4	0	Nots	-
		Mem	11.40			Mem	-
		Dop	0.39			Dop	-

confirming that the number of notifications alone is not a good measure of the addiction of users. Although, it must be noted that all addicted users tend to receive a large amount of notifications: 7000 or above.

We now focus more in detail on the users found addicted and their Memory and Dopamine levels at the end of the simulation. Figure 6 shows the Notifications bivariate distribution of addicted users, but the top 30% of users per Memory level at the end of the simulation are highlighted with a yellow marker, and the top 10% is highlighted with a red marker. The plot shows that the

Table 3. Simulation values of users with highest notification count, Memory and Dopamine.

	Top Nots	Top Mem	Top Dop
Nots	68,681	66,297	40,399
Mem	28.68	39.50	35.20
Dop	0.45	0.56	0.69
Group	Ne1	Ne2	Ne2

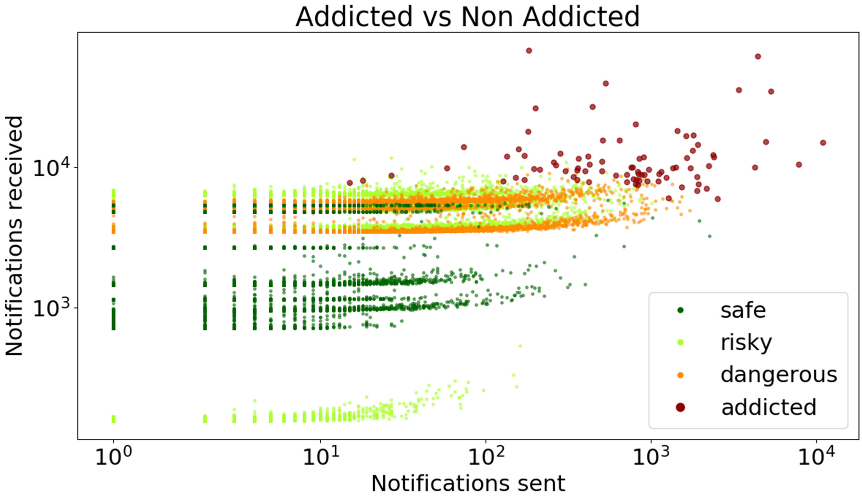

Fig. 5. Notification sent and received, Memory, and Dopamine of all users in all groups. (Color figure online)

most severe cases of addiction are connected to an higher number of notifications, mostly received. However, the plot also shows that there is no correlation between the notifications sent and received. This is counter-intuitive because one would expect that the more a user sends notification (and interacts with other people), the more other users are encouraged to interact with her/him. However, as described in [19], passive activities are the most popular ones.

Figure 7 shows the Dopamine-Memory bivariate distribution of addicted users, but the top 30% of users per notification count are highlighted with a yellow marker, and the top 10% is highlighted with a red marker. In this distribution we see that at low Memory levels correspond low levels of Dopamine (see black and yellow markers). Additionally, an higher notification count is usually bound to an higher Memory (and Dopamine) level. On the other hand, the nodes marked as the top nodes per notifications does not confirm this trend, and are instead more scattered. Interestingly enough, the three markers corresponding to the users who were found with the highest notification count (TN), highest

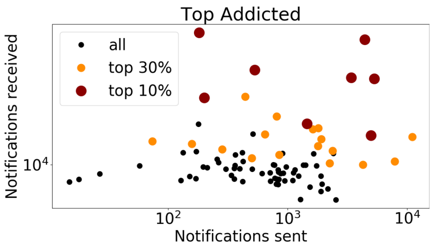

Fig. 6. Users with highest memory. (Color figure online)

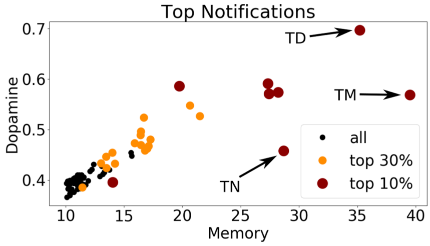

Fig. 7. Users with most notifications. (Color figure online)

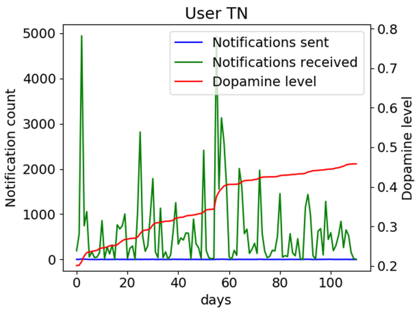

Fig. 8. Notifications and dopamine level for user TN.

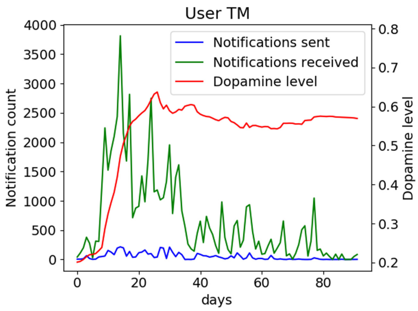

Fig. 9. Notifications and dopamine level for user TM.

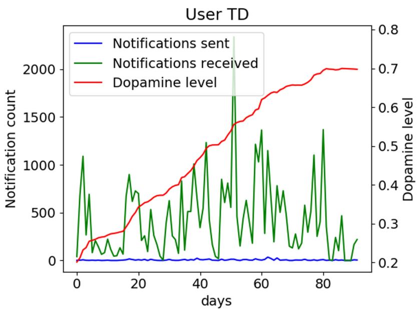

Fig. 10. Notifications and dopamine level for user TD.

Memory level (TM) and highest Dopamine level (TD) (see Table 3), are the users that distances the most from the others.

6 Conclusions

Addiction is a complex phenomenon, which has several consequences on the brain and the behaviour of people. In the last decade, the introduction of new technologies and the advent of Social Media have changed the way of how people communicate, giving rise a new kind of addiction, namely the social network addiction, for which users engage in different online activities excessively and/or compulsively.

In order to investigate this phenomenon, researchers have started to study Internet addiction, to unveil the mechanisms affecting the user's life. In this context, the applied approaches are based on the analysis of different factors, such as biological, social and psychological aspects.

The sociological and psychological factors can be used to predict the susceptibility to Internet addiction. However, it is difficult to measure accurately how they affect the user's behaviour. Therefore, in this work, we apply a novel approach, which studies the Internet addiction analyzing only the structure and the mechanisms at the basis of social network sites. In particular, simulating the computational model of Dopamine System and using the real data of 18 groups of Facebook, we are able to study how the notifications affect significantly the user's behaviour.

Our work can be further developed in different ways. In the future, we want to extend our analysis considering other typologies of Facebook groups and, in particular, monitoring their activities for longer periods. Moreover, we plan to collect also data of different social networks, such as Twitter and Instagram, to compare the results of our analysis and study how the user's behaviour is different according to the used platform. Besides, we want to investigate deeper the role of the *intensity* on the addiction development.

The Dopamine System is also linked to the human perception of the satisfaction, stimulating the attention, the memory and the learning. Therefore, it is possible to extend ulteriorly our work to test satisfaction of the user in human-computer interactions.

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