# A Community Detection Approach for Smart-Phone Addiction Recognition

Fabio Cozzolino[1], Vincenzo Moscato[1], Antonio Picariello[1] and Giancarlo Sperli[2]

[1]*DIETI, University of Naples Federico II, Italy*

[2]*ITEM National Lab, CINI, Naples, Italy*

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Abstract: In this paper, we present a novel approach for Smart-Phone Addiction recognition that leverages *community detection* algorithms from the *Social Network Analysis* (SNA) theory. Our basic idea is to model data concerning users' behavior while they are using mobile devices as a particular social graph, discovering by means of SNA facilities patterns that better identify users with a high predisposition to smart phone addiction. Eventually, several experiments on a sample of users monitored for several weeks have been carried out to verify effectiveness of the proposed approach in correctly recognizing the related addiction degree.

## 1 INTRODUCTION

During the last years *Psycho-Informatics* has attracted more and more the interest of researchers in order to better understand human behavior within the modern "data-rich" world: it consists of the application of novel methodologies for acquisition, management and analysis of vast quantities of psychological data, combining behavioral psychology and computer science techniques (Markowetz et al., 2014).

Indeed, one of the most natural way for eliciting nowadays persons' habit is the analysis of their smart phones' data. Unfortunately, the variety of functionalities that such devices offer – including the use of the Internet for web browsing, on-line games, digital cameras, GPS navigation, and a lot of interactive and social applications – can deeply capture attention of users, who could be dangerously distracted from real events ((Hooper and Zhou, 2007)). Several recent studies (Leung, 2008) have shown how their excessive use, namely *Smart-Phone Addiction*, can generate different complications for users' health, especially psychological pathology: lack of self-control, abstinence, insomnia, social isolation, depression, difficulty of concentration, as well as signs of irritability, restlessness, stress and mood changes (Chóliz et al., 2016; Ha et al., 2008; Ben-Yehuda et al., 2016).

In according to the most recent vision, Smart-Phone Addiction can be defined as "an unstoppable and uncontrollable desire of using a smart phone despite its negative and harmful effects" (De-Sola et al., 2017). The smart-phone addiction does not easily fit the standard classification of psycho pathological disorders provided by the *Diagnostic and Statistical Manual of Mental Disorders* (DSM). Thus, trying to recognize persons' predisposition with respect to such new pathology, by means of the application of novel methodologies and techniques from Psycho-Informatics, turns out to be very important.

The main idea behind our work is to propose a novel methodology based on the application of *community detection* algorithms from the *Social Network Analysis* theory on a particular "social graph" that considers users' behaviors during the usage of their mobile phone. In particular, we provide answers to questions such as: How much smart-phone addicted is a particular user? What is the app preferred by a smart-phone addicted user?

To these aims, we designed and realized a framework for monitoring and evaluating users' behavior with respect to the use of mobile devices for supporting smart-phone addiction diagnosis and assessment. Successively, we have analyzed the collected data for identifying possible social patterns that characterize users with a high predisposition to smart phone addiction, in conjunction with the analysis of well-known self-assessment tests that are currently used by psychologists to determine the onset of such pathology.

Eventually, an experimental evaluation was carried out on a significant sample of users (aged between 19 and 50 years) monitored for several week in order to verify the reliability and effectiveness of



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the proposed approach in correctly recognizing and calssifying the related addiction degree.

The paper is organized as in the following. Section 2 provides a review of the Related Work on smartphone addiction problem. In Section 3, we describe the proposed methodology for evaluating users' smartphone addiction with respect to their mobile devices. System architecture and experimental results are then presented and discussed in Sections 4 and 5. Finally, conclusions are reported in Section 6.

## 2 RELATED WORK

The most diffused clinical methods – based on psychometric questionnaires and interviews – for smart phone-addiction prediction presents several limitations that can be synthesized in the following points (Markowetz et al., 2014): i) coarse temporal granularity, ii) considerable costs, iii) distortion and poor objectivity of the available data, iv) impossibility of specialists to perform an ongoing patient's assessments and interventions, v) subjectivity of evaluations.

In more details, researchers actually rely on specific clinical experiments and self-assessed psychometric tests to perform diagnosis of user's mental illness related to the smart phone addiction pathology. Even though these methods have found a widespread application in research, they are not used yet in clinical practice due to difficulty in managing the related data and to the cost of obtaining and storing them.

Several works have recently offered solutions to the smart phone addiction problem to overcome the discussed limitations.

First of all, several correlations between the excessive usage of smart-phones and the *Internet Addiction* (which literature is quite consolidated) have been commonly observed in many studies (Ben-Yehuda et al., 2016), even if a recent review (De-Sola Gutiérrez et al., 2016) discusses some peculiar characteristics that clearly distinguish the two phenomena. The authors have shown that smart-phone addicted users are mostly young and female that seek social gratifications, while Internet-dependent individuals are more likely to be males and socially introverted.

The majority of works focusing on smart-phone addiction proposed statistical approaches to correlate smart-phone addiction to different mental problems.

(Bian and Leung, 2015) defined a statistical model that underlines how some smart-phone usage patterns within a social context can be considered specific symptoms of smart-phone addiction. A different perspective has been then analyzed in (Van Deursen et al., 2015), where authors demonstrate as social stress can influence a smart-phone addiction behavior. In addition, (Samaha and Hawi, 2016) and (Sano and Picard, 2013) discovered interesting relationships among smart-phone addiction, level of stress and school performances.

Concerning frameworks to support the smart-phone addiction analysis, (Lee et al., 2014) realized a system, namely SAMS (*Smart-phone Addiction Management System and Verification*) able to perform a statistical analysis of relationships between smart phone apps and the possible levels of dependency. Furthermore, the *Smart-phone Overdependence Management System* (SOMS) (Lee et al., 2016) has been implemented to analyze user behavioral models that can directly cause excessive dependence on smart phones and also to prevent and to monitor excessive smart-phone usage managing the assessment of patients. Finally, in (Lawanont and Inoue, 2017) it has been designed an architecture for the recognition of smart-phone addiction based on a classification model that analyses only some particular psychometric variables (such as average/minimum/maximum duration of smart phone usage per unlock, number of apps' context-switches, average duration of smart phone, number of unlocks, number of reebots, etc.) acquired by mobile devices.

Summing up, the results derived by the adoption of SAMS and SOMS, an other very recent studies (Lawanont and Inoue, 2017) showed strong correlations between dependency on smart-phones and evaluation of the daily usage of these devices, both by means acquisition and analysis of some specific psychometric variables and statistics relating to the interaction between users and mobile applications. Table 1 summarizes the main prominent approaches.

## 3 METHODOLOGY

Here we propose a *Multi-source Smart phone Addiction Analysis* (MSAA), a novel approach for recognizing users affected by the smart-phone addiction syndrome. We model the interactions between users and mobile devices as a particular social graphs leveraging community detection algorithms from Social Network Analysis theory to infer useful social patterns that describe different categories of social addiction degree.

The MSAA approach is formed by four main phases:

- the first stage concerns acquisition and cleaning of data generated by the different actors (users/participants and psychologists/supervisor);

Table 1: Smart-phone addiction approaches.

| Authors | Outcome |
|---|---|
| (Bian and Leung, 2015) | Identification of some smart phone usage patterns within a social context as symptoms of smart phone addiction symptoms. |
| (Van Deursen et al., 2015) | Analysis of social stress's influence on smart phone addiction behavior. |
| (Samaha and Hawi, 2016) | Identified relationships among smart phone addiction, level of stress and school performances. |
| (Sano and Picard, 2013) | Use of wearable sensors and mobile phones for stress recognition. |
| (Lee et al., 2014) | Identification of relationships between smart phone apps and the possible levels of dependency. |
| (Lee et al., 2016) | Analysis of user behavioral models that can directly cause excessive dependence on smart phones. |
| (Lawanont and Inoue, 2017) | Analysis of psychometric variables for smartphone addiction classification. |

- in the second phase, we model the gathered information through a graph data structure, namely *Initial Global Graph* (IGG);
- the third phase produces an enriched version of IGG, namely *Final Global Graph* (FGG), by computing new edges based on the analysis of three different types of relationships (between users, between users and apps and between apps);
- the fourth and last stage performs a community detection algorithm on FGG for classifying users into four communities related to different levels of smart-phone addiction combining self-assessment test scores and the data obtained by the monitoring phase.

### 3.1 Knowledge Base Building

Formally, we model users' behavior while they are using their smart-phones as a directed a-cyclical graph, namely *Initial Global Graph* (IGG).

**Definition 3.1** (Initial Global Graph)**.** *An* Initial Global Graph *is the pair* $IGG = (V,E)$*, V being a set of Vertices, composed by four entities:* users, supervisors, tracking days, apps*; E being a set of Edges, formed by three types of relationships:* user-to-supervisor, user-to-tracking day, tracking day-to-app.

Table 2 describes in more details both entities and relationships in the IGG graph.

The IGG has been implemented by means of a particular *property graph*, in which both nodes and edges are particular Abstract Data Type (ADT). Supervisor/clinical and user have both personal attributes but on one hand a supervisor can also choose test's type, psychometric variables and weights for the *Recency Frequency Duration* (RFD) analysis (Lee et al., 2014); on other hand, user node has the obtained score to the assessment test. Furthermore, several features related to the number of locks, reboots, average, maximum and minimum usage for unlock and pedometer values have been chosen for app nodes.

In Figure 1 an example of IGG is shown.

### 3.2 Knowledge Discovery Process

In this step, we perform an enrichment of IGG by computing new edges between the existing nodes. We leverage three different types of relationships: between users, between users and apps and between apps. These relationships are generated by means of a knowledge discovery process that aims to infer several useful correlations between involved entities from different points of view.

The *user-to-user* edges are focused on the difference between smart-phone addiction levels of two users. More in details, we compute the *Smart-phone Addiction User Level* (SAUL) for each user, which corresponds to the sum of two terms: the self-assessment test score ($TS$) and the average weighted sum of the different psychometric variables related to the smart-phone usage. The $SAUL$ value is defined as in the following:

$$SAUL = TS + \sum_{j=1}^{N_{PV}} \left( \frac{\sum_{i=1}^{N_{TD}} w_j \cdot PV_{ji}}{N_{TD}} \right) \tag{1}$$

$N_{PV}$ and $N_{TD}$ being respectively the number of psychometric variables related to the smart-phone use and the tracking days for each user, $PV_{ji}$ representing the $j-$psychometric variable related to $i-$th monitoring day and $w_j$ corresponds to the weight assigned

Table 2: Initial Global Graph entities and their relationships.

| | Label | Meaning |
|---|---|---|
| **Nodes** | *Supervisor* | The clinician/supervisor that monitors the various users.<br>She/he registers to the platform the self-assessment tests for users.<br>She/he selects weights to be attributed to the psychometric variables. |
| | *User* | User/participant who executes the self-assessment test.<br>She/he is then monitored for a given period. |
| | *TrackingDay* | Single day during which a user is monitored.<br>It contains the daily values of the psychometric variables for a given smartphone. |
| | *App* | Single app used by a user during a tracking day.<br>It contains different daily usage data of the app. |
| **Edges** | *Monitored* | Relationship between supervisor and monitored user. |
| | *Produced* | Relationship between the psychometric variables of a tracking day and users. |
| | *Related* | Relationship between data about used apps and tracking days. |

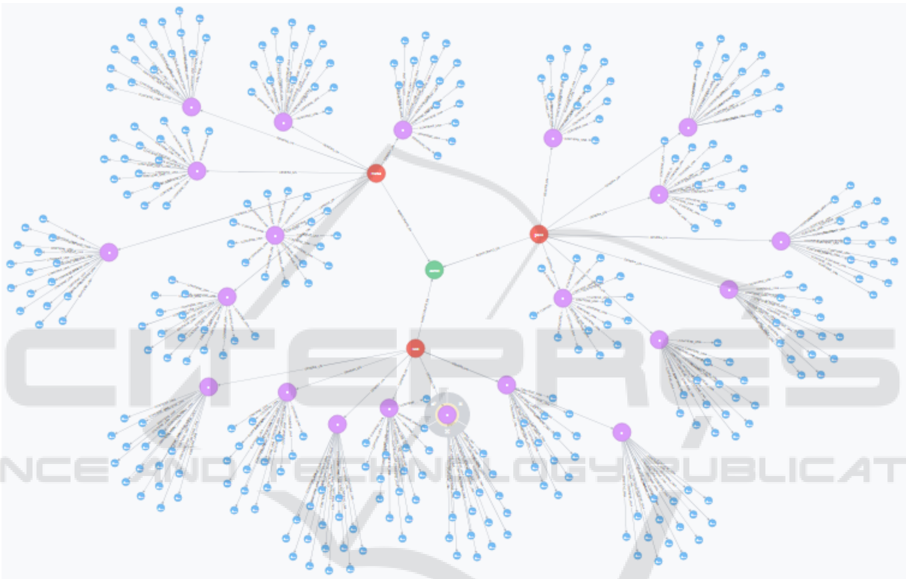



Figure 1: Example of IGG graph at the end of the monitoring of 3 users. It is possible to note that the presence of a Supervisor node (in green), 3 User nodes (in red), 7 Tracking Day nodes (in purple) for each user and several App nodes (in blue) for each tracking day.

to of $j-$th psychometric variable. Successively, the edge direction is assigned by comparing the $SAUL$ coefficients of user pairs, since it indicates a greater dependence of the source user node with respect to the destination one. Finally, we compute the relationship weight as difference between the SAUL coefficients of the analyzed user pairs.

The second family of relations is composed by *user-to-app* relationships that connect each user to the related most used apps according to a RFD analysis for each tracking day. In particular, the RFD analysis is based on the following three parameters: i) Recency (R) corresponds to the elapsed time since the last use of the application by a user $u$ within a certain period $T$; ii) Frequency (F) is the number of times a user $u$ has interacted with the application $a$ within a certain period $T$; iii) Duration (D) represents the total duration of effective interaction with the application $a$ by a user $u$ during the period $T$. This analysis aims to provide an estimation about user's preferences of a given application. The RFD score is defined as follows:

$$RFD = w_R \cdot R + w_F \cdot F + w_D \cdot D \tag{2}$$

$w_R$, $w_F$, $w_D$ being the assigned weights to each component of RFD analysis based on its importance and according to the application goals. Analyzing the RFD value it is easy to understand how the applications have been used more recently, more frequently and for longer times will probably be preferred by users.

Finally, the *app-to-app* edges represent the usage relationships between pairs of user apps in the same

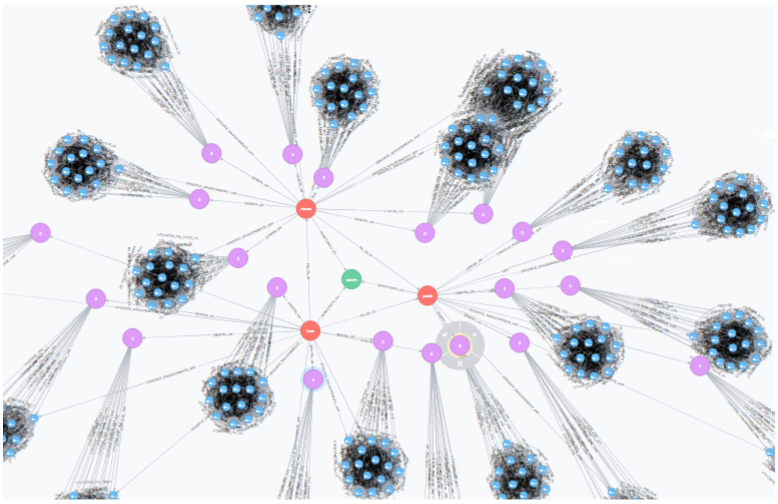

Figure 2: Example of FGG graph.

monitoring day. In particular, these relationships consider several parameters, such as the usage chronological order of apps in a single monitoring day, the differences in terms of duration/frequency of usage between apps, the differences in terms of the quantity of bytes transmitted/received via Internet connection between apps. The weight of each edge is computed as the difference between the pairs of homologous features related to two examined nodes.

In conclusion, we have an enriched version of IGG, namely *Final Global Graph* (FGG), inferring the discussed new edges for increasing information necessary to smart-phone addiction analysis. We define the FGG as in the following.

**Definition 3.2** (Final Global Graph)**.** *The* Final Global Graph *is the pair* $FGG = (V, E)$*,* $V$ *being a set of Vertices composed by* users, supervisors/clinics, tracking days *and* apps*;* $E$ *being a set of Edges composed by* user-to-supervisor, user-to-tracking day, tracking day-to-app, user-to-user, user-to-app *and* app-to-app *relationships.*

Figure 2 shows an example of *FGG*, derived from the IGG graph of Figure 1.

### 3.3 Smart-Phone Addiction Community Detection Algorithm

The FGG can be seen as a sort of knowledge base for supporting several applications. Here, we describe the proposed approach for community detection over the extracted FGG.

In our vision, the inherent semantic of user-to-user relationships plays a key role for identifying user nodes' groups according to their smart-phone addiction level. In addition, we also exploit the RFD analysis values between users and apps belonging to the "communication" and "social" categories (i.e. Whatsapp, Facebook, Messenger, etc), because, as shown in (Salehan and Negahban, 2013), they represent the most useful applications for smart-phone addiction.

In particular, we define a *Weighted Users Matrix* that jointly considers the two described contributions to identify groups of users suffering of the same pathology.

**Definition 3.3** (Weighted Users Matrix)**.** *A* Weighted User Matrix *is the matrix:*

$$\Theta = \{\theta_{ij}\} = \begin{cases} (1 - \Delta_{SAUL_{ij}}) + (1 - \sum_{a \in A} \Delta_{RFD_{ij|a}}) \; if \;\; i \neq j \\ 0 \quad if \;\; i = j \end{cases}$$

*$A$ being a subset of apps in FGG, $\Delta_{SAUL_{ij}}$ is the difference of SAUL values between user $i$ and user $j$ and $\Delta_{RFD_{ij|a}}$ represents the sum of difference of $RFD$ analysis between two users $i$ and $j$ w.r.t. apps in $A$.*

Following the idea discussed in (Gupta and Kumar, 2016), we propose as community detection approach a vertex selection strategy that guarantees high coverage and good conductance on expansion of communities. However, we enhance the methods in (Gupta and Kumar, 2016) in according to: (i) the *data-model*, that integrates both information about users and their behaviors with respect to used smart phone's apps modeled by a property graph data structure; (ii) the *comparison* of users' behavior with respect to the apps relevant for smart-phone addictions; (iii) a new way to build the user-to-user matrix combining topological features and nodes' attributes.

In the following, we report the algorithm exploited for community detection.

More in details:

Algorithm 1: Community detection algorithm.

1: **procedure** *SA_Community_Detection*(FGG)
2: $\quad \mathcal{C} \leftarrow \emptyset$
3: $\quad$ *Compute_Matrix* $\theta$
4: $\quad$ **while** *more_visited_nodes* **do**
5: $\quad\quad C_i = \emptyset$
6: $\quad\quad u \leftarrow \arg\max_{u \in U} \{\sum_{v \in U} \theta_{vu}\}$
7: $\quad\quad C_i \leftarrow C_i \cup \{u\}$
8: $\quad\quad$ **while** $(\phi(C_i) - \phi(\hat{C}_i) \geq 0)$ **do**
9: $\quad\quad\quad u \leftarrow \arg\max_{u \in U} \{\sum_{v \in U} \theta_{vu}\}$
10: $\quad\quad\quad C_i \leftarrow C_i \cup \{u\}$
11: $\quad\quad$ **end while**
12: $\quad\quad \mathcal{C} \leftarrow \mathcal{C} \cup C_i$
13: $\quad\quad i \leftarrow i + 1$
14: $\quad$ **end while**
15: $\quad$ **return** $\mathcal{C}$
16: **end procedure**

- (lines 5-7) – the algorithm identifies the nodes showing the highest weight degrees as seed nodes. The weighted degree of node $u$ is computed as the sum of column related to user $u$ of the Weighted User Matrix.
- (lines 9-11) – successively, the *conductance* measure has been used to evaluate the quality of community during the expansion phase: in fact, the increase of users in the examined community corresponds to a decrease of conductance value. The conductance is defined as $\phi(C_i) = \frac{cut(C_i)}{min\{deg(C_i), deg(\bar{C}_i)\}}$, where $cut(C_i)$ denotes the size of a cut induced by $C_i$, $\bar{C}_i$ is the complement set of $C_i$ and $deg(C_i)$ is the sum of degrees of vertices in $C_i$.
- (lines 8-11) – once a seed node is identified, we perform an incremental expansion of the community for including the user that maximize the decreasing value of conductance. This is an iterative process until the conductance difference related to communities computed in successive steps does not assume a negative value.

# 4 SYSTEM ARCHITECTURE

The system consists of a client-side application, to be installed on the users' mobile devices, and a web server-side application, responsible for the data acquisition and analysis through the methodological approach previously illustrated.

The entire system architecture together with the adopted technologies are shown in Figure 3, that has been deployed – at the moment – only for Android Platforms..

More in details, the client-side consists of an Android app: after the sign-up procedure, users can execute a self-assessment test whose typology is chosen by clinicians. In addition, once the mobile device has been set to start the smart-phone addiction recognition process, the user can access to a personal web page on the server, containing the summary data concerning personal test score and the current daily monitoring statistics (both in terms of apps' usage and of interactions with the smart phone).

The Android app continuously monitors the running applications on the mobile device (Apps Usage Statistics module), and also, the different user/smart-phone interactions (Smart-phone Usage Statistics module), locally storing the usage records (mainly on a SQLite database but also through Shared Preferences mechanisms) by means of the Data Persistence module. Furthermore, users can perform a real-time self-monitoring of their smart phone usage level (Self-Usage Check module) by viewing along the monitoring period both the usage data related to the individual apps and the entire interaction with the mobile device. The data acquired by the mobile device using Android apps are locally and daily stored and sent to the web server at the end of the observation week of monitoring (Statistic Server Upload module).

From the server side, the clinician performs the registration operations to the system (Sign up), setting also the type of test to be submitted to the users and all the weights related to the psychometric variables. The clinician can access to a personal web page containing the summary data (at various levels of detail) of the users involved in the monitoring process. In particular, it is possible to view the information related to the daily statistics and those resulting from several analytics (Graph Analysis, RFD Analysis, Link Analysis and Graph Community Detection). Daily usage records from the Android app at the end of the monitoring period are then stored stored into Neo4j graph database. All the data processing and analytics facilities have been implemented using Scala functions within the Apache Spark framework.

# 5 EXPERIMENTS

## 5.1 Dataset and Experimental Environment

To test the reliability and the effectiveness of the developed system, several experiments were carried out on a sample of about 50 users (aged between 12 and 77) monitored for a period of 7 days (from Monday

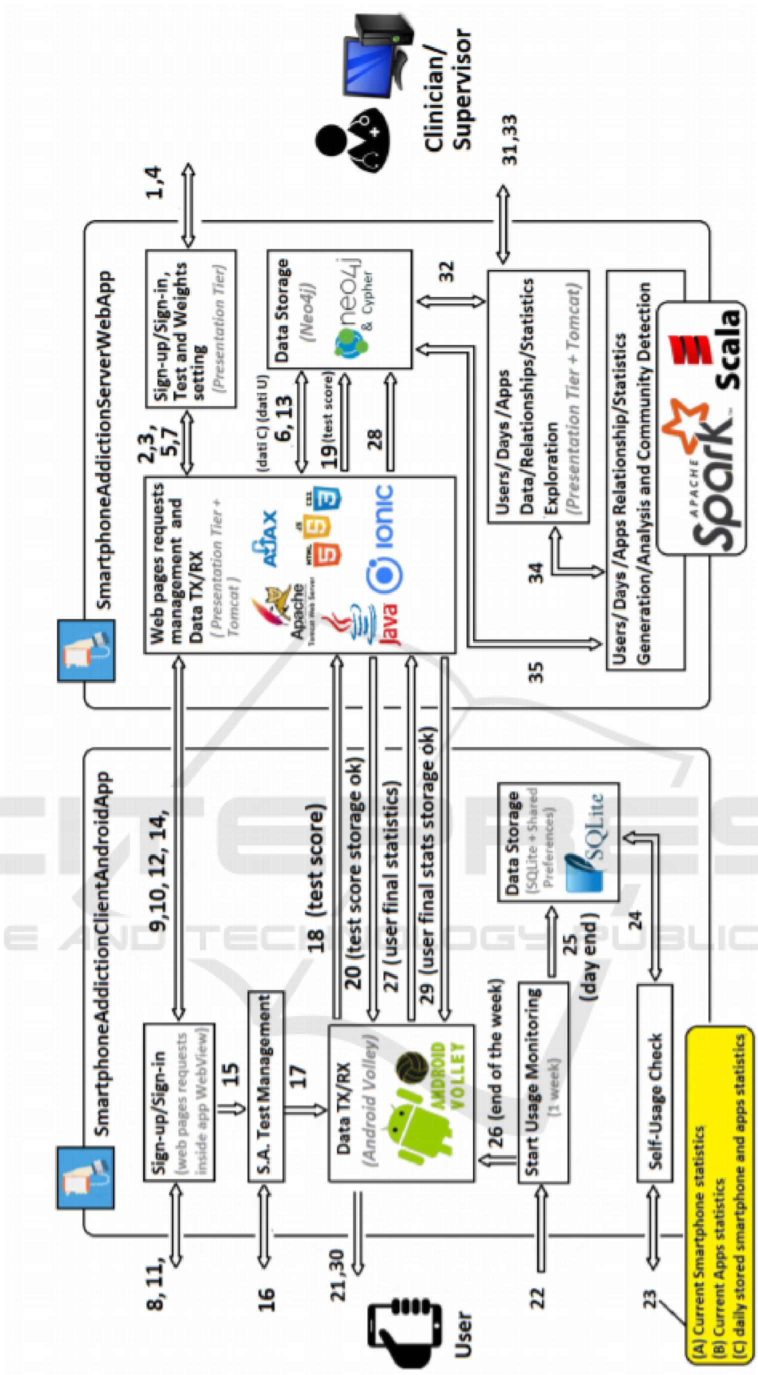


Figure 3: System Architecture and Data Flow.



to Sunday).

Figure 4 shows the characterization of the users. Note that we selected users in order to have the same number of samples with respect to different age groups (12-17, 18-27, 28-40, 40-60, 60-77). People were randomly selected from a urban area, related (relatives, friends) to students of our Lab, and no a-priori knowledge was used except that they used extensively their smart phones for work or fun[1]. The dataset is also composed by information about users' behavior with respect to the use of mobile devices (i.e. bytes transmitted/received via Internet or data con-

[1]The participants provided informed consent (by parents in case of minors) and all the assessed data were preserved in a suitably protected database.

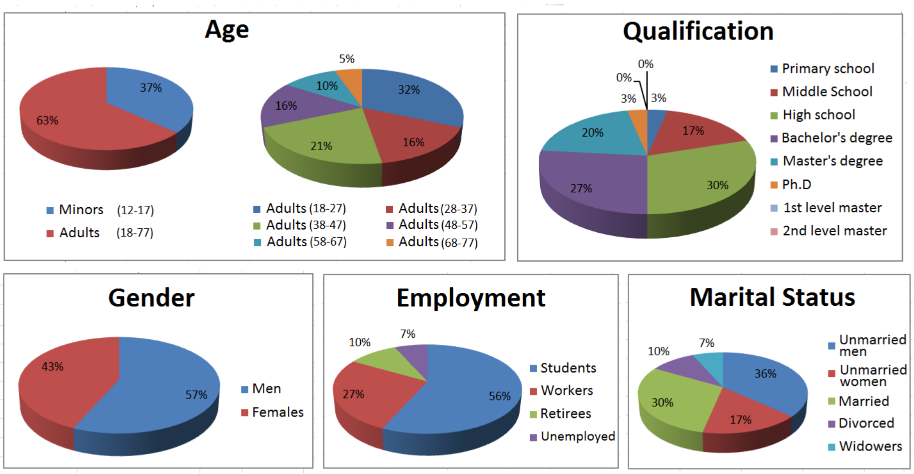


Figure 4: Dataset characterization.

nection between apps and so on). In this evaluation we show how the use of our system offers interesting perspectives, automatically detecting and classifying behaviours and life-style of users.

The main characteristics of the used client and server side hardware/software infrastructure for experiments are summarized in the Table 3.

## 5.2 Experimental Protocol

The experimental protocol is composed by 4 main stages.

The first stage consists of the registration of the clinician/supervisor to the system by creating a proper account, together with the setting of the particular type of test to be administered to the participants (choosing between IAT, UADI, NMP-Q, MPACS and SAS-SV) and the setting of the psychometric variables weights related to the RFD analysis and to the calculation of the SAUL coefficient of each user.

The second stage consists of explaining to the potential participants the aims of the experiments: if one chooses to participate, the Android application will be installed on her/his smart phone, also registering the necessary information within the system and the subsequent execution on the app of the specific assessment test of the level of smart-phone addiction. The application will compute the test score and send it to the server.

In the third stage, all the subjects – that have completed the test – can start the weekly monitoring of their devices. Monitoring acts as a background service allowing subjects to close the application and use their smart phone normally.

In the fourth stage, at the end of the monitoring period, the clinician/supervisor uses the data related to all users who have completed the monitoring and, through appropriate interface, obtains different types of statistics (at various levels of granularity) as well as the result of the community detection algorithm.

The aim of the provided evaluation is to:

- detect the kind of applications that exerts more influence on users and may represent a possible feature for predicting smart-phone addiction;
- detect the users' categories that shows a possible correlation with smart-phone dependence;
- analyze the usage patterns for better discriminate addicted vs not addicted users;
- compare the outcome of our proposed technique with respect to surveys methods.

## 5.3 Popularity and Category Applications Analysis

First of all, we have conducted a *popularity analysis* of the applications w.r.t. the weekly usage of users' smart-phones . The top 10 ranked applications (out of a total of 124) on the basis of the duration and frequency of their average daily use can be seen in Table 4.

The contrast between duration and frequency of use for each application is due to the related *category*. WhatsApp, Messenger, Instagram and Snapchat, belonging to the Social/Communication category, have a greater tendency to be used more frequently, with less usage time. Other categories such as Game and Media & Video, to which applications such as YouTube or the FarmVille game belong, for example, are used less frequently: however, once a user runs these applications, the usage time is extended.

According to the study of (Salehan and Negahban, 2013; Lee et al., 2014), which shows a correlation between the use of applications belonging to the social

Table 3: Hardware/software infrastructure.

| | | | |
|---|---|---|---|
| Client-side | Hardware | Category | Smartphones |
| | | Manufacturer and/or model | Samsung, Huawei, Honor, Oppo, Xiaomi, Motorola, Vivo, HTC, Meizu, Cubot |
| | | CPU | da 1.9 GHz Quad Core<br>a Quad core 2.3 GHz + Quad core 1.7 GHz |
| | | RAM | 2-4 GB |
| | | Storage | da 16 GB (only internal storage)<br>a 128 GB (with micro SD extention) |
| | Software | O.S. | Android 6.0 (Marshmallow) + |
| | | Database | SQLite |
| | | Framework | Android Volley |
| | | Libraries | Android MPAndroidChart |
| Server-side | Hardware | Category | Ultrabook |
| | | Manufacturer and/or model | Dell XPS 14 |
| | | CPU | Intel i7-3667U Dual-core 2.00 GHz, 2.50 GHz |
| | | RAM | 8 GB |
| | | Storage | 500 GB (SSD) + 32 GB (SSD) |
| | Software | O.S. | Windows 7 64 bit |
| | | Database | Neo4j |
| | | Framework | Apache Spark, Apache Tomcat |
| | | Libraries | GraphX |

category and the smartphone dependence, in our case there is a high percentage of daily use (both in terms of frequency and duration) of this category highlighting a potential presence of a smart-phone addiction.

### 5.4 Smart-Phone Addiction Detection via Community Detection

The goal of such experiments is to compare the results proposed community detection algorithm (based on the combination of SAUL values from different tests and psychometric variables) in distinguishing smartphone addicted (S.A.) users from not smart-phone addicted (No S.A.) with respect t the outcomes provided by the MPAC test.

Figure 5 summarizes the obtained results.

The achievement of a lower percentage of S.A. users compared to that produced only by the MPAC test follows the results of previous studies (Montag et al., 2015a; Lin et al., 2015; Boase and Ling, 2013) which showed how the total weekly use of the smart phone is overestimated by the participants which are not very reliable in providing an effective estimate of their interaction with the mobile device (both in emotional terms through the answers to the items/questions of the self-assessment test and in terms of quantitative estimation of the number of weekly hours used with the device as answer to further questions that are integral to those of the test).

We want to note as the users classified as S.A. by our algorithm have shown, as a result of the RFD analysis, a clear preference in the use of applications according to the ordering: 1) Whatsapp, 2) Facebook and 3) Youtube.

In addition, a further survey concerning these users showed that this preference was also found in the top 10 used apps in terms of the usage frequency only. In turn, for what concerns only the duration, the resulting ranking showed how users show a preference in the order: 1) Youtube, 2) Whatsapp, 3) Facebook.

These results confirmed the findings of previous studies (Montag et al., 2015b; Olivencia-Carrión et al., 2016) which identify the WhatsApp application as one of the driving forces behind the use of smart phones, attributing to its overuse a high potential correlation with smart phone dependency.

Eventually, it should be noted that the majority of S.A. users belong to the group 18-27, confirming the trend that sees the phenomenon of smart- phone addiction is growing among the youth population.

## 6 CONCLUSIONS

In this paper we introduced a novel methodology for smart-phone addiction classification based on the application of community detection algorithms from the SNA theory.

In particular, we:

Table 4: Ranking of the top 10 applications based on the duration and frequency of their average daily use.

| Rank | Sorting by usage duration | | | Sorting by usage frequency | | |
|---|---|---|---|---|---|---|
| | App name | Frequency (%) | Duration(%) | App name | Frequency (%) | Duration(%) |
| ***1*** | ***Whatsapp*** | ***18.86*** | ***17.48*** | ***Whatsapp*** | ***18.86*** | ***17.48*** |
| 2 | ***YouTube*** | ***10.02*** | ***8.69*** | ***YouTube*** | ***10.02*** | ***8.69*** |
| 3 | Android browser | 0.28 | 5.52 | Facebook | 7.06 | 4.97 |
| 4 | Facebook | 7.06 | 4.97 | Messenger | 5.22 | 1.19 |
| 5 | Amazon shopping | 0.48 | 4.48 | Instagram | 5.07 | 1.27 |
| 6 | Messenger | 3.28 | 4.34 | Snapchat | 3.45 | 2.09 |
| 7 | Amazon Kindle | 1.03 | 3.92 | AliExpress | 3.28 | 4.34 |
| 8 | Zynga Poker | 0.76 | 3.71 | Fifa calcio | 3.12 | 1.48 |
| 9 | Google Maps | 1.27 | 3.00 | Amazon shopping | 3.04 | 0.37 |
| 10 | AliExpress | 3.45 | 2.09 | Google Maps | 2.89 | 0.87 |

| S.A. levels | MPACS test results (based only on the score) | | S.A. Community Detection (mixed approach) | |
|---|---|---|---|---|
| | number of users | percentage | number of users | percentage |
| No S.A. users | 16 | 53,333% | 18 | 60,000% |
| Low S.A. probability u | 6 | 20,000% | 8 | 26,667% |
| High S.A. probability | 3 | 10,000% | 2 | 6,667% |
| S.A. users | 5 | 16,667% | 2 | 6,667% |
| total | 30 | 100% | 30 | 100% |

Figure 5: Results of the comparison between the score of the MPACS test and the outcome of the proposed community detection algorithm.

- modeled data related to users' behavior with respect to the use of mobile devices as a particular social graph;
- discovered by means of the SNA algorithms patterns that better characterize users with a high predisposition to smart phone addiction;
- designed and realized a system supporting smartphone addiction analysis;

- performed several experiments on a sample of users to verify the reliability and effectiveness of the proposed approach in correctly recognizing the related addiction degree.

We think that the empirical study reported in this paper represents an important starting point to illustrate the advantages of the inclusion of Social Network Analysis tools and methodologies in the psychological/psychiatric field.

The combination of self-report data and actual behavioral monitoring provides a clearer picture of a patient, as well as a more in-depth view of his potential dependency status, useful to psychiatric doctors. Future work will be devoted to extend experimentation increasing the number of human subjects and comparing our approaches with different and more recent ones.

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