Pompilos, a Model for Augmenting Health Assistant Applications with Social Media Content J.UCS Special Issue

Abstract: Caused by habits such as poor diets, lack of physical activity practice or smoking, non-communicable diseases were elected by the World Health Organization as one of the greatest challenges of the twenty-first century, despite the thousands of information produced in social media that are focused on the prevention of this type of disease. This paper presents the Pompilos Model, that aims to improve computer-aided social support by suggesting beneficial health resources and revealing influence on the health of others for fostering better health behaviors in social relations. For evaluating the model's feasibility, we did a random experiment by one and a half month with two groups to assess the influence of messages related to the prevention of chronic diseases such as a healthy diet, physical activity practice and weight loss from monitored twitter profiles on the habits of users of health assistant web application for managing food intake, physical activity practice and weight control. Messages related to the prevention of chronic diseases such as healthy diet, physical activity practice and weight loss from monitored twitter profiles were directed to an intervention group as a way to re-engage users in their care activities. We have found a correlation between message reading and access to the application history feature among intervention users.

1 Introduction

According to data from the World Health Organization, chronic noncommunicable diseases accounted for 68% of global deaths in 2012. Care for this type of disease transcends the patient's engagement by unfolding to his family, friends and acquaintances, who may influence their treatment positively or negatively. Social support can be understood as the ability of the social network to alleviate the harmful effects of stress and other health risks.

Social Cognitive Theory (SCT) states that behaviors are learned and reinforced by social interactions (Bandura, 2001). Self awareness of how one can influence the health of others might also lead, not just to improvement of one's well-being, but also to the improvement of well-being of people surrounding. For example, a person aware that his eating habits are influencing people close may start to make better choices to help them in obtaining a better health.

Additionally, according to Milani and Lavie (2016), the current model of care can no longer cope efficiently with the challenges of this century. The aging of the population, the increasing incidence of chronic diseases and the imbalance between the demand for doctors and the formation of new professionals, created the need to elaborate a new model of care. In this new model, technology plays an important role in providing continuous monitoring, access to real-time information, communication with health professionals, support in disease management, and fostering social support (and beneficial social relationships).

Hence, computer aided healthcare must be aware that sometimes people do not have the right partner that helps them having beneficial health gains. Thus, that help can come from people existent in their social network. Direct connected nodes of an ego could be a match for a certain health related activities, sometimes these nodes could serve as bridges to aid the formation of new beneficial ties.

In essence, social support is the beneficial influence of social relations in health of people (House et al., 1988; Berkman et al., 2000). In a computing context, social support is successfully achieved by Internet applications such as chats, blogs, forums, wikis or video sharing (Vianna and Barbosa, 2017). However, few studies deal with the possibilities and opportunities of integrating the ever growing amount of computational devices and data for improvement of social support.

Today we are immersed in a world of computing devices and data. Data generated by personal devices, such as smartphones, mimic the behaviors of their owners, and then shall be applied to reveal aspects that influence in health, or to find people which the contact can influence the improvement of health. We present Pompilos, a model for enhancing health care applications with social media content and for awareness users about the impact of their behavior on health of others. Thus, this paper is organized as follows: section 2 presents some related works; section 3 describes the proposed model; section 4 presents the prototype created for evaluating or model; section 5 exposes the results found in two executed experiments; finally, section 6 shows final remarks about this work.

2 Related Works

This section presents five works that were focused on improving social support on individual level or are techniques for identification of social awareness with social media data, which are the goals of the proposed Model. At the end of this section is shown a comparison between these works in terms of *pervasiveness*, *adaptability with patients behavior*, *social support availability* and *how they enhance awareness about social influence on health*. Those works belonging to large projects are grouped for the sake of objectivity.

2.1 WANDA

WANDA (Lan et al., 2012; Alshurafa et al., 2014b,a; Sideris et al., 2015; Alshurafa et al., 2016) is a remote health monitoring system that uses patients baseline data and contextual information (collected by patients' smarphones) to improve NCDs care. According to Lan et al. (2012), monitoring systems failed to achieve significant improvements in heart failure treatment. In general they tend to be invasive and reactive. *WANDA* is a proactive, non-invasive platform integrated with smartphones, which has an analytics engine and a social platform. The engine analyzes patients' data that are collected through automatic sensing to provide custom monitoring and notifications, while the social platform adds cooperation and competition features among system users.

WANDA has gained great improvements since its first publication. WANDA remote monitoring system was already used to predict the success in care of certain risk factors related to cardiovascular diseases, adherence of physical activity practice, daily questionnaire completion, blood pressure measurement of the Women's Heart Health Study participants, treatment adherence prediction after intervention by social support, and to identify patients who are most likely to be successful in their treatment to receive custom care plans in advance.

2.2 Patient Journey Record System

Patient Journey is a metaphor that understands that the patient, as well as a traveler, is on a journey, and he will need assistance to deal with situations he is not used to in different stages of the disease (Martin et al., 2011, 2012). *Patient Journey Record System (PAJR)* is a patient-centered framework proposal that aims to integrate information systems, social networks and digital democracy, so that different agents can construct a health support system collaboratively, taking into consideration that each patient has his own journey.

PAJR was already used to analyze the responses given by patients with chronic diseases to semi structured questionnaire questions asked by "care guides". The analysis performed by the PaJR verifies the severity of the reports made by the patients and classifies according to their severity, identifying in advance the need for intervention in the patients.

The system evaluation was took from November 2010 to December 2011 in a controlled experiment where 153 patients participated in the intervention group and 61 in the control group. Overall the intervention group had a 50% lower admission number than the control group. In addition, the model used by the system was able to classify 100% of cases of unplanned urgent events.

According to authors, although the system has achieved good results, there is still a need for further evaluation.

2.3 Accessible telehealth - Leveraging consumer-level technologies and social networking functionalities for senior care

Accessible Telehealth (Dhillon et al., 2013) is a conceptual framework for elderly care. The framework design was elaborated by reviewing the existing absences between different types of care platforms, namely: telehealth, health record, health information web sites and serious games, and by the collection of requirements made by interviewing patients. Within the functionalities identified are social and emotional support. An prototype was developed implementing features of social support in the form of social network, where users could create groups and search for friends.

An evaluation of the prototype was carried out by 43 seniors. In the evaluation, 35% of patients agreed that the social functionalities motivated them to use the system. While 31% agreed that the involvement of friends helped them manage their health.

2.4 Towards chronic emergency response communities for anaphylaxis

Schwartz et al. (2014) propose a workflow approach to help chronic patients facing emergency situations. In this approach, patients who face emergency situations and do not have the resources required to deal with the situation are able to trigger an alert request. This request is passed to those individuals (members of the system) who have the resources needed to help and are within a distance range that allows for timely intervention. Members may accept or reject the aid request. This type of mechanism, where patients request each other help in health situations, was called by the authors as "social medicine".

2.5 You Tweet What You Eat: Studying Food Consumption Through Twitter

Food consumption screening is done through questionnaires which has a high cost. Social networking users, such as twitter, often share information about foods consumed. Social network data analysis, such as Twitter data, makes it possible to identify diet trends at a geographical level (e.g., at a state or city level), as well as personal habits, and the relationship these habits have with the social network of individuals (Abbar et al., 2015).

Using a Naive Bayes model, the authors classified the type of food consumed according to the text of messages shared in Twitter. Crossing the information about food consumption and caloric level of foods it was possible to correlate obesity and diabetes at the state level and to validate them with the results published by the American Centers for Disease Control and Prevention (CDC).

The authors were also able to predict obesity and diabetes at individual levels. To do so, a regression model inferred the risk of obesity based on the type of food shared by users in their messages. Finally, social network analysis performed by the authors found that the probability of being obese or having diabetes increases when one is connected to other obese or diabetic nodes, that is, nodes of the same network share messages containing similar foods.

2.6 Related Works Comparison

The previously presented works are compared in terms of pervasiveness, adaptation according to users profile, social support and awareness of social situation. Table 1 summarizes this comparison. The column *Pervasive* indicates if the work proposes the provision of assistance to users anytime and anywhere, that is, if it is pervasive (Satyanarayanan, 2001). *Adaptive* indicates if the work proposes the adaption of its operation according to users' behaviors or situations they are inserted, in other words, if its supports context awareness (Dey et al., 2001). Column *Social Support Enabled* indicates if the work proposes, in some manner, the participation of others in improving the health of its users. Finally, *Social Aware* indicates if the work proposes a mean for awareness the social influence of others on the health of its users, or the influence of its user on health of others, in some way that it can recommend connections that might benefit the health of its users, or improve the understanding of how users' behaviors influence the health of others.

Title	**Pervasive**	**Adaptive**	**Social Support Enabled**	**Social Aware**
WANDA (Lan et al., 2012; Alshurafa et al., 2014b,a; Sideris et al., 2015; Alshurafa et al., 2016)	Yes	Yes	Yes	No
Patient Journey Record System (Martin et al., 2011, 2012)	No	Yes	Yes	No
Accessible Telehealth (Dhillon et al., 2013)	No	No	Yes	No
Towards chronic emergency response communities for anaphylaxis (Schwartz et al., 2014)	Yes	Yes	Yes	No
You Tweet What You Eat (Abbar et al., 2015)	No	No	No	Yes

Table 1: Related Works Comparison

WANDA and *Towards chronic emergency response communities for anaphylaxis* are understood as *pervasive* once they provide a platform that can be used anytime and anywhere by its users, providing continuous care. They are also *adaptive*, as so is *Patient Journey Record System*. WANDA is able to predict engagement of users in its care according to they behaviors. *Patient Journey Record System* checks users' answers to questionnaires to identify in advance the need of intervention. By its turn, *Towards chronic emergency response communities for anaphylaxis* is aware of users location and resources possession to indicate the possible caregivers in emergency situations. With exception of *You Tweet What You Eat*, all other works offer some functionality of *social support*. *WANDA* detects the need of social intervention to improve engagement, *Patient Journey Record System* is based on contacts between patients and caregivers, *Accessible Telehealth* offers a social network to improve the collaboration among users, and in *Towards chronic emergency response communities for anaphylaxis* the users can request the help of others. Finally, just *You Tweet What You Eat* is *social aware* once its model considers the influence of others in the probability of having a health condition. Thus, different from the related works presented in this chapter, Pompilos aims on integrating pervasiveness, adaptability and social data to improve social support by giving user awareness of their social context. That is, give users social recommendations for the improvement of their health, as also to show how users behaviors impact on health of people close.

3 Pompilos Model

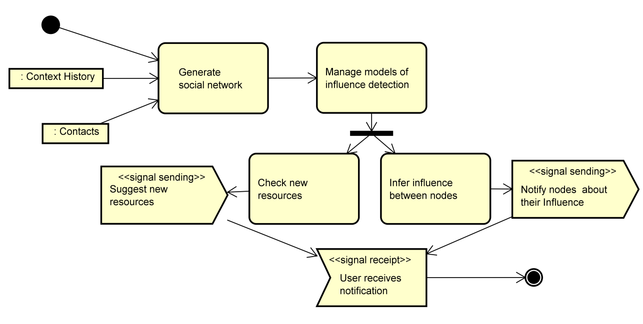
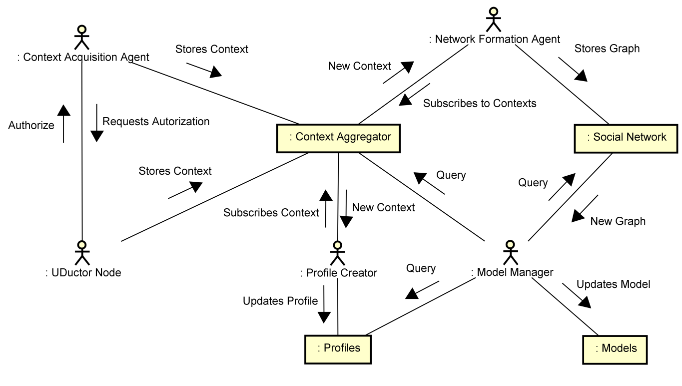


Figure 1: Pompilos General Model

The essence of Pompilos Model is expressed in Figure 1 within an activity diagram (Group, 2015). This diagram exposes a black box model showing the hierarchy of activities that must be realized in order to accomplish Pompilos' goals of improving social support by means of revealing influence on health of others and suggesting beneficial health resources.

Contacts and *Context History* data are used as input to *Generate social network* of users. Social networks and context information are then used to *Manage models of influence detection*, that is, create and train models that can identify the influence of someone behaviors on health of others. *Check new*

Figure 2: Social Network and Model Generation Dynamics



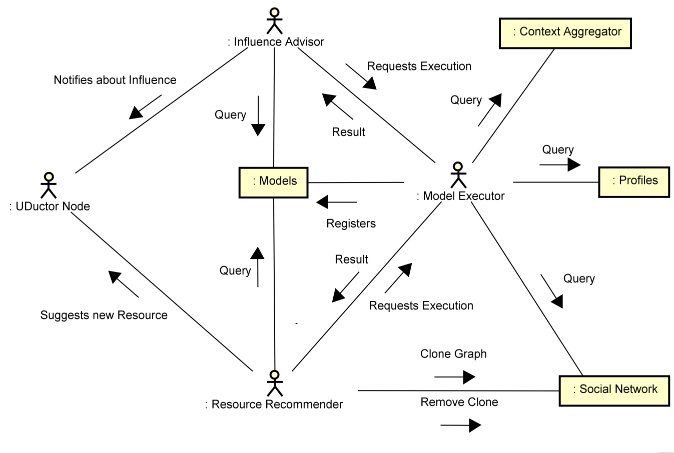
resources and *Infer influence between nodes* are executed in different nodes' data, in order to *Suggest new resources* that may benefit users' health and *Notify nodes* about their Influence. Finally, *User receives notification* regarding the new resources and node influence information generated to them.

3.1 Social Network Generation and Models of Influence Management Dynamics

The participants and dynamics responsible for accomplish the actions of *Generate social networks* and *Manage models of influence detection* and their interactions are expressed as a communication diagram (Group, 2015) in Figure 2. In this communication diagram and following, the actors represent types of software agents and the objects represent data storage components. Software agents types are supposed to have many instances that have autonomous behaviors, while data storage components are responsible to proxy the storage and retrieval of large amounts of data. Both, agents and data storage components, must interact with each other in order to realize the actions defined in the general model.

The *U'Ductor Node* represents instances of the U'Ductor middleware (Vianna and Barbosa, 2014). This instances may represent people, that generate contexts from smartphone activities, or places, that generate contexts from users visitation, resource sharing or location related status (e.g. temperature or air humidity). *Context Acquisition Agent* instances may impersonate U'Ductor's users as a mean to collect context data of user's activities on different applications. For example, a Context Acquisition Agent may be authorized to grab the Twitter activity generated by its user, which can be a like or re-tweet on others tweet. Personal Node and Context Acquisition Agent store the collected context data in a *Context Aggregator*. *Network Formation Agent* instances use contexts data,

Figure 3: Influence Notification and Resource Suggestion Dynamics



like contacts, phone calls, visited locations or any other relevant information received from the Context Aggregator to form social networks which are stored by *Social Network* storage component.

Different models to predict influence between nodes exist. So, distinct instances of *Model Manager* will co-exist, aiming to discover influences of nodes by testing different models with data from context history, profiles and social network. The findings of Model Manager are then stored in the *Models* data storage component to be used later to infer influence on nodes. Finally, *Profile Creator* instances are responsible for creating summarizations of users' context histories. For example, this summarization can indicate the engagement of users' in a particular treatment or care plan. Profile information are stored in *Profile* data storage component and may be useful to the creation of new models of causal influence.

3.2 Influence Notification and Resource Suggestion Dynamics

Figure 3 shows a communication diagram where is expressed the participants and dynamics of the General Model's activities *Check New Resources* and *Infer Causal Influence between Nodes* (Figure 1). The interaction of *Influence Advisor* and *Resource Recommender* with others components are very similar. Both select the most appropriate model for their tasks in Models data storage. After the selection of the model, a request for execution is made to some instance of a *Model Executor*. These instances of Model Executor run the requested model using data from Context Aggregator, Profiles and Social Network, according to the parameters of the request.

After receiving the result from a *Model Executor*, Influence Advisor and Resource Recommender might interpret that result and execute further processing in order to send to Personal Nodes the influence that they exercise on others nodes and to recommend new beneficial health resources. In particular Resource Recommender may want to *clone social network graphs* in order to simulate new connections and infer its outcomes.

4 Evaluation

As way to demonstrate the applicability of the proposed model in the prevention of non-communicable diseases, we developed MyUDuctor, a mobile and online assistant for diets, weight management and physical activity practice needed to prevent and control risk factors for chronic non-communicable diseases. Like any other assistants, it allowed scheduling and recording of care activities, as well as allowing the user to visualize the progress of their care. However, different from the existing care applications, MyUDuctor collected, in social networks, messages related to the practice of physical activities and healthy eating. Such messages were presented to users as a form of social support, which is recognized as a motivational factor for reinforcing user engagement in their care activities.

The next sections explain the existing features of MyUDuctor and the process of recommending messages related to the prevention of non-communicable diseases.

4.1 MyUDuctor, a Health Assistant Application

MyUDuctor was publicly available at https://app1.uductor.com. To access the application, the user should have a Google account. This restriction was made to ensure the authenticity of the user's e-mail address since some of the communications the application were made through electronic messages.

The first time the users authenticated, the application displayed the free and informed consent form. In this form, the user could also configure the notifications receiving permissions and access to location data. The use of the application was only allowed after the user checked the option "I have read and I accept the terms and conditions set forth above" and press the "I accept" button. In this way, the free and informed consent term was accepted electronically and online, allowing users from different locations to participate in the experiment. A copy of the informed consent form signed by the person in charge of the research was sent by e-mail to the users after the acceptance of the term in the application.

After accepting the informed consent form, users were directed to the main application screen (Figure 4). This screen described all the features in the application, as well as provided links so that users could access these actions. Optionally users could access these same features in the options menu or by the

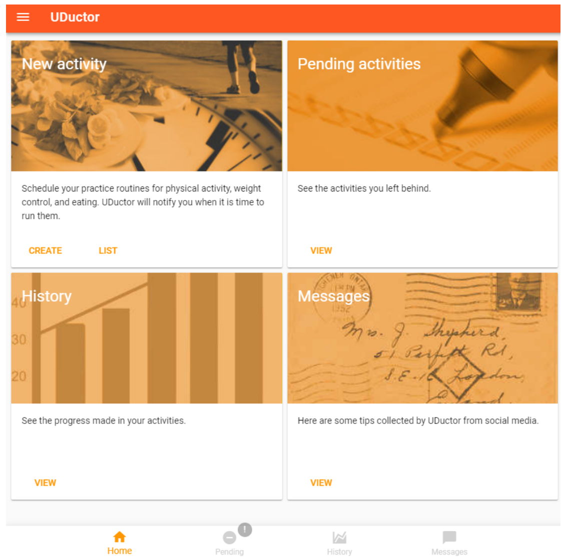


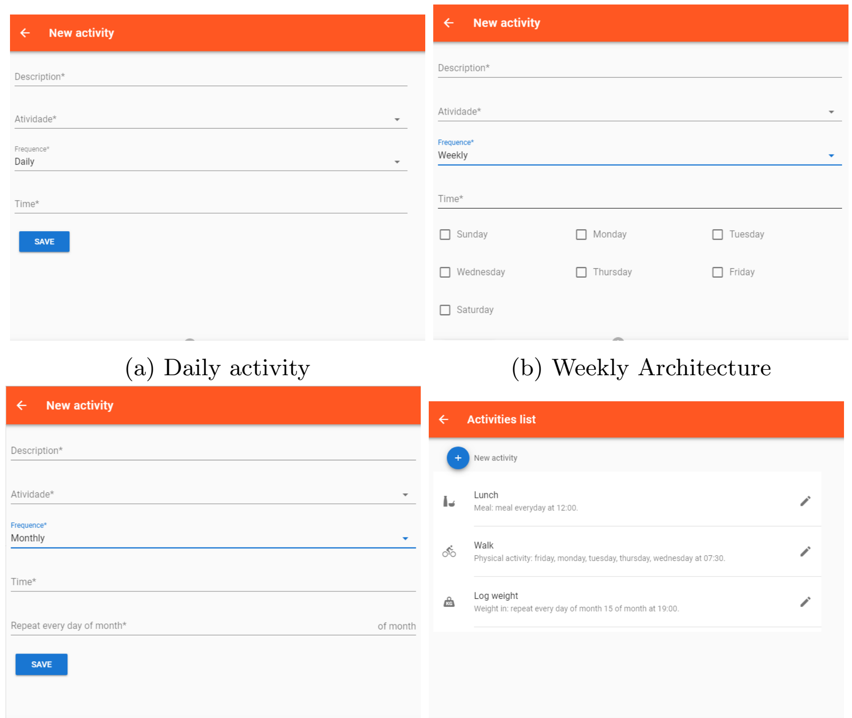
Figure 4: Application main screen

shortcut bar. The application provided five main features: *New Activity*, *Activity List*, *Pending Activities*, *History*, and *Messages*.

The "New activity" feature allowed the users to define the recurrence with which they would be advised of the need to carry out their activities. There were three types of possible activities, all related to the prevention of risks of noncommunicable diseases: *Physical activity*, *Meal*, and *Weight*. Users could configure activities to be performed daily in a certain hour (Figure 5a), weekly with a repetition rate per day of the week (Figure 5b), or monthly repetition with a repetition rate per day of the month (Figure 5c). In turn, the "Activity List" feature allowed the users to edit the recurrence of previously registered activities (Figure 5d).

The users received reminders for those activities that they had scheduled. Reminders for activities that the user was required to perform were emailed to them. Optionally, users were able to receive notifications via smartphone as long as the permission to receive notifications had been accepted by the users.

Activities that the user did not register appeared in the "Pending Activities" action (Figure 5d). When users clicked on any items in the pending activities list, the application displayed a report form according to the type of activity. The "Physical activity report" allowed the users to record what types of activity they performed, the pace of these activities, and for how long time the activities were performed (Figure 6b). For example, in the same report the user could indicate that he walked for 20 minutes at a moderate pace and ran for 10 minutes at a



(a) Daily activity (b) Weekly Architecture

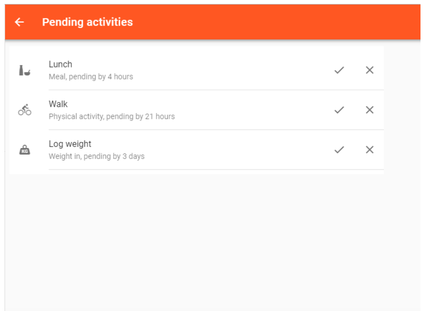
(c) Monthly monthly (d) Activities list

Figure 5: Activities editing

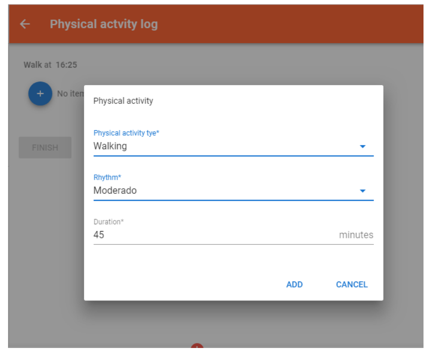
low pace.

The “Weight Report” allowed the users to enter their height and weight (Figure 6c), in this way it was possible to calculate the user’s minimum and maximum weight limits (WHO, 2018a). The “Meal Report” allowed the users to enter the portions that they consumed in the meal for each food category (Figure 6d). When inserting a food portion, the application indicated the appropriate number of portions per day and presented some portion equivalences for some types of foods according to the one proposed by Philippi et al. (1999).

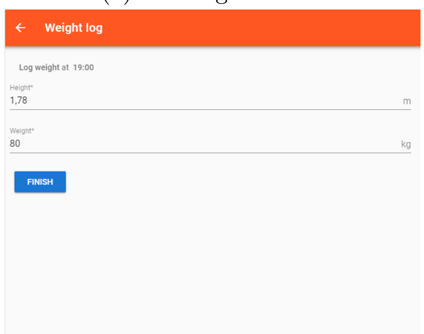
The “History” feature allowed the users to graphically view records made for each type of activity in a period. The history of physical activity (Figure 7a) indicated the activity summary performed by the user and the green-time recommended activity time for adults by (WHO, 2018b). The weight history (Figure 7b) presented, in addition to the user’s weight records, the minimum and maximum limits according to their height (WHO, 2018a). The meal history (Figure 7c) presented the summary of portions consumed by the user by type and the recommended amount for the same period, as proposed by Philippi et al.



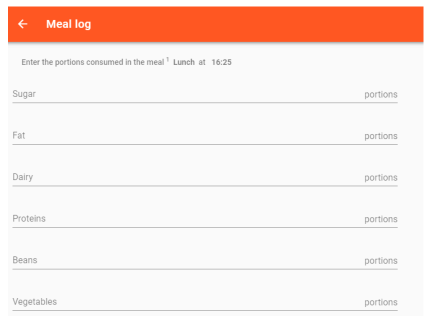
(a) Pending activities



(b) Pending physical activity log



(c) Pending weight log



(d) Pending meal log

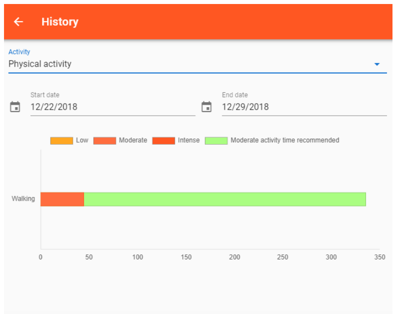
Figure 6: Pending activities

(1999).

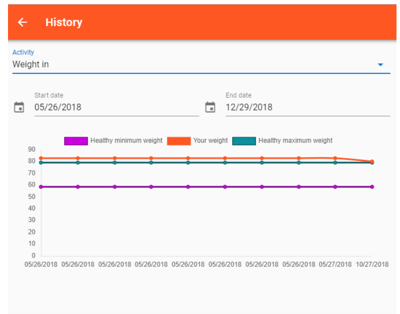
The application notified its users whenever a new message relevant to the prevention of chronic disease risk factors was identified (Figure 22). The list of recommended messages could be accessed by the user through the “Messages” action (Figure 8). Users had the possibility to ”like” or go to the source of each message received.

4.2 Messages Recommendation and Rank from Twitter’s Health Profiles

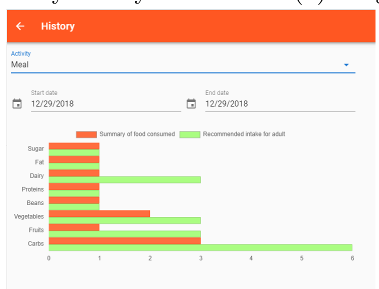
To recommend the messages related to the practice of physical activity, healthy eating, and weight control, it was necessary, firstly, to identify profiles, on the social network Twitter, that publish these types of messages. First, a seed profile was defined to be examined. To do so, the profile of the ministry of health (@minsaude) was chosen. Then a review of the messages sent by the profile related to healthy eating and physical activity was reviewed. If the related



(a) Physical activity history



(b) Weight history



(c) Meal history

Figure 7: History

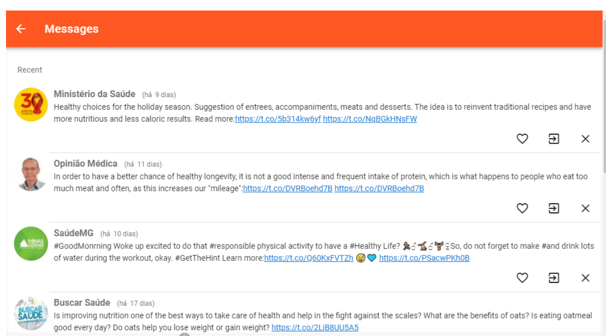


Figure 8: Messages

message had hashtags, these hashtags were used to search for Twitter messages to identify more related profiles. In the end, the following profiles were selected: @BuscarSaude, @saudavelebarato, @realfoodbrasil, @rederms, @saudavelcomida, @BlogSaudeBetter, @WorldBoaForma, @fitcomdaniele, @CamilaGramelick, @DetoxReceitas, @opiniaomedica, @juntoemisturadi, @belagil, @SES_RS, @SaudeMG, and @minsaude.

All messages sent by profiles with up to two years of publication were registered in a database. In the end, 24,971 messages were collected. Of these, 4,761 were classified as, “Healthy Eating”, “Physical Activity”, “Weight Control” or “Unclassified”. To perform the classification a web page was made available. The classified messages feed an artificial intelligence algorithm that uses them to detect new messages related to the practice of physical activity, healthy eating, and weight control has been trained. The algorithm used machine learning techniques and reached an overall accuracy of 90.68% in message classification.

A profile monitor agent was notified whenever one of the profiles sent a new message. These messages were then forwarded to a specific agent, which verified whether the messages were related to the practice of physical activity, healthy eating, and weight control. If the messages were related to one of those topics these were then kept for further quality analysis by the researcher in charge.

A rank of twitter care profiles was publicly available on the web at https://app1.uductor.com/rank. The monitored twitter profiles were notified about the rank in order to encourage them to improve the posting of non-communicable diseases prevention-related messages. The score of each profile took into account a Bernoulli distribution (Goyal et al., 2010) of users' engagement in terms of likes, followed links and the use of application's features in a 24 hours window by the intervention users after receiving the message.

5 Results

Two experiments were run concomitantly in order to assess the engagement of the application's users and the behavior of social network profiles in regards to the posting of messages related to non-communicable diseases prevention. The methods and findings of these two experiments are presented in the following sections.

5.1 Findings about MyUDuctor usage

To asses engagement of the application's users a randomized experiment was designed. contained two variants of the application, called *Control* and *Intervention*. The health message recommendations feature was enabled on the Intervention variation and disabled on the Control variation. Users were randomly assigned to one of the variation as they registered in the application. The application was promoted by direct messages and to four different university discussion lists at the dates 10/12/2018, 10/15/2018 and 10/16/2018. A total of 45 users have registered in the application, 23 have been assigned to the Intervention version and 22 in the Control version.

Users from the Control variation had a greater usage of food and weight logging features, while the users from the Intervention group had a greater usage

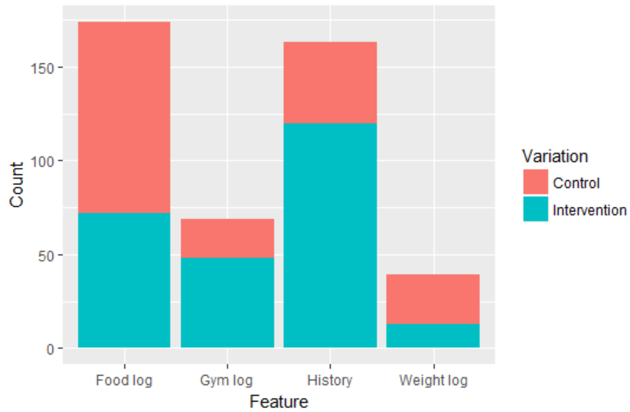


Figure 9: Total features usage

the History and gym logging features. Figure 9 shows the number of times each type of feature was accessed by the users. The Figure 10 shows the distribution of features usage through time. The Messages and Messages Interaction features were added to that plot, where its possible to observe that Intervention users have used the application for longer. Users of the intervention variation accessed the application for more days, on average 10% more.

Figure 10: Distribution of features usage through time

A robust fitting of linear model was applied to check if History, Message

Interactions, and Messages feature correlated in some way. Therefore, a strong relation was detected as demonstrates Figure 11 by the three lines that have the same trend over the distribution. Following a Wald test for multiple coefficients was applied in each feature distribution: History *p-value* $= 0.013$, *p-value* < 0.05; Message *p-value* $= 0.022$, *p-value* < 0.05; Message Interaction *p-value* $= 0.028$, *p-value* < 0.05. Hence, it was possible to reject the null hypothesis and state that Messages and Message Interactions features have possibly influenced the use of History feature by the Intervention users.

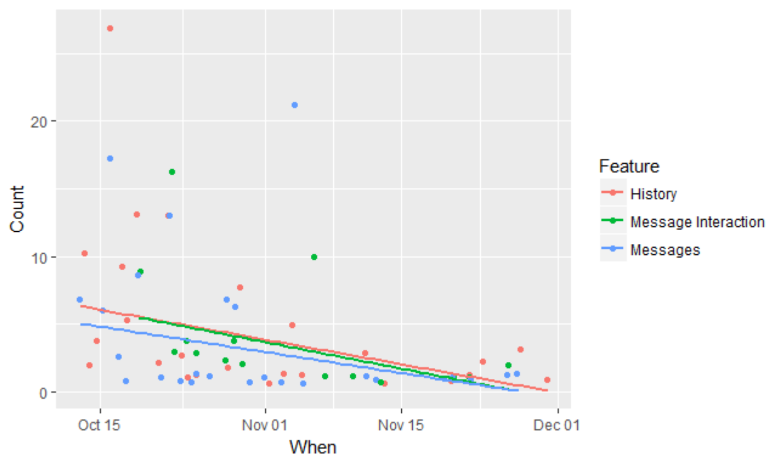


Figure 11: Distribution of History, Message Interactions, and Messages features

5.2 Twitter Profiles Behavior's Analysis

The selected Twitter profiles were monitored from 07/08/2018 to 12/01/2018. In total, 7,011 messages were processed, from that 470 were classified as non-communicable diseases prevention messages and 420 passed the quality check. Quality check was done to ensure the delivery of messages that did not stimulate the cult of body image Boepple et al. (2016); Simpson and Mazzeo (2017), so that the messages sent by the platform had, for the most part, educational bias (Smahel et al., 2017). Also, messages should be self-contained, or at least had a link pointing to more information.

By the day 10/23/2018 a contact with each monitored Twitter profile was made through direct messaging. The message presented the My UDuctor application and had a link pointing to the Twitter's Health Profiles Rank. The profiles @opiniaomedica and @BuscarSaude accessed the rank once, as the others profiles did not accessed the rank. Figure 12 presents the distribution non-communicable

Figure 12: Distribution of the sending of non-communicable diseases prevention message by the monitored Twitter profiles

diseases prevention messages sent by the monitored Twitter profiles. The vertical line indicates the moment when the profiles were notified about the application, and red dots represent messages that did not pass the quality check, while the blue dots did.

A causal inference with Bayesian structural time-series model test (Brodersen et al., 2015) was made to check if the contact made had an effect in the tweeting behavior of Twitters' profile. *Table 2* summarizes the results of the test. In general, tests results were not statistically significant and could not have meaningful interpretations. However, two profiles were exceptions and they are highlighted in Table 2. It seems that contact did a positive effect, in the profiles @juntoemisturadi e @opiniaomedica. It is also important to notice that the profile @opiniaomedica had an improvement in the quality of messages after the contact was made, as shown in Figure 12.

6 Conclusions

Prevention of non-communicable diseases is a global concern as these types of diseases account for a significant part of global deaths. The current model of care can no longer cope efficiently with the challenges of this century, hence technology might provide continuous monitoring, access to real-time information,

Profile	Before Intervention			After Intervention			Causal Inference Test	
	Messages	Daily mean	Standard deviation	Messages	Daily mean	Standard deviation	p	Alpha
BlogSaudeMelhor	72	0,67	0,71	17	0,44	0,55	0,06	0,05
BuscarSaude	121	1,13	0,80	43	1,10	0,72	0,42	0,05
CamilaGramelick	0	0,00	0,00	1	0,03	0,16	0,00	0,00
DetoxReceitas	16	0,15	0,41	8	0,21	0,47	0,25	0,05
juntoemisturadi	1	0,01	0,10	3	0,08	0,35	0,00	0,05
minsaude	48	0,45	0,83	18	0,46	0,85	0,48	0,05
MundoBoaForma	57	0,53	0,78	20	0,51	0,76	0,49	0,05
opiniaomedica	9	0,08	0,28	7	0,18	0,45	0,05	0,05
realfoodbrasil	3	0,03	0,17	2	0,05	0,22	0,30	0,05
rederms	5	0,05	0,21	1	0,03	0,16	0,36	0,05

Table 2: Causal inference test

communication with health professionals, support in disease management, and fostering social support.

This paper presented the Pompilos model, that aims to improve computer aided social support by suggesting beneficial health resources and revealing influence on the health of others for fostering better health behaviors in social relations. The presented model is also able to integrate the ever growing amount of computational devices and data for improvement of social support

For evaluating the model a mobile and online assistant for diets, weight management, and physical activity practice was developed and tested by 45 users for one month and a half. Users' experience was augmented with the receiving of non-communicable diseases prevention messages from monitored Twitter's profiles. This feature correlated in an improvement of the applications's History feature usage, suggesting that users were more concerned in following their health behavior. Besides that, the monitored Twitter profile behavior's were analyzed and seems that at least for one profile the awareness of social influence has performed a positive effect. However, this evidence is small and will be addressed in future works.

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