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Asensio-Cuesta, S.; Blanes-Selva, V.; Conejero, JA.; Portolés, M.; Garcia-Gomez, JM. (2022). A user-centered chatbot to identify and interconnect individual, social and environmental risk factors related to overweight and obesity. *Informatics for Health and Social Care*. 47(1):38-52. <https://doi.org/10.1080/17538157.2021.1923501>



The final publication is available at

<https://doi.org/10.1080/17538157.2021.1923501>

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A user-centered chatbot to identify and interconnect individual, social and environmental risk factors related to overweight and obesity

Article

A chatbot to identify and interconnect individual, social and environmental risk factors related to overweight and obesity

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Abstract

Objective: To assess the feasibility of using a user-centered chatbot for collecting linked data to study overweight and obesity causes in a target population.

Participants: In total 980 people participated in the feasibility study organized in three studies: (1) within a group of university students (88 participants), (2) in a small town (422 participants), and (3) within a university community (470 participants).

Methods: We gathered self-reported data through the Wakamola chatbot regarding participants diet, physical activity, social network, living area, obesity-associated diseases and sociodemographic data. For each study, we calculated the mean Body Mass Index (BMI) and number of people in each BMI level. Also, we defined and calculated scores (1-100 scale) regarding global health, BMI, alimentation, physical activity and social network. Moreover, we graphically represented obesity risk for living areas and the social network with nodes colored by BMI.

Results: Students group results: Mean BMI 21.37 (SD 2.57) (normal weight), 8 people underweight, 5 overweight, 0 obesity, global health status 78.21, alimentation 63.64,

physical activity 65.08 and social 26.54, 3 areas with mean BMI level of obesity, 17 with overweight level. Small town's study results: Mean BMI 25.66 (SD 4.29) (overweight), 2 people underweight, 63 overweight, 26 obesity, global health status 69.42, alimentation 64.60, physical activity 60.61 and social 1.14, 1 area with mean BMI in normal weight; University's study results: Mean BMI 23.63 (SD 3.7) (normal weight), 22 people underweight, 86 overweight, 28 obesity, global health status 81.03, alimentation 81.84, physical activity 70.01 and social 1.47, 3 areas in obesity level, 19 in overweight level.

Conclusions: Wakamola is a health care chatbot useful to collect relevant data from populations in the risk of overweight and obesity. Besides, the chatbot provides individual self-assessment of BMI and general status regarding the style of living. Moreover, Wakamola connects users in a social network to help the study of O&O's causes from an individual, social and socio-economic perspective.

Keywords: mHealth; obesity; overweight; Chatbot; assessment; gamification; public health; Telegram; user-centered design

Introduction

Overweight and obesity (O&O) pose a severe health problem worldwide, and its solution is one of the most critical public health challenges for this century (1). The percentage of overweight people has continued to increase in the last four decades in countries such as the United States, the United Kingdom, Canada, Spain, Austria, Australia, Italy, France and Korea among others... [1]. According to the World Health Organization (WHO), in Europe, more than 50% of the population is overweight, and 20% obese (2).

The O&O is associated with individual behavioural risk factors, such as unhealthy habits, improper diet, and physical inactivity (3), but also it appears to have a social component (4). Fowler and Christakis's (5) found evidence of the "contagion" of obesity among people in close social circles. It seems that processes of O&O contagion are most common within friends and family networks, peer networks and cultural groups (6).

Currently, mobile Health (mHealth) applications are becoming an increasing platform for health-promotion among overweight and obese populations. Self-monitoring is the most common functionality, followed by physical activity support, weight assessment, healthy eating support, goal setting, motivational strategies, social support, and personalized feedback (7).

In the context of the mHealth applications, a chatbot represents an innovative approach to address challenges in the telecare and prevention domains. A Chatbot is a conversation platform that interacts with users via a chatting interface. Fadhil & Gabrielli in 2017 (8) pointed out that chatbots can increase users' engagement and self-empowerment by providing a better experience and save costs for the healthcare system. Moreover, chatbots can implement mobile app stickiness strategies to increase use (9) and emotional engagement (10).

Chatbots are gradually being adopted into the healthcare industry and are generally in the early phases of implementation. Chatbot with a health focus, for example, Florence (getflorence.co.uk), Molly (sense.ly), Lark (lark.com), Koko (itskoko.com), have recently gained interest in academia and industry with both inconclusive (11). Focusing on obesity research, Filler et al. (2017) (11) developed a text-based healthcare chatbot supporting patient and health professional teams and apply it in a preliminary randomized controlled trial on childhood obesity. Fadhil & Gabrielli (2017) (8) presented a chatbot system to promote healthy and sustainable eating behaviour as a possible application scenario for supporting primary care interventions to prevent weight gain in adults. Holmes et al. (2018) (12) described the design and development of the Weight Mentor Chatbot, a self-help motivational tool for weight loss maintenance (12). D. l'Allemand et al. (2018) designed and evaluated the feasibility of a chatbot to encourage loss of weight (13). More recently, the

Elena+ chatbot offers coaching sessions focusing on psychoeducational training and activities in the fields of COVID-19 information, physical activity, sleep, anxiety, loneliness, mental resources and diet and nutrition (14).

Moreover, chatbots can collect data from users offering a better experience than thought traditional online questionnaires. Previous studies state that chatbots can be more engaging for users than online questionnaires (15,16), users associated them with entertainment, social connections and novelty (17). Online questionnaires are routinely used in health care to collect information from patients, recent studies indicate that patients preferred a chatbot questionnaire over a web survey. Also they felt the chatbot questionnaire more rapid (18). Moreover, the chatbot surveys could result in higher-quality data (19).

Moreover, Chatbots can be integrated into multiple common social platforms such as Telegram, WhatsApp, Facebook, etc. In these platforms, chatbots can not only fetch, share or collect data but also connect users (20) creating linked data, where the data from a user is connected to the data of other users in a social network. For chatbots in the field of O&O, this capacity could support the study of the O&O social risk factors, helpful to guide obesity prevention strategies in the context of public health initiatives (21).

In this paper, we present Wakamola; a chatbot developed to collect linked data for identifying overweight and obesity causes in population networks. Wakamola also allows user's self-assessment of obesity risk according to their lifestyle. Moreover, as part of Wakamola, we show the web tool to graphically represent the results from collected data as a social network, showing the Body Mass Index (BMI) or global status from lifestyle in the network nodes. The results of three studies are reported also compared to validate the feasibility of Wakamola to collect data to study obesity and overweight risk factors at individual and social network levels.

2. Materials and Methods

2.1. Ethics

Ethical approval was obtained for this study from the Ethical Committee of the Universitat Politècnica de València (UPV, Ethical Code: P7_12_11_2018).

2.2. Hypothesis

Our hypothesis was that Wakamola was a feasible tool for collecting linked data to study overweight and obesity causes in a target population.

2.3. Selection of Participants and Study Design

We started the feasibility study by conducting an assisted presential study among a group of university students. Then we performed two additional studies targeting two different populations, the first one in a small town and the second in a university community. Thus, up to the present we have carried out three studies with Wakamola, first one with 88 students with a data collection duration of 2 hours with face-to-face support, the second study coincided with the launch of the chatbot that took place in a small town in València (Spain) named Tavernes de la Valldigna (Tavernes) with 422 participants with data collection in 1 month, and third in the UPV (Universitat Politècnica de València) community with 470 participants with data collection for seven days.

In the group of university students, participants were recruited face to face from a Design Engineering School. To recruit participants in the local study (Tavernes) a call to participation was published through the city council press and on its social networks locally. However, after this, the Wakamola's launch had repercussion in general press, radio, tv and webs. Thus, since the chatbot was available in Telegram to everyone who connected a

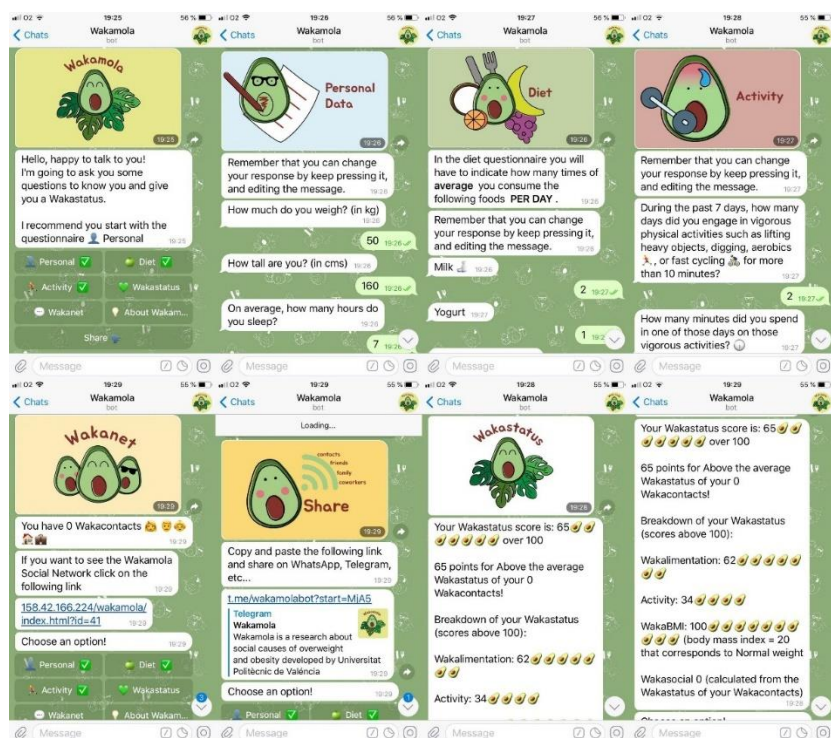
significant number of participants was registered from outside the town. At the UPV study, the call for participation was broadcasted by email to the university community by the Vice-Rectorate for Social Responsibility and Cooperation, and the Vice-rectorate for Campuses and Sustainability, with the support of the Network of Healthy Universities to which the UPV belongs. The research was briefly explained in the email and accompanied by a link to a tutorial video called “Wakamola in 10 steps” that reached 331 views (22), and to the Wakamola website (23). All participants, 18 years and older (Adult, Older Adult), all sexes that completed the questionnaire, were included in the study.

2.4. Instruments and Variables

Wakamola has been developed under a user-centered design approach by a multidisciplinary team including software developers, graphical designers, and clinicians (24). Wakamola chatbot simulates a conversation with the user about diet, physical activity, potential diseases, demographics, and social network. This conversation is structured in 6 sections (see Figure 1): Personal, Diet, Activity, Status (Wakastatus), Social net (Wakanet), Share and an About the Wakamola’s Project. Moreover, Wakamola includes a web tool viewer that shows the network and basic statistics of the sample from collected data graphically. Wakamola has been implemented as a multi-language chatbot, including Spanish, English and Catalan.

The Wakamola chatbot uses a colloquial tone to recall human-to-human interaction (25) and improve users emotional connection (15). Moreover, it includes emoji in the messages that contribute to a more realistic and friendly conversation (8) (see Figure 1) . In Tables 1, 2 and 3 in the Supplementary Material, the Wakamola questions about personal, diet and physical activity are shown.

Figure 1. Wakamola screenshots of Personal, Diet, Activity, Wakastatus and Wakanet sections.



In the Personal section, there are 16 questions about weight, height, gender, age, level of education, marital status, how many people are at home, main activity (i.e. study/work), zip code, sleep hours and cigarettes consuming. Besides, the chatbot asks about the existence of a previous diagnosis of hypertension, diabetes, high cholesterol, or cardiovascular disease. Clinicians have defined these questions for further data analysis regarding O&O factors.

The Diet Section has been adapted from the “Short questionnaire on frequency of dietary intake” (26). This section includes 51 questions regarding food types and consuming frequencies. Diet questions responses are scored based on the “Spanish diet quality according to the healthy eating index” (27) and the Mediterranean Diet Pyramid (28).

The Activity section includes seven questions adapted and scored according to the short form of the International Physical Activity Questionnaire (IPAQ) (29) (Eq. 2), normalized between 0 and 100.

$$\text{IPAQ} = \text{Intensity (METs)} * \text{Frequency (days / week)} * \text{Duration (minutes / day)} \text{ Eq. (2)}$$

In the IPAQ, the physical activity is measured in METs-min-week, for example for walking activity the intensity is 3.3 METs, for moderate physical activity intensity is 4 METs and for vigorous physical activity intensity is 8 METs. There are three 3 categories of the activity index: (1) Low activity: user do not register physical activity or it registers but it does not reach the medium and high categories; (2) Medium activity: physical activity that reaches a record of 600 METs-min/week (e.g. walking: 3.3 Mets x 30 minutes x 7 days = 693 METs); (3) High activity: physical activity that accumulate 1,500 METs-min-week.

In the Wakastatus section, a global status score named Wakastatus is showed to the user; it is calculated from collected data about diet, physical activity, BMI and social network.

The Wakastatus score is the sum of 4 scores normalized between 0 and 100, with the best value being 100 (Wakaalimention, Wakaactivity, WakaBMI, Wakasocial). The Wakalimention score is based on food consumption collected in the diet section, and it is an indicator that measures the quality of the diet as a determinant of nutritional health (27). In total, 51 items (foods) (26) are classified according to the categories of the Healthy Eating Index (IASE) (27). The Wakalimention is the sum of the score obtained in each of the food groups, normalized between 0 and 100. Finally, the score is classified into three groups according to the “Short questionnaire on frequency of dietary intake” (26): categories: ≥ 80 points "healthy"; ≥ 50 and < 80 points "need changes"; < 50 points "unhealthy". The Wakactivity score corresponds to the International Physical Activity Questionnaire (IPAQ)

result (29), normalized between 0 and 100. The WakaBMI score is obtained by calculating the Body Mass Index (30) and assigning a score between 0 and 100. We calculate the Body Mass Index (BMI) score from the personal data section (weight and stature), assigning 100 points for Normal weight 18.5–24.9 kg/m²; 75 point for Overweight 25–29.9 kg/m² or Underweight <18.5 kg/m² ; 50 points for Obesity (Class 1) 30–34.9 kg/m² ; 25 point if Obesity (Class 2) 35–39.9 kg/m² ; 0 points Extreme obesity (Class 3) ≥ 40 kg/m² .

The Wakasocial score is a value between 0 and 100 that is calculated from the Wakastatus of the user's social network and the number of contacts. For example, to reach a score of 10, a user needs 32 friends and be 5 points below the average of her/his Wakastatus.

In the Wakanet section, the number of users' contact is shown. Moreover, the user can access the Wakamola's graphical viewer web tool through a link (Figure 2). When the user accesses the viewer tool, a social network graph can be shown coloured according to BMI or Wakastatus. The user's node is highlighted, along with information about BMI or Wakastatus. Also, a message is displayed to the user indicating the position in the ranking of Wakastatus scores of the shown social network; if it is in the top 10, it is showing a congratulatory message. Besides, the option "communities" shows the nodes grouped into communities within the social network based on Louvain algorithm (31). Finally, the tool displays below the graph a table with statistics such as the sample size, and the Wakamola's scores that configured the Wakastatus.

Finally, the Share section shows a message with the user's number of contacts, and an invitation message with a link to start the chatbot and a brief description. When another user opens the invitation's link and starts the chatbot, users become connected. This process creates the social network in Wakamola and enables its spread between users and communities.

Figure 2. Wakamola's social network graphical viewer screenshot from data collected from a group of university students.



2.5. Data Collection

In the three studies, the chatbot asked participants about the previous week's diet (food frequency), physical activity, sitting and sleeping time, among other activities. Then, Wakamola scores are calculated. Moreover, the chatbot gathered the connection time and the frequency of connections per participant.

2.6. Data Analysis

For the statistical analysis, we used the Statgraphics Centurion XVII software. The Tableau software (version 2020.1) was applied to obtain the distribution of mean BMI by zip codes was obtained. Finally, for the analysis of the social network, the Wakamola's graphical viewer web tool was used.

3. Results

In total 980 people started the Wakamola chatbot in the three studies of which 670 participants answered all questions were included in the study, 74 participants of 88 in the students' group, 197 of 422 in the local study and 399 of 470 in the UPV study (up to 470).

Table 1 shows the BMI values obtained and the cases detected with underweight, normal weight, overweight, and obesity in the Student's group compared with the Tavernes and UPV study. Table 2 shows the Wakamola scores calculated in the three study.

Table 1. BMI values and cases detected with an underweight, normal weight, overweight and obesity in the Student's, Tavernes's and UPV's cases of study.

BMI (kg/m ²)	Students' group Total (n=74)	Tavernes' study Total (n=197)	UPV's study Total (n=399)
Mean (DS) level	21.37 (SD 2.57) normal weight	25.66 (SD 4.29) overweight	23.63 (SD 3.7) normal weight
Maximum	29.32 nearly obesity	40.40 obesity Class 2	BMI 62.42 obesity Class 3
Minimum	16.54 underweight	17.30 underweight	16.04 underweight
underweight (BMI <18.5)	8 people	2 people	22
overweight (BMI >= 25)	5 people	63 people	86
Obesity (Class 1) 30–34.9	0 people	20 people	24 people
Obesity (Class 2) 35–39.9	0 people	5 people	3 people
Extreme obesity (Class 3) ≥40	0 people	1 person	1 person

Table 2. Wakamola scores in the Student's, Tavernes's and UPV's studies.

Wakamola scores (0-100 scale)	Students' group Total (n=74)	Tavernes' study Total (n=197)	UPV's study Total (n=399)
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Status	78.21	69.42	81.03
BMI	98.31	82.87	90.77
Alimentation	63.64	64.60	81.84
Activity	65.08	60.61	70.01
Social	26.54	1.14	1.47

Moreover, we observed that the time of connection per user was similar in the students' group with 36.27 minutes (SD=21.52) and Tavernes study with 32.46 minutes (SD97.49), a lower in the UPV case 26.31 (SD= 69.16). The number of connections per user was 1.07 (SD=0.25) in the Student group, 1.15 (SD= 0.56) in the Tavernes study and 1.0 (SD=0.0) in the UPV study, indicating a low user engagement after the first use.

3.1. Students's group

In total, 88 students started the chatbot, but 74 students answered all questions (54 women and 20 men). The mean age was 20.7 years (DS 1.17), and the mean weight was 61.65 (SD 10.21). No participant indicated obesity-related diseases such as hypertension, diabetes, high cholesterol, cardiovascular disease. The average hours of sleep were 7.02 hours. Only 4 men and 2 women were smokers.

The food with the highest frequency of consumption (times/week) were olive oil (12,72 times/week). Tale 3 illustrates the mean number of servings per week in the Student's group, Tavernes's and UPV's studies compared to the Mediterranean Diet Foundation recommendations (28).

Table 3. Comparison of weekly food consumption (mean values) with the Mediterranean Diet Foundation recommendations (28) for the Students group, Tavernes and the UPV studies

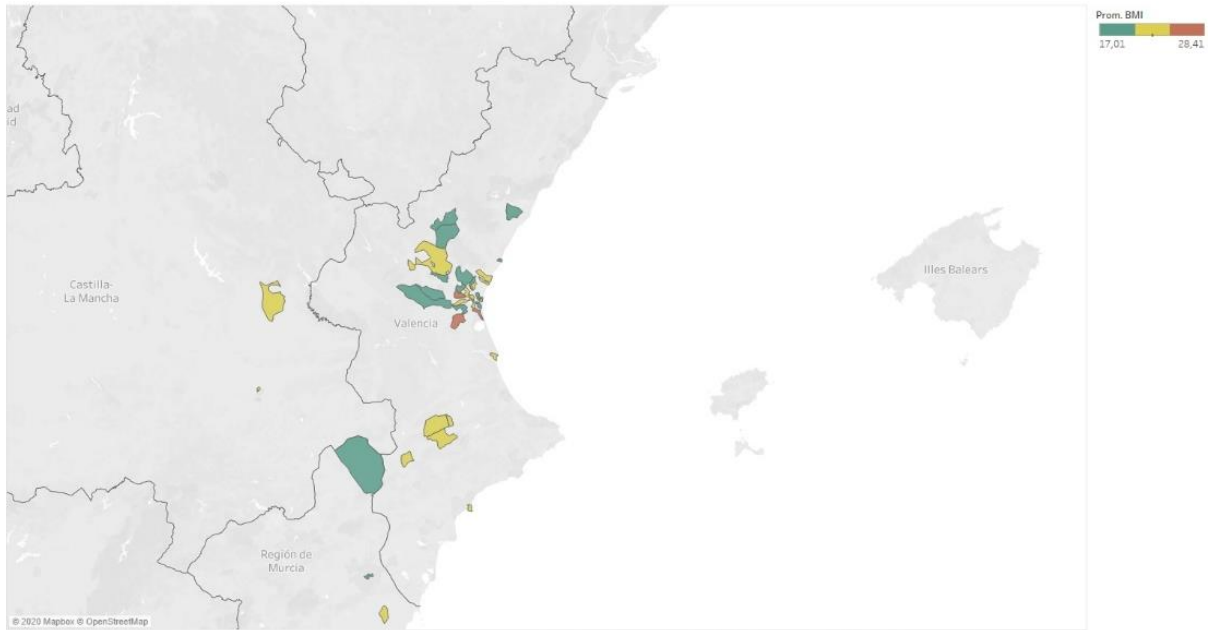
Type of food	Students group Mean Servings/week	Tavernes Mean Servings/week	UPV Mean Servings/week	Recommendations based on the Mediterranean Diet Foundation (28)
Olive oil	12,72	15,55	14,30	14 servings/week (2 servings daily, every meal)
Milk and derivatives	6,86	7,19	7,08	14 servings/week (2 servings daily)
Cereals and derivatives	5,83	5,86	6,15	7-14 servings/week (1-2 servings every meal)
Vegetables	3,17	3,21	3,51	≥14 servings/week (≥2 servings every meal)
Fruits	2,83	2,82	3,32	7-14 servings/week (1-2 servings every meal)
Nuts	2,65	2,54	2,78	7-14 servings/week (1-2 servings daily)
Meats	2,27	2,24	2,60	Poultry 2 servings/week Red meat <2 servings/week
Sausage	2,13	1,78	2,03	≥1 servings/week
Fish	3,71	2,71	3,18	≥2 servings/week
Seafood	0,54	0,45	0,64	≥2 servings weekly
Legumes	2,04	2,03	2,36	≥2 servings/week
Sweetmeats	1,22	0,89	1,16	<2 servings/week

Other oils	2,36	2,03	1,97	Undefined
French fries	1,18	0,62	0,98	Limit consumption, occasional
Alcohol drinks	0,78	0,92	0,94	Serving size based on frugality and local habits. Wine in moderation and respecting social beliefs
Butter	0,67	0,79	1,00	Limit consumption, occasional
Soft drinks with sugar	0,62	0,38	0,52	Limit consumption, occasional

The mean activity of the participants was 674.20 METs-min/week corresponding to a moderate level of activity (29).

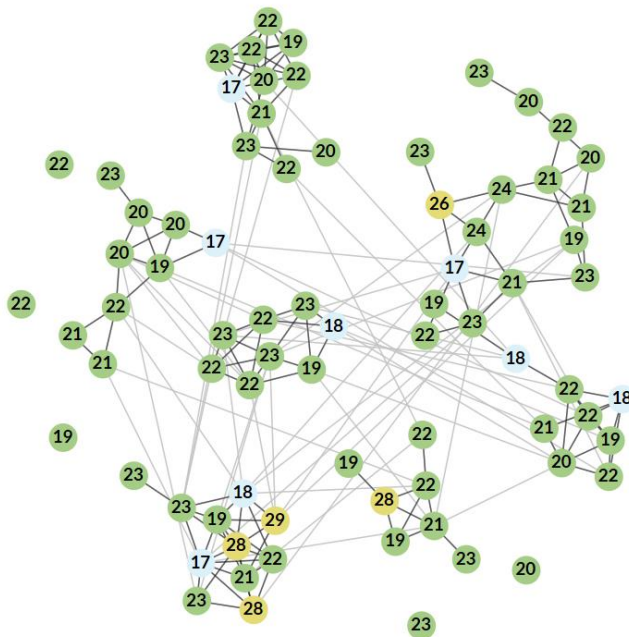
Participants were from 53 different zip codes with a mean BMI of 21.37 (DS 2.57). Figure 4 illustrates the mean BMI by zip code of the Valencian Community, coloured by weight. We found three zip codes with mean BMI level of obesity, 17 with overweight level and the rest with normal weight level according to their mean BMI.

Figure 4: The distribution of mean BMI by zip codes in the Valencian Community coloured according to weight: underweight (blue), normal (green), overweight (yellow) and obesity (red) in student's group.



We applied the online viewer tool to interpret collected data and showed it as a social network graph (32) with 74 nodes and 185 relations, and 11 communities (Figure 5).

Figure 5. The Student's group social network representation with BMI showed inside nodes, colours based on BMI: blue (underweight <18.5), green (Normal weight $18.50-24.9$), yellow (overweight ≥ 25), red (obesity ≥ 30).



3.2. Local launch study (Tavernes)

In total, 422 people started the chatbot, although only 197 answered all the sections and were included in the analysis (97 women and 99 men, 1 other). The mean age was 35.21 years (SD 10.84), mean weight was 75.21 (SD 15.93). We found 15 people with hypertension, diabetes 5 cases, high cholesterol, 35 cases, and with cardiovascular disease 7 people. The mean hours of sleep were 7.13 hours. Most of the participants were non-smokers, 29 smokers (17 men and 12 women).

The mean BMI was 25.66 (SD 4.19), the Table 1 shows BMI values obtained, and the cases detected with underweight, normal weight, overweight and obesity in the Tavernes's compared with the other studies.

The participants indicated a mean weekly consumption of olive oil of 15.55 servings,

followed by milk and derivatives (5.21), cereals and derivatives (3.84), vegetables (3.21), nuts (2.82), and fruits (2.54). They consumed 0.38 servings sugar drinks and 0.92 alcohol drinks weekly (See 1. OECD. Obesity and the Economics of Prevention. 2010. 268 p.

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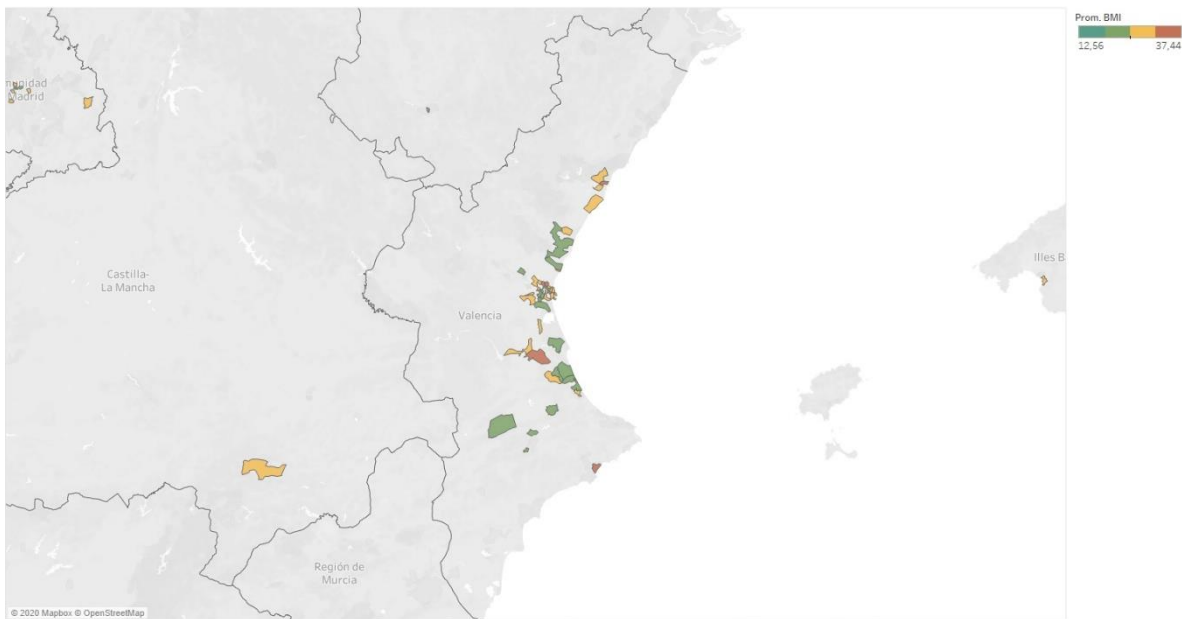
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).
The mean activity of the participants was 504.08 Mets-min/week corresponding to a low activity level (29).

Participants were from 167 different zip codes with a mean BMI of 25.66 (Ds 4.29) that indicates a normal weight. Figure 6 shows the distribution of mean BMI by zip codes in the Valencian Community coloured according to weight: underweight (blue), normal (green), overweight (yellow) and obesity (red).

From the town of Tavernes (zip code 46760) 35 people completed the entire questionnaire, with a mean BMI of 24.74 indicating normal weight. The rest of the cases corresponded mainly to postal codes of the Valencian Community. In the Valencian Community with the highest representation, five postal codes were observed with a mean BMI level corresponding to obesity, 20 with overweight levels and the rest with a normal weight level. Although there were also participants from other communities. This was due to the widespread media coverage of the study launched in the town, which caused chatbot users to spread to other locations. In Tavernes town, the main obstacle observed for participation was the unknowledge of Telegram by a large part of the population.

Figure 6. The distribution of mean BMI by zip codes in the Valencian Community coloured according to weight: underweight (blue), normal (green), overweight (yellow) and obesity (red) in local launch study (Tavernes).



With the online tool, a social network graph was built (32) with 197 nodes and 12 relations, 7 communities with at least two nodes.

3.3. UPV's study

A total of 470 participants participated in the UPV's study, of which were eliminated those who had not completed all the questions and 3 cases for showing erroneous values, leaving a total of 399 participants (183 women, 213 men, 2 others), of which 249 were students and 226 workers. With a mean age of 29.43 (DS 12.19) years, mean weight of 70.13 (DS 14.88). About diseases associated with O&O, 22 participants indicated that they had been diagnosed with hypertension, 3 diabetes, 47 high cholesterol, and 13 cardiovascular diseases. The mean hours of sleep were 7.09 hours. Most of the participants were non-smokers, 39 smokers (16 men and 23 women).

The mean BMI was 23.63 (SD 4.23), which corresponds to normal weight ($18.5 \leq \text{BMI} \leq 24.9$), the maximum BMI 62.42 (obesity type 3) and the minimum 16.04 (underweight), Table 1 shows the BMI values obtained and the cases detected with underweight, normal weight, overweight and obesity in the UPV's study compared with the other studies.

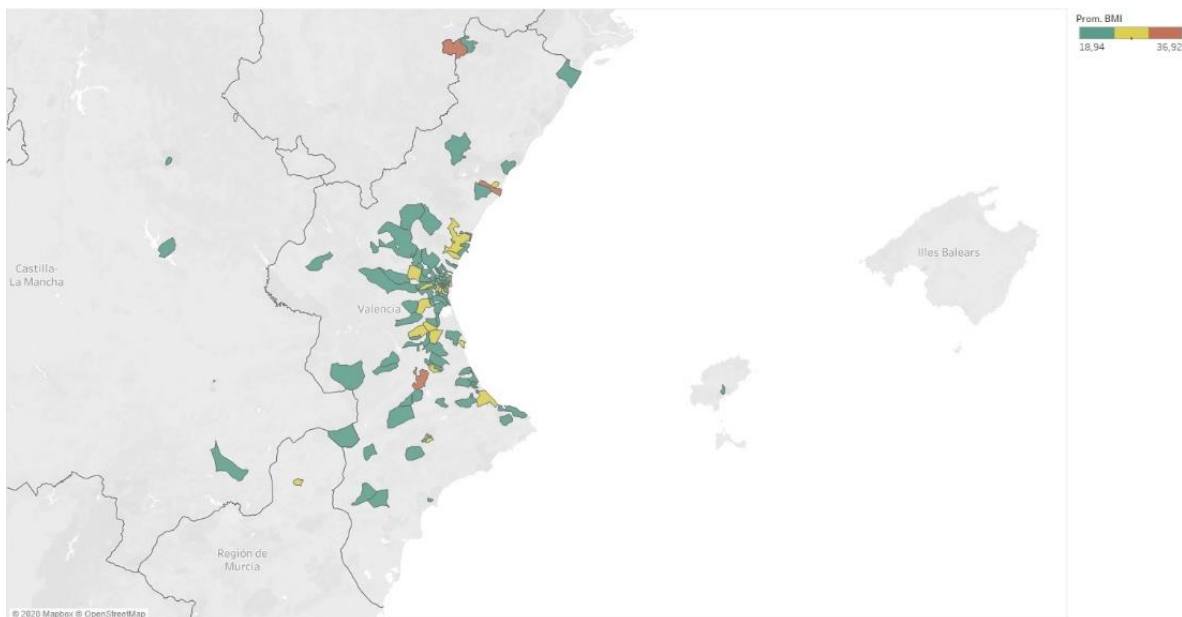
The participants indicated a mean weekly consumption of olive oil of 14.30 servings, milk and derivatives 4.70; cereals and derivatives 3.79; vegetables 3.51; nuts 3.32, fruits 2.78; 0.52 servings sugar drinks and 0.94 alcohol drinks. Table 3 illustrates the mean number of servings a food type is consumed per week in UPV's study compared to Student's and UPV's studies.

The mean activity of the participants was 775.93 METs-min./week corresponding to a moderate level of activity (29).

Participants were from 436 different zip codes with a mean BMI of 23.63 (DS 3.7) corresponding to a normal weight. Figure 7 illustrates coloured the mean BMI by zip code

of the Valencian Community, as it is the community with the largest number of postal codes of the participants. With 3 areas in obesity level and 19 in overweight level.

Figure 7. The distribution of mean BMI by zip codes in the Valencian Community coloured according to weight: underweight (blue), normal (green), overweight (yellow) and obesity (red) in UPV's study.



Applying the online tool to interpret collected data as a social network graph (32) we obtained 399 nodes, 47 relations, 11 communities with at least two nodes.

4. Discussion

Wakamola was able to collect linked data from 670 users in in the three studies successfully. Here we compare their results and discuss differences.

The mean BMI was in a normal weight level in the student's group (21.37 (DS 2.57)) and the UPV's study (23.63 (DS 3.7)), but in the overweight level in the Tavernes's study. This results could reflex the age impact in the BMI, numerous studies have reported age-related increases in body weight and fatness after young adulthood (33), the mean age was

in the students' groups 20.7 years (DS 1.17), 29.43 (Ds 12.19) in the UPV's study and 35.21 years (Ds 10.84) in the local launch study mean age.

The global health status was from higher (healthier) to lower 81.03 in the UPV's study, 78.21 in the student's group and 69.42 in the Tavernes's study. Accordingly the alimentation score indicated healthier in the UPV's study (81.84), followed by Tavernes's case (64.60) and student's (63.64) . The mean physical activity score was also higher in the UPV's (70.01) study, followed by students (65.08) and Tavernes's (60.61) study. In summary, it could be concluded that the UPV's study participants have the healthier lifestyle regarding diet and physical activity. Regarding social activity, students are much more active than the participants in the other two studies, the face-to-face session helped users to understand the sharing functionality to create the network.

From the perspective of diet habits, we observed that in the Students' and UPV's studies the diet habits are equal, that could be explained because the students are a subgroup of the UPV university community, and it could be influenced for the same social-economic environment. In the local launch study (Tavernes) the food consumption during the week habits is quite close to the other studies, only with few differences in some food types (see Table 3).

The UNESCO recognized the healthy eating pattern that is the Mediterranean Diet that has been described as a graphical pyramid to clarify its application (28,34). We note in the three studies that the most consumed food is olive oil that would correspond to the recommendation of the daily consumption in each main meal in the Mediterranean diet pyramid. The pyramid places the daily consumption of milk and derivatives in the third level, below fruit, vegetables and cereals, although in the three studies it is observed that this type of food is in the second position. The pyramid recommends less consumption of nuts than

fruit, but the consumption of nut is lightly higher than fruit in the three studies. Cheese consumption in all studies is in the seventh position, which would be according to the recommendations of the pyramid level. Finally, the consumption of meat, white fish, seafood and legumes is below milk and derivatives in the three studies, also following the recommendation of the pyramid. Moreover, in the last positions in the three studies are sweets and sugary drinks and alcohol, also following the pyramid. From the perspective of the Mediterranean diet levels, we could affirm that in the three studies the participants' diet habits approximate the recommendations, although the consumption of milk products and derivatives is higher than recommended level.

Moreover, according to the Mediterranean Diet Foundation recommendations (28) (Table 3), the weekly consumption of legumes is slightly higher than the recommended in the study of the UPV, the consumption of sausages and meat slightly exceeds the recommendation in the three cases, the consumption of fruits, nuts, vegetables, cereals, dairy products, fish, seafood is below the recommended values. The consumption of olive oil is slightly above that recommended in the UPV and Tavernes studies. The consumption of butter, alcohol, chips, sugary drinks is less than once a week, except for French fries in students that reaches 1.8 servings a week with an occasional and limited consumption recommendation.

From a public health perspective, Wakamola's food consumption results could support the detection of nutritional problems in a population, directing the population's nutritional recommendations and focusing effective intervention programs at the population level. Moreover, future research in Wakamola will include nutrition recommendations based on public health guidance for healthy eating, such as Mediterranean Diet Foundation recommendations (28), the "Food-Based Dietary Guidelines in Europe" for all countries in

the EU plus Iceland, Norway, Switzerland and the United Kingdom (35), and the “Dietary Guidelines for Americans” that provides advice on what to eat and drink to meet nutrient needs, promote health, and help prevent chronic disease (36).

From the perspective of physical activity, Wakamola has confirmed in the Students group and UPV’s studies that the mean level of activity corresponds to levels of moderate activity, but it is observed a low level of activity in the Tavernes’s study, according to the IPAQ index (29). Moreover, the hours that the participants remain seated weekly are high, being in student’s group 4.36 hours/day, 5 hours/day in local launch’s study (Tavernes) and 4.54 hours/day in UPV’s study, but more than 4 hours sitting per day is associated with a higher risk of having central obesity in men and a higher risk of overweight-obesity and overfat in women compared with those sitting less than 4 h per day (37). Regarding the sleeping hours in the three studies, the mean values are 7 hours/day that is a recommended value to a good rest in adults (38), 7.09 hours in the UPV study, 7.02 hours for students and 7.13 in the local study.

From the living areas perspective in the three studies carried out, it is possible to identify living areas (zip codes) with overweight and obesity prevalence based on the mean BMI indicator, this could focus the study of these areas with problems, to determine what factors are influencing in the overweight and obesity of the population, such as the socio-economic level, the access to green and sports areas, the presence of points of sale of fresh vegetables, and others. Besides, such identification could help to focus on measures to solve the problem of overweight and obesity, as well as in prioritizing actions for the solution and prevention.

Regarding the creation of the Wakamola’s social network in the studies, it is observed that, except for the of the students with face-to-face support during the data collection, it was

not possible to obtain a vast network and communities. That could be because users do not understand how to share Wakamola in the current technological platform. Thus, it will be necessary to review the share procedure in Wakamola improving its usability and user engagement to be able to obtain vast Wakamola's social networks. The Wakamola social network could contribute not only to the study of the social influence on diet and physical activity habits but also for the users to compare themselves with the others in their population and community.

From the analysis of the connection time and the number of connections per user, we observed that the time spent on self-assessment was close to half an hour in the Students' group (36.27 minutes, SD=21.52), Tavernes (32.46 minutes, SD= 97.49), and UPV (26.31 minutes, SD= 69.16). In the Students' group (presential assisted session), we observed that the connection time in a Wakamola was mainly explained due to the high number of questions in the diet section (51 items) and the difficulty of sharing process to create the social network. Standard deviation in Tavernes and UPV is greater than in the presential and more controlled sessions. This could be explained by how the times are calculated; since there is no session, we used the time logs on the user messages and compared the earlier and the later message on the same day. This creates the possibility some users start using the bot, take a long break, and continue a few hours later. Moreover, the number of connections in the three studies indicated that almost all users used the Wakamola chatbot only once for their status evaluation. Still, they didn't use it as a periodic monitoring tool. Accordingly, the Wakamola future improvements need to focus on enabling the user to choose to use Wakamola on the web or multiple social platforms, reducing required user input in the diet section, increasing the engagement through user's monitoring graphs, personalized recommendations about diet and physical activity, general information about healthy habits,

and gamification strategies such as awards, rankings, and goals and improve the logging of the user activity through concepts like session and real usage time.

Moreover, the actual Wakamola is reactive and responds only after the user connection. In the future, to trigger user's interaction, we plan to send personalized messages for reminding user's reevaluation, asking for goals, or providing recommendations, among others. Finally, to spread Wakamola chatbot to new users and communities, we plan to intensify the Wakamola presence in social media (39,40), forums, congresses and courses regarding healthy lifestyle, nutrition and sports.

The main strength of this study is the use of a chatbot as novel technique to interact with people for obesity risk self-assessment and for collecting data to study eating habits (food frequency), physical activity, sitting and sleep time. However, we are aware of the limitations of this preliminary studies, the cohort might not be representative of the target populations due to selection bias and sample size. Moreover, Wakamola is only available for Telegram app users; for these reasons, our results are not necessarily representative of the general populations under study.

5. Conclusions

The results obtained in this study highlight the feasibility of using Wakamola chatbot to collect linked data from populations to study the influence and interconnection of personal characteristics, diet, physical activity, social relations and the socio-economic environment in the prevalence of O&O. Besides, Wakamola as an obesity risk self-assessment tool, can inform users about overweight and obesity risk, helping to raise awareness about the problem.

Wakamola provides results that would help developing practical actions that contribute to

solving the serious public health problem of overweight and obesity.

Based on the principal limit identified in the discussion, our next steps are the development of Wakamola as a multiplatform chatbot to extend the studies to large populations and controlled trials, improving the network creation procedure, and include personalized recommendations.

Author Contributions: Funding acquisition, J.M.G.-G.; investigation, S.A.-C., J.A.C., J.M.G.-G.; software, V.-B, M.-P; supervision, S.A.-C. and J.M.G.-G.; writing—original draft, S.A.-C., J.A.C., J.M.G.-G. and V.-B.

Funding: Funding for this study was provided by the authors' various departments, and partially by the Crowd Health Project (Collective Wisdom Driving Public Health Policies (727560)).

Acknowledgements: The authors gratefully acknowledge the Tavernes de la Valldigna (Spain) city council, and the UPV's Vice-Rectorate for Social Responsibility and Cooperation, and the Vice-rectorate for Campuses and Sustainability for their support to this study. We also acknowledge Shabbir Syed-Abdul and Yu-Chuan (Jack) Li from the International Center for Health Information Technology (ICHIT) at Taipei Medical University for their support associated with the Crowd Health Project.

Conflicts of Interest: The authors declare no conflict of interest.

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