Analysis of the Big-Five personality traits in the Chatbot “UC - Paraguay”

Alethia Hume, Luca Cernuzzi, José Luis Zarza
Universidad Católica “Nuestra Señora de la Asunción”
Deparatamento de Electrónica e Informática (DEI)
Asunción, Paraguay
ORCID: 0000-0002-1874-1419 / 0000-0001-7803-1067 / 0000-0003-0069-4287

and

Ivano Bison
University of Trento
Dipartimento di Sociologia e Ricerca Sociale
Trento, Italy
ORCID: 0000-0002-9645-8627

and

Daniel Gatica-Perez
Ecole Polytechnique Federale de Lausanne (EPFL)
IDIAP Research Institute
Martigny, Switzerland
gatica@idiap.ch

Abstract

In the context of the project “WeNet: Internet of us”, this paper analyzes a possible relationship between the “Big-five” personality traits (Extraversion, Agreeableness, Conscientiousness, Emotional Stability and Openness to Experience) and the experience of social interaction mediated by a Chatbot for a community of students at the Universidad Católica “Nuestra Señora de la Asunción”. The personality data comes from self-reports of users provided through questionnaires. In particular, we analyzed: i) the general experience at the participants level, comparing the Big-five traits of the biggest group of survey participants (i.e., 777 students) with regard to the more reduced group of the Chatbot participants; ii) the participation and the time level; and, iii) the questions/answers level analysis as an indicator of the participation in social interactions. Finally, we introduce a preliminary discussion about the evolution of the network of interaction according to some traits of the Big-five. The results suggest that the personality traits are to some extent correlated with: the active participation (Agreeableness and Openess); the type of contribution for help and answers (Agreeableness, Neuroticism and Openness); and, the network of interactions evolution over time (Openness and Neuroticism), although further experiences are required to verify the preliminary trends.

Keywords: Diversity, Social Interaction, Personality, Big-Five, Chatbot

1 Introduction

Internet has grown for more than two decades as the main platform for virtual social interaction [1, 2]. This has been further accentuated since March 2020[1], when the World Health Organization has declared a global

[1] `https://www.itu.int/en/ITU-D/Statistics/Pages/facts/default.aspx`

pandemic due to the disease COVID-19 [3, 4]. Most countries have adopted mitigation measures to reduce potential transmission, including restrictions on mobility and face-to-face social events. Thus, virtual social interaction, mediated by technology, has been growing exponentially since 2020.

There are many technological platforms that support virtual communication and social interaction. And they can be used in a wide variety of ways. In particular, this study is part of the interdisciplinary project "WeNet: Internet of us" (https://www.we-net.eu), funded by the European Union (EU). The basic idea of WeNet is to create a digital platform that matches users who want to solve complex tasks or answer questions by leveraging the diversity of their communities. The matching is based on profile data and self-learning algorithms.

The concept of diversity is quite broad and can have several connotations. Some of these, which may be relevant to social interaction in order to help solve problems or respond to needs, are related to the different competence that people may possess, different habits and daily routines, different personalities, and so on. So, for example, if a student needs help to consolidate his or her Mathematics knowledge, he or she would look for someone with such competencies. Possibly used to having lunch at the university with his classmates, if he were interested in having vegetarian food for lunch, possibly in the company of a vegetarian, he would look for people with such characteristics even if they are not his classmates. If he or she is looking for a more convenient and comfortable means of travel to the university, he or she could look for other students with vehicles that travel a similar route to his or her own and at convenient schedules. Likewise, he or she might not want to share a ride with a driver who only listens to certain musical genres or who is too talkative. In short, we could go on and on with examples where diversity is an opportunity to address particular needs.

Within the WeNet project, two pilot experiences have been carried out simultaneously at the University of Trento (Italy), the National University of Mongolia, the University of Aalborg (Denmark), the Universidad Católica "Nuestra Señora de la Asunción" (Paraguay), the London School of Economics (United Kingdom) and the University of Jilin (China). The first experience has been focused on a survey to begin to analyze and model diversity among students, based on social practices - understood as the set of their competence, knowledge and motivations. The second one has been focused on the use of a chatbot to ask questions and requests for help.

In particular, one of the survey dimensions of the first experience focused on personality traits. For this purpose, the widely used model known as "Big-five" [5] was adopted, as it characterizes personality according to five major traits: Extraversion, Agreeableness, Conscientiousness, Emotional stability, and Openness to experience. On the other hand, the second experience has been mostly focused on social interaction mediated by a Chatbot. The main objective of this study is to analyze the role that personality, modeled according to the five traits, plays in social interaction in the context of an experience such as the use of a chatbot.

Specifically, data obtained in Paraguay with a group of students from the Universidad Católica "Nuestra Señora de la Asunción" are analyzed. In particular, it is intended to answer the research question: Through experience, what kind of correlation is it possible to identify between the person's personality profile and the diversity of questions and answers?

This study is an extension of the paper presented at CLEI2021 [6]. Indeed, we improved the section 2 including some notes on the Big-five and discussing experimental results of each trait with regard to the use of internet technologies. Moreover, we considerably improve the analysis of results in different aspects. First, we analyzed the general experience at the participants level, comparing the Big-five traits of the biggest group of survey participants (i,.e., 777 students) with regard to the more reduced group of the chatbot participants (see Section 4.1). Second, we reshape the analysis of participation and the time level (see Section 4.2). Third, we significantly improved the questions/answers level analysis (see Section 4.4), specifically taking into account the length of questions and answers. Finally, we introduce a preliminary discussion about the evolution over time of the network of interaction according to some traits of the Big-five (see Section 4.5). Such analysis requires of further experiences to verify the preliminary trends. Accordingly, we have improved the discussion (see Section 4.6).

The rest of the paper is structured as follows. Section 2 presents the background on the Big-five and related work with emphasis on both the identification of correlations between the personality profile (represented in terms of the Big-five elements) with respect to the use of specific technologies, and the use of Chatbot to mediate and foster social interaction. Section 3 describes in more detail both pilot experiences carried out at the Universidad Católica "Nuestra Señora de la Asunción" within the framework of the WeNet project. Section 4 presents the results of the analysis of the correlations between personality and the use of the Chatbot to ask questions and requests for help and to respond to other participants. Finally, the study ends with a closing discussion and some possible future research lines.

2 Related work

In the specialized literature, there is an abundance of papers analyzing possible correlations between the five personality traits, the Big-five, and the adoption and use of certain technologies.

Let us start presenting the main findings in the literature in relation to each of the Big-five.

Extraversion. Individuals who score high tend to be sociable, talkative, assertive, and active; those who score low tend to be retiring, reserved, and cautious. Extraverts do not regard online socialization as a substitute for offline socialization; they tend to make friends offline and keep them in touch online [7]. Prior studies on Social Network Sites (SNS) have consistently found that extroverts not only spend more time on SNS [8], they had more Facebook friends [9, 7], and also are central in many social networks [10].

Agreeableness. Agreeableness reflects the individual's interpersonal orientation in social life. Individuals who score high tend to be good-natured, compliant, modest, gentle, and cooperative. Individuals who score low on this dimension tend to be irritable, ruthless, suspicious, and inflexible. Agreeable individuals were also found to be more persistent in investigating frustrating Websites that are user-unfriendly and difficult to navigate [11].

Openness to Experience. It reflects the openness and creativity of individuals to experience. Individuals who score high tend to be intellectual, imaginative, sensitive, and open-minded. Therefore, they are likely to become innovators and early adopters of new technologies and services [12, 13]. Those who score low tend to be down-to-earth, insensitive, and conventional.

Conscientiousness. This trait reflects self-restraint and motivation and a sense of responsibility for achievement. Individuals who score high tend to be careful, thorough, responsible, organized, and scrupulous. Those scoring low on this dimension tend to be irresponsible, disorganized, and unscrupulous. Conscientious people are self-disciplined and intrinsically motivated to success [14], therefore, they are less likely to use leisure mobile apps because they regard them as distracting and unproductive.

Neuroticism. This dimension describes an individual's ability to withstand stress. Individuals who score high tend to be anxious, depressed, angry, and insecure. Those scoring low on Neuroticism tend to be calm, poised, and emotionally stable. The distrust inherent in neurotic people makes them more likely to regard new technologies and services as threatening and stressful thereby reducing their use of Internet [15, 13]. In addition, neuroticism was also found to be negatively correlated with the perceived usefulness and behavioural control [14], which in turn reduced people's intention to adopt new technologies.

Different studies have tried to find relationships between personality traits, considered as a whole and not each one separately, with regard to new technologies. In particular, regard the acceptance and use of SNS, an interesting study refers to the adoption and use of social networks [16], considering a hedonic perspective for the analysis, where acceptance is more related to the pleasure generated by their use rather than on the basis of their usefulness or the productivity gained with their use. Other researchers found that extraversion and openness were the strongest predictor of SNS activities (e.g. gaming, SNS interaction, etc.), while conscientiousness, neuroticism, and agreeableness only correlated with a few of the SNS activities [17, 18].

Other studies focuses on the adoption and use of smartphones [19], showing that several aggregate characteristics obtained from smartphone usage data can be indicators of personality traits. Along the same lines in [20] the authors analyze the impact of personality traits with respect to smartphone acceptance in terms of perceived usefulness, perceived ease of use, and behavioral intention to use the new product. Complementarily, the impact of personality traits on the adoption of different types of mobile applications has been studied [21], including a model to automatically determine a user's personality based on their installed applications. Recently, users intention to use health devices adopting IoT technology has also been studied [22]. Even some authors have proposed to enrich the Unified Theory of Acceptance and Use of Technology with personality, defined by the model of the Big-five [23].

More specifically, the Big-five model appears in several papers on chatbots, but mainly linked to the personality of the chatbot (i.e., the one it projects in its interactions) or the design of the chatbot to respond to a specific personality profile. An important aspect to highlight is that in all the articles they note the relevance of the relationship between the personality of the chatbot and that of the user, which in the traditional model of a chatbot, are the two agents in communication. Some examples of studies along these lines are the following. In [24] authors investigate how users perceive the personality of the *Chatbot* agent, using the Big-five model, and whether the perceived personality of a text-based *Chatbot* affects the user's experience. Instead, our research approach is different. We do not derive personality from behaviors because we already capture the personality traits using a self-reporting method through a questionnaire, but we do use personality to explain the behaviors with respect to the use of internet technologies.

Another study [25] proposes a chatbot personality model and an algorithm that allows the chatbot to adapt its personality in real time as it interacts in a conversation with the user, assuming that people relate better to other people who have similar personality traits to them. The personality model focuses primarily on two key personality traits: Extraversion and Agreeableness. Another paper focuses on the user experience of chatbot interfaces, studying the impact of a personality match between a chatbot agent and the user [26]. This study found that personality has a significant positive effect on the user's experience of *Chatbot* interfaces, but this effect depends on the context, the job they perform, and their user group.

It is also worth noting that chatbots are generally used in various social interaction contexts including the educational setting [27], but mostly in automated customer service, in various areas such as sales, e-health, and in various types of service companies. In all these applications, however, the emphasis is not on social interaction in the way it is considered in WeNet because the chatbot is traditionally a software agent that simulates the behavior of a human, in a text-based interaction, and not a means to facilitate and encourage social interaction between people. In the case of the *Chatbot* experience, within the framework of the WeNet project, the role of the *Bot* has not been to "talk" with the participants, but to provide them with information and suggestions to help them interact with other participants.

The originality of the present study therefore lies in focusing mainly on the role of personality in the use of a chatbot as a mediator and facilitator of social interactions between people to request and receive help.

3 Chatbot Ask for Help - Paraguay

Within the scope of the WeNet project, a pilot experience was carried out that seeks to encourage communication between different people to respond to their needs through the use of the Internet, by mean an application of Chatbot in this pilot experience. Specifically, in this paper we restrict to the experience carried out at the Universidad Católica "Nuestra Señora de la Asunción" (hereinafter UC) in Paraguay in order to analyze the possible impact of personality-related aspects in relation to the use of technologies as a means to ask for and/or offer some kind of help. Technology use in this case takes place using the Chatbot application, while requests or offers for help are interpreted as a form of social interaction and are implemented in the application as questions and answers.

3.1 Diversity Model

To identify aspects that make up the user's personality profile, we took data collected through a more general survey to measure diversity. This consisted of a closed questionnaire, which was applied with the objective of collecting data necessary to build the diversity model and train the algorithms that will be used in the pilot iterations that will follow. Thus, the survey inquired about: (i) Habits linked to the university routine handling, the relationship with peers and the use of university spaces; (ii) Housing choice, urban and extra-urban mobility, as well as some eco-sustainable behaviors; (iii) Lifestyles, including eating styles, body care and physical activity; (iv) Free time management during the academic year; (v) Cultural consumption; and (vi) Main psycho-social traits.

In order to ease the respondents' work, the entire questionnaire was covering three dimensions on: (1) socio-demographic aspects, (2) psycho-social profile, and (3) social relations and cultural activities. Several standard scales were used to measure the different aspects of interest. In particular, in this paper we are interested in the personality aspect, which was measured according to the five-factor personality model scale textit("Big Five Inventory") [28].

The data collection was carried out using the *LimeSurvey*[2] platform and was addressed to all UC students from the different careers and campuses throughout the country. A total of 1560 responses were obtained, of which 521 corresponded to complete responses to the entire survey and, more specifically, 777 responded to questions about diversity, including those related to the Big-five.

3.2 The Chatbot

Data regarding technology use behavior were collected by a chatbot application. All students who successfully completed the diversity survey and indicated that they would be interested in participating in future related studies under the same project were invited to participate in the Chatbot experience. To be included in the study, participants had to be willing to register on the WeNet platform and use the Chatbot, via the instant messaging application *Telegram*, thus requiring the installation of the latter in case they did not already have it. The application is available for *iPhone and Android*, but also has a version for computer use.

There were 58 responses from students interested in participating in the study, but only 22 users installed the app. From this group, one of them didn't produced any usage data and another fail to response the questions of the diversity survey related to personality aspects, both users were excluded from our analysis for these reasons. Finally, most parts of the analysis included 20 participants of the experience, although

[2] `https://www.limesurvey.org/`

one of them decided not to specify its gender, and therefore had to be excluded from the gender related analysis.

The experiment lasted for two weeks. During this time, participants were encouraged to interact with other UC students, asking questions and answering requests or giving advice to other users on a topic of interest. The topics were freely chosen by the participants, who could ask any type of question. In addition, each participant could contribute according to his or her time availability; there was no *a priori* minimum or maximum expected participation.

An important point to highlight about the Chatbot has to do with the possibility of remaining anonymous, since Chatbot shares the "name" with other users, but in case the user wishes to be completely anonymous, he/she can use a pseudonym since there are no limitations on the name established by each user when registering in the WeNet platform.

On the other hand, it is also relevant to clarify that although *Telegram* allows sending images, polls, etc. to other users, the Chatbot, in this first experience, was limited to text messages that were send to all participants, while direct interactions were not supported. We hope to extend its functionalities in the future.

3.3 Chatbot experience evaluation

The experience was evaluated by means of two instruments. First, a survey was carried out and all participants were asked to complete it. This yielded 20 valid responses, which are summarized below. Secondly, discussion meetings were held with a sub-group of the participants. Two meetings were organized in order to adapt to the time availability of each participant. The meetings were held virtually and included a total of 7 participants.

The survey included questions aimed at evaluating the use of Chatbot in 5 dimensions: user experience, location, time and space, badges, and messages. There was also the option to leave additional comments via a free text field. Overall we can see that the experience was very positively rated which is very encouraging for future pilots.

To summarize, most participants found the chatbot easy to install (76%) and most participants found it easy to send messages (81%), however, 38% of participants stated that they did not find it easy to answer questions. On the other hand, the absolute majority of participants found it easy to decide whether they liked an answer (95%), all had the necessary resources to use the chatbot (100%), most participants were knowledgeable in using the chatbot (71%). With respect to location, time and space, it can be seen that the afternoon (43%) and evening (62%) were the easiest times to ask questions on the Chatbot. It was convenient for almost everyone (95%) to write questions from home. It is easy to hypothesize that the lock-down situation has facilitated this situation since most of the people at the time of the experience were mainly at home and there were no face-to-face activities at the UC.

The incentive mechanisms were also well accepted. Only one participant indicated that they did not like the badges; the majority liked them (67%), felt they were not a distraction (72%). They further indicated that the badges enhanced the experience (62%) and encouraged them to contribute to the chatbot (Yes 67%, Indifferent 24%).

Regarding the usefulness of the chatbot, participants indicated that it was helpful in acquiring new ideas (71%) and that it was useful for: asking for help (in favor 66%, but indifferent 29%), giving help to others (95%), meeting other students (95%), feeling part of a community (100%). They also indicated that they felt comfortable using the chatbot to ask questions (90%), comfortable using the chatbot to answer questions (90%), satisfied with being able to give an answer (85%), satisfied with the answers to their questions (agree 62% and strongly agree 28%). On the other hand, the Chatbot was reliable for 71% of the participants, pleasant for 85% and fun for 95%.

Finally, all users agreed that they were interested in the chatbot experience and 76% expressed that they would continue to use the chatbot in their daily lives, which is very positive since 66% said they do not use other chatbots in their daily lives.

The second instrument to evaluate the experience was discussion meetings. They were guided by a series of questions, used as conversation starters. Regarding the overall experience, participants agreed that it was very sociable, entertaining and fun, giving them the opportunity to meet new people in a pleasant environment. In addition to this, the questions that arose in the Chatbot generated curiosity, especially about the possible answers to those they did not know how to answer.

Regarding the positive characteristics, the almost addictive effect that it generated in some people was highlighted, although opposing responses were identified regarding ease of use. Some participants responded that it was simple to use, while others highlighted difficulties in its use. On the other hand, among the negative characteristics, the lack of clarity or guidance regarding available functionalities and their use was highlighted, some functionalities were discovered by chance. Also noted was the absence of any kind of feedback regarding the answers given, i.e., whether they were accepted or not.

With respect to the incentive mechanisms that included both the use of badges and the use of messages, it was mentioned that they were motivating to some extent. Specifically, with respect to the badges, they considered that the motivational effect could have been more important if the mechanism for obtaining them had been clearer. Regarding the messages, it was noted that the terminology was very formal with respect to the language and topics covered in the chatbot.

Based on the identified limitations or difficulties, some extension suggestions for the Chatbot also emerged. For example, allowing the use of multimedia files, the gamification of badges, the possibility to see the global list of unanswered questions, the publication of the best answer to a question. It was also suggested the possibility of associating questions to topics and allowing to see what was asked and answered on a specific topic, or even the possibility of establishing profiles with the history of questions and/or answers, so that when making answers, one can have the option of setting them as private or public.

Another interesting point was the issue of privacy, since on the one hand it was pointed out that anonymity gives a level of trust and freedom to interact with people. In other words, participants felt comfortable exchanging messages without knowing the identity of the other person. On this same point they stressed that in other social networks they would be more careful and that if their data had been more exposed or if they had (by default) been less anonymous, this would have affected their way of interacting with the Chatbot. At the same time all the participants we chatted with used their real names, not pseudonyms.

The participants also emphasized that the Chatbot's usefulness depends on the questions that are asked and gave some suggestions regarding other needs that could be covered more explicitly by the application or other specific applications integrated to the WeNet platform. Among them, we can mention the possibility of receiving information related to each faculty; receiving guidance in academic processes; being informed about extracurricular activities; receiving guidance from students in higher courses; receiving support to cope with stress during exam periods; selling, exchanging or buying academic books or other types of books; as well as a space where it is possible to open chat rooms related to specific topics or ask for recommendations of places to eat certain types of food, etc.

Finally, knowing that the participants are all UC students, the Chatbot was perceived as a safe communication space. According to what they expressed, the chatbot allowed them to open horizons because of the diversity of students, it is not the same as a group of classmates. With respect to the location of each participant, although it could intervene depending on the type of question, in this experiment no major influence was noted due to the nature of the topics discussed.

3.4 Experience limitations

The number of users who participated in the experience with the Chatbot was lower than expected, especially considering the number of initially registered users and the number of responses obtained in the diversity questionnaire. This low number of participants limits us in statistical terms as it does not allow us to make important generalizations.

The short duration, two weeks, may also influence the analyses since the levels of leisure, occupation, need to ask for help and other aspects related to the life of the students may be different between different periods of the academic semester. Especially when talking about personality and behavior, it may be interesting to evaluate data obtained over a longer period of time in order to be able to make more consolidated statements.

Another possible limitation, although we consider it minor, is that the application could not be thoroughly tested because it still had some bugs that could affect the user experience. However, based on the evaluations of the experience, carried out with the participants, we consider that this effect is not very significant. Some problems occurred during use, and only at times when there were peaks of simultaneous participation, at the same time there was just one dropout in the group of participants who never really initiated the experience. In other words, all the participants who started the experience continued until the end.

4 Big-five analysis on the Chatbot Ask for Help - Paraguay

As mentioned before, the data of 20 UC students from various faculties participating in the use of the Chatbot over a period of two weeks were used for the analysis. The total number of messages transmitted during the experiment included questions, answers, notifications and commands. Of these messages, 211 were identified as questions and 614 as answers. Then, from the identified questions, 184 received an answer claimed as the best answer by the author of each question. This information was analyzed in order to identify possible correlations with respect to the model of the Big-five major personality traits: Extraversion, Agreeableness, Conscientiousness, Neuroticism and Openness to Experience. Additionally, other aspects regarding time, length (of the question/answer), and the network of interactions were also included in the analysis in order to better explore the various factors of the personality having an effect on a given behavior.

4.1 Participants levels descriptive

As the first part of the analysis, we test whether and how much the chatbot participants are different from the sample of respondents as a whole. Regarding gender (table 1), although there is a percentage difference between men and women, however Fisher's exact test (table 2) tells us that there is no difference between the total respondents and the chatbot participants.

	Participants Chatbot		Participants Survey	
	N	%	N	%
Men	9	45.0	282	36.3
Women	11	55.0	495	63.7
Total	20	100.0	777	100.0

Table 1: Participants by Gender. *Note: An additional case without sociodemographic information and big five participated in the chatbot.*

Pearson chi2(1)	0.6376	Pr=0.425
gamma	−0.1790	ASE=0.221
Fisher's exact	0.483	
1 sided Fisher's exact	0.282	

Table 2: Testing gender distribution among survey participants and chatbot participants.

Similar results are found for personality trait scores (table 3). The Kolmogorov–Smirnov (K–S) test is used to test a null hypotheses of a common population distribution given samples between two groups was drawn from a specified distribution. The Combined K–S statistic is the relevant one for our hypothesis of equal distributions between total sample and chatbot participants, which we would accept due to the high p-values of all big five; the only exception is extraversion, where we would reject due to the low p-values (.087).

	D	P-value	Exact
Extraversion	0.2748	0.107	0.087
Agreeableness	0.0893	0.998	0.994
Conscientiousness	0.1155	0.958	0.931
Neuroticism	0.1969	0.440	0.392
Openness	0.2186	0.312	0.270

Table 3: Two-sample Kolmogorov-Smirnov test for equality of distribution functions of big five distribution among survey participants and chatbot participants. (Combined K-S values).

4.2 Participation over the time

Knowing how our sample is composed in relation with the body of respondents, we are also interested on seeing how the participation of users evolves over the time and whether a correlation can be derive from this factor with regard to gender and/or personality.

In table 4 we first present a summary regarding the number of questions and answers written by users. It shows that there is a heterogeneous distribution of both the number of questions and the number of answers written by the users. Also, it can be seen that there is an approximate ratio of 1 to 3 between the number of questions and the number of answers. This was to be expected, since one participant's question was answered by several others. On the other hand, it is noted that the minimum and maximum number of questions and answers show a very pronounced variation. That is, there is one participant who asked only 1 question or request for help and one who asked 24; there is also one participant who offered only 2 responses

	Each user made	
	Questions	Answers
Mean	11.1	30.7
Median	10	26.5
Standard Deviation	8.3	20.1
Mín	1	2
Máx	24	70
Sum	211	614

Table 4: Summary of question and answer numbers grouped by user

and one who offered 70. However, the standard deviation is not particularly high in both cases (questions and answers), which finally indicates that, in general, there was good participation in the group.

Next, the tables 5 and 6 present some of the analyses conducted on the days the chatbot was used. The days were grouped into four groups defined as follows: group 1 (days 1-2) is the initial phase where participants explore the app; group 2 (day 3) is the moment of excitement of being able to get in touch with other people and get to know each other, it is also the day with the highest number of interactions; group 3 (days 4-8), in this phase the euphoria gives way to the search for shared themes and interests; group 4 (days 9-15), the app has become fully operational, only those who find the tool interesting and adopt it as a new communication system remain.

	Total			Men			Women		
	Obs.	N.	%	Subj.	N.	%	Subj	N.	%
Days 1-2	16	46	21.8	7	21	25.9	8	20	18.2
Day 3	15	100	47.4	6	34	42.0	8	61	55.5
Days 4-8	9	40	19.0	4	18	22.2	4	16	14.6
Days 9-15	8	25	11.9	3	8	9.9	4	13	11.8
Total	19	211	100.0	8	81	100.0	10	110	100.0

Table 5: Question generated

	Total			Men			Women		
	Obs.	N.	%	Subj.	N.	%	Subj	N.	%
Days 1-2	16	131	21.3	7	55	22.6	8	68	20.4
Day 3	18	275	44.8	8	111	45.7	9	161	48.3
Days 4-8	17	134	21.8	8	50	20.6	8	70	21.0
Days 9-15	14	74	12.1	6	27	11.1	7	34	10.2
Total	20	614	100.00	9	243	100.0	11	333	100.0

Table 6: Answer generated

Traits act differently over time in both question-and-answer generation (table 7 and 8). For questions we find significant relationships with agreeableness, neuroticism, and openness. However, while we observe high scores for agreeableness, neuroticism in group 2 (day 3) and a progressive reduction of the score in the following days, openness on the contrary progressively increases over time. The explanations that we can cautiously propose are that for agreeableness their interest was more attracted by the fact that they had to understand how the app works [11], which we remember as being very limited being a version that allowed only one-way communication and did not offer many possibilities of configuration. For neurotics, as already reported in the literature [15, 13], they tend quite quickly to abandon its use. Finally, the openness that instead increase their presence over time, also in accordance with the literature that sees them as explorers of all that is new [12, 13].

Also, in the answers we find a significant relationship with neuroticism, openness and conscientiousness. While for the first two what has just been said is applicable, for conscientiousness we can advance the hypothesis that more than an interest, subjects with high levels in this trait felt obliged at least in the first days to interact with the app, as they had agreed to participate in the experiment. However, after having the first two days, they reduced their active presence.

	Extraversion	Agreeableness	Conscientiousness	Neuroticism	Openness
Days 1-2	50.0	64.2	75.5	38.4	69.2
Day 3	45.2	73.9	73.6	51.2	67.2
Days 4-8	50.4	66.4	73.0	31.4	76.1
Days 9-15	37.8	53.3	75.3	35.7	78.6
Total	46.3	68.2	74.1	43.2	70.5
F.	1.69	6.93***	0.17	9.2***	5.63***

Table 7: Big five average score of questioners by period and one-way analysis. Legend: (**) sig.<0.05; (***) sig. <0.01

	Extraversion	Agreeableness	Conscientiousness	Neuroticism	Openness
Days 1-2	48.5	75.1	77.0	37.9	71.1
Day 3	46.7	75.3	71.6	50.8	66.7
Days 4-8	45.8	72.1	70.7	46.2	69.6
Days 9-15	47.2	72.2	70.6	36.1	75.8
Total	47.0	74.3	72.5	45.5	69.2
F.	0.24	1.41	3.03**	15.85***	8.58***

Table 8: Big five score of respondents by period. Legend: (**) sig.<0.05; (***) sig. <0.01.

4.3 Supplementary Analysis

To delve a little deeper into the analysis of the number of questions and answers per day, the table 9 shows the linear correlation between the number of questions, answers, different questioners and different respondents per day of the experience.

Factor 1	Factor 2	Correlation Value	p-value
Number of questions	Number of answers	0.9966	0.000 00
Number of questions	Different questioners	0.8422	0.000 08
Number of answers	different respondents	0.6823	0.005 06

Table 9: Pearson Linear correlation between number of questions, number of answers, different questioners and different respondents per day of the experience.

From the *p-values* in the table, it is possible to affirm that the greater the number of questions, the greater the number of answers; that is, there were almost always several answers to a question. Moreover, as the number of questions increases, the number of different questioners also increases, which in principle would mean that there is no tendency for questions to be concentrated in a few participants. The same trend is observed in the responses and respondents, where the correlation is slightly lower but still high.

Analyzing now the distribution of the number of questions and answers by time slot (1 hour) and by day, as shown in figures 1 and 2, it is observed that there is a concentration of both from midday onwards and especially from 17:00 until after midnight. This information also coincides with what was expressed by the participants themselves in the evaluation meetings held. Finally, these two figures also show a greater movement of messages (questions and answers) at the beginning of the experiment, possibly associated with the novelty and initial enthusiasm to understand what the experience was about.

The time elapsed (measured in minutes) between a question being asked and the corresponding answers being written was also analyzed in this experience. Table 10 shows a summary of the measures of this variable.

It can be seen that at least half of the questions have had an answer in the order of 2 minutes, which indicates a fairly fluid and fast interaction among the participants. Likewise, it can be seen that the value of the standard deviation would imply that many users took great care in answering questions even after some hours of their emission and that those questions were left without an answer considered as the best one up to that moment.

When we talk about a person's response time, we are particularly interested in analyzing whether his or her personality can influence his or her promptness to give an answer, and for this purpose a correlation

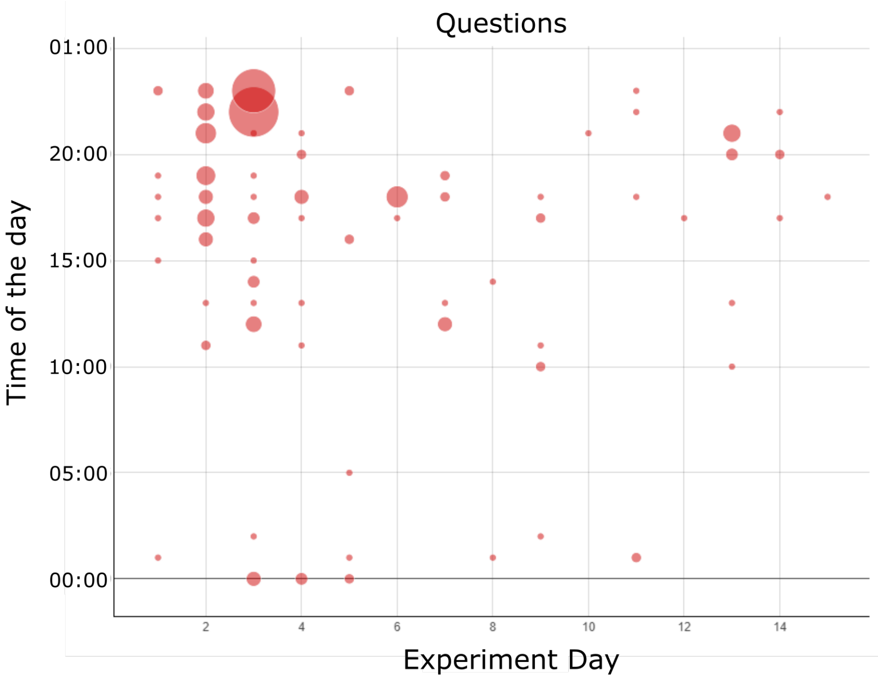

Figure 1: Number of questions per day and time of the experiment

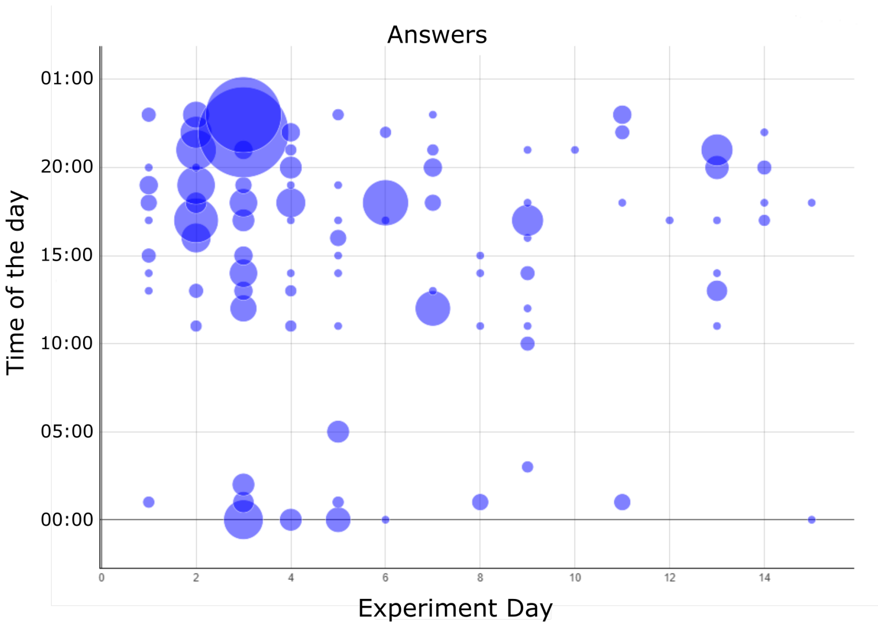

Figure 2: Number of answers per day and time of the experiment.

Summary measure	Delay (minutes)
Mean	51.91
Median	2
Mode	1
Standard Deviation	199.75
Minimum delay	0
Maximum delay	2865

Table 10: Summary measures of delay in answering questions (in minutes). N = 614 Answers.

analysis has also been carried out between personality factors and the time taken to answer the questions.

Personality trait	Delay (in minutes) Correlation value	p-value
Extraversion	−0065 88	0.111 11
Agreeableness	−0060 24	0.145 28
Conscientiousness	−0023 58	0.568 92
Neuroticism	−0157 72	0.000 13
Openness	0.068 50	0.097 59

Table 11: Spearman correlation coefficients between Personality Traits and the delay in minutes in answering a question since it was written. N = 614.

The table 11 shows the summary of these correlations, where it can be seen that there is a weak negative correlation between Neuroticism and the delay in writing a response. That is, there seems to be an indication that the greater the emotional stability, the more willing people are to offer a response.

As part of the supplementary analysis, we also considered it interesting to explore a possible correlation between the gender of the participants and their activity levels, in this case measured through question response time. For this analysis, however, we identified that the data sample does not meet the requirements to apply the Student's t-test for the comparison of means of Response Delay in relation to the author's gender. As an alternative, nonparametric tests have been performed for that purpose, the results of which are shown in table 12. From it, we can conclude that there are no significant differences in the response time to the questions in relation to the gender of the respondent.

Null hypothesis	Test	Sig.	Decision
Medians of Delay are the same across categories of Gender.	Independent-Samples Median test	0.133	Retain the null hypothesis
Medians of Delay are the same across categories of Gender.	Independent-Samples Mann-Whitney U Test	0.350*	Retain the null hypothesis
Medians of Delay are the same across categories of Gender.	Independent-Samples Kolmogorov-Smirnov Test	0.182	Retain the null hypothesis

Table 12: Non-parametric tests for means of response delay in relation to respondent's gender. Asymptotic significances are displayed. The significance level is 0.05. *Exact s is displayed for this test

4.4 Personality traits and question/answer level analysis

Considering the main focus of this study, a correlation analysis between the personality trait scores of Chatbot users, according to the Big-five, with respect to the number and length of questions and answers has been performed. Spearman's correlation coefficient was used for these calculations. It should be noted that due to the small number of participants, the statistical significance represented by the *p-values* may not be sufficiently representative to accept the hypotheses of rank correlation.

The Table 13 shows the analysis of the personality with respect to the amount of questions asked by the users. It can be seen, from the highest correlation value, that there seems to be a relatively strong positive correlation between conscientiousness and the number of questions.

Personality trait	Number of Questions	
	Correlation Value	p-value
Extraversion	-0.4667	0.2054
Agreeableness	0.2000	0.6059
Conscientiousness	0.6167	0.0769
Neuroticism	0.2970	0.4047
Openness	0.3571	0.4316

Table 13: Spearman's Correlation Coefficient between number of questions asked (in total) and Personality Traits

The analysis of the relationships between personality traits and the number of answers is summarized in table 14. These values show that there could be a relatively strong positive correlation between Agreeableness and the number of responses. However, similar to the considerations made with respect to the number of questions, due to the low statistical significance it is not possible to state this with certainty.

Personality trait	Number of Answers	
	Correlation Value	p-value
Extraversion	-0.2667	0.4879
Agreeableness	0.6000	0.0876
Conscientiousnes	0.4545	0.1869
Neuroticism	0.3417	0.3037
Openness	0.4524	0.2604

Table 14: Spearman's Correlation Coefficient between the number of responses made (in total) and the Personality Traits

In line with the research focus of the experiences carried out under the WeNet project, one of the questions that has aroused our interest is *How to appreciate a measure of the differences present between the participants who have formulated the questions and the writers of their respective best answers, with respect to personality traits?*. In the absence of a mature diversity model and given the information available from the Chatbot experience, we have developed an approach to measure and observe these differences.

Let $N = 146$ be the total number of questions and their corresponding best answer (whose authors have all measured personality traits). Let Q_i be the *i-th* question and A_i be the best answer to question Q_i, $1 \leq i \leq N$; $QB5_{ij}$ and $AB5_{ij}$, with $1 \leq j \leq 5$, the personality traits of the authors of (Q) and (A), respectively. To calculate the difference in traits between the questioner and the respondent we use the following formula D_i.

$$D_i = \frac{1}{100} \sum_{j=1}^{5} |QB5_{ij} - AB5_{ij}|$$

Where, values of D_i close to 0 indicate high similarity and values close to 1 indicate large difference of personality trait scores. We make the corresponding caveat that this value only represents an *ad hoc* approach for this particular case that allows us to formulate some conjectures.

Figure 3 shows a clustering of the average differences in the region roughly encompassed by the interval [0.15, 0.35] closest to the 0 end; that is, there appears to be little difference between the values of the personality traits of the users who write responses that are considered best for each question. More evidences and analysis are required to confirm this trend.

A preliminary examination of questions and answers length is presented here. The table 15 compares question and answer length by gender. Analysis of variance shows that there is a significant association between gender and response length, where it is men who write longer sentences. However, this difference in patterns, which we see later, disappears, meaning that it can be produced by other factors such as time and personality traits.

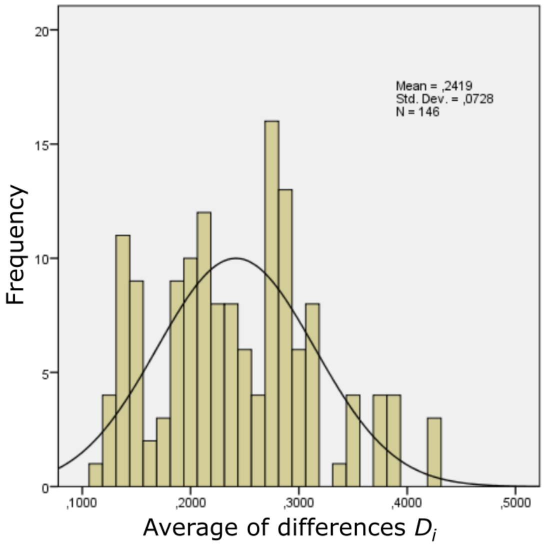

Figure 3: Average differences between the personality traits of the questioner and the person who writes the best answer.

	Questions	Answers
Men	91.3	67.3
Women	66.7	52.7
Total	77.1	58.9
F. fisher test	11.6***	6.4**

Table 15: Total Average of questions and answers and total questions and answer generated during the two weeks by gender. Legend: (**) sig.<0.05; (***) sig. <0.01

For personality traits, correlations from table 16 show a weak positive relationship between extroversion and length of responses. While a weak, in this case negative relationship is observed between question length and mean question length with agreeableness and with mean answer length for neurotics.

	Questions			Answers		
	N. of questions	Length of words	Average length (words/questions)	N. of answers	Length of answers	Average length (words/answer)
Extraversion	0.169	0.105	0.196	0.269	0.462*	0.321*
Agreeableness	−0.286	−0.554*	−0.431*	0.194	0.218	−0.018
Conscientiousness	0.135	−0.060	−0.035	0.064	0.216	0.230
Neuroticism	0.006	−0.172	−0.291	0.073	−0.291	−0.486*
Openness	−0.072	−0.056	−0.106	0.098	0.182	0.145

Table 16: Pearson correlation by Big Five and questions and answers. Legend: (*) sig.<0.1

The problem with the previous estimates is that they are based on the relationships between pairs of variables and do not consider the effects that various factors have in producing a given behaviour. Just to understand, all five personality traits are present in each person, what changes is their intensity. Just as the time of use and the type of interaction between the subjects' changes over time. Failure to consider these aspects risks failing to capture what real contribution personality traits have in influencing question and answer length. To do this, we need to move to more complex linear models that allow us to estimate the contribution of each trait net of the other variables.

To avoid cluster effects because the same subject produced multiple questions and/or multiple answers, we will use multilevel regression models. Multilevel models are particularly appropriate for research designs where data for participants are organized at more than one level (i.e., nested data). The units of analysis in our case are the singles questions or answers (at a lower level) who are nested within our participants to the chatbot (at a higher level).

Below are four models. The first two relate to the length of questions (table 17) and answers (table

18), respectively. The second two models deal with the total daily number of answers given (table 19) and the total number of questions and answers produced per day (table 20). Question and answer length and number of questions/answers were transformed into logarithms, as they did not meet the normal distribution requirement.

	B	SD
Women	−0.113	0.117
Period		
Days 1-2	Ref.	
Day 3	0.020	0.124
Days 4-8	0.014	0.147
Days 9-15	0.153	0.172
Big five		
Extraversion	−0.001	0.003
Agreeableness	−0.010	0.003***
Conscientiousness	−0.001	0.003
Neuroticism	−0.009	0.003**
Openness	−0.009	0.005*
_cons	5.928	0.550***
Number of obs	189	
Number of groups	16	

Table 17: Multilevel linear regression on ln(question length) - Random intercept. Legend: (*) sig.<0.1; (**) sig.<0.05; (***) sig. <0.01

	B	SD
Women	0.150	0.206
Period		
Days 1-2	Ref.	
Day 3	−0.407	0.119***
Days 4-8	−0.304	0.134**
Days 9-15	−0.361	0.162**
Response Delay (ln form)	0.078	0.024***
Length of question (ln form)	0.426	0.057***
Big five		
Extraversion	−0.002	0.005
Agreeableness	0.000	0.005
Conscientiousness	0.002	0.005
Neuroticism	−0.012	0.006**
Openness	−0.015	0.009*
_cons	3.425	1.003***
Number of obs	576	
Number of groups	19	

Table 18: Multilevel linear regression ln(answer length) - Random intercept, random slope (gender). Legend: (*) sig.<0.1; (**) sig.<0.05; (***) sig. <0.01

It is clear from the first two models that agreeableness, neuroticism and openness are negatively associated with question length while neuroticism and openness are negatively associated with answer length. In other words, as the scores within these traits increase, the length of the questions and/or answers decreases. Response length is also significantly affected by how much time elapsed from publication to response, and the length of the question (both are treated as logarithms). The former might refer to the time it takes the subject to process and write the answer, the latter to the fact that the more elaborate the question the longer it will be, the more it will require an equally elaborate answer. However, the length of questions and answers, as we have seen, are influenced by the length of the question, which could depend on the type of topic covered and its complexity which, in turn, affects the length of the answer.

There is, nevertheless, one question that remains unexplored, how much do personality traits influence who will collaborate the most? Who will produce the most responses? Who will be more active in the

	B	SD
Women	0.146	0.187
Period		
Days 1-2		
Day 3	0.982	0.383**
Days 4-8	−1.161	0.295***
Days 9-15	−1.328	0.279***
Length (question/answer)	−0.005	0.002***
Length*Period		
Length*Days 1-2		
Length*Day 3	−0.003	0.005
Length*Days 4-8	0.006	0.003**
Length*Days 9-15	0.004	0.002*
Big five		
Extraversion	0.010	0.005**
Agreeableness	0.001	0.004
Conscientiousness	−0.002	0.005
Neuroticism	0.006	0.006
Openness	0.017	0.007**
_cons	−0.153	0.860
Number of obs	126	
Number of groups	19	

Table 19: Multilevel linear regression on ln(daily number of answer) - Random intercept. Legend: (*) sig.<0.1; (**) sig.<0.05; (***) sig. <0.01

	B	SD
Women	0.027	0.230
Period		
Days 1-2		
Day 3	0.864	0.430**
Days 4-8	−1.484	0.308***
Days 9-15	−1.831	0.298***
Length (question/answer)	−0.007	0.002***
Length*Period		
Length*Days 1-2		
Length*Day 3	−0.003	0.006
Length*Days 4-8	0.006	0.003*
Length*Days 9-15	0.006	0.002**
Big five		
Extraversion	0.012	0.006**
Agreeableness	−0.002	0.005
Conscientiousness	−0.002	0.006
Neuroticism	0.004	0.006
Openness	0.018	0.008**
_cons	0.654	0.967
Number of obs	139	
Number of groups	19	

Table 20: Multilevel linear regression on ln(daily total number of answer/questions) - Random intercept. Legend: (*) sig.<0.1; (**) sig.<0.05; (***) sig. <0.01

chatbot? The models of tables 19 and 20, try, in the limited number of cases available, to give this. In both, with the same gender, length of the question, and period in which the answer was given, there clearly emerges a positive effect in this case of the personality traits of agreeableness, and openness. The result is perfectly in line with the findings in the studies of [17].

4.5 Evolution of network interaction

To close our analysis, we were interested in exploring how the network of interactions evolves over time in relation with personality traits. In other words, whether and how much do personality traits influence the interaction of users over time? In order to explore this aspect, first, the data in Table 21 provide a summary of the network connections over time. In this table we can note fewer active nodes and interactions during the first days of the experiment, this is to be expected since users are probably still joining and starting to understand the dynamics of the application. Then, on day 3 we can notice a peak in interactions both in terms of number of active nodes and in the number of interactions. After this momentum probably once the novelty passed, the numbers stabilize in a slightly lower value, we believe that it is interesting to analyze which are the users that stay and maintain the network of interactions at this point and which ones are on the contrary those that tend to disappear. For personality traits, the correlations show interesting results, although not surprising at this point, for Openness and Neuroticism that are shown in figures 4 and 5.

	Nodes	Tot.Edges	Tot. Edges >1	%
Days 1-2	16	90	26	28.9
Day 3	20	128	66	51.6
Days 4-8	18	77	40	51.9
Days 9-15	14	45	18	40.0

Table 21: Network connections over time.

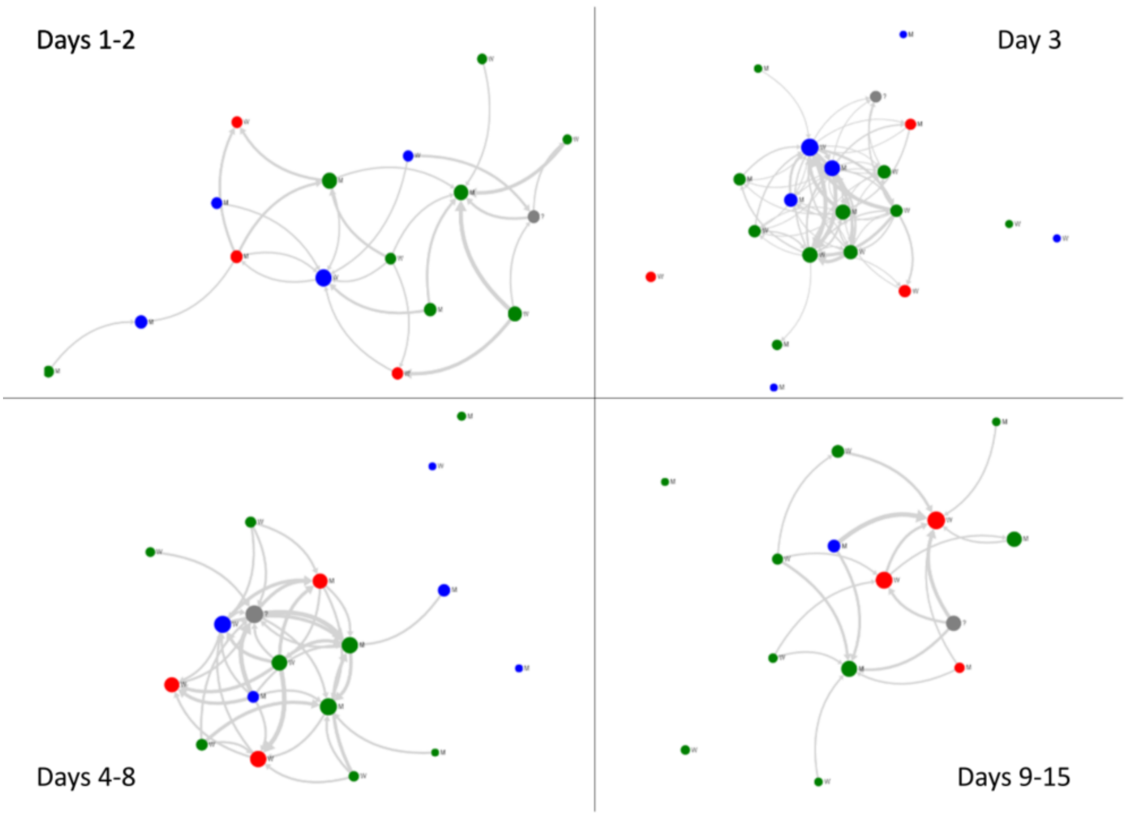

Figure 4: Openness & gender only edges with frequencies greater than one. Legend: "RED" Max (GT.mean+sd); "GREEN" Intermediate (mean to mean+sd); "BLUE" Lower (0 to mean); # "GRAY" Missing (==.)

More precisely, in figure 4 we see a rather heterogeneous distribution of the interactions among users with the different level of openness at the beginning (days 1-2 and 3). In other words, there are comparable numbers of nodes of the different colors red, green and blue. Then, as expected, the blue nodes begin to decrease (days 4-8) up to the point in which they almost disappear when the app becomes fully operational and only those that finds it interesting remain (days 9-15). This configuration tell us that it is expected users with higher openness, max and intermediate, will be the ones hoarding the interactions in time and therefore maintaining the network.

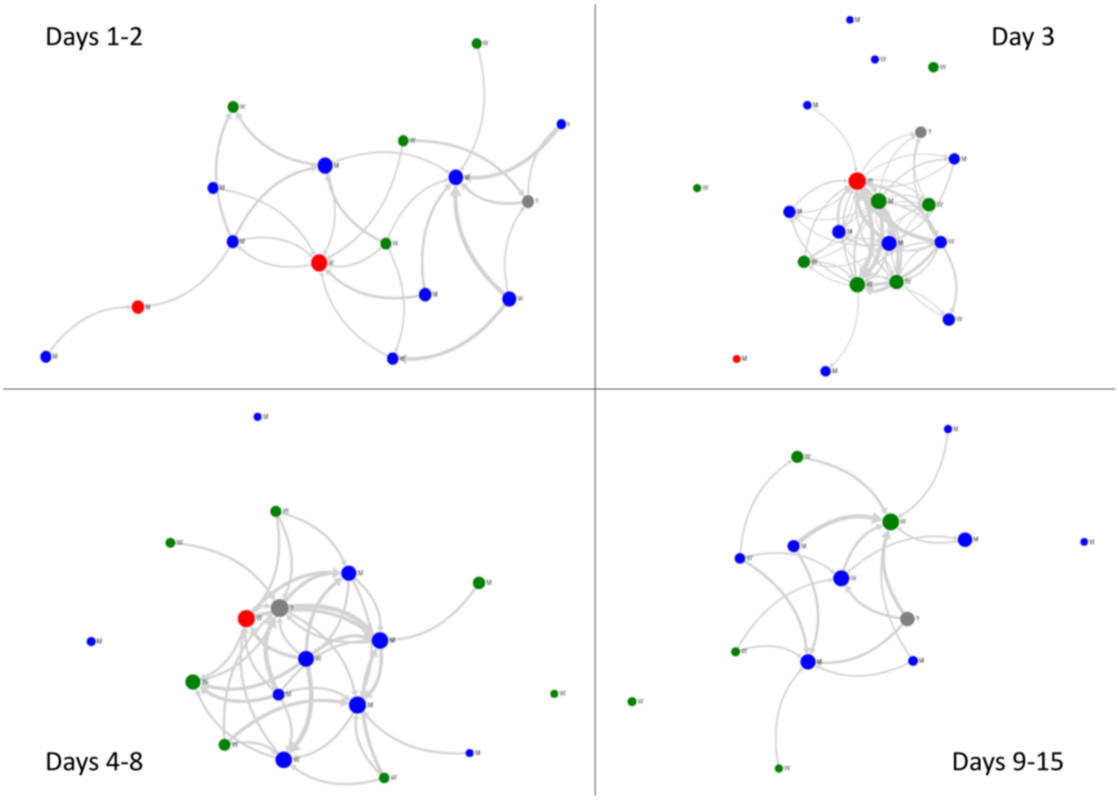

Figure 5: Neuroticism & gender only edges with frequencies greater than one. Legend: "RED" Max (GT.mean+sd); "GREEN" Intermediate (mean to mean+sd); "BLUE" Lower (0 to mean); # "GRAY" Missing (==.)

In a similar but opposite way, the figure 5 shows that the distribution of nodes with different levels of neuroticism is again more or less heterogeneous at the beginning (days 1-2) while the red nodes (Max level) rapidly decrease in the following days, up to the point of completely disappearing on the last group (days 9-15). As mentioned at the beginning these results are coherent with previous studies and the characterization of this trait. Opposite to the case of openness, we can see that it is expected users with lower neuroticism, blue and to a lesser extent green nodes, will be the ones hoarding and preserving the network of interactions in time.

Finally, due to the small number of participants, it is important to highlight this finding are to be considered preliminary and more analysis over a longer period of time, and with a larger number of participants is needed in order to validate this work.

4.6 Discussion

The main results show very positive opinions about the use of the chatbot in terms of user experience and its main functionalities. All participants agreed on their interest in the Chatbot experience and 76% expressed that they would continue to use Chatbot in their daily lives, which is a very encouraging result in terms of future pilots to be carried out within the framework of WeNet. There were even suggestions on how to extend the experience with the Chatbot, which are being taken into account for future work. In addition, there has been an interesting participation in the group of students, with no concentration of questions / requests for help or answers in a few actors. This result is very interesting because it does not reflect the local culture, which in a group or in an environment of social interaction usually leaves space of protagonism to few actors and the rest prefers to attend with a more spectator role. This has possibly been facilitated by the more entertaining and social focus of the experience as evidenced in the focus groups at the end of the experience. Moreover, knowing that all the participants were part of the UC educational community generated an atmosphere of trust that facilitated social interaction. At the same time, also in the discussion groups, the importance of anonymity was highlighted, which provided a certain level of freedom to interact with the other participants. This also responds to a large extent, as expressed by the participants, to the fact that the profile of each user was not specifically known, which also helped to avoid prejudices and removed them from the commitment of having to satisfy some kind of expectation with their questions and/or answers.

More specifically, regarding the Big-five personality traits, several considerations emerged. We test whether the chatbot participants are different from the sample of respondents as a whole. Both regarding gender and personality trait scores, there is no difference between the total respondents and the chatbot participants.

Big-five traits act differently over time in both question-and-answer generation. The results suggest that there may be correlations between Conscientiousness and the number of questions or requests for help asked, as well as between Agreeableness and the number of answers given. Although the statistical significance of these results is not guaranteed, they are intuitively reasonable. Moreover, the data suggest that students who formulate questions or requests for help tend to select as the best answers that of other participants who have personality traits similar to their own. This is in line with the hypothesis that all the literature suggests with reference to human interactions and hence the design of chatbots to facilitate their interaction with users. However, it is not entirely clear whether these data are due to the group of participants sharing common personality traits as a basis or what other factors might be involved in confirming the generalizability of these data. We are planning also to use descriptive characteristics, lifestyle and values, to increase the interactions among students.

A preliminary examination of questions and answers length shows that there is a significant association between gender and response length, where it is men who write longer sentences. However, this difference can be produced by other factors such as time and personality traits. For personality traits, correlations show a weak positive relationship between Extraversion and length of responses. While a weak negative relationship is observed between question length with Agreeableness and with answer length for Neurotics. Applying multilevel models to better analize the possible correlations, it results that Agreeableness, Neuroticism and Openness are negatively associated with question length while Neuroticism and Openness are negatively associated with answer length. That is, as the scores within these Big-five traits increase, the length of the questions and/or answers decreases.

We also analyzed how much do personality traits influence who will be more active in the Chatbot. As a first aproximation emerges a positive effect of Agreeableness, and Openness.

Finally, we preliminary explored how the network of interactions evolve over time in relation with Big-five traits. Early results indicate that people with high Openness scores tend to remain more active throughout the experience being the main drivers of the interaction. Something similar can be said of participants with low Neuroticism values.

If we would like to consider the participants proactivity levels in terms of response times (delay in minutes) to the questions posed, we see positive values in general given that the waiting time to start receiving answers to a question in at least half of the cases is 2 minutes or less. On the other hand, there are cases in which the delay of the answers are higher, but we also see that this value has no correlation with the gender of the participants and even the correlation that is identified with respect to personality is quite weak. This leads us to look for other explanations such as the fact that some questions were simply difficult to answer, added to the fact that in some cases some questions were asked at times when most of the participants were not very active, so it took them longer to visualize and answer them. These results could also be partially confirmed in the discussion meetings held with the participants.

5 Conclusions and Future Work

This study is part of the activities of the “WeNet: Internet of us” project (https://www.we-net.eu) funded by the European Union (EU), whose ultimate goal is to encourage interaction, mediated by a technological platform, between diverse people to respond to a need.

In particular, this study has focused on the analysis of the role played by personality, modeled according to the Big-five traits (Extraversion, Agreeableness, Conscientiousness, Neuroticism and Openness to Experience), in social interaction through the use of a Chatbot application to ask questions/requests for help and provide answers.

Related to this main objective, we can identify at different points of our analysis that there is indeed evidence of a correlation between the Big-five personality traits and various aspects related to the interaction. More specifically we saw that personality can influence the active participation (Agreeableness and Openess); the type of contribution in term of length of questions / requests for help and answers (Agreeableness, Neuroticism and Openness); and, the network of interactions evolution over time (Openness and Neuroticism). It is worth noting the personality is not a substitute for the skills and knowledge that allows a given question to be answered, just as personality alone cannot predict what questions will be asked. As we seen, personality acts in different ways. Only some traits correlate with the number and length of responses (in other words there are some subjects who are more likely to answer than others, precisely because they have a given personality). Some subjects are more active on the net just because they have a given personality. However, further analyses need to be carried out in order to understand the perception of the quality of the answers, that is if the answers that are considered the best are related to the personality. It is important to highlight that, in the social science context the level of correlations are lower than in the natural sciences context, making acceptable our findings. However, the results have to be confirmed in further studies increasing the number of the participants.

Additional future works consist in the need to deepen the analysis already pointed out in section 4.6 of the correlations between personality traits, in particular Agreeableness, Neuroticism, and Openness, with respect to number and length of questions, requests for help made, number and length of answers and selection of the best answers. In addition, it is interesting to incorporate some of the recommendations of the users in order to facilitate the experience and avoid possible usability problems influencing the results. Also, based on the limitations mentioned in section 3, in a future experience it would be interesting to monitor and analyze over a longer period of time, and with a larger number of participants in order to validate the correlations found. In a next stage, it is also expected to incorporate the information obtained from the study to more specific scenarios.

Acknowledgment

This research has received funding from the European Union's Horizon 2020 FET Proactive project "WeNet: Internet of us", Grant Agreement No: 823783.

The contribution to this study by the author José Luis Zarza has been elaborated with the support of CONACYT - Paraguay, as part of a master's thesis. The content of this study is the sole responsibility of the authors and in no case should it be considered as reflecting the opinion of CONACYT.

References

[1] R. J. Swickert, J. B. Hittner, J. L. Harris, and J. A. Herring, "Relationships among internet use, personality, and social support," *Computers in Human Behavior*, vol. 18, no. 4, pp. 437–451, 2002. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0747563201000541

[2] Y. Candrasari, "Mediated interpersonal communication: A new way of social interaction in the digital age," in *Proceedings of the 2nd International Media Conference 2019 (IMC 2019)*. Atlantis Press, 2020, pp. 537–548.

[3] F. Wu, S. Zhao, B. Yu, Y.-M. Chen, W. Wang, Z.-G. Song, Y. Hu, Z.-W. Tao, J.-H. Tian, Y.-Y. Pei *et al.*, "A new coronavirus associated with human respiratory disease in china," *Nature*, vol. 579, no. 7798, pp. 265–269, 2020.

[4] World health organization. coronavirus disease (covid-2019) situation reports (2020). [Online]. Available: https://www.who.int/emergencies/diseases/novel-coronavirus-2019/situation-reports

[5] O. P. John, S. Srivastava *et al.*, *The Big-Five trait taxonomy: History, measurement, and theoretical perspectives*. University of California Berkeley, 1999, vol. 2.

[6] J. L. Zarza, A. Hume, L. Cernuzzi, D. Gatica-Perez, and I. Bison, "The impact of personality in using technology to ask and offer help: The experience of the chatbot "uc — paraguay"," in *2021 XLVII Latin American Computing Conference (CLEI)*, 2021, pp. 1–10.

[7] C. Ross, E. S. Orr, M. Sisic, J. M. Arseneault, M. G. Simmering, and R. R. Orr, "Personality and motivations associated with facebook use," *Computers in Human Behavior*, vol. 25, no. 2, pp. 578–586, 2009, including the Special Issue: State of the Art Research into Cognitive Load Theory. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0747563208002355

[8] K. M. W. Kathryn Wilson, Stephanie Fornasier, "Psychological predictors of young adults' use of social networking sites," *Cyberpsychology, Behavior, and Social Networking*, vol. 13, no. 2, pp. 173–177, 2010. [Online]. Available: https://www.ingentaconnect.com/content/sbp/sbp/2001/00000029/00000004/art00010

[9] E. Y. Ong, R. P. Ang, J. C. Ho, J. C. Lim, D. H. Goh, C. S. Lee, and A. Y. Chua, "Narcissism, extraversion and adolescents' self-presentation on facebook," *Personality and Individual Differences*, vol. 50, no. 2, pp. 180–185, 2011. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0191886910004654

[10] D. C. Feiler and A. M. Kleinbaum, "Popularity, similarity, and the network extraversion bias," *Psychological Science*, vol. 26, no. 5, pp. 593–603, 2015, pMID: 25838113. [Online]. Available: https://doi.org/10.1177/0956797615569580

[11] R. N. Landers and J. W. Lounsbury, "An investigation of big five and narrow personality traits in relation to internet usage," *Computers in Human Behavior*, vol. 22, no. 2, pp. 283–293, 2006. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0747563204001128

[12] I. Constantiou, J. Damsgaard, and L. Knutsen, "Exploring perceptions and use of mobile services: user differences in an advancing market," *International Journal of Mobile Communications*, vol. 4, pp. 231–247, 01 2006.

[13] T. L. Tuten and M. Bosnjak, "Understanding differences in web usage: The role of need for cognition and the five factor model of personality," *Social Behavior and Personality: an international journal*, vol. 29, no. 4, pp. 391–398, 2001. [Online]. Available: https://www.ingentaconnect.com/content/sbp/sbp/2001/00000029/00000004/art00010

[14] M. H. B. Jörg Uffen, Nico Kaemmerer, "Personality traits and cognitive determinants—an empirical investigation of the use of smartphone security measures," *Journal of Information Security*, vol. 4, no. 4, pp. 203–212, 2013. [Online]. Available: https://www.ingentaconnect.com/content/sbp/sbp/2001/00000029/00000004/art00010

[15] S. Devaraj, R. F. Easley, and J. M. Crant, "Research note: How does personality matter? relating the five-factor model to technology acceptance and use," *Information Systems Research*, vol. 19, no. 1, pp. 93–105, 2008. [Online]. Available: http://www.jstor.org/stable/23015423

[16] P. A. Rosen and D. H. Kluemper, "The impact of the big five personality traits on the acceptance of social networking website," *AMCIS 2008 proceedings*, p. 274, 2008.

[17] D. Liu and W. K. Campbell, "The big five personality traits, big two metatraits and social media: A meta-analysis," *Journal of Research in Personality*, vol. 70, pp. 229–240, 2017. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0092656617300843

[18] J.-L. Wang, L. A. Jackson, D.-J. Zhang, and Z.-Q. Su, "The relationships among the big five personality factors, self-esteem, narcissism, and sensation-seeking to chinese university students' uses of social networking sites (snss)," *Computers in Human Behavior*, vol. 28, no. 6, pp. 2313–2319, 2012. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0747563212002014

[19] G. Chittaranjan, J. Blom, and D. Gatica-Perez, "Mining large-scale smartphone data for personality studies," *Personal and Ubiquitous Computing*, vol. 17, no. 3, pp. 433–450, 2013.

[20] V. Özbek, Ü. Alnıaçık, F. Koc, M. E. Akkılıç, and E. Kaş, "The impact of personality on technology acceptance: A study on smart phone users," *Procedia-Social and Behavioral Sciences*, vol. 150, pp. 541–551, 2014.

[21] R. Xu, R. M. Frey, E. Fleisch, and A. Ilic, "Understanding the impact of personality traits on mobile app adoption–insights from a large-scale field study," *Computers in Human Behavior*, vol. 62, pp. 244–256, 2016.

[22] T. Prayoga and J. Abraham, "Behavioral intention to use iot health device: The role of perceived usefulness, facilitated appropriation, big five personality traits, and cultural value orientations," *International Journal of Electrical and Computer Engineering*, vol. 6, no. 4, pp. 1751–1765, 2016.

[23] S. Lakhal and H. Khechine, "Relating personality (big five) to the core constructs of the unified theory of acceptance and use of technology," *Journal of Computers in Education*, vol. 4, no. 3, pp. 251–282, 2017.

[24] E. Ruane, S. Farrell, and A. Ventresque, "User perception of text-based chatbot personality," in *International Workshop on Chatbot Research and Design.* Springer, 2020, pp. 32–47.

[25] A. Yorita, S. Egerton, J. Oakman, C. Chan, and N. Kubota, "Self-adapting chatbot personalities for better peer support," in *2019 IEEE International Conference on Systems, Man and Cybernetics (SMC).* IEEE, 2019, pp. 4094–4100.

[26] T. L. Smestad and F. Volden, "Chatbot personalities matters," in *International Conference on Internet Science.* Springer, 2018, pp. 170–181.

[27] P. Bii, “Chatbot technology: A possible means of unlocking student potential to learn how to learn,” *Educational Research*, vol. 4, no. 2, pp. 218–221, 2013.

[28] M. B. Donnellan, F. L. Oswald, B. M. Baird, and R. E. Lucas, “The mini-ipip scales: tiny-yet-effective measures of the big five factors of personality.” *Psychological assessment*, vol. 18, no. 2, p. 192, 2006.