On the Prevention of Privacy Threats: How Can We Persuade Our Social Network Users?

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Abstract Complex decision making problems such as the privacy policy selection when sharing content in online social networks can significantly benefit from artificial intelligence systems. With the use of Computational Argumentation, it is possible to persuade human users to modify their initial decisions to avoid potential privacy threats and violations. In this paper, we present a study performed over 186 teenage users aimed at analysing their behaviour when we try to persuade them to modify their initial decisions in online social networks with different arguments. The results of the study revealed that the personality traits and the social interaction data (e.g., number of comments, friends, and likes) of our participants were significantly correlated with the persuasive power of the arguments. The findings from this analysis will help to model OSN users and define persuasive strategies for argumentation dialogues in this domain.

Keywords Persuasion · Argumentation · Privacy · Social Networks

1 Introduction

Deciding which privacy policy is the best when making a publication in an Online Social Network (OSN) is not an easy task for human users because it requires to take multiple factors into account (i.e., the potential receivers, the information to be shared, the users’ preferences, etc.). In many situations, the information regarding those factors can be incomplete or unknown, as the reachability of the publication or other users’ preferences. Another relevant feature that characterises online communication is that, once the content is published online, it can be downloaded and stored by anyone with access to it. Therefore, it is important to make sure that the content published will not cause future privacy issues. Additionally, if more than one user appears
in the publication, it is even easier to violate any privacy preference of the rest of the users involved, leading to privacy conflicts between users. The multi-party privacy conflicts (Such and Criado [2016]) are a common type of privacy threats happening in OSNs. This problem combined with the great increase of users in OSNs (Statista [2019]), mostly teenagers who are initiating in their usage and have limited abilities for self-regulation and complex decision-making (Albert and Steinberg [2011]), has raised the interest of privacy management assistance research.

A natural way to approach the existing privacy management problem in OSNs is with the use of Computational Argumentation. This approach can be seen as a direct improvement of recommendation technologies (Chesñevar et al. [2009]) since added to the recommendation, a justification (i.e., an argument) is also provided to the user. An effective way to avoid and reduce the number of potential privacy threats is to persuade the author to adapt the initial privacy configuration since it may be harmful to him/her or any of the other users involved. The best way to persuade the author is by making him/her understand the reasons why the privacy threat is happening with the use of arguments. Using different messages and warnings make possible to persuade OSN users to modify their initial decisions (Alemany et al. [2019b]). However, the perceived persuasive power of these messages may vary from one message to another (Thomas et al. [2017]) or even from different representations or structures of these messages (Thomas et al. [2019]). In the OSN privacy domain, these persuasive messages may approach different privacy aspects. Based on the previous definition given in (Ruiz-Dolz et al., [2019]), up to four different types of argument might be considered depending on the source from which they can be supported: Privacy, Content, Risk, and Trust. Furthermore, arguments can be represented and structured following different reasoning patterns. Argumentation schemes group the most common patterns of human reasoning (Walton et al. [2008]).

In this paper, we present a complete study of the persuasive power of the four different argument types and five different argumentation schemes which we considered to be the most adequate for teenagers in an OSN environment. Previous work such as Mairese and Walker (2010) and Wu et al. (2018) show how users’ personality can be a key factor when directly interacting with them. Therefore, we have investigated any potential correlation between personality traits and arguments. Additionally, since obtaining those traits may not be possible in some social network environments and behaviour is usually influenced by personality (Golbeck et al. [2011]), a study of the correlation between the most common social interaction features with the persuasive power of arguments has also been performed. Therefore, the main contributions presented in this work are the following:

- Quantify and measure the persuasive power of arguments used as a privacy threat prevention mechanism.
- Study and analyse the existing significant correlations between the persuasive power of arguments and the Big Five personality traits.
- Study and analyse the existing significant correlations between the persuasive power of arguments and thirteen different social interaction features.

All these key findings are contextualised in the OSN educational domain with teenager participants. This is considered to be one of the most important target popu-
lations when working on this domain, since they are very active and easy to convince to share their personal information.

The rest of the paper is structured as follows. Section 2 reviews the most relevant work regarding privacy management and argumentation in the OSNs domain. Section 3 presents the application domain of this work and introduces the study research questions. Section 4 presents the design of the study carried out in this work. Section 5 presents the results observed in our study. Section 6 provides an interpretation of the findings, describes their relevance, and defines the limitations and the future work related to this research. Finally, Section 7 summarises the most important conclusions reached at the end of this paper.

2 Related Work

Three main research topics can be identified in this work: (i) privacy management systems, (ii) Computational Argumentation, and (iii) argument persuasion.

Regarding the privacy management topic, multiple approaches have been considered in the literature. *Primma-Viewer* is a collaborative privacy management tool proposed in (Wishart et al., 2010). This service provides users with the capability of editing a publication privacy policy with an invitation, once the content has already been published. *FaceBlock* (Pappachan et al., 2014) is another project created to manage user privacy settings in images. This system works with a set of rules defined by each user based on their privacy preferences. If any of those rules are triggered by the system, a notification is sent to the user warning of the privacy violation and allowing to modify the content of the publication. *PriMa* (Squicciarini et al., 2014) is a privacy protection system that semi-automatically generates a set of rules based on the preferences available from the user profile configuration. Those rules are an indicator of the appropriate privacy configuration for each user and therefore, can be used to prevent privacy violations. There are also privacy management systems based on a poll to decide the best configuration. *CoPE* (Squicciarini et al., 2011) is a collaborative privacy management system where each user can decide a specific privacy configuration for each publication. The system decides the best policy considering the most voted configuration. Finally, there are also automated privacy management systems based on an internal negotiation process. Both *PriNego* (Mester et al., 2015) and *PriArg* (Kökcıyan et al., 2017) have an underlying negotiation protocol to compute the best privacy configuration for a specific situation. *PriNego* proposes a multi-agent based protocol to negotiate the privacy configuration chosen when making a publication. Each agent represents a user and tries to reach the best deal with other agents regarding its user preferences and priorities. On the other hand, *PriArg* is also a multi-agent based protocol to automatically negotiate the privacy configuration for a publication. However, in *PriArg* the negotiation is approached with argumentation. The agents represent real social network users that have an ontology with information from the network, the relationships between users and the content being published. Considering all these data, each agent can generate arguments to achieve a deal trying to satisfy the user privacy preferences. There are some common weak points in all these privacy management systems. All of them are focused on privacy conflicts where
multiple users are involved in the same publication. But, the case of a user choosing a dangerous configuration for itself is not considered. There is also an important limitation if we seek to provide the user with an explanation of why should the configuration be changed. None of the existing privacy management tools gives the user a reasoned explanation nor tries to persuade him/her.

When trying to reach an agreement, explaining our viewpoint, or trying to convince another person, it is very common to make use of arguments. An argument is defined as a set of propositions that can support the veracity of the main statement (the conclusion). Thus, with arguments, it is possible to provide a set of coherent reasons supporting some specific idea. Therefore, the use of Computational Argumentation can be seen as the natural way to approach a decision-making problem in which a human user must be persuaded. In (Hadoux and Hunter, 2019), it is possible to observe the relevance of analysing the persuasive power of arguments and user preferences, when developing decision making assistance AI systems. Several works using argumentation in the OSNs domain can be identified in the literature. As described in Heras et al. (2013), argumentation in OSNs can have many different applications, such as enhancing dialogues or helping to structure user opinions. It is also possible to use Computational Argumentation techniques to model the dialogue between different users sharing their preferences in an Online Social Network (Heras et al., 2008a,b), and to persuade students to use specific learning objects in an educational environment (Heras et al., 2017). Therefore, as Fogues et al. (2017, 2015) propose, argumentation seems the most coherent way to approach a persuasion problem framed in an educational context in OSNs. In (Kokciyan et al., 2017), an argumentation protocol to define the best privacy policy when a multi-party privacy dispute is triggered is proposed. However, not many works in which all the topics of our research converge (i.e., privacy management, Computational Argumentation and human user persuasion) have been identified. In addition to the main flaws identified before, the existing related work in argumentation in social networks is mainly focused on studying the multi-party privacy conflicts too. However, as described in (Wang et al., 2011), it is very common to find users regretting their own publications in OSNs. Since we are focused on an educational domain, we need a system that considers not only privacy disputes between different users involved in the same publication but also potential self privacy violations. When defining an argument, several parameters should be taken into account (e.g., the content, the reasoning pattern, the language, etc.) to maximise its persuasive power. The reasoning pattern of an argument is defined by the underlying logic of its elements. Argumentation schemes were conceived as common patterns on human reasoning (van Eemeren and Kruijer, 1987). This concept has been further developed in both (Kienpointner, 1992, Walton, 1996), where the most common argumentation schemes are reviewed. In (Walton et al., 2008), up to sixty generally accepted argumentation schemes that can be found in common dialogues have been identified. Therefore, the use of argumentation schemes is a convenient way to define the reasoning patterns of the arguments of our study.

Finally, regarding the persuasion of arguments, some related works have also been identified. In (Thomas et al., 2018), an argumentative system to make users change their behaviour in the healthy eating domain is proposed. The persuasiveness eval-
uation of the semi-automatic generated arguments is described in (Thomas et al., 2019). Furthermore, a study of the impact of personality, age and gender on message type susceptibility (Ciocarlan et al., 2019) has also been done. Considering these works altogether, it is possible to infer relations between elements like personality and effectiveness of argumentation schemes. However, to the best of our knowledge, no one has directly analysed the persuasive power of arguments on teenagers, but behaviour may differ substantially between a teenager and an adult in the OSNs domain (Christofides et al., 2012).

Therefore, with this paper, we put together these three research topics and present new results which will help to push forward all the identified limitations on these topics: (i) with our arguments, we consider both self-disclosure and multi-party privacy conflicts; (ii) we approach the privacy management assistance problem from a more explainable and educational perspective; and (iii) we study teenager persuasion with arguments in OSNs, which has not been analysed in the literature yet. Our study results provide a new perspective on human (i.e., teenager) persuasion in the privacy management domain. We propose different, but related, user models based on two human aspects which we use to analyse the persuasive power of arguments: the personality and the social interactions. This way, it is possible to optimise the chosen argument by the privacy management assistance system for each specific user.

3 Background: Argumentation Framework for Online Social Networks

Aimed at preventing privacy conflicts and minimise the number of privacy violations, an Argumentation Framework for Online Social Networks was proposed in (Ruiz-Dolz et al., 2019). It is defined as a tuple \( \langle A, R, P, \tau_p \rangle \) where:

- \( A \) is a set of \( n \) arguments \([\alpha_1, \ldots, \alpha_n]\)
- \( R \) is the attack relation on \( A \) such as \( A \times A \rightarrow R \)
- \( P \) is the list of \( e \) profiles involved in an argumentation process (i.e., a privacy dispute) \([p_1, \ldots, p_e]\)
- \( \tau_p \) is a function \( A \times P \rightarrow [0, \ldots, 1] \) that determines the score of an argument \( \alpha \) for a given profile \( p \)

Each argument \( \alpha \in A \) is defined by three parameters \( \alpha = (\beta, T, D) \): the claim of the argument \( \beta \) is represented as a binary variable which determines whether an argument claims that a publication should (not) be published. The type of the argument \( T \) labels each argument with one of the four different argument types considered by the argumentation framework: Privacy, Trust, Risk and Content arguments. Each type of argument comes defined by the source from which the support \( D \) is retrieved. This last parameter is a numerical value ranged between 0 and 1 computed from the data retrieved from the social network that serves as the justification of the claim. When higher the value, the stronger the support of the argument. In this work, we will refer to the four types of arguments as argument types being different than argumentation schemes that are classes of arguments depending on its reasoning pattern rather than its topic. A relation \( r \in R \) is represented as a tuple \( r = (\alpha_i, \alpha_j) \) indicating that there is a bidirectional attack between arguments \( \alpha_i \) and \( \alpha_j \). An argument \( \alpha_i \),
attacks another argument $\alpha_j$ and vice-versa, if they have opposite claims (e.g., both $\alpha_1 = (-1, T_1, D_1)$ and $\alpha_2 = (+1, T_2, D_2)$ are attacking each other).

Each user profile $p \in P$ involved in the argumentation process is defined as a 3-tuple $p = (\nu, \rho, M)$ by the preference values $\nu$, the personality $\rho$, and a set of miscellaneous information $M$. Preference values $\nu$ are represented by a 4-dimension vector which models the preferences of each user regarding each different type of argument based on previous interactions with the user. The results of the study presented in this paper provide additional information on these preferences based on user social interaction and user personality $\rho$. The personality of each user is represented with a 5-dimension vector modelled with the Big Five personality traits [Rothmann and Coetzer, 2003]. These traits are: Openness, Conscientiousness, Extraversion, Agreeableness and Neuroticism, which represent the five most significant aspects of human personality. The last element of the user profile tuple $M$ is the set of information which can be inferred from each user profile such as the age, the gender or the social interaction in the network. The method proposed to instantiate all the parameters of the framework in a real OSN environment was presented in [Ruiz-Dolz et al., 2019].

Finally, we define the scoring function $\tau_p$ as the function that takes an argument $\alpha$ and a profile $p$ as input and determines the value of the argument in the context of a specific user profile. In order to obtain this score, function $\tau_p$ is defined as,

$$\tau_p(\alpha, p) = \alpha_\beta \cdot \alpha_D \cdot p_\nu_t$$  \hspace{1cm} (1)

where $\alpha_\beta$ is the claim of the argument, $\alpha_D$ its support and $p_\nu_t$ the preference value that the user $p$ has towards the argument type $t \in T$.

The process of generating arguments is thoroughly explained in [Ruiz-Dolz et al., 2019] and starts when a potential privacy violation is detected when publishing content in the social network. Then, the set of relevant information (i.e., user profiles, post content, reachability of the publication, etc.) is gathered and retrieved from the OSN. With this data, the system can generate computational arguments (i.e., 3-tuple elements). Once all the arguments are generated, the system determines the set of acceptable arguments (either in favour or against making the publication) based on the score function and the claim of each argument. Finally, the system translates the arguments in their computational shape into human readable text with the use of templates.

The final step is the human-computer interaction. To interact with a human user, the argumentation system has available the set of arguments mentioned before. However, the system also needs to know which dialogue strategy may be more effective during the interaction process. The present work attempts to shed light on the persuasive power of argument types and schemes, to be able to define more refined dialogue strategies prioritising the most persuasive arguments.

### 3.1 Research Questions

This theoretical framework was proposed to be integrated into PESEDA, an educational social network [Argente et al., 2017; Alemany et al., 2020]. However, deciding
the dialogue strategies when interacting with human users is still a challenge. Therefore, we carry out this study to answer the following research questions that arise when designing this interaction:

RQ1. Which reasoning pattern (i.e., argumentation scheme) is more persuasive for teenage OSN users?
RQ2. Which topic (i.e., argument type) is more persuasive for teenage OSN users?
RQ3. How do the personality traits of teenage users influence the persuasive power of arguments?
RQ4. How do the online social interaction behaviour of teenage users influence the persuasive power of arguments?

If it is possible to find any behavioural pattern regarding these questions, the arguments could be generated by the argumentation system following different strategies for each user depending on their personality traits or their social interaction behaviour.

4 Study Design

To answer the proposed research questions, we designed the following study based on three questionnaires and the social network usage. Questionnaires were used to retrieve the personality traits of the participants (Big Five personality test), the persuasive power of types of arguments (Questionnaire A), and the persuasive power of argumentation schemes (Questionnaire B). Participants also used our social network PESEDIA (Argente et al., 2017; Alemany et al., 2020) during one month from where we collected the online social interaction data. The context of the study, the measures and instruments, the procedure, and the participants are presented below.

4.1 Context of the Study

PESEDIA is an educational OSN aimed at teaching its users the basic privacy competences in social networks. This social network provides a free environment similar to other OSNs (e.g., Facebook, Instagram, etc.). The chosen way to teach users is by gamification, with scores and a global ranking to reward the most active and participatory users. It is possible then, to nudge the users to do activities and participate in debates without forcing them (Alemany et al., 2019b). To find answers to the research questions proposed, this study has been carried out in PESEDIA with teenage participants ranged from 12-15 years old. The study lasted one month, with the social network active and accessible 24/7 for participants. An ethics and law committee from the Universitat Politècnica de València reviewed and approved the study performed. Specifically, they reviewed that the social network PESEDIA met the GDPR laws about users’ privacy protection and management of their data.
4.2 Measures and Instruments

To model the participants, we measure their personality and online social interactions. A Big Five personality traits test aimed at measuring the personality traits (Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism) of children and teenagers (Mackiewicz and Cieciuch, 2016) has been used. Furthermore, we have also divided the participants into clusters based on their personality traits. Four major clusters have been recently identified in the literature: Average, Self-centered, Reserved, and Role model (Gerlach et al., 2018). This clustering is proposed as a way to group samples with similar social perceptions and with similar expected behaviour.

Our hypothesis to use these clusters in our study is that among similar characterised participants, it will be possible to observe stronger behavioural patterns, reducing the noise and leading to more solid findings. Thus, we have split our samples into four different personality-based groups to observe if those same clusters could be found in our population and if any behavioural pattern towards argument persuasion could be detected in each specific cluster. We ran the K-Means algorithm until its convergence to generate the mentioned clusters.

In some situations, it may not be possible to retrieve users’ personality traits. Therefore, in our study, we have also considered the data from their social interaction behaviour in PESEDIA. Thirteen different features representing participants’ social interaction in the OSN have been used in our study to model PESEDIA users as an alternative to their personality: number of friends (#friends), number of status updates (#status_upd), number of likes (#likes), number of shares (#shares), number of comments (#comments), number of private posts (#ppprivate), number of public posts (#pppublic), number of posts shared with friends (#ppfriends), number of posts shared with collections of friends (#ppcollections), number of uploaded photos (#photos), number of posts deleted (#deletes), the average length of text posts (avg_textsize), and the time spent on the network (time_spent). Previous work identified in the literature pointed out that these features could be closely related to user personality (Amichai-Hamburger and Vinitzky, 2010; Golbeck et al., 2011; Adali and Golbeck, 2012; Huang, 2019). Therefore, these features represent an alternative dimension to personality from which it is possible to model OSN users.

Finally, the persuasive power of arguments (for schemes and types) has been computed as the number of times an argument beats others. Our metric is based on (Dittrich et al., 2000) work. Therefore, we define the persuasive power for an argument $\alpha_i$ as follows,

$$s(\alpha_i) = \frac{\sum_{j \in C} b_{ij}}{|P| \cdot (|C| - 1)}$$

where $b_{ij}$ refers to the number of times the argument $\alpha_i$ beats another argument $\alpha_j$ ($i, j \in C, i \neq j$). An argument $\alpha_i$ beats another argument $\alpha_j$ if it is considered more persuasive by our participants in the questionnaires. In our study, the classes $C$ are represented as argumentation schemes and types of arguments. Regarding the parameters $|P|$ and $|C|$, they represent the number of participants and the number of options inside a class and they are used to compute the maximum number of times an argument class can beat each other. The result is a 0-1 normalised value. We have
Imagine: You are going to upload a post like the one below to your social networks with a public privacy policy

You should not make this publication because...

ARGUMENTS

Please read carefully the following arguments that try to persuade you to not perform such an action and rank them from most persuasive (1) to least persuasive (|C|).

Fig. 1: Template of the persuasive power questionnaires.

ARGUMENTS

RANK VALUES

1 2 ...

used questionnaires to measure the persuasive power of arguments, different ones for schemes and types. There, participants were faced with the same situation (Figure 1): they are going to make a publication in the network and they are told not to do it. The way of persuading the participant not to make the publication is with the use of arguments, so they had to rank these arguments, from the most persuasive argument (1) to the least persuasive one (|C|). Next, we describe how these questionnaires have been designed.

4.2.1 Questionnaire A (Schemes)

This questionnaire has been designed to capture the persuasive power of different argumentation schemes on a user (RQ1). We decided to consider the following five schemes in our study: Argument from Consequences (AFCQ), Argument from Popular Practice (AFPP), Argument from Popular Opinion (AFPO), Argument from Expert Opinion (AFEO), and Argument from Witness Testimony (AFWT). With these schemes, it is possible to capture users behaviour when facing some of the most common reasoning patterns (Walton et al., 2008) used in social network privacy-related persuasive dialogues. Furthermore, we are able to analyse how practical reasoning and different source-based arguments are able to persuade teenager OSN users. By using these schemes, our goal was to see if teenagers were more concerned about recommendations based on the consequences of their actions, an expert opinion, similar user experiences, popular behaviours, or previously affected users.

Arguments from Consequences show the participant the consequences of doing some specific action, sharing some content in our case. With this scheme, we can measure the importance each participant gives to the effect of their actions in the so-
cial network. Arguments from Popular Practice try to persuade evidencing that there is a common popular practice among other similar people regarding some specific topic. In this case, with AFPP we can observe the importance that participants give to an argument based on their friends’ activity. Similarly, Arguments from Popular Opinion try to persuade with the use of a generally accepted opinion. Therefore, AFPO allows us to observe participants’ preferences towards the generally accepted opinion regarding their privacy. Arguments from Expert Opinion base their reasoning pattern on some expert opinion regarding a specific topic. These argumentation schemes make it possible to observe users’ reliance in a privacy domain expert. Finally, Arguments from Witness Testimony make the reasoning taking into account the experience of a person in the same knowledge position. With this scheme, it is possible to measure the trust that our participants give to someone with their similar expertise level in privacy management.

In this first questionnaire, the arguments that represent these five argumentation schemes in the OSN domain and that participants ranked by their perceived persuasive power are the following (You should not make this publication because...):

- Making the publication could have bad consequences for your privacy (AFCQ)
- Most of your friends would not publish this content (AFPP)
- Everyone knows that publishing this is a mistake (AFPO)
- The monitors are experts in social networks and they believe that making publications of this type could be dangerous (AFEO)
- A user of the PESEDEIA network who has made similar publications considers that it can be dangerous (AFWT)

4.2.2 Questionnaire B (Types)

This questionnaire has been created to observe the persuasive power on our participants of the four different types of arguments considered by the argumentation framework (RQ2). These types are: Privacy, Trust, Risk, and Content arguments. Privacy arguments are generated regarding each user privacy preferences towards the audience of his/her publications (i.e., private, friends, public, or friends collection). Therefore, Privacy arguments will try to persuade the participants considering their privacy preferences and configuration. Trust arguments are the ones generated taking friendships between users into account. This type of arguments will try to persuade the participant making him/her understand that other persons may be harmed if the content gets published. Risk arguments consider the publication reachability in the network, computed as explained in [Alemany et al., 2018, 2019a]. Then, a Risk argument will be generated if the scope of the publication exceeds the user expected audience. Finally, Content arguments are generated regarding the own content of the publication. Six different types of content (i.e., location, medical, alcohol/drugs, personal information, family/association, offensive) (Caliskan Islam et al., 2014) are considered by our argumentation system. In this case, the degree of participants’ persuasion may variate with the type of content included in the publication due to its sensitivity (Schomakers et al., 2019). The arguments that participants ranked by their perceived persuasive power in this questionnaire and represent the four argument types are the following: (You should not make this publication because...)
• you have chosen public privacy settings. (Privacy)
• some of the people who appear might get upset. (Trust)
• it could be read by strangers. (Risk)
  ◦ you are revealing your location. (Content: Location)
  ◦ you are giving out personal medical information. (Content: Medical)
  ◦ others may think you consume alcohol/drugs. (Content: Alcohol/Drugs)
  ◦ you are revealing personal data about yourself. (Content: Pers. Information)
  ◦ you are revealing a friend’s personal information. (Content: Fam./Assoc.)
  ◦ you might offend some other user. (Content: Offensive)

where items represented as (●) refers to Privacy, Trust, and Risk types of arguments and items represented as (◦) refers to the different contents (Location, Medical, Alcohol/Drugs, Personal Information, Family/Association, and Offensive) of Content-type arguments. This questionnaire was done by participants as many times as different contents of Content-type of arguments are in order to avoid biases on users’ perception of information sensitivity (Schomakers et al., 2019).

4.3 Procedure

The study was carried out on the PeSedia social network where teenage users used it during one month. To prevent interferences, we included a registry controller (using a secret token) to avoid undesired registrations that could affect the security of the participants and the study. The questionnaires described above to measure participants’ features were integrated in the own social network and they were progressively enabled in the on-site sessions. They were not required to complete them at any specific moment, but participants were motivated through gamification techniques. During the whole period of the study, the participants had fully access to the PeSedia social network to share their experiences and feelings.

We organised three on-site sessions of 90 min in equipped labs at the university to use as control points of the study. These three on-site sessions were distributed at three points in time: session 1, at the beginning of the one-month period; session 2, in the middle; and session 3, at the end. The aim of these sessions was to clarify any doubts that might arise among the participants about the functionality and features of the social network. Each session started with a brief explanation of the potential activities that they could do related to testing and understanding functionalities of the social network, and then participants had time to interact using the social network. In the first session, we introduced PeSedia to the participants and they signed up on the social network. Then, they had to complete basic activities that focused on customising their user profiles, setting up their general setting options, and building their friendship relations. Before finishing the first session, the personality test was made available for the participants to complete it. In the second session, we requested participants to complete the questionnaires about persuasive power (Questionnaires A and B). In Questionnaire A, participants ranked the five argumentation schemes in a decreasing persuasive ordering. In Questionnaire B, participants faced six different instances of the questionnaire considering one specific content category at a time. They ranked the four argument types in a decreasing persuasive ordering in
each instance of the questionnaire. Arguments were displayed in a different order in each round to avoid the order effects. Finally, in the third (and last) session, we presented the participants with a summary regarding their behaviours and answers to the questionnaires to conclude the study.

Figure 2 depicts the sequence at which each element of our study was completed by the participants. Thus, following this procedure we were able to obtain the Big Five personality traits and the thirteen OSN interaction features used to model our participants. Using the Equation 2 together with the answers to the Questionnaire A and Questionnaire B, we were able to calculate the persuasive power of every argumentation scheme and argument type considered in our study.

4.4 Participants

A total of 218 teenagers participated in the study. From this total population, 215 participants completed the personality test and 212 completed both questionnaires A and B. We excluded the participants who did not complete all of the control sessions and the proposed questionnaires (29 participants) as well as the participants who decided not to participate (3 participants did not log into Pesedia). Finally, 186 participants completed the study (103 males, 83 females, $M_{age} = 13.15$, range: 12–15 years old). We included the participants in the experiment taking into account their age in order to have a sample of the teenage population (participants older than 12 years old). All of the selected participants were attending high school in different school centres of the Valencia area at the time of the experiment. In our study, we modelled our participants considering two different dimensions: the personality and the social interaction behaviour in the OSN. Furthermore, we investigated if stronger behavioural patterns

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1 Contact the authors to get access to an anonymised version of the data gathered in this study.
could be identified when grouping our population by gender (i.e., male/female) and by personality clusters (i.e., Average, Self-centered, Reserved, and Role model).

The first modelling dimension considered in this research is the personality. We used the Big Five personality traits to represent the personality of our participants. Figure 3 depicts the distribution of the Big Five values among our participants. We observed that our population presented a trend to high Extraversion values. The rest of the traits were almost normally distributed among the whole participants. Neuroticism and Conscientiousness show a slight trend towards lower values, while Openness and Agreeableness traits tended to higher values.

From these five personality trait values, we grouped our participants into four different personality clusters. Those clusters had the following composition: the Average cluster \((C_1 = 44, \text{56.8% males)}\); the Self-centered cluster \((C_2 = 38, \text{68.4% males)}\); the Reserved cluster \((C_3 = 52, \text{48.1% males)}\); and the Role model cluster \((C_4 = 52, \text{63.5% males)}\). Figure 4 shows the Big Five personality traits distribution of the clusters found in our study. Each cluster is defined by the means of averages of each personality trait z-score. Therefore, it is possible to observe how depending on the cluster (i.e., Average, Self-centered, Reserved and Role model) the personality trait average z-scores of its members follow different distributions.

Comparing the clusters found in this work with the clusters proposed in (Gerlach et al., 2018), it is possible to observe strong similarities between them. The Silhouette Coefficient (SC) (Rousseeuw, 1987) of the computed clusters is 0.173 meaning that some clusters could be overlapping (SC ≈ 0) but the samples are not being misclassified (SC > 0). The Reserved personality type is characterised by negative z-score values on Neuroticism and openness, while the rest of the traits (Extraversion, Agreeableness, and Conscientiousness) are slightly higher to 0. The Role model personality type is characterised by negative z-score values on Neuroticism and positive z-score
Fig. 4: Personality clusters observed in our participants data. (●) Is the position of cluster centres represented as the average z-score of each cluster personality traits. The error bars represent the standard deviation of each trait in each cluster. The dotted lines represent global average values (Z=0) for each personality trait.

values for the rest of the traits. For both clusters, the personality traits of our participants followed the same distributions as (Gerlach et al. [2018]) clusters. The Average personality type is characterised by z-score values close to 0 for all personality traits. In our study, this cluster follows this trend with slightly higher z-score values on Neuroticism and Openness. Finally, the Self-centered personality type is characterised by negative z-score values on all the personality traits except for the Extraversion trait. By comparing it with our cluster, we found some differences between those. However, we found a strong relationship with the original cluster in which Self-centered was based, called Undercontrolled, which was introduced in (Asendorpf et al., 2001) work. In (Gerlach et al., 2018), the Undercontrolled personality group is said to strongly influence the new proposed Self-centered cluster. From the clusters observed in our population, we can support this statement. The Self-centered cluster observed in this work has a positive Neuroticism z-score, similar to the original Undercontrolled group. Furthermore, significant differences were observed regarding the Conscientiousness trait in our Reserved and Self-centered clusters. Studies have shown how Conscientiousness is the most variable trait with the age (Donnellan and Lucas, 2008). Therefore, we think the observed differences were mainly due to the important age gap between the participants of both studies.

Finally, the second dimension used to model OSN users in our analysis is their online social interaction behaviour. During our study, a total number of 2195 likes, 7650 comments, 1309 shares, 846 photos uploaded, and 7788 status updates (from them
761 were private, 769 were public, 5774 were disclosed to friends, and 484 were disclosed to specific lists of friends) were registered in the PESEDEIA database. The participants had a mean of 12 friendships and regretted 2761 actions made (which they undid/delete). Figure 5 depicts how these thirteen features were distributed among our participants. We decided to exclude the outlier values in the figure with the aim of making emphasis on those values on which the different social interactions were predominant. The most common social interactions were comments and status updates. We observed an average of 41 comments and 42 status updates per user. However, the number of comments made by our users were more scattered, with a user who made 202 comments (not represented in Figure 5 for being treated as an outlier) and a user who never made a comment during the experiment. It is also interesting to observe the high average number of deletes per user (i.e., 15), which represents a high number of regrets of the content published in the network. We also observed that in general, users preferred to share publications with friends only rather than publicly, privately or considering specific collections of friends.

At the end of the study, we collected 186 different combinations of the Big Five personality traits and 18942 different OSN interactions. Furthermore, we also collected: 930 persuasive pairwise comparisons of argumentation schemes, one per participant (186) and argumentation schemes (5); and 4464 persuasive pairwise compar-
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5 Results

5.1 Persuasive Power of Arguments

From the results of the study, we have calculated the persuasive power of all the argumentation schemes and types considered in this work (Figure 6). Therefore, it is possible sort the five argumentation schemes taking into account their persuasive

Fig. 6: Box diagram of the persuasive power of arguments observed in our experiments. (△) represents the mean of each distribution.

Table 1: Pairwise rank comparative between argumentation schemes. This table represents the number of times an argumentation scheme (rows) beats another argumentation scheme (columns).
Table 2: Pairwise rank comparative between argument types. This table represents the number of times an argument type (rows) beats another argument type (columns).

|       | Content | Privacy | Risk | Trust | TOTAL |
|-------|---------|---------|------|-------|-------|
| Content | -       | 623     | 659  | 681   | 1963  |
| Privacy | 493     | -       | 605  | 634   | 1732  |
| Risk   | 457     | 511     | -    | 616   | 1584  |
| Trust  | 435     | 482     | 500  | -     | 1417  |

Table 2: Pairwise rank comparative between argument types. This table represents the number of times an argument type (rows) beats another argument type (columns).

power as follows (RQ1): AFCQ $\succ$ AFEO $\succ$ AFWT $\succ$ AFPP $\succ$ AFPO. *Argument from Consequences* seemed to be the most effective scheme for persuading our participants with a score of 0.61. Following, we have the *Argument from Expert Opinion* scored with 0.53, *Argument from Witness Testimony* with a score of 0.47, *Argument from Popular Practice* with a score of 0.46 and finally, *Argument from Popular Opinion* was the less persuasive scheme with a score of 0.43. These results mean that teenagers, in general, can be persuaded easier by showing the consequences of their actions or with recommendations made by experts rather than nudging them with recommendations made by someone similar to them or with popular trends or opinions.

On the other hand, we sorted the argument types taking their persuasive power into account as follows (RQ2): Content $\succ$ Privacy $\succ$ Risk $\succ$ Trust. Content arguments were the most persuasive with a score of 0.59. Following, we have Privacy arguments with a score of 0.52, Risk arguments with score of 0.47 and Trust arguments with a score of 0.42. Meaning that teenagers are more concerned about sharing sensitive content rather than being read by unknown users or endangering other parties privacy. Similar to the previous analysis with argumentation schemes, Table 2 represents a direct comparison between the ranking position of every pair of argument types. Here, we also observe how arguments with a higher persuasive power score are ranked, in general, in a higher position than the rest. If we consider each round of the questionnaire B independently to analyse the effect of each content type on the persuasion of the argument, the following persuasive ordering is observed: Offensive $\succ$ Personal $\succ$ Family $\succ$ Medical $\succ$ Alcohol/Drugs $\succ$ Location. Therefore, although Content arguments were found as the most persuasive type of arguments, depending on which type of content was considered in each round, users’ susceptibility was different. Our study revealed that teenagers are more concerned about sharing offensive content with a score of 0.64, closely followed by sharing personal information with a score of 0.62. The concern with these specific types of content matches the new trends in social networks of self-presentation ([Chua and Chang](#4194) 2016). The next most concerning types of content were family/association and medical content with scores of 0.59 and 0.58 respectively. Finally, revealing alcohol/drug consum-
5.2 Personality Impact on Argument Persuasion

In order to be able to adjust our argumentation system to increase the persuasive power of the arguments for our target population, we analysed the personality impact on the persuasive power (RQ3) of argumentation schemes and argument types. For this purpose, we have calculated the Spearman \( \rho \) rank correlation between the persuasive power of arguments and the Big Five personality traits. In order to ease the interpretation and visualisation of the results, we have grouped correlations into three correlation-strength categories based in the ones proposed in (Corder and Foreman, 2011). Weak correlations stand for correlation values between 0 and 0.2; we consider a Moderate correlation if its correlation value is between 0.2 and 0.6; finally, a Strong correlation stands for correlation values higher than 0.6.

5.2.1 Argumentation Schemes

The significant correlations found considering argumentation schemes and personality traits are represented in Table 3. Analysing the impact of the entire set of participants personality traits on the argumentation schemes persuasive power, two significant correlations have been detected. Two weak negative correlations between Extraversion and Arguments from Expert Opinion, and Agreeableness and Arguments from Popular Practice have been found. When our users have high scores on the Extraversion trait, an Argument from Expert Opinion may not have a great persuasive power. Similarly, when having a high score on the Agreeableness trait, the argumentation system should not use an Argument from Popular Practice. Since it is possible to characterise even more our users, we tried to find more significant correlations

| Participants | O | C | E | A | N |
|--------------|---|---|---|---|---|
| All          | - | - | - | - | - |
| Gender       |    |    |    |    |    |
| Male         | - | - | - | - | - |
| Female       | - | - | - | - | - |
| Personality Cluster |    |    |    |    |    |
| Average      | - | - | - | - | - |
| Reserved     | - | - | - | - | - |
| Self-centered| - | - | - | - | - |
| Role model   | - | - | - | - | - |

Table 3: Significant correlations of argumentation schemes persuasive power and personality traits. The significance is represented as: * \( p < 0.05 \), ** \( p < 0.01 \). The correlation strength is represented as: Weak = +/−; Moderate = + + / − −; Strong = + + + / − − −.
by dividing the participants by gender and personality clusters. Four significant correlations have been found for our male participants. The two positive correlations found imply that the use of Arguments from Witness Testimony in dialogues with male users with higher Extraversion and Agreeableness traits may have greater persuasive power. Negative correlations found make us think that the use of Arguments from Popular Practice and Arguments from Expert Opinion in dialogues with male users with higher Agreeableness and Extraversion traits respectively may not be the best decision in terms of persuasion. On the other hand, a positive significant correlation has been found in our female samples. Neuroticism and Arguments from Popular Practice are positively correlated, meaning that when the score in the Neuroticism trait is high, the persuasive power of an Argument from Popular Practice may also be high. Finally, when clustering our participants, it is recommendable to use Arguments from Popular Practice when dealing with Reserved users with high scores in Neuroticism. Conversely, if the Reserved user has high scores in either Extraversion or Neuroticism traits, the use of Arguments from Expert Opinion may not be as persuasive as expected. When trying to persuade Self-centered users with a high score in Conscientiousness, we observed that Arguments from Consequences may not have a decreased persuasive power. Finally, regarding Role model users, the analysis of the results show that Arguments from Expert Opinion may be more persuasive when having a high score in the Conscientiousness trait, but Arguments from Popular Opinion can be less persuasive than expected in this situation.

5.2.2 Argument Types

Three significant correlations have also been found analysing the impact of personality traits on the persuasive power of argument types as depicted in Table 4. When considering all the samples as a unique group, a negative correlation between Extraversion and Privacy arguments has been detected. This finding means that users
with high values in the Extraversion trait may not find Privacy arguments as persuasive as expected. No significant correlations have been found when dividing the participants by gender. Therefore, no more specific policies than the generic ones can be inferred when considering the gender of our participants. However, when dividing our samples by personality clusters, significant correlations have been found for Reserved and Self-centered participants. From those grouped in the Reserved personality cluster, a negative significant correlation has been detected. This correlation implies that the use of Risk arguments if Reserved users have a low score in the Openness trait is an effective way to persuade them. Finally, the persuasive power of Content arguments may increase when used with Self-centered users with a high Extraversion score.

5.3 Social Interaction Impact on Argument Persuasion

In some environments, obtaining the Big Five personality traits may not be possible. Therefore, in order to model our OSN users before analysing the persuasive power of arguments, we proposed an alternative to the personality based on the social interaction behaviour of our participants. This way, we analysed if there existed any correlation between the persuasion of arguments towards each participant depending on their social interaction behaviour (RQ4). To measure the impact of these thirteen features on the persuasive power of arguments, we have calculated the Spearman $\rho$ rank correlation between them and the persuasive power of arguments. The interpretation of the correlation values is done the same way as the previous section. Furthermore, if personality traits are available, we have also considered making a complete analysis, taking into account personality clusters. This way, it is possible to combine the results of both analysis, thus observing even more useful correlations to define dialogue strategies.

5.3.1 Argumentation Schemes

The significant correlations found considering argumentation schemes and social interaction data have been represented in Table 5. Considering all the participants as a unique set, three different correlations can be found regarding argumentation schemes.
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persuasive power. We found a positive correlation between Arguments from Popular Opinion and the number of private publications, meaning that users that usually share its posts with private configuration give more importance to the popular opinion in their privacy configuration decision making. The negative correlations found imply that the persuasive power of Arguments from Popular Practice may be lower when used with users that usually share content with specific collections of friends, and Arguments from Popular Opinion can be not as persuasive as expected with users that share long-text publications. Otherwise, if we divide our samples by gender, it is possible to observe six significant correlations. Two significant correlations have been found in our male samples. When trying to persuade a male user with a low number of likes, Arguments from Popular Practice seem to have higher persuasive power. It is also possible to observe that, if our male user has a lot of posts shared with friend collections, Arguments from Popular Practice may not be as persuasive as expected. Regarding female samples, four significant correlations have been found. Arguments from Popular Opinion have shown an increased general performance with female users that make a huge number of either private or public posts. Similarly, Arguments from Expert Opinion seemed to perform well with female users with a big amount of status updates. Conversely, Arguments from Consequences are not the best option to persuade female users that usually share their posts with friend collections. Moreover, in the case of being able to obtain users personality traits, we can divide our samples into the four personality clusters and observe several additional correlations. Average personality samples have shown three significant correlations between argumentation schemes and social interaction features. When interacting with Average users which have a big amount of friends or posts shared with friends, Arguments from Expert Opinion have shown an increased persuasive power. Additionally, if the number of private posts made by the user is not very high, we can expect a greater persuasive power from Arguments from Popular Practice. Reserved personality samples have shown four significant correlations. Arguments from Consequences have shown a greater persuasive power on Reserved users with a big number of friends, status updates and publications shared only with friends. However, Arguments from Witness Testimony presented a decreased persuasive power for Reserved users with a high number of publicly shared posts. Users with a Self-centered personality have performed worse with Self-centered users with a great number of private publications. On the other hand, if the Self-centered user tends to make long text publications, we observed that Arguments from Consequences had a lower persuasive power than the usual, and Arguments from Witness Testimony presented higher persuasive power values. Finally, Role model personality samples have shown four significant correlations. Those correlations imply that the use of Arguments from Consequences with Role model users with long text posts have an increased persuasive power. Namely, Arguments from Expert Opinion have shown an increased persuasive power with Role model users that make a great number of comments on other users’ publications. Arguments from Popular Opinion used to convince Role model users who tend to share their publications with specific collections of friends have shown an increased persuasive power. However, Arguments from Consequences presented a decreased persuasive power in this same situation.
5.3.2 Argument Types

Regarding the four different types of arguments, we have found the correlations shown in Table 6. No significant correlations can be observed when considering all the participants in the same group. Considering our samples divided by gender, it has not been possible to find any significant correlation in the female subset. However, regarding the male samples, two positive and a negative significant correlation have been found. The use of Trust arguments on male users with a high number of status updates and publications made with specific friend collections have shown an increased persuasive power. Despite this, Risk arguments presented a decreased persuasive power when interacting with male users with a high number of deletes. Moreover, if it is possible to obtain the personality traits of the users, we can further characterise the samples by dividing them into the four clusters. Several additional significant correlations have been also found when clustering our samples into the four personality clusters. Samples belonging to the Average and Reserved groups have not shown any significant correlation. However, Risk arguments present a decreased persuasive power when used with Self-centered personality users that tend to share posts privately. Finally, Trust arguments have presented an increased persuasive power with Role model users who frequently make status updates and make comments in other user’s posts.

6 Discussion

This paper presents a new study designed to measure how persuasive can arguments be, and how this persuasion can variate together with user descriptive features when trying to prevent privacy threats in OSNs. For that purpose, we presented two different questionnaires aimed at capturing users’ persuasive preferences regarding five different argumentation schemes and four different argument types (part of the argumentation framework proposed in [Ruiz-Dolz et al., 2019]). Participants ranked the arguments shown to them in a decreasing persuasive ordering. From the results of these questionnaires, we quantified the persuasive power of arguments using a new
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| Model Features | User 1 | User 2 | User 3 | User 4 |
|----------------|--------|--------|--------|--------|
| Gender         | Male   | Female | Female | Male   |
| Cluster        | Self-centered | Role model | Reserved | Average |
| Gender         | Male   | Female | Female | Male   |
| Cluster        | Self-centered | Role model | Reserved | Average |
| Personality    |        |        |        |        |
| Openness       | -      | -      | ↓      | -      |
| Conscientiousness | ↓  | ↑      | -      | -      |
| Extraversion   | ↓      | -      | -      | ↑      |
| Agreeableness  | -      | -      | -      | ↑      |
| Neuroticism    | ↑      | ↓      | ↑      | -      |
| Network Activity|        |        |        |        |
| #friends       | -      | -      | ↑      | ↓      |
| #status_upd    | ↑      | -      | ↓      | -      |
| #likes         | ↓      | -      | -      | -      |
| #shares        | -      | -      | -      | -      |
| #comments      | -      | ↑      | -      | -      |
| #ppprivate     | ↓      | -      | ↑      | -      |
| #pppublic      | -      | -      | -      | -      |
| #ppfriends     | ↑      | -      | ↑      | -      |
| #ppcollections | ↑      | -      | -      | -      |
| #deletes       | -      | -      | -      | ↑      |
| #photos        | -      | -      | -      | ↑      |
| avg_textsize   | -      | ↑      | -      | ↓      |
| time_spent     | -      | -      | -      | -      |

Table 7: Five different user models. (-) represents an average value, (↑) represents a value above the average and (↓) represents a value below the average.

Furthermore, we modelled our participants considering two different sets of features: the personality and their social interaction behaviour in the network. Considering these two user models, we explored how the persuasive power of the argumentation schemes and argument types suffered variations together with the models’ features. The results of the analysis carried out in this work make it possible to understand how teenager users’ personality and social interaction behaviour correlate with the persuasive power of arguments. In this section, we provide a detailed interpretation of the results together with the main limitations of our research and the future work plan.

6.1 Interpretation of the Results

This work sets the starting point to develop the human interaction part of argumentative educational systems to help with privacy management in OSNs. The findings of this work also point out that personality traits and social interaction features are representative OSN user features when dealing with a persuasion problem. Therefore, these features represent a powerful way to model human users when approaching a problem of these specifications. 

We can observe how different user
models may perceive arguments with a modified persuasive power. Thus, with the observed results, we can organise the available argumentation schemes and argument types following different user tailored persuasive strategies which will be more effective than the one based on the general persuasive power of arguments (i.e., AFCQ ≻ AFEO ≻ AFWT ≻ AFPP ≻ AFPO and Content ≻ Privacy ≻ Risk ≻ Trust).

Furthermore, argumentation schemes have been previously investigated and classified by experts of many different disciplines such as spanning philosophy, communication studies, linguistics, computer science and psychology (Walton and Macagno, 2015). Thus, several clusters of schemes have been defined grouped according to their general category. The schemes we work with belong to the general categories of “practical reasoning arguments” (AFCQ); and “source-dependent arguments”, concretely, to its subcategories of “arguments from position to know” (AFEO and AFWT) and “arguments from popular acceptance” (AFPO and AFPP). Recently, a relation between this classification and Cialdini’s principles of persuasion has been established (Josekutty Thomas, 2019). Thus, the “Consistency” principle of persuasion, by which people like to be consistent with the things they have previously said or done, relates to one’s practical behaviour (AFCQ); the principle of “Authority”, by which people follow the lead of credible, knowledgeable experts, relates to source-based arguments (AFEO and AFWT); and the principle of “Consensus”, by which individuals will conform to what the majority regards as acceptable, relates to arguments from popular acceptance (AFPO and AFPP). First, we can see how our findings detect a preference order “Consistency” ≻ “Authority” ≻ “Consensus” for the persuasion principles in our social media domain. Second, although there is still no specific research that orders these persuasion principles by their persuasion power in the context of social media, similar research in the healthy eating domain concluded an order “Authority” ≻ “Consensus” and “Consistency” (no significant difference between these two) and stated that persuasive power is highly influenced by the domain (Josekutty Thomas, 2019).

Based on these mappings between argumentation schemes and persuasive principles, we can contextualise our findings within essential concepts of persuasive psy-

| Persuasive Power | User 1 | User 2 | User 3 | User 4 |
|------------------|-------|-------|--------|--------|
| AFCQ             | ↑     | ↑     | ↓      | -      |
| AFEO             | ↑↑    | ↑↑    | ↓↓     | ↓      |
| AFWT             | ↓     | -     | -      | ↑      |
| AFPP             | -     | ↓     | ↑↑     | ↓↓     |
| AFPO             | ↓     | -     | -      | ↑      |
| Content          | ↓     | -     | -      | -      |
| Privacy          | ↑     | -     | -      | ↓      |
| Risk             | ↑     | -     | ↑      | ↓      |
| Trust            | ↑     | ↑     | -      | -      |

Table 8: Persuasive power of argumentation schemes and argument types for five different users. (-) represents an unmodified value, (↑) represents an increased persuasive power and (↓) represents a decreased persuasive power.
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6.2 Limitations and Future Work

The study performed in this work has been carried out in a real educational social network with teenager participants in the age range of 12 to 15. This environment provides solidity to the presented results, but also entails several limitations. First, due to the specificity of our population, the presented results may vary when considering a wider range of OSN users. On the one hand, different cultures may have a significant impact on teenager behaviour. On the other hand, advanced and experienced OSN users may find more persuasive different arguments. Thus, as the first important aspect of future work, we consider to open this study to a wider range of participants and to include the age or nationality as an additional modelling feature. Furthermore, it is important to emphasise that the arguments analysed in this work are contextualised in the OSN domain and the framework presented in (Ruiz-Dolz et al., 2019). This means that further argumentative configurations remain unexplored in the OSN privacy domain and in different domains.

In this paper, we present a correlation analysis between the features of OSN user models and different argumentation schemes and argument types. However, we do not analyse the relation between the reasoning pattern and the data source when generating persuasive arguments. Thus, it also remains future work to study how do these two factors together influence argument persuasion. Furthermore, we have presented an interpretation of the findings of our study. But no formal definition of the automatic generation of user tailored persuasive strategies is done. We plan as future work to use the data and findings presented in this work to formally define and explore the automatic estimation of the persuasive power of arguments when used in the OSN privacy management domain. Finally, our last step will be to integrate all the components with the PESEDIA privacy assistance argumentation system. This is our
first step in the intersection of Computational Argumentation and persuasion lines of research, aimed at enhancing the persuasion of privacy management assistance argumentation systems.

7 Conclusion

At the beginning of this work, we have raised four different research questions aimed at having a better understanding of human persuasion in OSNs. To answer our proposed research questions, we used different reasoning patterns and types of content-based arguments. In this research, we have been able to answer all the four different research questions. For that purpose, we proposed a new metric to quantify the persuasive power of arguments. Then, we have calculated how persuasive were both argumentation schemes and argument types for OSN teenager users (RQ1, RQ2). We also explored any existing significant correlation between user descriptive features (Personality: Table 3 and Table 4, Social Interaction: Table 5 and Table 6) and the persuasive power of arguments (RQ3, RQ4). The observed correlations make it possible to have a better perspective on the variations of the persuasive power of arguments when used to persuade different human beings. Furthermore, it has also been possible to observe how a better characterisation of users by features which might imply behavioural similarities (i.e., gender and personality clusters) allowed us to find more and better correlations between the user models and the persuasive power of arguments. Therefore, we can also conclude that behavioural patterns can be identified among both male and female user groups, and four personality clusters of OSN teenager users.

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