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Small group dynamics:

interweaving sociophysics and experimental psychology

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No man is an island entire of itself; every man is a piece of the continent, a part of the main; if a clod be washed away by the sea, Europe is the less, as well as if a promontory were, as well as any manner of thy friends or of thine own were; any man's death diminishes me, because I am involved in mankind. And therefore never send to know for whom the bell tolls; it tolls for thee.

John Donne

Abstract

The intent of our work was to study the dynamics of the individuals interacting in virtual way within a small group, with the aim to define first an experimental framework of research, and then to refine some psychological perspectives about the virtual small group dynamics.

A small group of humans engaged in a common conversation can be considered as a good example of a complex system. The group dynamics is rather complex and not predictable from the individual characteristics. Within small groups, the transitions between states of disorder and states of order, such as the spontaneous emergence of a common jargon or the emergence of a broad consensus for a particular topic, are very frequent.

The virtual experimental environment developed was inspired by a classical chat-room interface, with some expedients to keep track (in a stylized way) of the dimensions of interest in our study, such as the self-perception and the emotional non-verbal contents (mood). We performed a quantitative investigation, measuring the frequencies of messages exchanged, the mood accompanying such messages and a self-assessment of the social space.

The core of the experimental sessions was to study the relations between the affinity among individuals and their communication dynamics. As first step, we designed three different experimental tasks (social problems), with a crescent degree of social complexity, in order to test the impact of different social constraints on the evolution of the affinity network, as well as on the dynamics of communication. In such way we defined the "cognitive recipes" used by the subjects to solve the required social problems, showing that the complexity of the task affects the relations between the affinity and communication networks, influencing at the same time both the affinity and the opinion.

As second step, we deeply explored the opinion dynamics within a small virtual group engaged in a discussion on a specific topic. Within such aim, two ingredients (the personality factors and the subjective opinion about the topic of discussion) were added. We explored the relations among the subjective variables (*i.e.* personality, gender, age), the individual opinions, the affinity network and the communication patterns emerging from the small group interaction. The purpose of this last experimental step was to investigate the different "layers" existing in a small group context (individual level,

group level and intermediate level) and their mutual influences, with the aim to provide some psychological insight for the modelling of the opinion dynamics inside a small group. Our results suggest that such levels are deeply linked each others.

Finally we refined an existing model of opinion evolution and affinity dynamics, fitting real experimental data. In such a way we demonstrated experimentally the validity of the the model. Successively, we investigated the sensibility to the initial conditions of a simulated group interaction, obtaining for different values of the parameters involved into the model a completely different global dynamics. The differences shown by such scenarios have been explored, providing some sociophysics explanations and some psychological interpretations.

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Chapter 1

Introduction

The main purpose of this work is the study of the dynamics of small groups of humans that communicate through a "virtual" tool (*i.e.* chat room). We face this task from an experimental and theoretical point of view. We extend the investigation to several scenarios, studying the impact of different experimental constraints on the interactions between the individuals, on the emerging social relations, on the communication patterns and on the opinion dynamics. We propose a study carried out with numerical simulations based on the experimental observations. In such way we shall try to put into evidence the collective effects that characterize the dynamics of small groups.

The psychological literature provides several studies about the dynamics of small groups and the emergences of group phenomena (for a comprehensive overview see [1]). The small group is classically defined as composed by around $8-12$ individuals which share the same environment, where frequent and regular interactions happen. The interaction among the members of the group are characterized by some cognitive and affective factors, deriving from the merging of individual and group processes, as resulting from the interdependence among the individuals.

In order to approach the small group as complex system we consider the smaller system, the individual, and the bigger system, the group, as two interacting entities, where the local *individual* dynamics shape the global *group* dynamics, and vice-versa. Furthermore, the interaction among the members surely happens within a specific context, represented by the constraints imposed to the group, and the resources and tools available to the members [2]. The interactions that originate such dynamics can affect several group phenomena, such as the emergences of communication topology [3–6], the social identity, the in-group out-group effect [7–9], and the social influence process [10–12].

The group dynamics can be defined as the phenomena resulting from the contents, structures and individual processes occurring within the group.

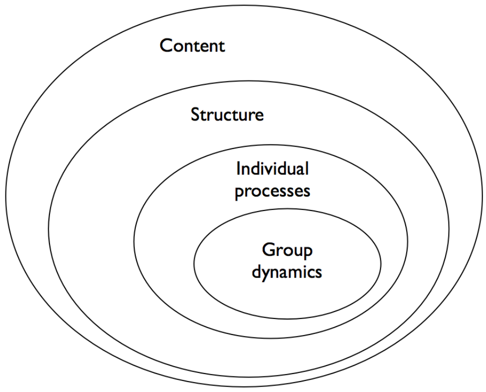


FIGURE 1.1: Different layers of analysis of the interactions in small group. The content is the most superficial level, the structure defines the topology where the processes can arise. The dynamics are considered as the result of the complex relations among the three "external" levels.

Using the schematic representation in Fig. 1.1, we shall describe the different layers of analysis of the interactions (*i.e.* virtual communications) in the small groups explored in our work.

The content level is the most superficial one, and it is the easier level to access. It includes everything the members do and say explicitly. The analysis of the contents requires a certain expertise, but it is a habitual performance in daily life. The contents include the stated objectives, or the agenda, or the topic under discussion; so that the contents is the most visible aspect by all the members of the group, and by the external observers. Within the real environment, the verbal and non-verbal exchanges represent the content of the communications. In our experiments, we refer to the content as the mood of the messages exchanged within the chat environment.

The structure is the second level of the analysis of the interactions. The structure is defined as the "network" of messages, affecting the way in which the group organizes the expression of contents. The use of a particular language, the sequence of communications, the modalities of decision making and the roles of the individuals determine the structure.

In certain contexts the structure can be explicit, and in such case the members are aware of it (*i.e.* working or training groups). The structure, coupled to the contents, allows a first assessment of the organization of the group.

The analysis of the structure gives a good snapshot of the group. The structure is what remains relatively stable over the time and thus provides the more reliable elements of evaluation, since the structure describes the regular behaviours of the group. The norms, the presence of a leader, the hierarchy of communications are further factors determining the structure. Therefore, the analysis of the structure can reveal the operational role of the individuals.

In addiction, analysing the communication structures, it is possible to study the dynamics of social groups using tools from the complex and social networks theories [13–17]. Through the study of the communication network, we can observe both the processes and the structures of communication.

Successively, we have the individual processes level. Traditionally, the psychological literature refers to the individual processes as the cognitive (*i.e.* perceptions, attention, memory, thought and language) and dynamical *(i.e.* needs, emotions, motivations) mechanisms. Contrary to the contents and to the structure, the mental processes are not directly observable: what can be observed are only the results of such process (*i.e.* expression, behaviour). In such way, within a context of small group in virtual interaction, the individual processes can be understood or deduced considering the communication patterns, the evolution of the structure of relationships and the contents exchanged.

While the contents and the structures are in some way the structural elements, the processes represent the individual mechanisms, influencing and influenced by such structural elements.

The group dynamics is the less obvious and less explicit level that we take into consideration. The dynamics can be interpreted through the observation and the analysis of the three previous levels. The group dynamics is the emergent behaviour showed by the group. The group dynamics is affected by the processes, by the the structure

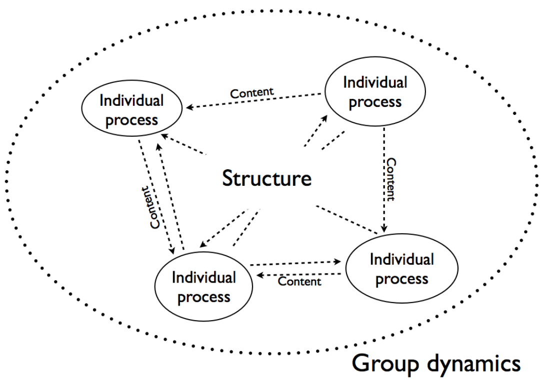


FIGURE 1.2: The group dynamics is determined by the individual processes and the structure and contents exchanged. Through a numerical approach we can study, given the individual processes, how the observables are determined, and the resulting dynamics

and the contents, but the group dynamics also influences the contents, the structure and processes. There is therefore a circular relationship between all levels taken into account.

Such considerations summarize part of our approach to the small group dynamics. We explored the communication among the individuals within a small group in a virtual environment, linking all the different layers mentioned above, considering the mood of the communication (content), studying the interaction networks (structure), the evolution of such networks (process), pointing out the phenomena emerging (dynamics) and eventually how such phenomena reverberate on the precedent layers.

Once the experimental data are collected, we try to hypothesize the individual processes that originates part of the dynamics observed. In other words we try to translate the empirical observation into a numerical approach, based on the experimental data related to the contents and to the structure, describing the individual processes and interpreting the group dynamics (*i.e.* in our model the opinion dynamics) (Fig. 1.2).

Through the sociophysical approach we assume the individual processes and the interaction rules (*i.e.* the conventional content (*opinion*) and the communication structure) explaining the group dynamics. In such way our research faces the issue of interest, the small group dynamics, with an empirical approach and simulation models, seeking experimental confirmation of the existing models and widening the experimental results through simple numerical models and computer simulations.

This work is organized as follows: we first describe the theoretical framework in Chapter 2, consisting in an overview on the literature regarding the study on the group dynamics, both from a social, psychological and sociophysical point of views, highlighting the advantages of a multidisciplinary and "complex" approach.

Successively the experimental framework is presented in Chapter 3, with the explanation of the general methods and the statistical procedure used to analyse the experimental data.

In Chapters 4, 5, 6, the steps of our research are presented, starting from the baseline of our study and providing a first comparison between two different experimental tasks (*i.e.* Blank *vs* Topic condition, Chapter 4), and an exhaustive report about the results of the three different experimental conditions, with increasing social complexity (*i.e.* Blank *vs* Topic *vs* Game condition, Chapter 5). The results of the last experimental session are discussed in Chapter 6 (*i.e,* Opinion condition). In Chapter 7, we refer to the sociophysical approach to the small group dynamics, and an opinion dynamic model is proposed (*i.e.* Opinion and affinity model evolution: the repulsion dynamics). The general considerations of our study are summarized in the conclusions, Chapter 8).

Chapter 2

Theoretical framework

In this chapter we present the roots of our research. The following paragraphs are not meant as a deep and comprehensive explanation of the methods that have been developed within each theoretical corpus, but rather as a general overview about the multidisciplinary nature of our work.

First of all, we focus on the social psychology and on the social cognition, highlighting the contribution of the psychological literature to the explication of the small group dynamics and of the social phenomena emerging from the social interaction.

Subsequently, we link the previous consideration to the implications deriving from considering the small group as a complex system, explaining the different levels of analysis that can be applied to description of the small group dynamics. We refer to the graph theory to explain how such dynamics, considered as the complex networks dynamics, can be investigated, and to the social network analysis to interpret some network measure, both from the local and global point of view.

Eventually we discuss about the sociophysics approach to the social dynamics, how such domain tries to model what happen within a group of people. The sociophysics approach represents a large part of the rationale of our experiments, that can be thought both as an experimental verification of the reference models. Furthermore, the sociophysics approach gives us the opportunity to explore the direct mechanisms for the interpretation of the experimental data.

On the basis of the experimental observations, that we will describe in Chapters 4, 5 and 6, we try to infer the mental processes of the individuals and how such processes determine and are determined by the group dynamics, essentially with a measure of the correlation between the processes. In the psychological approach the processes are often represented by linear models, usually obtained from the analysis of experimental data.

Through the sociophysics approach we hypothesize non- linear processes that determine the group dynamics and, in retrospect, we try to adapt the model to the experimental observations. In this way it is possible to speculate how non-linear processes can give rise to the observed dynamics.

All the research areas presented in this chapter, apparently far apart, are merged by our work, each maintaining his role, starting from a diverse starting point and contributing to the same goal, the small group dynamics.

2.1 Social psychology and social cognition

The focus of the social psychology is the interaction between the individual and the social environment (*i.e.* between individuals and the group), considering both the relations within the group and the relations among the groups. In such a way the social psychology aims to figure out both the relationship that the individuals establish with them and with the society.

In the past century, many leading researchers have attempted to define the peculiar features of a group of people.

Lewin has defined the group as “a dynamic whole based on the interdependence of its members (or rather, the sub-parts of the group). It is important to emphasize such point because many definitions of group used the similarity among the members rather than their interdependence as a constitutive factor” [18]. For Sherif and Sherif the group is “a social unit which consists of a number of individuals in relationships, with status and role (more or less) defined and, in some measure, stable in time. The group has a set of values and norms that regulate the behaviour of the members, at least in matters of importance for the group ” [19]. Tajfel and Turner, in the 1986, have conceptualized the group as “a collection of individuals who perceive themselves as members of the same social category, sharing a certain emotional involvement. The group members reach a certain degree of social consensus on the evaluation of their group, and their are recognized as belonging to the group” [20]. Around the 90’s, Brown simplifies the definition of a group, summarizing it into the following sentence: “A group exists when two or more people self-define themselves as members of the group, and when the existence of the group is recognized by at least one other person” [21].

What emerges from all these definitions is that the group can not be considered as a simple agglomerate of people; rather, to define a group, one have to consider in some way also the qualities of “being in group”. All the features pointed out by the definitions of the group refer to something arising within the people in interaction, both regarding the interdependence among members, the roles and the norms, and something distinguish who belong from who do not belong to the group.

The interactions among individuals appear to be a necessary criterion to establish the existence of a group, while the direct relationships are not essential for a simply assembly.

Such assumptions allow us to differentiate between at least two types of human groups: the small groups, or groups face-to-face, related to the micro-social scale, and social groups, or collective, related to macro-social scale.

The number of the members of a group is an important feature to take into account to investigate and to interpret the kind of relationships established between the people who belong to it, and consequently the kind of emerging dynamics that one can expect. Traditionally, a couple of people is defined as a dyad, three people form a triad, from four to twelve members we have the small group, up to thirty members we have the median group, and over thirty individuals the large group.

The intra-group dynamics depends on the size of the group. In the dyad there is a preponderance of the affective dynamics, that guarantees the group existence. The communicative aspect is very important, because a mutual interaction is necessary for the existence of a dyad. Within the triad the communicative aspect changes, since two of the three elements may temporarily interact with each other, excluding the third individual. The small group is one of the fundamental patterns of social interaction, since a lot of social and functional activities takes place in groups of this size. The larger groups tend to give rise to the spontaneous formation of sub-groups of such dimension. Finally, the larger groups are characterized by "less affective" relationships, and in such a context the individuals are more predisposed to uniformity and identification.

The small group is characterized by some essential factors, which emphasize the difference with smaller and larger group. The small group is a special social dimension, showing a fusion of features of dyadic relationship and collective behaviours.

Due to the low number of the members, up to 10-12, frequent and regular interactions can take place. As consequence, within the small group the members can have a precise perception and a mental representation of each other person. The members of a small group often pursue a common target, share theirs interests, and at the same time within the small group diverse needs of members emerge.

Differently from larger groups, within the small groups the individual/local features (*i.e.* the subjective variables and the peer-to-peer relations) have a relevant weight on the group/global evolution, so a challenge in the study of the small group dynamics is to establish relations between the individual and local aspects and the small group dynamics. The psychological and subjective dimensions, related to the individuals, and the social dimensions, rooted in the collective and structural features of society and of social life, are deeply intertwined. From the social point of view we can interpret the change of opinion (or whatever) as the effect of a "push" or "force" exerted by the group on the individual (*i.e.* social pressure). Through the psychological approach we try to understand how such force originates within the interpersonal relationships and intra-personal processes.

The small group is characterized by a strong interdependence among members, by feelings of union among the members, by the differentiation of roles, by a sharing and the creation of beliefs, rules, jargon, typical of the specific small group. The affective and cognitive ingredients colour and give meanings to the relationships within the small groups, giving rise to different dynamics. One way to investigate the relationships among members is to consider the communications occurring within the small group interaction, as we will explain in the next paragraphs.

The relation between the individual and the group is a central issue both to understand the personal attitude and to explain the collective behaviour. At the collective level, the group is approached taking into account the shared rules, the roles of the members, the purposes and the goals pursuit; in general the aim is to study the push towards the consensus and cohesion, or alternatively, the disintegrating forces. Regarding to the individual level, the bull's eye of the researchers is largely oriented towards the areas of emotions and cognition, with a privileged attention to the interpersonal relationships, with the aim to understand the mechanism bringing to the mental representation of the social environment.

Many studies of social psychology describe the emergence of peculiar phenomena focusing on the group/global dynamics. Known phenomena drive the small group towards the consensus. The social conformity, defined by Turner [22] as the shift of one or more "discrepant" persons towards the majority of the group, is a function of an explicit or implicit pressure exercised by the members of the group. As consequence of the group pressure, people can be prompted to the adherence to the prevailing opinions, even when such opinions are in conflict with their own way of thinking.

The study of Asch [10] about the phenomenon of social compliance explains why people conform to majority: complacency (the subjects give a public answer in order to not to look different from others), acceptance (people shift towards the majority opinion because of fear of failure), convergence (an affective motivation pushing to the conformity, because fight against the majority opinion is stressful and unpleasant).

According to Festinger [12], the group pressures towards the opinion uniformity have the function to preserve the social reality (the reality built and shared by the individuals, as reference point and as a way to identify themselves as member of the group).

Moreover, the theory of cognitive dissonance [23] describes the tendency to be coherent to the way of thinking and the way of acting. If an individual feels a dissonance between his mental and behavioural processes, he try to reduce the discomfort by changing certain aspects of his behaviour or of his inner world, made up of ideas, beliefs and opinions. Such vision of Festinger well synthesized the circularity of the relation between the individuals and the social environment, between the personal opinion and the opinion of the group.

Together with the cohesive forces that lead people to the uniformity of opinion, the small group can be characterized also by some forces tending to the divergence of opinion. Within the group, the presence of a deviant, defined as someone who claims a different opinion from those of the majority, can be perceived as a threat to the cohesion of the group. The group can increase the communication rate in order to bring the deviant towards the group opinion, and when the attempts fail, there is a dramatic fall of the communications towards the deviant. The more the members are cohesive, the stronger the aversion to the deviant.

Another possible expression of the dissent is made up of minority opinion. The studies on the minority influence [24–26] has highlighted the power of the minority to persuade and of convert the majority. According to Moscovici, the influence of the minority is quite different from the effect exercised by the majority.

The majority mainly produces complacency, while the minority may have an indirect and hidden influence, which consists in an effective change of the opinion of the individual with respect to a given issue.

Obviously, such phenomena are mediated by the will, by the desires and by the needs of the individual, biased by the mental representation made on the social environment.

Many insights from social cognition indicate that every information coming from the social environment to our senses undergoes an interpretation processes based of the individual present and past knowledge. People actively elaborate the information, giving them specific meanings and personal values [27–30]. This process would allow the human beings to categorize, and then to recognize the world and and interact with it. Often, however, this mechanism requires a large processing capacity and an amount of time that would not allow an easy and real time interaction with the environment [31].

The human beings tend to interpret the social world basing on the mental representation of the environment. The limited calculus capacity that characterizes the human brain compels to the selection of the informations to take into account. As example, a recent work demonstrates the importance of cognitive constraints for the size of the social network [32, 33]. The number of people with whom an individual can maintain a stable and "rich" social relationship is around 150 people. This number would represent a sort of cognitive limit of the human ability to recognize and keep track of the cognitive and affective events within a group.

In order to study the psychological activities implied in the social cognition, we refer to the concepts of heuristics and mental schemes. The mental schemes can be considered as a kind of short-cuts of thinking that gets judgements and makes decisions, based on limited information [34, 35]. The cognitive heuristics should be considered as meta-algorithms which, by producing, selecting and removing mental schemes, permits the human decision making and problem solving processing that we observe in the social dynamics. While the heuristics are substantially stable and hard-wired in the cognitive system, the mental scheme are learned by the individuals through the experience. Individuals use these rules when certain conditions are met.

Heuristics examples are: availability (*i.e.* the rules must be learned in previous analogous experiences), accessibility (*i.e.* the rules must be easily and quickly available) and perceived reliability (*i.e.* the rules must be perceived as trustworthy). The literature testifies that these three conditions may differ with respect to situational issues (*e.g.* the context or recent activation) or with respect to the individual factors (*e.g.* mood, expectations) [36]. Recently the operative translation of the concept of cognitive heuristic, mainly accomplished by Gigerenzer and Kahneman [37, 38], has opened a new direction in the exploration of the human social interactions. Their approaches are based on the social cognition theories and consider the cognitive systems as a satisfier more than an optimizer system. The implicit assumption suggests to observe the strategies used by the subjects to integrate the social information incoming during every social interaction, in accordance with the particular constrain they are facing.

Summarizing, the perception of the outside world is not the same for every individuals, while sharing the same environment. So, in a context of small group, the members may share a similar mental representation of the social environment, or not.

As consequence, the group dynamics could arise in a complex way from the merging of the all social environment representation built by the members of a group, as something more from the sum of all individuals point of view on the group.

In our work we take into account such consideration, gathering some data about the "hidden" network, different from one individual to another, that can affect the interactions among the members and the opinion dynamics. We consider such network as the affinity among the individuals.

For affinity we intend the strength of the relation between people, on their coupling in terms of social closeness [32, 33]. In other word, the affinity between two individuals can be considered as a "force" that influences the permeability with respect to the others' opinion within the own system of attitudes and opinions.

Let us report the point of view of the three major authors, that brought us to treat small groups as complex systems.

Bion and Tuckman focused on the different states and the different behaviours of the group development, while Lewin, with his "Social field theory", brings the concept of the small group towards the dynamical system.

The experiences of Bion, an influential British psychoanalyst, with small groups [39] suggested the hypothesis of the existence of a specific group mentality, functioning as a unit, resulting from the group processes. The existence of a "collective mental activity" when people gather together in group prompt to consider the global behaviour of the small group. The theory proposed by Bion argues that in every small group, two different aspect have to be considered: the work group, and the basic assumption group. The work group refers to the group functioning, depending on the task and on the target that the group tries to accomplish, while the basic assumption group refers to the underlying processes and the implicit movements that deeply influence the group behaviour. Bion focused on the behaviour of the latter, identifying three basic assumptions: *dependency*, *fight-flight*, and *pairing*, based on the emotional and affective relationships among the members rather than on the functional and goal-oriented relations.

Beyond the psychoanalytic meanings given to Bion's basic assumptions, not so important for this dissertation, it is interesting to point out that in the study of group dynamics we have to take into account the different kinds of processes that can emerge within the group, characterized by diverse content and different structures, that affect and constrain the dynamics observed.

Tuckman [40, 41], with his study on the development of the small groups, gives some insights to the evolution of the relationships among the members. Tuckman identifies five different stages describing the small group. Every phase is characterized by different kinds of processes and features. During the *forming* phase, the members become familiar with each other and with the group, and some issues of dependency and inclusion emerge. The communications among the members are tentative and polite, and the members behaviour is generally compliant. After that, the small group passes through the *storming* stage, where the disagreement and the dissatisfaction emerge, and the group is characterized by polarization phenomena and coalition formation. Successively, within the *norming* phase, the arising processes of cohesion bring to the unity; the roles, the norms and the relationships are established. The communication, as well as the "we-feeling", increases. During the *performing* stage the processes are generally directed to the goals achievement, characterized by a mutual cooperation to the decision making. Eventually, in the *adjourning* phase, we have the completion of the tasks, the reduction of the dependency, with a consequent increase of the independence and of the emotionality related to the disintegration of the group.

A common interesting aspect deriving from the theory of Bion and Tuckman is that the small group is describable observing it's temporary configuration and the kind of relationships among the members, depending on the phase where the group is involved.

Lewin [18] considered the constant and complex interaction between the individual and the social dimension, studying the integration of the needs and expectations of the individual with the norms and the goals of the group. The group is not reducible to his members; the group is something more, or rather, something different from the sum of its parts.

The essence of the point of view pursued by Lewin is on the interdependence among the members of the group. This means that a change of any part affects the state of all the others. Such definition highlights the scope of the concept of group as a whole, recognizing and enhancing the two components that constitute its specificity: on the one hand the individuals who compose it, on the other the social field in which they act. The group is here considered as a dynamics system of relationships characterized by continuous interactions and by a deep interdependence among the members who are part of it.

Under these considerations, the group has to be studied in an integrated multidimensional perspective, including both the emotional dimension as well as the expectations, the needs and the desires, the feelings of each individual, as well as their thoughts, actions and behaviours. All the events occurring in the group are both the cause and the consequence of the interdependence between members, group and context.

The essential points of the theory of Lewin can be synthesized in a few key concepts:

- *the concept of a whole.* A group does not represent only the sum of its members;

- *the concept of interdependence.* A group is defined not so much by the similarities among its members, rather by the fact that the members are dependent on each other. In such way a change of a part has an impact on the rest of the group;
- *the concept of dynamics.* A group is not a static reality, as a place of activities and multiple processes. Within the group the forces, the tensions and the conflicts determine changes and transformations. A group is not only a place where the interactions happen, but should be seen as a crucible of forces and processes driving the evolution of the group;
- *the concept of equilibrium.* The groups tend to the stationary states. Because of the dynamics, such equilibrium is not definitive, but almost stationary.

The new events occurring inside or outside the group constantly change his structure. In other words, within the group there is an ongoing conflict between the forces that lead to cohesion, designed to keep an individual within the group, and the forces pushing towards disintegration of the group. Referring to the group as a complex system implies to take into consideration both the organization of the elements that compose it, and the events that constantly cause the evolution of the group. Ultimately, the group lives within a system of both positive and negative tensions, observable within the network of relationships between the members, and the group behaviour consist in a sequence of operations aimed to solve such tensions, to re-establish a more or less stable equilibrium.

2.2 Small groups and complex systems

A complex system can be described consisting by many diverse but interrelated and interdependent elements, linked through many interconnections [42, 43]. Due to their characteristics, the complex systems are not reducible to only one level of description, taking into account only the microscopic level or only the macroscopic level. The complex systems exhibit certain properties that emerge from the non-linear interaction of their parts which cannot be predicted only from the properties of the parts [44–46].

So a very interesting feature of the complex systems is the mesoscopic level, the network of interactions and feedbacks between the macroscopic and the microscopic level. Such feature is maybe the most interesting characteristic of the complex system: the possible amplification of a small local phenomenon, bringing the whole system into a state qualitatively new.

One of the main reasons underlying the emergence and development of the study of complex systems is to find the simple models that can explain and reproduce those phenomena that seem to have not a deterministic nature.

The concepts of order parameters and the control parameters are very important for the study of complex systems. The order parameters are defined as the observables that describe the macroscopic behaviour of the system, while as the control parameters may be considered as the particular configurations and processes that determining the macroscopic evolution. In many cases, when a control parameter is changed, the systems are subjected to a series of qualitative changes.

Under this perspective, a system is both something more and something less, maybe something different, than the sum of its parts.

Another interesting phenomenon derived from the relation among the elements is the emergence of the self-organizational processes, for which the system organized itself in a specific spatial, temporal or functional structure without any need of a specific intervention from the outside [47, 48]. The organization of the elements may impose some constraints that inhibit certain potentials of the singular elements, but, at the same time, a self-organized system shows some qualities that would not exist without the self-organization. Such qualities are an example of emerging properties. In many dynamic systems, the global variables tend to settle into certain values or sets of values (attractors). The system may settles into a single state (a point attractor) or a recurring cycle (a periodic attractor), depending by the parameters of the system.

The complex systems are neither rigidly ordered, nor highly disordered, showing an interesting behaviour between the fixed order and deterministic chaos. Such behaviour may shows many kinds of regularities generated by multiple rules, differentiating a complex behaviour by a completely deterministic or random dynamics.

The small group can be treated as a complex and adaptive systems. As it well explained by Arrow, McGrath & Berdahl [49] it is possible consider the small groups as open and complex systems, that interact with the smaller system (*i.e.* the members) embedded within them and the larger systems (*i.e.* the collective) within which they are embedded. All such systems have fuzzy and permeable boundaries, that both distinguish them to their members and their embedding context. Within such definition we can embrace the complex reality of the small group, that can be considered both as a macroscopic and microscopic entity, depending on the level of social analysis adopted. In our work, we refer to the small group as the macroscopic system, while the individuals represent the microscopic system.

As complex system, the small group dynamically evolves. The group behaviour involves the interactions across at least three levels of causal dynamics that continually influence the group. The local dynamics refers to the activity of a group's constituent elements: members using tools and doing tasks. The local dynamics gives rise to group dynamics (*i.e.* global dynamics) and are affected and constrained by them. The global dynamics refers to the evolution of system variables, emerging from and shaping the local dynamics. In addiction, the contextual dynamics refers to the impact of the features of the group's embedding contexts that affect and constrain the local and the global dynamics.

As every dynamical system, the group changes over time. This imply to take into account the qualitative and quantitative patterns exhibited by the dynamical variables describing a social entity over time. The local dynamics rules the activity of the system in its constituent parts and elements. The global dynamics rules the activity of the system properties emerging from the local dynamics. The contextual dynamics affect the system parameters influencing the overall trajectory over time. So, the interplay between the micro and macro levels of the system is a two-way influence; the global variables emerge from, and subsequently guide and constrain, the local dynamics.

Referring to the structure of a group, we refer to the global variables, understood as the emergent aspects of the system. In our experiments, we take into account such global variables considering the development of the communicative networks and of the affinity networks emerging during the small group interaction, as will be discussed in depth in later chapters.

The contextual parameters are the features of a system that affect the dynamic operation of local variables and hence constrain the pattern over time of global variables. In our experiments, as context parameters must be considered the interaction environment, the nature of the interaction (*i.e.* virtual interaction) and the experimental design. The impact of the contextual parameters on the small group affect the behaviour of the group both to adapt to the context features and to change some features of their immediate embedding contexts.

If we consider the small group as a complex system, we have to look to the evolution of the entire system not as a directional and causal effect of some specific features of the system on other features (the effects of one variable on another). A complex approach to the small group dynamics is then realized by taking into account the interactions among the variables at local level (the individuals and the communication network), considering the evolution of the system over time (the communication dynamics), and describing how such variables affect the trajectory of a given set of local or global variables of a given small group (the group dynamics).

In our study we face with what can be thought as the mesoscopic level, between the emerging dynamics and the individuals that composed the small group. Through the experimental framework and the different conditions, we gathered the data to explore the dynamics of such mesoscopic level, using a quantitative approach to provide a qualitative interpretation of the emerging dynamics.

We focus on the networks of communication and the relationship networks to put in relation the local, the global and the contextual dynamics, in order to describe what happen within the small group in virtual interaction. In other words we study how the complex networks of relationships between the members evolve, affecting the small groups dynamics.

2.3 Complex networks, graph theory and social network analysis

The complex networks provide a useful way to study the evolution of those systems whose behaviour emerges from the interaction among the elements that compose it. A complex network is a network with non-trivial topological features, with patterns of connection between their elements that are neither purely regular nor purely random. If the relation among the elements are non-linear, it's very likely that the system described with the network exhibits a complex dynamics.

The complex systems can be represented in terms of networks of interacting elements. There are many types of networks, but essentially they are characterized by a set of nodes and a set of connections between the nodes. For what concern the small group, the links connecting the individuals differ depending on what type of elements they connect, and what kind of network they describe. Within the small group, as example, the links among members may represent symmetrical relations such as friendship, or asymmetric, directional relations such as communication, influence, or in our study, the affinity among the individuals.

The nodes can be seen as a computing entities, processing the inputs and providing the outputs. Input and output comes and goes along the links that connect the nodes to the networks. Such connections determine the flow of information among the nodes, that can be unidirectional (*i.e.* the information goes from the node i to the node j) or bidirectional (*i.e.* the information goes from the node i to the node j, and vice-versa, from b to a,). The interactions among the nodes and the connections leading to the overall behaviour of the system, that can not be observed considering only the individual components. The properties of the network outweigh those of the nodes, resulting as something different with respect to the simple sum of individual behaviours. At the same time, the features and the number of nodes, as well as the topology of the network, affect the final behaviour of the system.

In such a way the complex networks allows to keep an eye on the local dynamics (the nodes and the links among the nodes), on the global dynamics (the evolution and the topology of the network), and on the contextual dynamics (the network features), considering the system as a graph.

	A	B	C	D	E	F
A	-	1	1	1	1	
B	1	-		1	1	
C	1		-			1
D	1	1		-		1
E	1	1			-	1
F			1	1	1	-

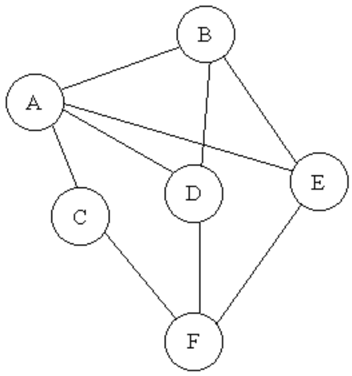


Figure 2.1: Network and adiacency matrix

In addiction to a graphical representation, as it shown it Fig. 2.1, a network can be represented also as a matrix (*i.e.* adjacency matrix). Such representation is useful when the network is formed by many elements, and it permits to map in a mathematical way the networks. Through the adjacency matrix we can represent both the directed or undirected network, and in the case of undirected networks, the adjacency matrix will be symmetrical.

The adjacency matrix is defined as a matrix NxN, where N is the numbers of nodes composing the network. The element of the adjacency matrix will be equal to 0 if the two corresponding nodes are disconnected, while, if the two nodes are connected, it will be different from zero, representing in such a way the weight of the connection.

The tools provided by the graph theory allows to consider several network/global parameters as, for example, the diameter of the network, understood as the greatest distance between any pair of nodes. To find the diameter of a graph, we have to find first the shortest path between each pair of nodes (*i.e.* the number of the links necessary to connect the pair at issue). The greatest length of any of these paths is the diameter of the graph. So, given two nodes i and j, we can define the distance d_{ij} (*i.e.* shortest path). If i and j are directly linked, we have $d_{ij} = 1$, while $d_{ij} > 1$. In this way the diameter of the graph gives an idea of the maximum number of links required to connect two different nodes.

Another relevant network/global parameter is the density of the graph, understood as the ratio between the actual number of the links and the maximum number of the possible links connecting the nodes of the graph at issue. The density indicates the general level of cohesion of a graph. Obviously, if the network is fully connected, the diameter will be equal to 1.

Together with the diameter and the density, the clustering is another important aspect of the topology of the network. Many algorithms and different methods can be applied to find the cluster configuration, but in general it defines an area of the network highly connected. So, the clustering coefficient may be defined considering the nearest neighbours of each node, and calculating the probability of a link between any pair of its nearest neighbours.

To better understand the significance of coefficient clustering, we can refer to a generic social network of people. In such network, the nodes are the individuals, and a links may indicate that two people know each other. The clustering coefficient indicates the probability that my friends are also friends with each other [50].

Such probability, also known as transitivity, is a typical property of the social networks. In terms of a generic graph G, transitivity means the presence of a high number of triangles. This can be quantified by defining the transitivity T of the graph as the relative number of transitive triples (*i.e.*, the fraction of connected triples of nodes) which also form triangles [13, 51].

The study of the clusters, beyond providing some important information about the topology of the network, gives us idea of the importance of interactions among the nodes, since it is affected by the structural position in which the node is located, and how, and how much, interacts with his neighbours.

Other indexes useful to study the topology of the network, but at the same time to define the properties of the specific node, are the measures of centrality.

The centrality degree of a node is the most studied parameter because allows to discriminate both the importance of a node and the structural features of a network. In the undirected graphs, the centrality degree of a given node is determined by the number of links emerging from the node, equivalent to the number of nodes directly reachable, called first neighbours nodes. If the network is characterized by directed links, the centrality degree is determined by the in-degree (*i.e.* the number of the input links) and the out-degree (*i.e.* the emerging links).

For what concern the sociometric and the social network analysis, many measure of centrality, and consequently implications, are introduced from the middle of the last century [4, 5, 52]. The social psychology start to take into account the topology the features of the individuals (*i.e.* actors), in terms of closeness, direction of the communication and of information flow passing through an individual, as depending by his position within the network of communication. Bavelas [3] suggested that a useful way to understand the effects of different communication structures, affecting the process and the group dynamics is to conceive the group members as individuals in relation to each other, via communication links. In his study is pointed out the importance of the way in which the actors and their communicative links are ordered by a topological point of view.

Taking a cue from the topological mathematics, Bavelas conceived various quantitative indexes by means of which different types of network are described. One of the most relevant indexes is the concept of distance, understood as the minimum number of communication links that a member of the group must pass through to communicate with another individual. An important measure for the group is the index of centrality, which refers to the flow of information, and how much such flow is centred on one particular actor, or is distributed in uniform way among the members.

The relevance of an individual due to his position within the network can be summarized with the concept of closeness centrality and betweenness centrality degree [17, 50, 53, 54]. The closeness centrality is a measure based on the distance among nodes, defined as the inverse of the average distance from all other nodes. The betweenness centrality degree refers to the structural and topological centrality of a node, and using the formalization of the graph theory, is defined as the ratio between the shortest paths passing through a node and the number of the shortest paths connecting all the nodes of the network.

The network of relations among the individuals belonging to the small group, allow to observe the configuration of the relationships structure among the individuals. In our study we focused on the networks detected within the small group interactions, as it is described in Chapter 3. Considering the small group as complex system, and using the graph theory to study the local and global variables, we shed light on how such variables affect the local and global dynamics.

2.4 Sociophysics and opinion dynamics

A first contribution from the physics to the study of the social systems it was to introduce the methods and tools derived from the theories of non-linear dynamic systems and complex systems.

The sociophysics is a discipline that study the social phenomena from a physics point of view, often using the human/atom, social/atom, or human/particle perspective. The individuals in social context seem to behave, with a large degree of approximation, as particles that can be studied with the tools provided by the statistical physics.

The sociophysics considers that, within the groups of people, there are transitions between states of disorder and state of order, as example the spontaneous emergence of a common language or the emergence social norms [55, 56]. The focus of statistical physics on the social dynamics field is to understand how such phenomena emerge. Translating the meaning of order from the physics to the social sciences we refer to the concepts of consensus, uniformity, agreement; while the disorder may be translated with the concepts of disagreement or the fragmentation of the group.

A first difficulty occurring in the study of the social dynamics from the point of view of the statistical physics relies into the fact that the latter studies relatively simple objects, with-well known behaviours. The macroscopic phenomena are due to non-trivial collective effects caused by the interactions of a large number of simple elements. Human beings are exactly the opposite of such simple entities. The individual behaviour is surely more complex, and the contribution of the sociophysics is to model the interactions between individuals by defining few simple parameters.

The strength of the statistical physics approach is due to the fact that for many issues the qualitative properties of large scale phenomena do not depend on the microscopic details of the process. The higher level features, such as symmetry, the synchrony, or the conservation laws, are more relevant to the overall behaviour. Under such considerations, the statistical physics models are anyway useful to the social dynamics field, especially in order to explain the qualitative characteristics exhibited by such models based on the most simple and essential properties of the individuals, and their interactions.

The first step in this direction is realized by the comparison between the empirical data and the predictions of the model. Such procedure allows to check if the trend of the real data is close to what expected from the microscopic/individuals model, if the results are consistent or if the model needs to add some variables or to modify certain parameters. The opinions, the cultural and linguistic traits, the social status are treated as a small set of variables whose dynamics is determined by the social interactions.

Basically, the dynamics of the social systems tends to reduce the variability of the initial state, leading to a state of order, with all the agents that share the same characteristics, or, where not possible, to a state of disorder. The direction that takes the evolution of the system can be addressed using the appropriate concepts and tools from the statistical physics.

The challenge is to find those fundamental mechanisms of interaction that allow the emergence of consensus, of a shared culture, of the language, of the collective movements of a specific hierarchy, and what prevents them born.

Anyway, each model of social agents inevitably neglects many details. One way to remedy to such lack is to include the details within the definition of the noise affecting the dynamics of the system. The time-dependent noise is often used to represent the intrinsic variability of the individuals. On the other hand, such noise may give rise to spontaneous transitions of the agents from one state to another. In this direction, the crucial question is to understand and to define when and how the system reaches the stability, in respect of the perturbations emerging from the interactions between the agents and the effect of the noise.

Another important feature to take into account, as previously discussed, is the topology of the network of interactions. The traditional statistical physics often develops structures whose elements are regularly localized in a space, or simply it considers the hypothesis that each object interact with every other, thus ensuring that the mean field approximation is correct. This assumption generally allows to analytically treat the problem, but it is not very realistic regarding a social network, where it is much more plausible that the pattern of interactions is determined by a complex network of interaction among the individuals.

The agreement degree is one of the most important aspects of the dynamics of social group. In everyday life many situations in which it is necessary that a group reaches a shared decisions happen. The dynamics of agreement or disagreement between individuals are very complex, depending both from the individuals variables and the group tendencies. Within a statistical physics approach, the opinion is generally understood as any output produced by the cognitive system when exposed to an external information. The statistical physics works in the field of opinion dynamics with the aim to define the opinion of a population, considered as order parameter of the system, and the elementary processes that determine the various transitions between the states.

Some interesting ingredients of the various model of sociophysics and opinion dynamics can be summarized as *load-bearing structure* of the bridge between physics and social sciences [57]. Translate some concepts from physics to social sciences, and vice-versa, may seem a stretch, but generally changing the point of view on the object under investigation, at least adds something new to the old perspective. In sociophysics and opinion dynamics, the concept of opinion, was initially treated as spin (*i.e.* a binary variable assigned to an agent, or actor). The agents are generally distributed on a lattice, or on a graph, and in such way the spin and the eventual links among the agents are treated in a mathematical way, for the analytic explanation, or for the computer simulations. The interactions among the agents, following a physics approach, can be detected observing the correlations between their states. Such aspects of interaction can easily transposed into the concept of relation among individuals (*i.e.*interpersonal interactions), considered as information exchanges. The interaction between a pair of agent may favour the sharing of a common opinion or vice-versa, depending on the rules implemented within the interaction rationale. As example, in the voter model, an agent takes the opinion of his neighbours [58–61], while in the Sznajd model the opinion change depends on the occurrence of a pair of neighbours with the same opinion [62]; in Deffuant-Weisbuch [63] and in Hegselmann-Krause model [64] the interaction is subjected to the difference in opinion threshold, and finally in many model of Galam [65], the interaction and the change of the opinion are mainly based on several forms of majority rule.

Another interesting ingredient to take into account for social and opinion dynamics modelling is the "temperature". Conceptually similar to the time-dependent noise mentioned just above, the temperature is often used in order to modify the probability distribution of the interactions, including the external information, or a sort of memory term of past interactions. The temperature is also used to simulate the willingness to behave randomly, against rules [66, 67], putting into the model a certain amount of uncertainty.

Finally, a concept that plays an important role in the social dynamic models is the concept of "bounded confidence" (*i.e.* if two individuals interact, they should not be too different). Such consideration recalls the conceptualization about the interactions in physics: if two particles are too far from each other, they do not exert any influence on their own. However, if we consider that the distance within the concept of bounded confidence is not necessarily spatial, we have to define a different kind of space that influences the probability of interaction (in Hegselmann-Krause and in Deffuant-Weisbuch models the difference in opinion, in our experiments and in our model the affinity and the opinion).

Taking all the ingredients and concepts mentioned above, the sociophysics aims to find into the dynamics of opinion the factors leading, or not, to a stable or meta-stable state of equilibrium, and studying the eventual phase transitions emerging, to find a set of mathematical rules describing the mechanisms for the opinion evolution and the opinion changing.

In the mathematical models, the opinion is considered as a variable, or a set of variables, represented in numerical way. This may seem simplistic, considering the complexity of people. However, in the majority of the situations faced in everyday life, people have a limited number of positions for a specific issue: the democrats or republicans, Windows or Apple, buy or sell.

The opinion dynamics models can be grouped into two major classes. Early models have dealt with binary opinions, taking a cue from physics , where agents behave as magnetic spins; so the opinion could have only two states $(-1, +1)$. In this case, the social agents update their opinion under the pressure of social influence, according to the dynamics of majority rule. The other class of models of opinion dynamics treat the opinion as a continuous variable, which dynamically evolves depending on the interactions between the individuals.

The Ising model [68], originally conceived to describe the ferro-magnetism mechanism in mathematical way, represents the baseline for the binary opinion dynamics [65]. The spin-spin coupling is viewed as the interaction of two agents, and the magnetic field as the majority opinion. In addition, the individual fields are then introduced to determine the personal preferences. Depending on the strength of individual fields, the system can reach a total consensus or a state in which both opinions coexist.

The continuous opinion models [69] are characterized by a range of opinion, expressed with a real or an integer number. The most famous model existing in literature are developed independently by Hegelsmann-Krause [64, 70] and by Deffuant-Weisbuch [63, 71, 72]. Such models consider a population of N agents, and the opinion of the agents change, respectively, taking the average opinion of all the agents in the system which do not differ too much of the agent opinion, or through a random binary encounters, if the opinions of the couple of agents are not too far.

The contribution of these models to the study of social dynamics is to explore different scenarios by numerical simulations, depending on small changes in the initial conditions or changing the parameters that define the models.

In the next paragraph we will present more in detail the Deffuant-Weisbuch model and its variation, made by our working group, coupling the opinion dynamics to the evolution of the affinity among the agents. These models are then used to fit the real data gathered in the opinion modality (see Chapter 6) and to realize a comparison of the discrepancy of real data simulation with the Repulsion model, as will be explained in Chapter 7.

2.4.1 Deffuant-Weisbuch model

The Deffuant-Weisbuch model [71, 72] considers a population of N agents, and at each instant of time t two agents i and j, randomly selected, meet. The key strength of the Deffuant-Weisbuch model is the simplicity of the rule of the opinion adjustment. If the opinions of the two agents selected are not too different, namely $|O_i - O_j| < d$, where d is the critical threshold taken as constant in time, the opinions of i and j get close, according to the following rules:

$$o_i^{t+1} = o_i^t + \mu(o_j^t - o_i^t) \tag{2.1}$$

$$o_j^{t+1} = o_j^t + \mu(o_i^t - o_j^t) \tag{2.2}$$

where μ is the convergence parameter, taken between 0 and 0.5 during the simulations.

The Deffuant-Weisbuch model explores several opinion dynamics (random encounters among agents, agents on a lattice, vectors of opinion), and the results seem robust across different conditions, exhibiting the more or less same clustering behaviour.

The results of such model demonstrate that the opinion distribution fundamentally depends by the critical threshold d, while the N and μ affect the convergence time and the width of the distribution of final opinions. The model, starting from an initial uniform distribution of opinion, shows one cluster (*i.e.* the uniformity) only for larger value of d ($d > 3$), and the maximum number of peaks (*i.e.* the basins of attraction in the space of opinion) decreases as function of d. Furthermore, for $d = 3$, the simulations shows from 2 to 7 significant peaks (*i.e.* clusters), and some isolated opinions, while for $d = 2$ a large number (around 500 for $N = 1000$) of small clusters is observed.

The main result of the computer simulations suggest that when the opinion exchange is limited by the similarity of opinions among agents (d), the dynamics yield isolated clusters among initially randomly distributed opinions. Initially all the agents were communicating either directly or indirectly through several connected agents, while, as the dynamics operate, the exchange of opinion only occurs inside the clusters.

2.4.2 Opinion and affinity model

In the celebrated Deffuant-Weisbuch [71] model the agents adjust their opinion as a results of random binary encounters whenever their difference in opinion is below a given threshold. The rationale behind the threshold reflects the humans' natural tendency to avoid conflicting interests and consequently ignore the perception of incompatibility between two distant cognitions. In this respect, the threshold value measures the average *openness of mind* [72] of the community.

In real life, the difference in opinion on a debated issue is indeed playing a crucial role. However, the actual outcome of an hypothetical binary interactions also relies on a number of other factors, which supposedly relate to the quality of the inter-personal relationships. Mutual *affinity* condensates the past interactions' history and contributes to select the preferential interlocutors for the future discussions. In this model [73, 74] the affinity is dynamically coupled to the opinion, and consequently updated in time. Moreover, the affinity is also translated into the concept of *social distance*, here introduced to drive the preferential interactions among the affine individuals. Macroscopically, the system shows an asymptotically organization in clusters of agents sharing a common opinion, whose number depends on the choice of the parameters involved. Most importantly, the proposed theoretical scenario captures the so-called *cognitive dissonance* phenomenon, a psychological theory pioneered by Leon Festinger [23].

The model consider a population of N agents, where, at every time t, the agent opinions are defined as $O_i^t \in [0,1]$. Moreover, a $N \times N$ time dependent matrix α^t is introduced, whose elements α_{ij}^t are defined within the interval $[0,1]$. Such elements specify the affinity of individual i vs. j, and the larger numbers are associated to more reliable relationships. Both the opinions vector and the affinity matrix are randomly initialized at time $t = 0$. At each time step t, two agents i and j, are selected according to a strategy based on their *social distance* (2.7). They interact updating their respective opinion and affinity values according to the following recipe:

$$O_i^{t+1} = O_i^t - \mu \Delta O_{ij}^t \Gamma_1\left(\alpha_{ij}^t\right) \tag{2.3}$$

$$\alpha_{ij}^{t+1} = \alpha_{ij}^t + \alpha_{ij}^t[1-\alpha_{ij}^t]\Gamma_2\left(\Delta O_{ij}\right) \tag{2.4}$$

where the functions Γ_1 and Γ_2 respectively are:

$$\Gamma_1\left(\alpha_{ij}^t\right) = \frac{1}{2}\left[\tanh(\beta_1(\alpha_{ij}^t - \alpha_c)) + 1\right] \tag{2.5}$$

$$\Gamma_2\left(\Delta O_{ij}\right) = -\tanh(\beta_2(|\Delta O_{ij}^t| - \Delta O_c)) \tag{2.6}$$

Here, $\Delta O_{ij}^t = O_i^t - O_j^t$, while α_c, ΔO_c are constant parameters. For the sake of simplicity is considered the limit $\beta_{1,2} \to \infty$, which practically amounts to replace the hyperbolic tangent, with a simpler step function profile.

Within this working assumption, the function Γ_1 is 0 or 1, while Γ_2 ranges from -1 to 1, depending on the value of the arguments. Γ_1 and Γ_2 act therefore as effective switchers. Notice that, for $\alpha_c \to 0$, Eq. (2.3) reduces to Deffuant-Weisbuch scheme [71]. To clarify the ideas inspiring the proposed formulation, we shall focus on specific examples. First, suppose two subjects meet and imagine they confront their opinions, assumed to be divergent ($|\Delta O_{ij}| \simeq 1$). According to Deffuant-Weisbuch's model, when the disagreement exceeds a fixed threshold, the agents simply remain to their positions. Conversely, in the present case, the interaction can still result in a modification of each other beliefs, provided the mutual affinity α_{ij}^t is larger than the reference value α_c. In other words, an individual exposed to the conflicting thoughts, have to resolve such dissonance in opinion by taking one of two opposite actions: if $\alpha_{ij}^t < \alpha_c$, the agent ignores the contradictory information, which is therefore not assimilated; when instead the opinion is coming from a trustworthy source ($\alpha_{ij}^t > \alpha_c$), the agent is naturally inclined to seek the consistence among the cognitions, and consequently adjust its belief. The mechanism here outlined is part of Festinger's cognitive dissonance theory [23]: contradicting cognitions drive the mind to modify existing beliefs to reduce the amount of dissonance (*i.e.* conflict) between cognitions, thus removing the feeling of uncomfortable tension. The scalar α_{ij} schematically accounts of a larger number of hidden variables (personality, attitudes, behaviours,..), which are non trivially integrated in an abstract affinity concept. Notice that the matrix α^t is non symmetric: hence, following a random encounter between two dissonant agents, one could eventually update his opinion, the other still keeping his own view. A dual mechanism rules the self-consistent evolution for the affinity elements (see Eq. (2.4)). If two people gather together and discover to share common interests ($|\Delta O_{ij}^t| < \Delta O_c$) they will increase their mutual affinity ($\alpha_{ij}^t \to 1$). On the contrary, the occasionally encounter with an agent characterized by a different viewpoints ($|\Delta O_{ij}^t| > \Delta O_c$), causes a reduction of the affinity value ($\alpha_{ij}^t \to 0$).

The logistic contribution in the Eq. (2.4) confines α_{ij}^t in the interval $[0, 1]$. Moreover, it maximises the change in affinity for pairs with $\alpha_{ij}^t \simeq 0.5$, corresponding to the agents which have not come often in contact. Couples with $\alpha_{ij}^t \simeq 1$ (resp. 0) have already formed their mind and, as expected, behave more conservatively.

The selection rule implemented is defined as follow. First the agent i is randomly extracted, with uniform probability. Then a new quantity d_{ij} is introduced, hereafter termed *social distance*, defined as

$$d_{ij}^t \quad = \quad \Delta O_{ij}^t (1 - \alpha_{ij}^t) \qquad j = 1, ..., N \qquad j \neq i. \tag{2.7}$$

The smaller the value of d_{ij}^t the closer the agent j to i, both in term of affinity and opinion. A random, normally distributed, vector $\eta_j(0, \sigma)$ of size $N - 1$ is subsequently generated, with mean zero and variance σ. The social distance is then modified into the new social metric $D_{ij}^\eta = d_{ij}^t + \eta_j(0, \sigma)$. Finally, the agent j which is closer to i with respect to the measure D_{ij}^η is selected for interaction.

The additive random perturbation η is hence acting on a fictitious 1D manifold, which is introduced to define the pseudo-particle (*i.e.* agent) interaction on the basis of a nearest neighbours selection mechanism. η is thus formally equivalent to a *thermal noise* [75]. Based on this analogy, σ is here labelled *social temperature* and set the level of mixing in the community. Notably, for any value of σ, it is possible that the agents initially distant in the unperturbed social space d_{ij}^t mutually interact: their chances to meet increase for larger values of the social temperature.

Numerical simulations are performed and the dynamical evolution of the system monitored. Qualitatively, asymptotic clusters of opinion are formed, whose number depends on the parameters involved. The individuals that reach a consensus on the question under debate are also characterised by large values of their reciprocal affinity. The final scenario results from a non trivial dynamical interplay between opinion and affinity: the various agglomerations are hence different in size and, centred around distinct opinion values, which cannot be predicted a priori. The dynamics is therefore significantly more rich, and far more realistic, than that arising within the framework of the original Deffuant-Weisbuch scheme [71], where the cluster number and the average opinions are simply related to the threshold amount. Notice that, in the model the affinity enters both the selection rule and the actual dynamics; such ingredient appear to be crucial to reproduce the observed self-organization.

2.5 Where psychology and physics yet meet: the psychological field

The concept of psychological field, proposed by Lewin around the middle of the past century [18], was inspired by physics, by means of analogies with the local field felt by a spin in a magnetic material. Other concepts of sociophysics also arose as analogies with physics, so let me try to draw a quick summary of the main concepts of classical (computational) physics and how they can be "translated" to the context of psychology.

In physics, a particle i is identified by its spatial coordinates x_i and velocities $\dot{x}_i$, and by some internal degrees of freedom y_i, which is the quantity related to the interactions (*e.g.*, mass, charge, magnetic moment or spin, ...). For simplicity we consider scalar x and y. We shall indicate by $\boldsymbol{x} = (x_1, x_2, \dots, x_N)$ and $\boldsymbol{y} = (y_1, y_2, \dots, y_N)$ the set of all N properties of particles.

There are interactions among objects: pair interaction, triplet interactions, etc. Let us consider only the pair ones.

In general the interactions are expressed by means of an energy function

$$H(x) = -\sum_i h_i y_i, \tag{2.8}$$

where h_i is the local field (the minus sign implies that the energy is lower if h_i and y_i have the same orientation). The local field h_i depends on the state y_j and position x_j of other particles j. For pair interactions

$$h_i = \sum_j f(y_j, x_i - x_j). \tag{2.9}$$

For instance, the local field could simply be represented as a decreasing function of the distance, like

$$h_i = \gamma \sum_j \frac{y_j}{(x_i - x_j)^2}. \tag{2.10}$$

The energy is then used to obtain the deterministic equation of motion, with the introduction of the inertia mass m,

$$m\ddot{x}_i = -\frac{\partial H}{\partial x_i}, \tag{2.11}$$

or equivalently

$$\begin{aligned} \dot{x}_i &= v_i, \\ \dot{v}_i &= -\frac{1}{m}\frac{\partial H}{\partial x_i}. \end{aligned} \tag{2.12}$$

The inertia mass is in principle different from the mass that originates the gravitation force, and is essentially a memory term. If the quantities y_i vary with time, other equations are required.

Although classical mechanics is deterministic and conservative, the motion of everyday objects is in general dissipative and (sometimes) stochastic. We can think that the above description is *microscopic*, including all interactions of all particles, but that our *macroscopic* perception is only able to observe collective quantities. In other words, it is like if we *project* the trajectory of the system from a highly (N) dimensional space onto a space with much less dimensions (M). It is in general impossible to perform this procedure exactly, and we therefore introduce *phenomenological* equations of motion, that retain some of the symmetries of the original ones.

For instance, we can introduce a dissipative friction and a stochastic force and get

$$\begin{aligned} \dot{x}_i &= v_i, \\ \dot{v}_i &= -\gamma v_i - \frac{1}{m}\frac{\partial H}{\partial x_i} + \eta(t). \end{aligned} \tag{2.13}$$

If the dissipation is strong (γ large), the term $\dot{v}$ is negligible with respect to γv, and we can assume that the velocity has no memory of the past

$$v_i = -\frac{1}{\gamma m}\frac{\partial H}{\partial x_i} + \frac{1}{\gamma}\eta(t), \tag{2.14}$$

so that we only have one dynamic equation

$$\dot{x}_i = -\frac{1}{m'}\frac{\partial H}{\partial x_i} + \eta'(t), \tag{2.15}$$

where $m' = \gamma m$ is the effective inertia (memory term) and we have rescaled the noise. If the internal variable y is not constant, there is a similar equation for its evolution.

The stochastic and the viscous terms represents the influence of the (chaotic) parts not included in this description. The central limit theorem assures that the exact form of the stochastic term is not very important, unless there are long-range correlations like in the proximity of a phase transitions.

In general one is not interested in the trajectory, but in computing the value of some observable $A(y)$. Given a trajectory $x(t)$, $y(t) = y(x(t)$ and we get $A(t) = A(y(t))$. If the system reaches a stationary state one is interested in computing the average value of A over a long enough trajectory, or averaged also over different initial conditions. If the trajectory visits the available space in short times, the system is said to be ergodic.

Chaotic and stochastic system are generally ergodic (again, with exceptions due to long-range correlations).

Given a stochastic system, in principle it is possible to write down the equation for the evolution of the probability distribution $P(x,t)$ (Markov or Master equation, if discrete or continuous in time)

$$\frac{\partial P(x,t)}{\partial t} = \sum_{x'} W(x|x')P(x',t) \tag{2.16}$$

but in general this is a highly-dimensional equation, difficult to solve. Assuming a smooth behavior in space (we already assumed a smooth time variation since we used a differential approach), we can get a diffusion-like equation (the Fokker-Plank equation), which is simpler and from which one can derive sometimes a closed equation for the observables. However, from a computational point of view, it is often easier to generate stochastic trajectories and average over them.

The equilibrium case is generally simpler to approach. We can assume that the asymptotic distribution is one that maximizes the entropy (or minimizes the information) given the constraints. For instance, in the case of conserved volume and average energy, the equilibrium distribution is

$$P(x) = \frac{1}{Z} \exp\left(-\frac{H(x)}{T}\right), \tag{2.17}$$

where

$$Z = \sum_x \exp\left(-\frac{H(x)}{T}\right) \tag{2.18}$$

is the normalization constant (partition function) and T is the temperature (that fixes the average value of the energy).

The computation of Z is however impossible in general (too many terms). However, we can profit of the asymptotic distribution in order to separate the variables that appear additively in the energy (due to the properties of the exponential). In this way one can reduce the number of degrees of freedom and concentrate on the difficult (non-separable) part of the system. Moreover, one is free to choose the dynamics, provided that the symmetries and the constraints (for instance the volume and the energy) are maintained.

Considering that one is interested in the average value of observables

$$\langle A \rangle = \sum_x A(y(x))P(x), \tag{2.19}$$

the idea is that of generating "fictitious" trajectories $x(t)$, such that averaging the same result of averaging over $P(x)$.

In practice, one writes a series of stochastic equations of the form

$$\begin{aligned} y'_i &= \sum_j f(y_i, y_j, x_i - x_j; \eta_i), \\ x'_i &= \sum_j g(y_i, y_j, x_i - x_j; \xi_i), \end{aligned} \tag{2.20}$$

where $x' = x(t+1)$, $y' = y(t+1)$ and all other quantities are computed at time t, η and ξ are random numbers, and the positions x_i may or may not evolve with time, according to the model.

This is the Monte Carlo technique. It consists in proposing a displacement Δx or Δy and computing the corresponding variation of energy ΔH, used to decide if the displacement is accepted or not. The simplest recipe for having $p(x)$ as asymptotic distribution, is to use the "golden rule" of the detailed balance

$$\frac{W(x'|x)}{W(x|x')} = \exp\left(-\frac{H(x') - H(x)}{T}\right), \tag{2.21}$$

where $W(x|x')$ is the probability of accepting the displacement ($\Delta x = x' - x$).

The Langevin or Fokker-Plank equation can be computed also in out-of equilibrium conditions, and assuming local equilibrium also the Monte Carlo approach can be extended to such cases.

In physics the interactions are generally symmetric, and this has the consequences that the asymptotic state is unique (with fixed boundary conditions, finite number of elements and short-range interactions) and is reached without oscillations. Again, in the presence of a phase transition this uniqueness is no more valid (ergodicity breaking).

A classical example of this approach is the Ising model, in which the state variables are the spins $Y_i = \pm 1$ and we completely disregards the dynamical variables. The "difficult" part of the energy is simply

$$H(\boldsymbol{y}) = -J \sum_{i,j} a_{ij} y_i y_j, \tag{2.22}$$

where the adjacency matrix $a_{ij} = 0, 1$ defines the topology of the interactions (for instance, a square lattice, a random network, etc.).

A formally similar system is given by neural networks

$$H(\boldsymbol{y}) = -\sum_{i,j} J_{ij} y_i y_j, \tag{2.23}$$

where now the interactions J_{ij} (that includes the adjacency term a_{ij}) need not to be symmetric, and therefore the dynamics can exhibit cycles and the asymptotic state is no longer unique.

2.5.1 Socio-psychological field

The above concepts suggest some application to the psychological domain. In this case x can be a real spatial variable, if we are interested in the displacement of people for instance in a crowd, or they can be other variables related to the efficacy communication, *i.e.*, they can be the variables used to establish the "distance" among two individuals, affecting the efficacy of the communication.

Almost all applications of these concepts to the psychological domain start by stochastic equations that can be considered the equivalent of a Monte Carlo dynamics. In practice, one starts from Eq. (2.20) without explicitly giving its derivation.

The variable y can be considered a sort of opinion, or the contents of the communication. In physics the interactions are symmetric (*i.e.* distance) but in psychology they do not need to be so, and therefore we can have different dynamical behaviours such as limit cycles, chaos, etc. In many cases, one in not interested in the real position of actors, but rather in their "social" distance, that does not generally obeys to the rules of Euclidean spaces.

Therefore, we can replace the "position" x_i with an affinity matrix α_{ij}, considering that for the spatial position the "distance" $||x_j - x_i||$ becomes $\alpha_{ij} = ||x_j - x_i||$, but that one can extend the problem to cases where one considers a "social" distance or its inverse, the affinity, for which $\alpha_{ij} \neq \alpha_{ji}$. We consider that α_{ij} is the affinity of person j to person i (*i.e.*, how much j influences i).

Lewin's psychological field can be considered the equivalent of Eq. (2.10)

$$h_i = \sum_j \alpha_{ij} y_j, \tag{2.24}$$

and for instance one can study the influence of highly influential individuals i (leaders or authoritas) such that $\alpha_{ji} \gg \alpha_{ij}$.

In particular, for what concerns the chat-line experiments, the affinity α_{ij} can be considered equivalent to the radial distance from origin of individuals j in the private radar of individual i (see Chapter 3).

The first applications are "consensus" theories, that are somewhat inspired by the Ising model and neural networks. In this cases one considers two (or more) opinions, and assumes that people change their opinion after an interaction with connected neighbours. One can be interested in the influence of temperature or topology in the asymptotic state (phase transitions), the influence of leaders or external fields, or in the dynamics of the system (oscillations due to parallel dynamics).

Another studied problem is the investigation of the form of the asymptotic distribution as a function of the initial distribution and of the form of the affinity. In the Deffuant model [71] the affinity α_{ij} drops to zero after a certain threshold distance, and this induces the formation of clusters of opinions (y_i is in this case a continuous variable). In this sense, peace mediators are those individuals with a larger threshold distance, so that they are able to "cross" the group boundary and promote consensus.

A more realistic case is to assume that the affinity also evolves in time, for instance according to previous agreements in opinions. In this case we can write equations of the form

$$
\begin{aligned}
y_i' &= \sum_j f(y_i - y_j, \alpha_{ij}; \eta),\\
\alpha_{ij}' &= g(y_i - y_j, \alpha_{ij}; \xi),
\end{aligned}
\tag{2.25}
$$

where one can introduce also memory (inertia) terms. For instance, stubborn individuals can be considered the equivalent of highly massive particles.

Similar equations have been studied in [73] and will be the subject of further investigation in Chapter 7.

These considerations constitute a basic knowledge for physics, but not for psychologists and I found them quite useful for focussing the “inspiration source” of many concepts in the modelling of complex systems.

Chapter 3

Experimental framework

In recent years we have seen a growing presence of virtual interactions, due to the technological development and to the massive diffusion of internet connections and of computers, and due to the innate need of communicating of the human beings, as evidenced by the use of Internet that people do, especially in the last decade, where there been a proliferation and a sharing of social networks [76–78].

Consequently the people more and more often coexist in a new environment of social interactions, similar in some way, but different with respect to the real environment [79]. As example, the virtual interactions are characterized by a predominant role of the writing form of communication, to the detriment of all the elements typical of the face-to-face communications, such as the speech language and all its features (*i.e.* tones, inflections, pauses), and those relating to non-verbal language (*i.e.* facial expressions, body gestures) [80].

The new technologies provide an high level of accuracy in the detection of the variables of interest, and the possibility of gathering a large amount of data, allowing the extremely refined experimental investigations. In that regard, we present a framework of research and an interface environment, based on a classical model of chat lines. Such experimental design allows us a precise extrapolation of the data, a quantitative investigation of the communications and the possibility to treat the group dynamics with the mathematical approach and with the tools and concepts deriving from the theory of complex networks and from the social networks analysis [13, 14].

We explore the communication flow of the messages sent or received by the subjects and the relationships among the individuals, analysing the frequency and the direction of the messages produced. Furthermore, we examine also the affective contents of the messages (*i.e.* mood) and the affinity network defined by the experimental subjects. The semantic contents of the textual messages is not been taken into consideration, so one challenge of our research is to interpret the group dynamics and the individual processes using a quantitative approach substantially based only on the number of messages exchanged and the displacements on the radars (Fig. 3.1). In such a way, a real advantage of this experimental framework is to introduce the dynamic developments in the study of social and psychological processes, avoiding the difficulties concerning the measurement of the communication structure and about the quantification of the relationships in a real environment.

The experimental framework we have developed was inspired by the models of communication topology [3, 4, 6], together with the implications deriving from the Lewin's field theory [18], and in general with the suggestions borrowed from the social cognition theories [30], and in last instance by the sociophysical model of opinion and affinity dynamics [73].

3.1 Interaction environment

A classical and obvious difficulty in the study of the human group dynamics is the effectiveness of data collection, and the standardization of the experimental settings. Nowadays the use of the modern information and communication technologies can easily solve such criticality, representing at the same time a new domain of research [81, 82].

The initial step of our work was to define and to realize the interaction environment: a chat room interface, consisting in a middle-ware platform built with Java language. Such platform was used to provide the resources for the communication among the participants and to collect the data related to the virtual interactions. We consider the chat room a great tool to study the dynamics of human social behaviour under controlled or nearly controlled experimental conditions, giving us the possibility to precisely collect all the events produced by the experimental subjects.

Each session (*i.e.* a small group (10 members) engaged in virtual interaction) guarantees the anonymity of the participants by the random assignment of a different avatar for each subject, thus excluding both the influence of the prior knowledge among the participants and all those features (*i.e.* age, gender, etc.) that could affect the mental representation of the others. Such a procedure standardizes the information available to the subjects at the beginning of any session.

We arranged a virtual environment in order to simulate an ecological situation of group discussion. Each participant had at his disposal an interface with two textual windows (Fig. 3.1), one for communicating with the rest of participants in a public way (*i.e.*

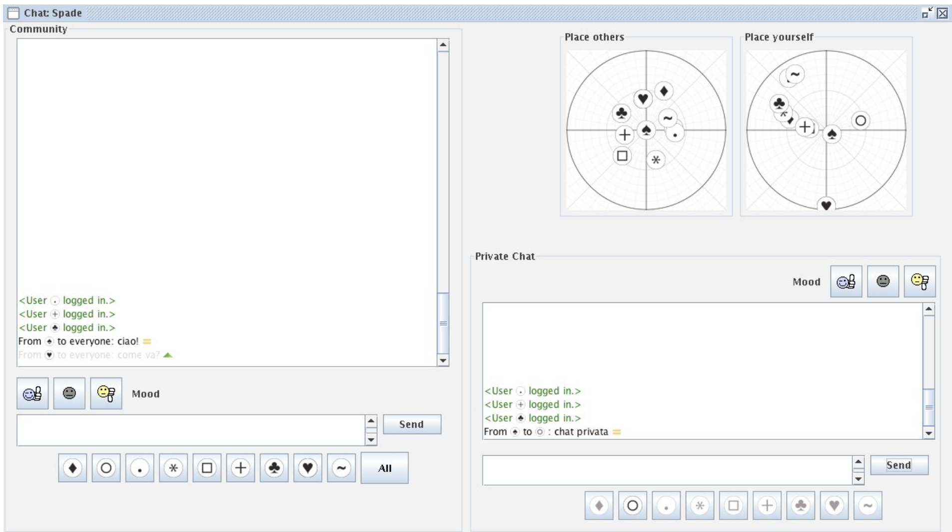


FIGURE 3.1: The experimental interface. On the left the community side, on the right the private side, each with its own space for entering messages and choosing the mood that accompanies the message. On the top-right there are two "radars", a spatial two-dimensional environment, labelled "place others" and "place yourself", manipulable by the subjects

community), and one for the communication in a private way (*i.e.* private chat). This should replicate respectively the loud and group conversations and the whispering or secret discussions. Within the community, a subject may address his message to one other up to all the participants, while within the private chat one may exchange the textual messages only with another person at once. The messages have also be accompanied by the information about the mood of the senders. So the subjects have to choose between a neutral, a negative or a positive mood, represented by a small icon with thumb up, down or neutral. This should condense the non-verbal content of a message, as usual in textual chats.

Moreover, to allow an interaction closer to the ecological experience, we added two "radars", manipulable by the subjects. In the public radar (place yourself) a subject may change his position, dragging and dropping his avatar within this space. The displacement of a subject in the public radar is instantaneously visible on the screens of the other participants. The distance between two subjects affects the contrast of the textual messages exchanged in the public side of the chat room. Such an effect is used to simulate the loudness variation of a spoken verbal exchange (the farther away is an individual on the radar, the dimmer is his message, analogously to what happens with sound and distance in a real environment).

In the private radar (place others) the subjects may change the positions of the others' avatars only, while the personal one was kept fixed in the center. Everyone has his/her own private personal radar. For all the experimental sessions, the subjects were instructed to properly manipulate this space moving closer to their own avatar those avatars perceived as more affine, and moving away the others. In other words, the subjects were asked to configure their private radar (affinity space) before the end of the experiment.

The public radar (place yourself) was thought in order to offer an equivalent to external non-verbal communication similar to changing place in order to be closer to a given person, while the private radar (place others) can be seen as a mnemonic aid for the representation of others' identities and their perceived social proximity.

Furthermore, the data related to the affinity network, resulting from the distances among the avatars in the private radar, allowed us to interpret the relation between affinity and communication (see Chapter 5) and between opinion, affinity and communication (see Chapter 6).

Within such experimental framework, 200 subjects, divided into 20 small groups of 10 members each, were engaged in the virtual discussions. We organised 4 different experimental tasks (*i.e.* social constraints) that we will describe in next chapters.

The subjects were asked to fill a questionnaire, in order to anonymously collect the socio demographic data like gender, age, educational qualification, years of schooling, and current profession. These data have been connected to the avatar assigned by the software for the statistical analysis. The experimental setting has been set up in a computer lab. At each subject was given a personal computer running the client chat; a server machine managed the message exchanging and data collection. Each subject was isolated from the others, in order to preserve the subjects' anonymity and to permit the interaction only through the chat. Each experimental session had a standardized duration of 60 minutes with the following temporal subdivision: 5 minutes dedicated to the collection of socio-demographic data, 10 minutes of standardized training in which the basic usage of the chat and the experimental task was communicated to the subjects, and 45 minutes of virtual interaction. The subjects were explicitly trained in the use of the radars, and were asked as part of the task to use them.

3.2 Procedures and methods

All the events produced by the participants are collected in a log file created by the software that manage the virtual environment, on the server side. This file is structured to collect all the informations available about the dynamics of the observable communications. In such way the file provides a list of all the events occurring within each experimental session.

TABLE 3.1: Experimental observables considered as order parameters of our study. The first 9 observables concern the communication dynamics and are labelled in this study as "Communicative dimensions", at the contrary the last 2 observables are related with the avatar positions on the radars and are labelled as "Spatial dimensions".

DIMENSION	**DESCRIPTION**
G_M	Messages globally sent, both in community and private chat
C_M	Messages sent in the community
C_M^{POS}	Messages sent with positive mood in the community
C_M^{NEG}	Messages sent with negative mood in the community
C_M^{NEU}	Messages sent with the neutral mood in the community
P_M	Messages sent in the private chat
P_M^{POS}	Messages sent with positive mood in private chat
P_M^{NEG}	Messages sent with negative mood in private chat
P_M^{NEU}	Messages sent with neutral mood in private chat
PUB_{RADAR}	(x, y) coordinates of the subject in the public radar (place yourself)
PRI_{RADAR}	(x, y) coordinates of the subject in the private radar (place others)

The data gathered during every experimental session have been manipulated to define some parameters useful to explore the evolution of the system, from the macroscopic (*i.e.*, the group) to the microscopic (*i.e.*, the individual) point of view.

In this analysis all the possible events excepted those related to the contents of the communication (*i.e.*, length, syntactic and semantic structure), and the mood that accompanied the textual messages, have been considered. An interaction between individuals i and j at time t is denoted by $M_{ij}^t = 1$ ($M_{ij}^t = 0$ for the absence of contact). Through a data mining of the log file we extracted the cumulated interaction matrices W,

$$W_{ij}^t = \sum_{\tau=0}^{t} M_{ij}^{\tau}. \tag{3.1}$$

The components of the matrices W are defined by the cumulative number of messages for each communicative dimension, obtaining in this way a different matrix for each communicative dimension considered (Tab. 3.1). The index is here and later omitted for simplicity's sake. Regarding the spatial dimensions, related to the two radars, we considered the Euclidean distances between the coordinates of i and j as a measure of their coupling.

We define the probability P_{ij}^t of having an interaction between subjects i and j before time t, normalized on the number of events involving the subject i, as

$$P_{ij}^t = \frac{W_{ij}^t}{\sum_j W_{ij}^t}. \tag{3.2}$$

The activity a_i^t, the rate of events involving the subject i, is defined as

$$a_i^t = \sum_{j=1, i \neq j}^{N} \frac{W_{ij}^t}{t}. \tag{3.3}$$

This parameter was collected from the public and the private communications, and from radar manipulation.

We tried to put into evidence the topological and metric characteristics of the interaction networks by introducing the centrality degree and the betweenness centrality degree, used in the theory of network analysis.

The centrality degree c_i^t is defined as

$$c_i^t = \mathrm{diag}(P^t)_i^2; \tag{3.4}$$

where diag is the diagonal of the matrix P_{ij}^t

In our framework the centrality indicates the sum of the probabilities of connection between a subject i and the rest of his network, at time t. We consider the centrality as a measure of the "social distance" between two individuals. As a consequence, the centrality would be defined on a continuous domain in [0, 1].

Finally the betweenness b_i^t provides the indications regarding the importance of the node with respect to the topological structure of the network [53, 54]

$$b_i^t = \sum_{j,k \in N, j \neq k} \frac{S_{jk}^t(i)}{S_{jk}^t}; \tag{3.5}$$

where $S_{jk}^t(i)$ are the shortest paths passing trough i and connecting j and k, while S_{jk}^t are the total number of shortest paths connecting j and k.

The most ambitious target that moved the development of the present framework was to study the cognitive heuristics used by humans during small group interactions, to explore and to build their representations of the social psychological field. Moreover, assuming the small group dynamics as prototypical events of the human social environment, we can presume the existence of some shared and adapted cognitive strategies, developed within the community to face with those tasks. Consequently we should expect to reveal a certain agreement among the adapted strategies (cognitive heuristics) shown by the subjects, and a certain degree of variation of such strategies between the different experimental conditions. The cognitive heuristics have been frequently defined as computational algorithms which operate on the available data (knowledge and perception) producing an adaptive answer/behaviour [34, 83]. Following such definition we used a linear regression modelling approach to relate the communicative observables (the behaviour of the subjects) with the affinity spaces (the subjects' representation of the group). In other words we try to model the average cognitive recipes used by the subjects to estimate their affinity with the others as a mathematical linear function of some predictors deriving from the experimental observables.

Summarizing, through the experimental framework proposed we analyse the virtual interactions among the individuals engaged in small group discussions, taking into account the emerging networks of interest (see Tab. 3.1), where the subjects represent the network nodes, and the communicative (*i.e.* messages) or affective (*i.e.* mood or affinity) relationships representing the link among the nodes, exploring the temporal evolution of such networks using the parameters presented in Eqs. (3.3), (3.4), (3.5).

Chapter 4

Blank *vs* Topic condition

Nowadays the "cyberspace" constitutes a natural-ecological environment (*i.e.* experimental setting) to explore and investigate the nature of the social dynamics between human beings. In the modern society, social groups are used to exploit internet-based communication devices, as suggested by the proliferation of social networks. The cyberspace provides a unique opportunity to track individual and collective dynamical behaviours in interactive settings.

The small group is considered as a complex dynamical system, describable as a network of relationships, where the subjects represent the network nodes. In this way, we have the possibility to explore the control parameters to be subsequently inserted into a model which takes into account the groups and the individual dynamics; and to investigate, through some order parameters, the emerging properties arising from the group dynamics.

In the present study, we present the baseline of our research, represented by two different tasks faced by the subjects.

4.1 Experimental design

In this preliminary study we basically focused on the structure of the communication network, by considering three different dimensions: the communicative dimension, visualizing the communication in terms of messages sent or received by the subjects and the relationships among the members of the group as influenced by the content and the number of messages produced; the quality of the interactions among the subjects and in particular the emotional moods that accompany the textual messages [84]; and the "spatial" dimension of the group interactions, namely the affinity space, defined by the private radars (*i.e.* place others), in which the subjects build their own social space representation of the group.

In order to study also the effect of the task on the subject's cognitive strategy, first we designed a control task, labelled as *Blank* condition, whose target was to introduce the smallest possible number of constraints and biases. Accordingly, we selected a classic everyday social problem, estimating the affinity with another subject by freely chatting for 45 minutes. The participants could interact using public and private messages, and were asked only to assess their affinity with the others, reporting them on their private radar before the end of the experiments. The experimental task proposed to the subjects (*Blank* condition) demanded them to interact freely, without any argument specified, only through the chat. This means that the subjects are completely free to adopt personal communication strategies to explore the social environment in which they are inserted.

The affinity with someone was introduced to the subjects as the perceived degree of similarity in terms of opinions, beliefs and attitudes, reflecting in this way the inverse of the "social distance" among the subjects.

The *Topic* condition was designed to introduce a first constraint affecting the small group interaction. The subjects were asked to participate in a role game where they belonged to an ethic committee that was charged to reform the law that controls the researches involving animals (*i.e.* animal experimentation). The requirements were to discuss about the given topic, developing before the end of the experiment one or more shared ethical positions, and assessing the affinity space accordingly. The experimental task proposed to the subjects (*Topic* condition) demanded them to discuss about animal experimentation. The subjects have been asked to support and negotiate its position during the entire discussion. This topic was chosen in order to polarize the opinions of the subjects in virtual interaction and to force the communication strategies of the subjects around a specific topic. The two experimental conditions should allow the exploration of the differences between the appropriate (*i.e.* optimal and stable) strategies required.

The sample of 100 individuals has been randomly spilt in two, respecting the balance for the gender, and each sub-sample (50 subjects) has been asked a different task. The two experimental procedures have been designed to study the effect of the task on the cognitive processes emerging within the small group in virtual interaction.

4.2 Procedure and methods

The experimental setting has been set up in a computer lab. At each subject was given a personal computer running the client chat; a server machine that managed message passing and data collection. Each subject was isolated from the other, in order to preserve the subjects' anonymity and to permit the interaction only trough the chat.

Each experimental session had a total duration of 60 minutes with the temporal subdivision described in Chapter 3. The subjects were explicitly requested to accomplish the experimental tasks (*i.e.* free discussion *vs* topic discussion) and to use the private radar (place others) to represent the social space in terms of affinity perceived.

4.2.1 Sample

The population selected for the experiment is composed of 100 subjects. The subjects were asked to fill a questionnaire, in order to anonymously collect socio demographic data like gender, age, educational qualification, years of schooling, and current profession. These data have been connected to the avatar assigned by the software. Each of the ten experimental sessions consists for a total of 51 males and 49 females. The average for each experiment has been around 5 females and 5 males, unknown to each other, with mean age equal to 23.8 years, std.dev. 2.83. The average age of education is equal to 16.3 school years, std.dev. 1.52.

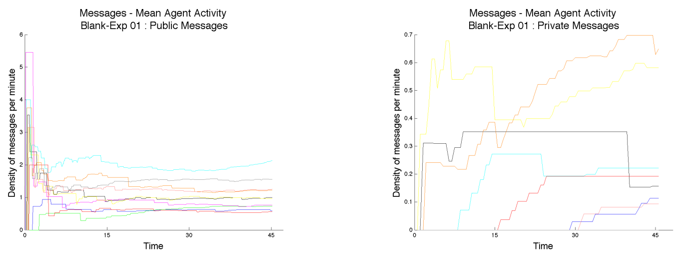
4.2.2 Data Analysis

Through the study of the order parameters referring to the Eqs. (3.3), (3.4), (3.5), we explore the development of the different networks defined by the communicative and spatial dimensions (Tab. 3.1) considered.

We studied the main differences among all the experimental observables taken into account data collected by the socio demographic questionnaire, computing the *student-t* statistic [85], considering the two series of five experiments as independent samples.

4.3 Results

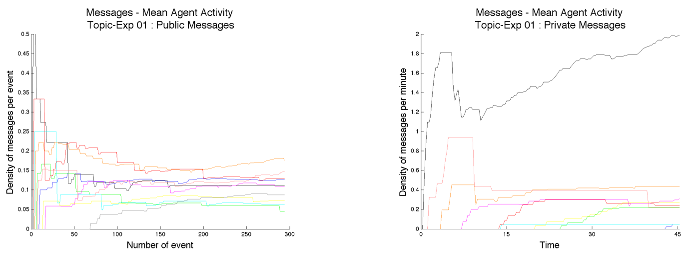
A first and rational class of observables related to human group dynamics is the "activity" (Eq. (3.3)). In order to analyse this dimension we consider the total amount of actions for each subjects during the 45 minutes of the experiment. As an example, the activity plot of the first of the ten experiments is shown in Figs. 4.1 and 4.2.



(a) Activity in Blank public messages

(b) Activity in Blank private messages

FIGURE 4.1: Public vs Private activity in Blank condition (average number of messages exchanged into the public or private area by a subject).The coloured lines identify different individuals. On the X axis is reported the time of the experiments and on the Y axis the density of messages per minute.



(a) Activity in Topic public messages

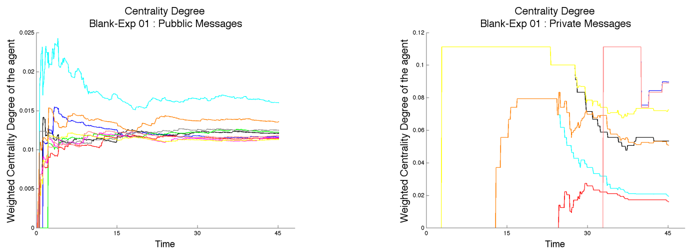
(b) Activity in Topic private messages

FIGURE 4.2: Public vs Private activity in Topic condition. The coloured lines identify different individuals. On the X axis is reported the time of the experiments and on the Y axis the density of messages per minute.

The Figs. 4.1 and 4.2 show the average activity of the subjects in the global message dimension for respectively the *Blank* and the *Topic* condition. After an initial phase, observed in every experimental session, where the subjects explore the chat environment and present themselves to each other, the system reaches very quickly (in less then 15 minutes) a stationary state where all subjects exchange a comparable number of messages, both in *Blank* and in *Topic* condition. A remarkable feature is the strong similarity of this observable in all the experiments.

The corresponding behaviour of the activity in the private chat is quite different, as it shown in Figs. 4.1 and 4.2. In this case the individual attitude in exchanging private messages seems different from each other, and the patterns appear as different for all the experiments. From a psychological perspective this two ways of communications have to be considered as theoretically quite different, because the nature of the communication in dyadic or group discussion.

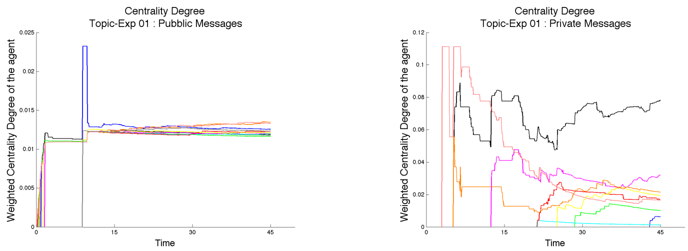
Another important class of observables are represented by the centrality degrees (3.4). These variables give qualitative and quantitative information about the group structure, and the communication dynamics among the individuals. As it shown in Figs. 4.3 and 4.4, the public centrality degree 3.4 quickly tends to a stationary state in both experimental conditions (*i.e.* *Blank* and *Topic* condition).



(a) Centrality degree in Blank public messages

(b) Centrality degree in Blank private messages

FIGURE 4.3: Public centrality degree in Blank condition. The coloured lines identify different individuals. On the X axis is reported the time of the experiments and on the Y axis the weighted centrality degree for all the subjects.



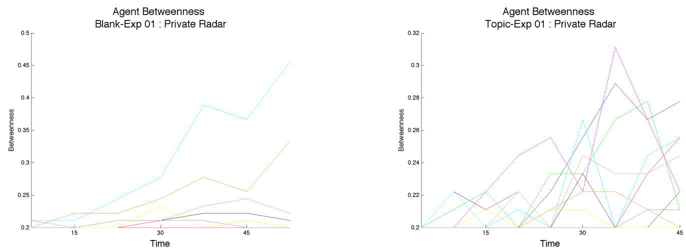
(a) Centrality degree in Topic public messages

(b) Centrality degree in Topic private messages

FIGURE 4.4: Public centrality degree in Topic condition. The coloured lines identify different individuals. On the X axis is reported the time of the experiments and on the Y axis the weighted centrality degree for all the subjects.

At the same time the centrality degree seems efficiently characterizes the private messages spaces, as shown in Figs. 4.3 and 4.4. Interestingly, we found that the average public centrality degree always tends towards a steady state around the value of 0.11. Such value indicates that for all the experimental sessions we observe in the community a fully connected network, where each person establishes a direct contact with all the other nodes of the network. Each node therefore has an equal probability of being connected with any other node, differently for the private chat.

The last communication observable we have taken into consideration is the betweenness centrality degree (3.5). As examples in Fig. 4.5 the temporal series of this parameter are reported for both the *Blank* and the *Topic* condition. In general, this measure has shown an average increasing behaviour over time, always assuming at the end of each



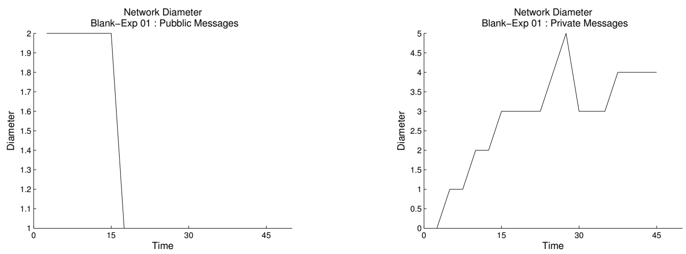
(a) Betweenness degree in Blank private radar

(b) Betweenness degree in Topic private radar

FIGURE 4.5: Temporal trend of the betweenness centrality degree in the private radar for Blank condition and Topic condition. The coloured lines identify different individuals. On the X axis is reported the time of the experiments and on the Y axis the value of the betweenness degree of the subjects.

session a particular structured hierarchy. Such observable reveals the nodes' relevance in the topological communication structure of the network.

The *Blank* and *Topic* modalities seem to be well differentiate by the average trend of the betweenness centrality degree. In the *Blank* condition, an hierarchy among subjects seems arise during the first 15 minutes of interaction, keeping its structure for the rest of the session. On the contrary, in the *Topic* condition, the evolution of the betweenness centrality degree appears more complex. In particular for the private radar, where the subjects configure their social representation of the small group, it appears to be less stable, evolving until the end of any experimental session with respect to the *Blank* condition (Fig. 4.5).

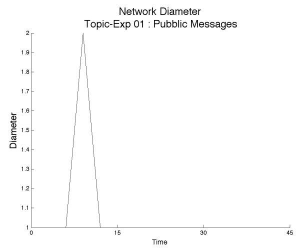


(a) Diameter in Blank public messages

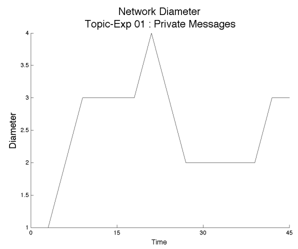
(b) Diameter in Blank private messages

FIGURE 4.6: Public and Private temporal dynamics of the network diameters in Blank condition. On the X axis is reported the time of the experiments and on the Y axis the diameter of the network.

The collective network dynamics is reported in Figs. 4.6 and 4.7 using the network diameter as order parameter. The public diameter for the community network messages shows a quite trivial behaviour in both the experimental conditions, because the full connected network configuration for both the experimental modalities. On the other



(a) Diameter in Topic public messages



(b) Diameter in Topic private messages

FIGURE 4.7: Public and Private temporal dynamics of the network diameters in Topic condition. On the X axis is reported the time of the experiments and on the Y axis the diameter of the network.

hand the diameter of the private network messages appears more informative for both the *Blank* and the *Topic* condition, showing a continuous process of clustering.

After a first preliminary exploration of the graphical behaviour of the experimental observables considered, we used some inferential statistics in order to profile the peculiar subjects strategies among the two experimental conditions.

The activity related variables shows many large differences on the subjects' communicative behaviour. In particular, the communication rates are significantly larger for the *Blank* condition public and private dimensions (*e.g.* activity C_M $(45')$; $t = 2.697$, $p. < .01$; activity P_M $(30')$; $t = 3.471$, $p. < .01$), as so as for the communications with "positive" and "negative" mood on the community and private chat (*e.g,.* activity C_M^{POS} $(45')$; $t = 4.611$, $p. < .01$; activity C_M^{NEG} $(30')$; $t = 2.139$, $p. < .05$; activity P_M^{POS} $(45')$; $t = 4.395$, $p. < .01$.

On the other hand, the neutral messages (*i.e.* the messages which have a neutral mood) in the community side show the opposite behaviour, and within the *Topic* condition the messages with a neutral mood prevail (*e.g.* activity C_M^{NEU} $(45')$; $t = -2.401$, $p. < .05$; activity C_M^{NEU} $(15')$; $t = -3.085$, $p. < .01$).

Finally we dedicated an apposite activity measure for the private radar (*i.e.* place others) management, that was just the number of adjustments/displacements the subjects done during the experiments. Such measure can be interpreted as reflecting the complexity of the social problem faced by the subject and the length/effort in the configuration of the affinity space (*i.e.* private radar). Interestingly also this observable distinguishes significantly the two experimental modalities.

In details the subjects within the *Topic* condition spent a larger period making more adjustments/displacements on their private radars, with respect to the subjects engaged in *Blank* discussion (*e.g.* activity PRI_{RADAR} $(45')$; $t = -2.826$, $p. < .01$). The observables related to the nodes' centrality degree on both the communicative and the radar networks delineate a similar scenario, highlighting some interesting additional aspects.

In our framework the centrality degree on the communication network indicates the weight of a subject on the entire communicative dynamics, while the same measure for the private radar space represents the degree of closeness that characterizes the subjects' average representation of the small group.

As happened for the variables related to the activity, the average centrality degree for all the communicative dimension is larger for the *Blank* condition (*e.g.* centrality degree C_M^{POS} $(45')$; $t = 3.616$, $p. < .01$; centrality degree C_M^{NEG} $(30')$; $t = 4.468$, $p. < .01$; centrality degree PM $(45')$; $t = 2.356$, $p. < .05$; centrality degree P_M^{POS} $(45')$; $t = 4.223$, $p. < .01$; centrality degree P_M^{NEG} $(45')$; $t = 2.064$, $p. < .05$), with the only exception of the neutral messages in community side, where coherently with the activity measures the average degree of the subjects within the *Topic* condition is greater than the others (*e.g.* centrality degree C_M^{NEG} $(45')$; $t = -4.030$, $p. < .01$).

The analysis of the centrality degree distributions on the private radar dimension has supported the previous results, the average closeness (*i.e.* the normalized average distance of a subject from the others considering all the subjects' private representations on their private radars) appear as larger for the *Blank* condition than for the *Topic* condition (*e.g.* centrality degree PRI_{RADAR} $(45')$; $t = 3.375$, $p. < .01$). This result suggests that the cohesion, or the degree of connection among the sub communities, is smaller in the task with more cognitive constraints, probably due in part to the polarizing nature of the experimental task in *Topic* condition.

The subsequent analysis of the betweenness centrality has confirmed and replicated accurately the previous results, and has indicated the betweenness as more stable and cleaner measure of the centrality degree for the private radar dimension (*e.g.* betweenness PRI_{RADAR} $(30')$; $t = -2.512$, $p. < .05$). As a consequence of a minor average centrality degree, the nodes belonging to the *Topic* condition are characterized by a greater average betweenness, that is the destruction of a single link could operate an abrupt change of the network topology.

4.4 Discussion of results

This study proposes a quantitative approach to the investigation of the existing relationship between the individual dimensions, considering the personal cognition of the interactions with others, and the group dimension, and its dynamical evolution. We have presented some preliminary results of our experimental framework, consisting of a standard chat environment with some enhancements, such as the social and spatial representation of subjects by mean of the "virtual" two-dimensional spaces (*i.e.* radars).

The chat was ergonomic and user friendly: all subjects performed the experimental task without problems, as demonstrated by the analysis of activity in time, where we do not observe any drop in interest and participation. The message rate was constant for the duration of a session, after an initial phase of "thermalization" of the group.

We can assume that the proposed interface is very efficient for the subjects with a high confidence with new technologies and the type of assigned task. We have developed a set of analytical tools, with the goal of detecting some relevant characteristics of the group dynamics. The analysis is independent of the semantic content of the exchanged messages, and the standardized interface avoids hard-to-detect non-verbal communications, still providing the expression of emotional contents.

The subsequent analysis, mixing social network theory and concepts from social and opinion dynamics, allows us to investigate quantitatively how people creates their social space in virtual interactions, exploring the role of topology and the structure of the group evolution.

It is possible to consider the communication topology, which characterizes a given communicative dimension, as a state variable characterizing the role of different final configurations with respect to the affinity dynamics. In other words, we have started investigating the process by which the mental schemes representing the small group arise.

The observables taken in account represent some potential order parameters to describe the virtual human community. The experimental data appear to be consistent with the classical psychological theories and description of little group dynamics. More precisely the differences between the public and private space with respect to many of the observables previously describe, confirm well known axioms in psychology: that is, individuals use different strategies with respect to the environmental condition (*i.e.* when they participate to a group interaction or when they are engaged into a dyadic conversation). Furthermore the knowledge of both microscopic and macroscopic dynamics are required in order to explore and understand the human group dynamics.

Obviously, the artefact experimental conditions, and the generality of the task presented may be considered as a too limited approach to the investigation of the social dynamics. For that reason further experiments are required to explore different aspects and processes. Nevertheless, the present data represent a baseline for the interpretation of futures experiments.

In conclusion, we present a framework to study the small group dynamics within a virtual setting. After a preliminary definition of some features of interest both at the individual and collective level, we have shown how it is possible to design real experiments affecting the communicative behaviour of subjects in interaction.

Chapter 5

Blank *vs* Topic *vs* Game condition

The study of the interdependence between the social environment and the people that are immersed in it, dates back to the first half of the twentieth century with the works of Kurt Lewin [18] known as "Field theory". This theory assumes the existence of an emerging object, the psychological field, which partially behaves as a sort of attracting force, producing intense and disruptive effects (*e.g.* revealable at a psychological and/or social level of description) specially within small groups.

Recent literature has approached the description of the psychological field, designing model of opinion formation in which the affinity between agents is introduced and coupled with the opinion/social dynamics equations [73, 82]. Sharing a similar opinions with a person towards whom we feel a low degree of affinity, might give rise to a psychological distress. The cognitive dissonance theory describes how such a process would result alternatively in a shift of the opinion, or of the affinity itself. In this way the cognitive dissonance could affect the psychological field postulated by Lewin, influencing the function between personality and environment to determine the behaviour of people in interaction.

The computational models linking affinity and opinion are perfects to test some very fundamental theories from social cognition. In particular, the group effect, introduced and structured by Asch, Sherif and Festinger [10–12] can be considered as the reference scenario to be assessed.

Given the previous theoretical scenario, it is possible to hypothesize different relations between cognitive dissonance and social influence, depending on the constraints imposed to the small groups involved in our study. The impact of type of task reflects on the interaction between emerging social relations (*i.e.* affinity) and communication. In such a way our purpose is to research the effects of the cognitive dissonance that affect the psychological field putting the social constraints (*i.e.* the experimental conditions) as the independent variables.

The dynamics of small groups has been the target of interesting research approaches in the latest years [86–89], and in this work we consider explicitly the interaction between the complex topology of the social structure of the experimental groups (*i.e.* affinity and opinion communities), and the cognitive processes characterizing the individuals' level.

The studies concerning the dynamics of communication within small human groups show how the relevance of the affinity group structure depends on and affects the different tasks faced by the subjects. The shape of the affinity group structure determines the constraints for the communicative exchanges, and influences the outcome in a group problem solving. Moreover the different "positions" into such an "affinity space" directly affect many aspects of communication and individual cognition, defined as a sense of belonging to the group, the personal satisfaction or frustration, and the motivations of the subjects to successfully accomplish the task [5, 6].

At the same time, people immersed in a social context tend to interpret the behaviour of others to make judgements and anticipate their behaviours, such as the role that they play in the group, their pleasantness, their perceived affinity. Often, people reach these judgements in the early stages of the interaction, the so-called first impression, in conditions of limited time and information [30].

The main goal of this study is to investigate how communication among people immersed into a virtual environment is related to the group affinities structure, in different conditions where the complexity of the psychological field increases. Furthermore, the three different tasks adopted as experimental conditions have been introduced to evaluate how different constraints affect the subjects' elaboration and interpretation process of the social environment.

5.1 Experimental design

In the present study we investigate how communication among people immersed into a virtual environment is related to the group affinities structure, in different conditions where the complexity of the psychological field increases. Furthermore, the three different tasks adopted as experimental conditions have been introduced to evaluate how different constraints affect the subjects' elaboration and interpretation process of the social environment.

A web based *chat room* provided the experimental environment for the investigation of the social interactions of a 10 people group, reaching a fairly accurate quantitative estimation of the interesting features related to the group communication. This work essentially studies the impact of three different tasks, the interaction between the emerging social relations (referred to as affinities) and the communication patterns.

From the theory we argue that the complex interaction between such dimensions could play a crucial role in modulate the social influence effect.

Within such a challenge we search for an experimental confirmation of Asch, Sherif and Festinger theories about social conformity, social assimilation and social comparison [90]; combining them with the cognitive dissonance theory into the theorical framework that drives our work.

We tested 150 interacting subjects, divided into 15 small groups (*i.e.*, 10 subjects per group, 5 groups per condition).

Specifically, within the first experimental task(*Blank* condition) the subjects were invited to discuss freely, within the second experimental task (*Topic* condition) they were asked to face with a specific topic introduced to polarize the opinions, and finally, within the third task (*Game* condition), the subjects were asked to face with a frustrated minority game based on a voting procedure. In the field of game theory, we can define a " Frustrated game" as a game in which the pay-off function depends in a complex way on the strategies of the various players, so it is not easy (or sometimes not possible) to find an optimal strategy [91–94]. The minority games are frustrated games because the strategy that leads to being in a minority (and winning) group may also lead to be in the majority (and losing) group following a change of another player. That is why a local perturbation may establish an "avalanche" of changes, that makes very difficult to reach the global optimum.

Finally the introduction of different experimental conditions (*i.e.*, different environmental constraints) allows to study how the increasing complexity of the resulting psychological field topology affects in different ways the communicative patterns adopted by the subjects.

5.2 Procedure and methods

The common aspect between the different conditions relies on the affinity estimation requirements. The concept of affinity was first introduced to the subjects as the perceived familiarity toward, and the emotional closeness with, another subject. Thus in each condition the subjects were asked to estimate before the end of the experiment their perceived affinity with the others.

We labelled as *Blank* condition the task in which the first five small groups interact. In this condition the subjects could interact freely (*i.e.*, the number and type of the arguments were freely determined by the subjects), without any specific constraint or requirement. The experimental task was to present themselves and their instances/opinions to the others throughout the communication, and to configure their private radar in accordance to their perceived feelings of affinity toward the others. Eventually they were not asked to reach any consensus.

The second tranche of five experiments was conducted using a different condition labelled as *Topic*. In this case the subjects were asked to talk about a specific topic, in particular about animal experimentation. The topic was deliberately chosen to strongly polarize the opinions within the group. Even in this condition the subjects were not asked to achieve a consensus, but only to mediate as much as they could in order to give strength to their "position" at the end of the session.

The last experimental session, labelled as *Game* condition, consisted in a frustrated minority game. In this case the subjects were required to discuss about three different features (*i.e.*, colour, shape, acronym) and to choose their favourite one. The experimental task required the subjects to belong to the second largest cluster in the each preference expression. Such a structure prevents the subjects to find a trivial strategy for winning the game. The collection of the preferences was performed in three different times, one every 15 minutes of discussion, by means of 3 different paper cards, one for the colour, one for the shape and one for the acronym. Only one preference could be expressed for a single time. After each voting phase the winners were to be announced to the subjects by the person responsible for the experiment.

5.2.1 Sample

We selected 150 subjects, 74 females and 76 males, randomly assigned to 15 small groups, approximately composed by 5 females and 5 males unknown to each other. The average age of the entire sample was 24.38 years (std.dev. 3.24), and the average of years of education was 15.59 years (std.dev. 1.57). The sample was divided into 15 different small groups, 5 groups for each experimental session. All the 15 experiments had a duration of 45 minutes, were held in a standardized setting in which every subject was isolated from the others to allow communication only through the chat.

Before each session the subjects filled out anonymously a form for the collection of the socio-demographic data, with the aim to control the effects related to sex, age, educational qualifications, years of education, and the current profession.

5.2.2 Data analysis

The dynamics and the structures of the complex networks created by the participants and their cognitive dynamics of communication were detected, and their relations estimated, in order to model the node's behaviour in the different regimes. A classical statistical approach has been used to test the experimental hypotheses and to refine the useful observables that will be taken into account. We have used the product-moment correlation of Bravais Pearson ($r.$) [95] to test the relations among the quantitative variables, and we have compared the different experimental conditions using the ANOVA [96, 97] and *Student-t* tests [85].

Then we have fit, with a preliminary linear regression method, the best linear models describing the relation between the affinity and the communicative behaviours adopted by the subjects in the different conditions. The resulting models could describe how the subjects assess their affinity with the others, and the way they promote/manage their status within the group (*e.g.* to win/cope the game/task). In order to achieve that, during the game proposed in the last experimental condition, it is shown how subjects reach a very good ability to face with the frustrated task they were participating. Since the game is introduced as major frustrated condition to study the relation between affinity and communication dynamics, we analysed the performances of the subjects only in a qualitative way comparing the results of the experimental votes with those produced by an appropriate random model to assess the randomness of the player's behaviour.

5.3 Results

In order to characterize the macroscopic aspects of the communicative dynamics we analysed the activity, centrality degree and betweenness for all the communicative sub spaces (*i.e.*, public messages, private messages, public radar, private radar), for each experimental task.

The dynamics of the public centrality degree for the 15 experiments, represented in Fig. 5.1, look very similar, and appears as characterized by the same features. The centrality degree of the public messages network tends to a stationary value, and provides

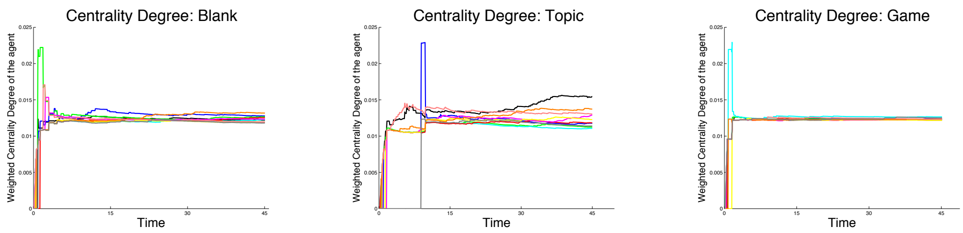


FIGURE 5.1: Time evolution of the centrality in the community side of the chat for the three different experimental conditions (Blank; Topic; Game). The color of the line identifies a different subject. On the X axis is reported the time of the experiments and on the Y axis the normalized centralities of the subjects. In all the modalities, the system tends in the first third of each experiment towards an order state, giving us a first indication about the structure of the network, a full-connected network, regardless of the task required.

a first indication about the communicative structure of the network. In the Fig. 5.1 a first effect of the social influence emerges. Regardless to the task faced by the subjects, the distribution of communication within the public space early reach an equilibrium state. In particular all the individuals, in every small group interaction, tend to stabilize the probability to send and receive a message to the others around the value of 0.11. Such a value indicates the presence of a fully-connected network (*i.e.*, each person exchanges messages with all other people within the network).

All the 15 small groups that participated in the experiments reached, in the first third of the session, a stationary state in their centrality degree, which remains unchanged until the end of the experiment. The first third of the experiments seems to correspond to the characteristic time for the construction of the first approximation of the perceived social structure (*i.e.*, preliminary social negotiation).

The measure of the centrality in the private space, reported in Fig. 5.2, clearly shows a very different dynamics with respect to that characterizing the public space. The private channel allows only the dyadic relationships between individuals and the trajectories within this space appear highly irregular, never reaching a stationary state during the first 45' of interaction. The task does not appear to trivially affect the dynamics of relationships in the private space, since this looks similar (*i.e.*, non-stationary) along the three tasks and the 15 experimental sessions. A first inspection of the public and private communication dynamics (Fig. 5.1 and Fig. 5.2) does not show any evident

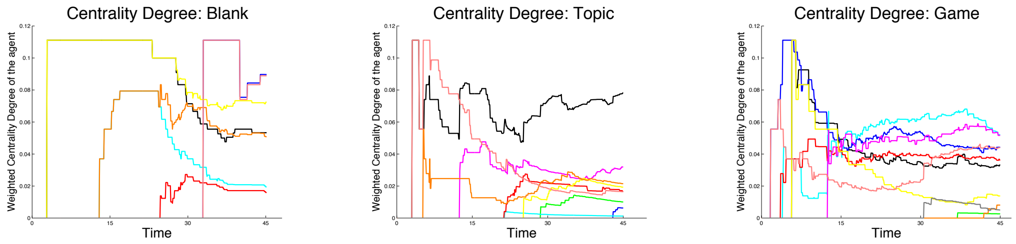


FIGURE 5.2: Time evolution of the centrality in the private side. The color of the line identifies a different subject. On the X axis is reported the time of the experiments and on the Y axis the normalized centralities of the subjects. The trajectories are highly unstable and never reach a stationary state.

TABLE 5.1: Significant average differences for the activity between conditions

	Blank Condition		**Topic Condition**
Observables	Average difference with Topic	Average difference with Game	Average difference with Game
Activity GM	81.7*	-	-107.1**
Activity CM	73.8*	-	-95.7**
Activity C_M^{POS}	106.3**	-	-127.4**
Activity C_M^{NEU}	-46.8*	-	44.1*
Activity PM	7.8*	-	-11.3**
Activity P_M^{POS}	5.2**	-	-7.6**
Activity PRI_{RADAR}	-	-20.1**	-

***: p. < .01, *: p. < .05 (Bonferroni Test for ANOVA)*

difference on the evolution of the communication patterns, depending on the different experimental conditions (*i.e.*, social constraints).

In order to answer to the main question posed by this work we have introduced the communicative and affinity variables as order parameters to investigate the virtual social dynamics, and the three experimental conditions as control parameters. First of all, the conditions were compared with respect to each communicative variables searching for significant differences in the communicative regimes.

Using the analysis of variance statistics (*i.e.*, ANOVA, with Bonferroni test for posthoc) the activity related to all the quantitative dimensions taken into account (Tab. 3.1) is

TABLE 5.2: Significant average differences for the Betweenness between conditions

	Blank Condition		**Topic Condition**
Observables	Average difference with Topic	Average difference with Game	Average difference with Game
Betweenness C_M^{POS}	.015**	-	-.15**
Betweenness C_M^{NEU}	-	-	.020**
Betweenness C_M^{NEG}	.051**	.032*	-
Betweenness PM	.078*	-.068*	-.146**
Betweenness P_M^{POS}	.056**	-.049**	-.105**
Betweenness P_M^{NEU}	-	-	-.109**

***: p. < .01, *: p. < .05 (Bonferroni Test for ANOVA)*

compared in relation to the varying experimental conditions (*Blank*, *Topic* and *Game*) (Tab. 5.1). As activity we reported the rough number of events which characterize the communicative dimensions and the private radar dynamics (*i.e.*, the total number of messages and displacements produced by a subject). The analysis reveals many significant differences mainly among the *Topic* condition and the *Blank* and *Game* conditions. The *Topic* condition appears to be the one that differs the most from the others two. In such a condition less messages are generally exchanged, with the only exception of the public messages with neutral mood. This is a first effect probably due/introduced by the task. Within this condition, the subjects seem to be more conservative on their opinion, avoiding, if possible, confirming or dis-confirming mood messages. The average activities suggest that, in the *Blank* and in the *Game* condition, people tend to behave similarly in terms of communication, with the only exception of the activity related to the affinity space.

The activity for the affinity space dimension is referred to the amount of the private radar manipulation (*i.e.*, the affinity space), and it is significantly different only between the *Blank* and *Game* condition. In the *Game* condition the subjects tend to manage more frequently their private radar, probably because of the nature of the task (*i.e.*,"frustrated game") and to the procedure of voting, that promotes the birth and the death of temporary alliance among the members.

In Tab. 5.2 is reported the average betweenness b_i^t (Eq. (3.5)) of the subjects for all the selected variables, which is used to compare with the ANOVA test the three experimental conditions.

This measure generally reflects the topological relevance of a node for the structure of the entire network; here, according to the definition given by Freeman [53, 54] provides a measure of "where" a node is located among the various nodes of the graph taken into consideration, and of how much such a node is *structural* for the network.

The data presented in Tab. 5.2 suggests some differences regarding the communicative patterns depending on the experimental task.

The average betweenness for the public messages with positive mood (C_M^{POS}) is greater in the *Blank* and *Game* conditions than in the *Topic* condition. Moreover no significant differences emerge between the *Blank* and *Game* conditions.

On the contrary the average betweenness b_i^t for the public messages with a neutral mood (C_M^{NEU}) appears to be significantly different only between the *Topic* and *Game* conditions, with the *Blank* condition that ranks among the others.

The average betweenness for the network formed by the public negative messages (C_M^{NEG}) seems to be significantly different in the *Blank* condition with respect to the other conditions. Such result indicates that in a context of free interaction, the subjects in a small virtual group tend to be involved in conversations exchanging also messages with negative mood (*i.e.*, dis-confirming messages), suggesting that, without any specific social constraint, the subjects can reduce their cognitive dissonance being involved in dis-confirming conversation.

The three previous results suggest the way the social influence effect could be modulated by the cognitive dissonance, within the tasks under investigation. The prevalence of positive messages, in the *Blank* and *Game* conditions, could indicate how the subjects involved in such a tasks tend to manage the more (*i.e.*, to be more affected/sensitive to) the collective level, as so as to promote the cohesion of the group. In other words the social effect appears to be promoted by the cognitive dissonance within such experimental conditions. On the contrary the *Topic* task appears as characterized by a prevalence of messages with neutral mood, as well as by a greater betweenness within such a space. Even this evidence support the previous hypothesis, here the cognitive dissonance elicited by the task is hardest to be solved with respect to the others tasks, consequently the tendency of the subjects to belong to the biggest group (*e.g.* one of the social influence effects) decreases.

Focusing on the peer-to-peer communication performed in the private side of the chat interface, the data shows that the average betweenness for private messages is significantly different in all three experimental conditions, with the only exception being the variable P_M^{NEU}. Such a variable presents a significant difference only between *Topic* and *Game* conditions. In particular, the subjects in the *Game* condition are more involved in conversation with neutral mood than the subjects in the *Topic* condition.

Table 5.3: Significant correlations for the different experimental session between the private radar betweenness and the observables under scrutiny

Observables	**Blank Condition**	**Topic Condition**	**Game Condition**
Activity C_M	$^{(15')}.51*$	ns	$^{(30')}.37*$
Activity C_M^{POS}	$^{(30')}.50*$	ns	$^{(15')}.38*$
Activity P_M^{NEG}	ns	ns	$^{(15')}.36*$
Activity PRI_{RADAR}	ns	$^{(30')}.53*$	ns
Centrality C_M	$^{(45')}.46*$	ns	$^{(45')}.51*$
Centrality C_M^{POS}	$^{(45')}.49*$	ns	$^{(45')}.44*$
Centrality PRI_{RADAR}	$^{(45')}.52*$	$^{(45')}.40*$	$^{(45')}.51*$
Betweenness $C^{POS}M$	$^{(45')}.67*$	ns	ns
Betweenness C_M^{NEG}	ns	$^{(15')}.35*$	ns
Betweenness P_M	ns	ns	$^{(30')}.46*$
Betweenness P_M^{NEG}	ns	ns	$^{(30')}.39*$

***: p. < .01, *: p. < .05*

The results related to the analysis of the public and the private communication seems to indicate two different regimes of interaction in the small groups involved in virtual discussion, which depends in different way on the social constraint imposed to the small group.

In order to characterize the dynamics determined by the individuals during the interaction, we have taken into account the values of all the considered observables in three different times of the interaction (*e.g.*, respectively after $15'$, $30'$ and $45'$ of interaction). In Tab. 5.3 the greater correlations between such observables and the betweenness in the private radar (*i.e.*, the affinity space) are reported. The betweenness degree of a subject i in the affinity network is determined by the entire group as the average degree of affinity perceived by the others towards him.

The betweenness in the private radar correlates with the number of messages sent in the community side of the chat during the first 15 and 30 minutes of interaction, with the amount of messages with positive mood sent in the community side in the first 30 and 15 minutes of interaction, respectively for the *Blank* and the *Game* conditions. For these two conditions the public messages network appears as a good observable to reveal the correlation between affinity and communication dynamics.

Moreover, when considering the messages with positive mood, for what concern the *Blank* condition, the betweenness in the affinity space appears to be strongly correlated with the position in the communicative network.

With respect to the *Topic* condition the activity in the private radar management, together with the participation in conversations with a negative mood in the community side, seem to be the best predictors of the betweenness in the affinity space.

The peer-to-peer communication occurring in the private chat appears to be correlated with the betweenness in the affinity space only within the *Game* condition, and always before the final vote (*i.e.*, only in the first 30 minutes). The communication in the private side seems to be the best observable to distinguish the *Game* condition from the others two conditions. The large correlation between the peer-to-peer communication in the *Game* condition, and the betweenness in the affinity space, of course partially depends on the sharing of the strategies of vote (*e.g.* establishment of "secret" voting negotiations, in order to satisfy the experimental request and to "win" to the game).

Eventually, the centrality in the private radar, indicating the degree of average affinity "received" by a subject, is correlated with the betweenness in every conditions.

The betweenness in our *affinity* network (*i.e.*, the private radar) defines the average affinity perceived by the group toward a subject. We choose such a variable to study the dynamics of the affinity between subjects with respect to their communication dynamics, and to study the impact of different social constraints on the affinity and communication dynamics.

We then isolated the communicative factors explaining the variance of this important dimension, summarizing them in three linear regression models, one for each experimental condition. The regression models could be seen as an estimation of the recipes through which the subjects have built their own social field.

The best regression model for the *Blank* condition can be written as

$$B(i) = \beta_1 (C_M)^{15'}_{Act(i)} + \beta_2 (C_M^{POS})^{45'}_{Cen(i)} + \beta_3 (C_M^{POS})^{45'}_{Betw(i)} + \epsilon(i) \tag{5.1}$$

The model summarizes the control parameters describing the way in which the subjects build their affinity network.

In the *Blank* condition the betweenness in the affinity space of a subject i ($B(i)$) appears to be related with the public activity in the first third of the interaction ($(C_M)^{15'}_{Act(i)}$), with the centrality in the communicative network defined by the messages with a positive mood during the entire session ($(C_M^{POS})^{45'}_{Cen(i)}$) as well as with the betweenness in the network formed by the messages with positive mood ($(C_M^{POS})^{45'}_{Betw(i)}$).

Table 5.4: Summary of the Blank model

r.	Adj.r	St.Err	S.S Model	S.S. Residual	F
.823	.656	.03	.081	.039	32.163*

*S.S.: sum of squares; *: p <.01*

Table 5.5: Predictors coefficients of Blank Condition's best model

Predictor	Stand.Coefficient	t	Sig
Activity $C_M\ ^{(15')}$	$\beta_1 = .599$	7.063	p.<.01
Centrality $C_M^{POS}\ ^{(45')}$	$\beta_2 = .277$	2.830	p.<.01
Betweenness $C_M^{POS}\ ^{(45')}$	$\beta_3 = .274$	2.783	p.<.01

As shown in Tab. 5.4, the linear regression model presented for the *Blank* condition explains the 65% of the variance of the betweenness in the affinity space, if we consider the predictors coefficients of *Blank* condition's best model shown in Tab. 5.5.

In other words, the dynamics of the affinity can be mapped (*i.e.*, approximated and predicted) quite efficiently considering only the public communicative dynamics, as we have done in our experiments.

The best significant regression model for the *Topic* condition shows many differences with respect to the *Blank* one, and can be summarized as follows,

$$B(i) = \beta_1 (PRI_{RAD})^{30'}_{Act} + \beta_2 (C_M^{NEG})^{15'}_{betw} \epsilon(i) \tag{5.2}$$

Given the conditions imposed in this session of experiments, the construction of the affinity networks appears to follow a completely different route with the respect to the *Blank* condition (Tab. 5.6). Surprisingly, the only best predictors (Tab. 5.7) of the final betweenness of subject i are his number (*i.e.*, activity) of adjustments in the affinity space during the first $30'$ of interaction ($(PRI_{RAD})^{30'}_{Act}$), and the betweenness in the network formed by the public messages with negative mood during the first $15'$ ($(C_M^{NEG})^{15'}_{Betw}$).

Noteworthy is the fact that the entity of the activity in the private radar is not public information, so its relation with the final affinity of a certain subject should be studied more in depth.

The best linear regression model for *Topic* condition explains only the 33% of the variance of the betweenness in the affinity space (Tab. 5.6).

Table 5.6: Summary of the Topic model

r.	Adj.r	St.Err	S.S Model	S.S. Residual	F
.589	.330	.04	.033	.060	13.057*

*S.S.: sum of squares; *: p <.01*

Table 5.7: Predictors coefficients of Topic Condition's best model

Predictor	Stand.Coefficient	t	Sig
Activity PRI_{RADAR} $^{(30')}$	$\beta_1 = .517$	4.410	p.<.01
Betweenness C_M^{NEG} $^{(15')}$	$\beta_2 = .271$	2.310	p.<.05

Table 5.8: Summary of the Game model

r.	Adj.r	St.Err	S.S Model	S.S. Residual	F
.656	.431	.07	.179	.224	11.592*

*S.S.: sum of squares; *: p <.01*

Table 5.9: Predictors coefficients of Game Condition's best model

Predictor	Stand. Coefficient	t	Sig
Centrality C_M $^{(45')}$	$\beta_1 = .508$	4.534	p.<.01
Betweenness PRI_{RADAR} $^{(15')}$	$\beta_2 = -.280$	-2.488	p.<.05
Activity PRI_{RADAR} $^{(45')}$	$\beta_3 = .267$	2.365	p.<.05

Finally, the best model for the *Game* condition, is

$$B(i) = \beta_1(C_M)^{45'}_{Cent} + \beta_2(PUB_{RAD})^{15'}_{Betw} + \beta_3(P_M^{NEG})^{45'}_{Act} + \epsilon(i) \tag{5.3}$$

Within the *Game* condition the subjects seem to assess their space of affinity mainly considering the centrality of the others in the community messages network, at the end of the experiment ($(C_M)^{45'}_{Cent}$), together with the betweenness in the public radar space during the first $15'$ of the interaction ($(PUB_{RAD})^{15'}_{Betw}$), and the number of negative messages sent in the private side of the chat during the whole interaction ($(P_M^{NEG})^{45'}_{Act}$) (Tab. 5.9).

As shown in Tab. 5.8, the best regression model for the *Game* condition explains the 43% of the variance for the betweenness in the affinity space.

Similarly to the regression model characterizing the *Topic* condition, and contrarily to that of the *Blank* condition, the regression model for the *Game* condition seems to take into account also the non-communicative variables, as the activity in the private radar or the betweenness in public radar.

Noteworthy, there seems not to be any relation between the vote expressed at the end of the *Game* condition and the affinities among subjects in the same experiments.

Finally, although the main topic of the present work concern the relation between affinity and communicative dynamics in such a conditions, the analysis of the vote strategies adopted by the participants in the *Game* condition demonstrate the groups efficiency in facing the proposed social problem solving. The graphs in Fig. 5.3 show the frequency distribution of the clusters size defined by the preferences expressed through the votes in the 5 experimental sessions of the *Game* condition.

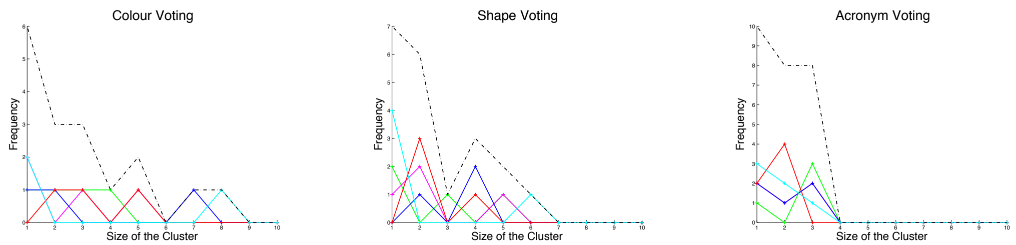


FIGURE 5.3: Distribution of the clusters size along the three vote (from left to right, from the first to the third vote). The graph shows the trend of the clusters size relative to the voting preferences. The line color identifies the different experiments, and the dotted line indicates their cumulative distribution. On the X axis are reported the sizes of the clusters, and on the Y axis are reported the normalized frequencies.

The winning strategy for our game, as it is demonstrated by the random model results in Fig. 5.4 is that of being in a group of one, two or three people. To face the task proposed by the game, people need to explore the environment and exchange information with others, possibly cheating. Indeed, the intermediate polls reveal that during the first two votes the subjects apparently adopt not optimal game strategies. The distribution of the final clusters size reveals that only in the third vote the subjects adopt the winning strategy, trying to belong to a small cluster composed mainly by two components, and never bigger than 3 (Fig. 5.4).

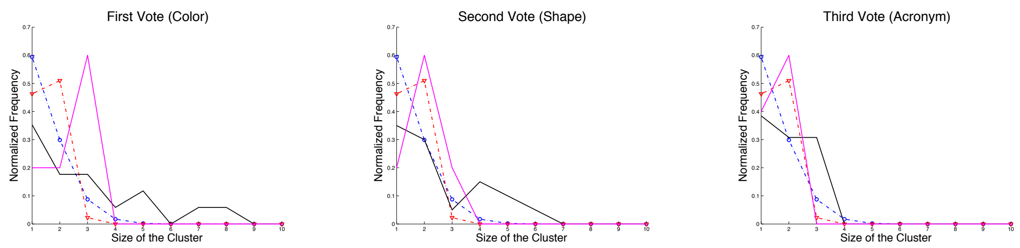


FIGURE 5.4: Comparison between a simulated random process of cluster size distribution and the experimental data (from left to right, from the first to the third vote). The dotted lines indicate the distributions generated by a random process (in blue the size distribution and in red the winning size probability distribution), the continuous lines show the trend of the experimental data (in black the size distribution and in pink the winning size probability distribution). On the X axis are reported the sizes of the clusters, and on the Y axis are reported the normalized frequencies. The subjects approximate the best strategy of vote with a global standardized error of 9%, 8%, 6%, respectively for the three votes

In the third vote, all the participants were able to be part of a cluster with a high probability of victory. The participants' voting strategies seem to approximate effectively the distribution of the probability of victory of the clusters size in the case of a random process of vote, but making a sort of correction on it and voting not at random.

5.4 Discussion of results

The main goal of the series of experiments presented in this work was to test the theoretical predictions deriving from the social cognition about the coupling between the people "affinity" and "opinion/behaviour". A secondary result is of course related with the predictability of the affinity between two subjects considering only some variables concerning the communication dynamics. Many relevant socio-physical models adopting the social cognition theories as a reference scaffolding assume a "mandatory" coupling between affinity and opinion. Our results suggest that such a socio-physical approximation is valid but related to the psychological field.

The affinity among individuals appears to be sensitive to different aspects related to the task, and the subjects appear to adapt the cognitive heuristics used to assess the affinity with the others, depending on the constraints imposed by the task.

A linear regression method has been used to test such hypotheses. The three *best* resulting models indicate the interaction parameters used by the subjects to define their affinity network. In particular the explained variance of the models is significantly greater in the *Blank* condition (65%), where the affinity dynamics appears to be more related to the number of interactions and to their moods. On the contrary in the *Topic* and in the *Game* condition the explained variances are respectively of 33% and 43%, suggesting how the constraint imposed by the task can eventually slow the dynamics and make them less effective (*i.e.*, more complex/frustrated).

Of course a part of information is lost with the contents of the messages, while in the *Blank* condition the mood and the semantic contents of the messages tend to be always correlated, for different reasons such the dimension of messages becomes less correlated in the other conditions. For instance in the *Game* condition the euphemism and the irony are frequently used by the subject to manipulate the others and win the game. In the same way, in the *Topic* condition the mood is no longer sufficient to classify the messages because their content can be deeply different and play a completely different role within the communication dynamics.

As a consequences the affinity within the *Game* and the *Topic* conditions result to be less related with the rough variables about the mood based communication dynamics.

A way to investigate the dependence between the affinity and the communication behaviour it was to study (and to compare) the betweenness dynamics of the subjects in the affinity space for the different experimental conditions.

For what concerns the general aspects of the communication dynamics, it emerges how the first $15'$ of interaction (at least when the entire session is $45'$ long), correspond to a sort of *characteristic time* for the construction of the first "stable social structure" in the public space.

Within the *Blank* condition, the betweenness of a subject in the affinity space appears to be related both to the amount of positive messages exchanged in the community space during the first $15'$ of interaction, and to the centrality and betweenness degree in the positive messages network in the whole experiment.

This result reveals that the relevance of a subject within the group is correlated, within the *Blank* condition, with the number of messages with positive mood produced. In other words, the more a subject promotes social aggregation, the greater become its social relevance (*i.e.*, his betweenness in the affinity space increases).

Such a result seems to partially confirm the general assumption, deriving from the social psychology and partially adopted by all the modern socio-physical models [98];

the assimilation process within certain conditions (*i.e.*, psychological field topology) is no longer related to the sheer opinion differences.

Apparently in contrast with part of the literature [90], this result actually generalises the overview suggesting that the assimilation process is very much affected by type of task (*Topic* versus other 2), probably because the effect of the cognitive dissonance on the psychological field determined/shaped even by the task itself.

Within the *Topic* condition, the betweenness in the affinity space is related with the frequency of the private radar adjustments in the first 30′, and with the centrality of the subject in the network of the negative public messages during the first 15′ of interaction.

The *Topic* condition creates a system which behaves differently from the one created by the *Blank* condition. Within the adopted constraints the dynamics of affinity are no longer related with the most diffused theoretical assumption of sociophysics. The more a subject manages its private affinity space, and participates actively in the negative messages network, the greater is his final betweenness in the general affinity space. This result could be explained as an effect both, of the group polarization, and of the in-out group effect [7, 8]. Finally, of course in the *Topic* task "sheer opinion differences" do matter because the topic matters to the participants. Nevertheless within this task the interesting result is that the affinity space appears as no longer correlated with the opinion, as well as with the communication among the participants. While the cognitive dissonance would suggest a decreasing of affinity between subjects belonging to different opinion, especially when the opinion is perceived as "relevant" by the subjects, in this case only the social influence appears as moderated by the task.

The betweenness in the affinity space defined within the *Game* condition is related with the number of the messages with positive mood sent and received by a subject during the entire session, with his betweenness in the public radar in the first 15′, and with the amount of private negative messages in the entire session Furthermore, in the *Game* condition, the votes seems not to be associated with the affinity. In other words in this condition the affinity between subjects appeared to be affecting the communicative dynamics of the group less than it does in the others two experimental conditions.

The regression models (Eqs. (5.1), (5.3), (5.2)) suggest that, while the betweenness in the *Blank*'s affinity space of a subject can be effectively forecast just taking into account the dynamics of its communication in the first 45′, the same challenge cannot be accomplished within the others two tasks. This evidence suggests a less trivial effect of the cognitive dissonance on the social influence, and in particular that a lack of correlation between affinity and communication dynamics can be provided by different reasons. Concerning the *Topic* condition we observe a decreasing of the social influence effect probably produced by the cognitive dissonance. On the contrary, in the *Game* condition we should get into consideration the structure of the problem solving required to the subjects.

The introduction of the *Game* condition allowed to study a very frustrated condition, in which the psychological field is distorted by the constraints of the game. Within such a condition we study how the social problem solving affects the coupling between affinity and communication.

All the participants of the *Game* condition appear to play so to belong in the third vote to a cluster of size equal to 2 or 3. Noteworthy such a dimensions are the most probable winning cluster size for a random process of 10 subjects (Fig. 5.3). In other words they were able to synchronize enough their vote with their knowledge of the network to maximize their probability of victory, at least in a random process approximation. During the first two votes the subjects apparently adopted other game strategies, and the distribution of the final clusters' sizes reveals that only in the third vote the subjects tried to win, determining only small clusters composed by one, two or three components (Fig. 5.4). The subjects game strategies seem to effectively approximate the best strategy (*i.e.*, to belong to a small cluster with a size around 2) for a random voting process, but making a correction on it and not voting at random. Noteworthy, in the *Game* condition, the different votes were not associated with the affinity. In other words the affinity between subjects appears in this condition less affected by and less affecting the communicative dynamics of the group, with respect to the others experimental conditions.

The affinity space does not appear as correlated with any composition of the clusters generated by the three votes, neither with the real preferences expressed after the sessions. This last result suggests that the affinity dynamics is not correlated, or directly affected by, the winning strategies within the *Game* condition.

To sum up, results show that in the *Blank* condition it is possible to forecast the final affinity between any two subjects using the *classical* socio-physical models, while this is no longer possible in more structured tasks. The interpretation of this result is that, in the absence of a specific task, people tends to structure their communication space according with their affinity, while for structured tasks others dimensions become more important.

The small group dynamics, as described by Lewin in the last century, are characterized by a different regime with respect to the big community of people. Probably the typical social problem solving represented by small group dynamics is faced using refined cognitive strategies shaped and adapted through the experience.

Our data suggest that when there is no *specific/external* tasks (*i.e.*, constraints) affecting the dynamics, the behaviour of the subject is easily foreseeable without considering (nevertheless very important) the semantic contents of the messages, starting from the structure of the communicative exchanges. In other words we could say that the *psychological field* of such systems can be approximated quite efficiently just considering the communication network. On the contrary, when an external field (*i.e.*, a specific task) is introduced the psychological field is no longer easy to approximate and at least the semantic content of the messages has to be get into account.

An interpretation of the data brings towards some principal considerations. The *Blank* condition is the more *un-frustrated* task is essentially well predicted using a linear model. In the other tasks, the subjects experience a sort of dissonance between the task requirements and their inner state. The results suggest that to face with such tasks, the subjects maintain partially separated such representations and developing an opportunistic mental representation of the community, not related only with their affinities.

Finally within the small group dynamics the predictions of social cognition inspired models appear as modulated by the complexity of the psychological field. The coupling between affinities and behaviours of the subjects follows easily such a theoretical predictions for unconstrained interactions, confirming the simplest socio-physical models. On the contrary, the relation between affinities and behaviours thus not disappear whenever the complexity of the psychological field increases, but it becomes just more complex to be "captured" without considering the external factors.

Chapter 6

Opinion condition

The main target of the work presented in this chapter is to explore the relations between personality, communication dynamics, affinity network and opinion dynamics.

Starting from the point of view proposed by Lewin in the "Field theory" [18], in this work we explore the role of the topology of the "psychological field", and the theorized interaction between personality and environment,

$$B = f(P, E) \tag{6.1}$$

where B, the behaviour of people, is a function of P (personality, or personal attitude) and E (environment).

We consider the aspects related to the subjective variables, some more crystallized (*i.e.* structure of personality, age, sex), other more fluid and in some way more context related (*i.e.* state anxiety, opinion toward a specific topic), taking into account the environment where the subjects interact (*i.e.* small group involved in virtual interaction).

We focused on the relation between such variables and the communication processes and small group dynamics, in order to widen the "psychological field" to a "socio-psychological field", exploring the mutual and dynamical influences between the order parameters (*i.e.* communication dynamics, group structure, etc). Our intent is to experimentally relate the Eq. (6.1) to the social environment, assuming it as shaping and shaped by the behaviour of people engaged in small group discussion, linking in this way the individual and the social dimension.

In the next paragraphs we will explore the correlations between personality and communication behaviours, and we will focus on the "weight" of the subjective variables, of the communication dynamics and of the affinity network on the opinion dynamics, pointing out the relevance of the emerging communication and affinity networks topology on the individuals' behaviour.

6.1 Experimental Design

The experimental task and the virtual experimental environment have been designed in order to investigate the small group opinion dynamics, considering the affinity network, the opinion dynamics, the community networks and the private chat networks of messages.

Every small group was involved in a discussion about the animal experimentation within a chat-room environment. The task required to the subjects is the same described for the *Topic* condition in Chapters 4 and 5.

In addiction, in order to gather some information about the structure of personality and the anxiety state of the subjects in interaction, we administered two self-report questionnaire before the begin of any experimental session.

The Five-Factor Adjective Short Test (*5-FasT*) [99–101] is a psychometric measure for the investigation of the Five-Factor Model (*FFM*) [102]. The *5-FasT* is configured as a rapid and effective tool for the measurement of personality in different settings. The *5-FasT* consists of a self-description of the subjects, realized by means of the compilation of a questionnaire. The subjects have to define themselves through a list of adjectives describing the personality traits, and for each adjective they have to indicate, by means of the choice on a Likert scale with five steps (1 = not at all , 5 = very much) how much the adjective at issue defines him. The *5-FasT* is easy to administer and to interpret, and the items are not particularly intrusive.

The *5-FasT* scoring classifies the subjects by means of 5 personality factors, describing the personality traits of the subjects (Tab. 6.1).

TABLE 6.1: *5-FasT* factors. Examples of adjectives defining the five personality factors

Factor	**Adjectives**
5-FasT Ne *Neuroticism*	melancholy, worried, anxious, pessimistic, confused, dissatisfied
5-FasT Su *Surgency*	assertive, energetic, brave, strong, active, original, enthusiastic
5-FasT Ag *Agreebleness*	appreciative, pacific, patient, calm, reasonable, sympathetic
5-FasT Cl *Closeness*	quiet, distant, closed, elusive, detached, introspective
5-FasT Co *Conscientiousness*	precise, methodical, organized, meticulous, provident

Table 6.2: Opinion collection. The first 4 opinions have been collected during the interaction in the small group virtual discussion, at the contrary the last 5 opinions were expressed before ($OpIN$, Emp, $TruSci$) or after the interaction ($OpFI$, $AbsOp$)

Opinion	Description
$Op^{(15')}$	Opinion expressed after 15 minutes of interaction
$Op^{(25')}$	Opinion expressed after 25 minutes of interaction
$Op^{(35')}$	Opinion expressed after 35 minutes of interaction
$Op^{(45')}$	Opinion expressed after 45 minutes of interaction
$OpIn$	Opinion expressed before the begin of the interaction
Op^{Fi}	Opinion expressed after the conclusion of the interaction
Op^{Abs}	Opinion in absolute value (0 = Adverse; 1 = Favourable)
Emp	Empathy for the animals
$TruSci$	Perceived trust in science

In a similar way, we administered a reduced form of a test for the anxiety ($STAI$) [103]. The $STAI$ measures two types of anxiety: state anxiety, or anxiety about a context, and trait anxiety, or anxiety level as a personal characteristic. Noteworthy, while the anxiety state usually changes frequently depending on the particular context to which the subjects is facing, the anxiety trait is defined as a more stable feature (*i.e.* a psychological trait changes slowly requiring a long time). In order to appreciate the potential role of anxiety within our framework we considered only the measure related to the state anxiety.

Furthermore, in order to track the opinion dynamics within our framework, we asked to the subjects to talk about a specific topic, in particular about animals experimentation, negotiating their opinion without any consensus to reach. After a standardized training phase, where the administrations were given to the subjects, the opinions of each participant were recorded through a self-placement within the values 0 - 100 (totally unfavourable - totally in favour). We gathered this information at the begin and at the end of any session, and after 15, 25, 35 and 45 minutes from the beginning of the interaction. Finally, to a further individuals profiling, we asked to the subjects also their feelings of empathy towards the animals, their perceived trust in science and their "absolute final opinion" (contrary or favourable) to the animal experimentation. The absolute final opinion request had the role to force the subjects to adopt only one of two possible votes, respectively labelled as unfavourable and favourable (see Tab. 6.2).

6.2 Procedures and methods

The data collected before, during and at the end of each experimental session has been used to examine the trend of the order parameters describing the evolution of the system, both from the local (*i.e.* individual and dyadic communication and affinity dynamics) and the global (*i.e.* opinion distribution and global group dynamics) point of view.

As described in the previous Chapters 4 and 5, we use the communicative dimensions shown in Tab. 3.1 for a precise and focused analysis of the dynamics of communication networks. Moreover, in the present work we focus on the relations between the personality traits of the subjects, the opinions' dynamics gathered and summarized in Tab. 6.2 and the order parameters defined by the Eqs. (3.3), (3.4), (3.5).

6.2.1 Sample

We selected a sample of 50 subjects (28 male and 22 female), with an average age of 25.88 (std.dev. 6.29). The sample has been divided into 5 small groups of 10 people. Every small group was composed by individuals unknown each others, and the number of male and female for each group was balanced in order to have the same distribution for each small group.

6.2.2 Data analysis

A classical statistical approach has been used to describe and to define the weight of the subjective factors on the dynamics of communication and on the opinion formation.

A discriminant function analysis [104] was applied in order to evaluate which parameters allowed us to classify a dyad as coherent or incoherent (*i.e.* equipped with the same or two different opinions), or to identify the best predicting factors of the individuals' opinion changing (*i.e.* the change of the opinion with respect to the initial one). We used the product-moment correlation of Bravais Pearson (r.) [95] to explore the relations between the personality factors, collected by the *5-FasT* and *STAI*, and the order parameters within the different communication networks, considering also the correlations between the personality traits and the opinion dynamics (Tab. 6.2). Furthermore, we adopted a linear regression method in order to define the best linear predicting model of the individuals' opinion shifts.

In order to characterize the subjects who don't change their opinion during the virtual interaction, we analysed their differences with respect to the other experimental subjects using the independent sample *student-t* test [85].

6.3 Results

We assume that certain local dynamics happen between the individuals. The local factors (*e.g.* personality) affect the mental representations of the social environment, the communicative behaviour adopted, as well as the opinion dynamics.

Under such considerations, we analyse the correlations among the *5-FasT* personality factors and the order parameters (Eqs. 3.3, 3.4, 3.5) related to the communicative dimensions showed in Tab. 3.1. Such a procedure has been adopted in order to assess the "local" variables showing a relevant impact on the communication dynamics.

TABLE 6.3: Significant correlations between the *5-FasT* personality factors and the communicative observables. For reasons of clarity only the correlations significant at level of $p < 0.01$ are shown.

Observables	**5-FasT Ne**	**5-FasT Su**	**5-FasT Ag**	**5-FasT Cl**	**5-FasT Co**
STAI	.423	*ns*	*ns*	*ns*	*ns*
Activity $G_M^{(15')}$	*ns*	.545	*ns*	*ns*	.369
Activity $G_M^{(30')}$	*ns*	.511	*ns*	*ns*	.403
Activity $G_M^{(45')}$	*ns*	.496	*ns*	*ns*	.395
Activity $C_M^{(15')}$	*ns*	.515	*ns*	*ns*	.362
Activity $C_M^{(30')}$	*ns*	.480	*ns*	*ns*	.395
Activity $C_M^{(45')}$	*ns*	.459	*ns*	*ns*	.391
Activity $Cpos_M^{(15')}$	*ns*	.473	*ns*	*ns*	*ns*
Activity $Cpos_M^{(30')}$	*ns*	.488	*ns*	*ns*	*ns*
Activity $Cpos_M^{(45')}$	*ns*	.476	*ns*	*ns*	*ns*
Activity $P_M^{(30')}$	*ns*	.373	*ns*	*ns*	*ns*
Activity $P_M^{(45')}$	*ns*	.382	*ns*	*ns*	*ns*
Centrality $Cpos_M^{(30')}$	-.416	*ns*	*ns*	*ns*	*ns*
Centrality $P_M^{(45')}$	*ns*	.376	*ns*	*ns*	*ns*
Betweenness$Cpos_M^{(30')}$	-.403	*ns*	*ns*	*ns*	*ns*
Betweenness $PUB\ Radar\ ^{(30')}$	*ns*	*ns*	*ns*	.381	*ns*

As shown in Tab. 6.3, the scores of personality factors respectively related to the *surgency* scale *(5-FasT Su)* and to the *conscientiousness* scale (*5-FasT Co*), show significant correlations with several communicative observables. The *5-FasT Su* predicts the subjects producing many messages in community or in private chat. Furthermore, such personality factor correlates with the probability to have a positive mood within the community messages. The *5-FasT Co* positively correlates with number of messages sent in the community side. As expected, the *5-Fast Ne* shows a positive correlation with the *STAI* scoring. Besides this, such personality factor is negatively correlated with centrality degree and the betweenness degree in the community positive messages network (CM^{30}_{pos}).

The subjects with an high degree in *neuroticism* appear, during first 30 minutes of interaction, to be less involved in positive discussion within the community. The others two personality factors (*5-FasT Ag* and *5-FasT Cl*) didn't show any significant correlation with the communicative variables, excepted for the correlation between the *5-FasT Cl* and the betweenness degree in the public radar.

Examining the correlations between the *5-FasT* factors and the opinion's related variables, we found that no *5-FasT* factors show a significant correlation with any opinions collected during the experiments, nor with the final opinion, nor with the difference, pure or absolute, between the initial and final opinion.

Such findings suggest that there are, at least, no trivial relations between the structure of the personality and what emerges in the opinion dynamics, but at the contrary such apparent independence seems to be related with the communicative behaviour and the interactions within the communication environment (*i.e.* emerging phenomena). Therefore, in order to forecast the opinion dynamics, we have to take into account also the interactions among the subjects.

In this direction we examined the local dynamics, focusing on the dyadic relationships, and on the emerging opinion dynamics. We applied a discriminant function analysis to mine the best model to distinguish the coherent from the incoherent dyads. A coherent dyad is defined as a couple of subjects sharing the same absolute opinion.

TABLE 6.4: Discriminant function parameters: Coherent *vs* Incoherent dyads

Parameters	Weight (β)
P_M^{NEU} $^{(15')}$	.145
Distance in PRI_{RADAR} $^{(15')}$	.096
Difference in 5-FasT Su	.296
Difference in 5-FasT Ag	.360
Difference in 5-FasT Cl	−.149
Difference in Age	.894
Total shift in opinion	−.279

The discriminant function reaches a canonical correlation of 0.76 and a relative reliability equal to 96,9%. The discriminant function represent a first linear approximation of a model characterized by seven parameters, as shown in Tab. 6.4. The probability to observe a coherent dyad increases depending on the number of neutral private messages in the first 15′, on the distance in the private radar in the first 15′ and on the difference in age. Such probability increases also depending on the difference in the *5-FasT Su* and

5-FasT Ag. A coherent dyad seems to be also characterized by the difference in *5-FasT Cl* and by the difference in the shift in opinion.

Only two others observables, respectively related to the communicative dynamics and with the mental representation of other (*i.e.* affinity) in the first 15' appear relevant in order to discriminate a coherent dyad. In summary, the best model take into account three different traits of personality, the difference of age between subjects, the amount of the opinion changing as well as the private messages and affinity representation in the early stages (*i.e.* 15 minutes) of interaction.

Consequently, taking into account the parameters in Tab. 6.4, it appears as possible, into a small group engaged in virtual discussion, to forecast whether within a dyad two individuals share the same final opinion or not.

Successively, we have directed our attention to the global dynamics shown by the single experiments.

In order to explore the dynamics of the average opinion within every experimental session, we defined the opinion centroid of each small group. As we can observe in Fig. 6.1, the opinion trends show different evolutions.

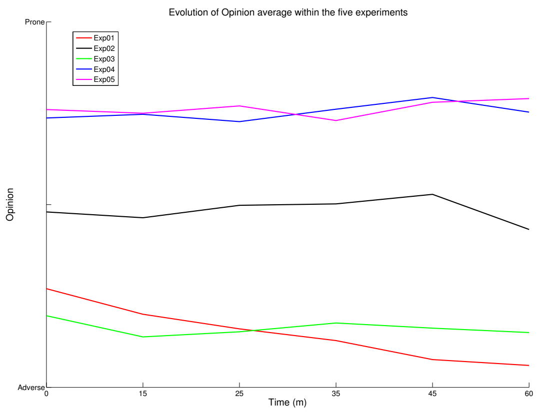


FIGURE 6.1: Time evolution of the average opinion within the 5 small group experiments. On the X axis are reported the time steps in which the opinions were collected (*i.e.* Op^{In}, $Op^{15'}$, $Op^{25'}$, $Op^{35'}$, $Op^{45'}$, $OpFi$), while on the Y axis is reported the average opinion for each experiment, from *adverse* (0) to *prone* (100). In order to facilitate the lecture of the slope and the trend of the trajectories, in the Y axis we took as extremes values 25 for the adverse and 75 for the prone. The coloured lines indicate the different experimental sessions.

The opinion centroids follow different pathways, showing a certain consistency between the initial average value of opinion and the final one, passing through a series of fluctuations due to the interactions among the subjects, and their shift in opinion. Subsequently, in order to observe the polarizing effect of the topic of discussion on the group dynamics, we investigated the trend of the opinions of the subjects that are located above or below the trajectory marked by the opinion centroid of each small group. In such a way we separate the group into two sub-clusters (Fig. 6.2).

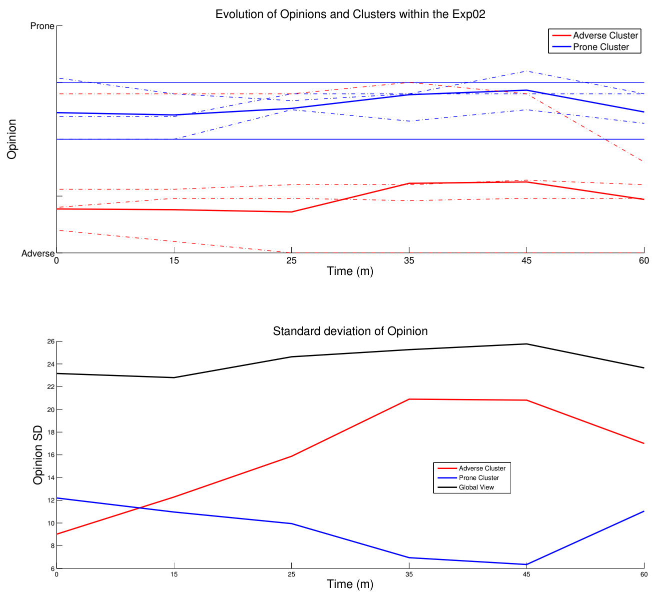


FIGURE 6.2: The figures report the opinion evolution of the subjects during the interaction. On the X axis are reported the time steps in which the opinions were collected (*i.e.* Op^{In}, $Op^{15'}$, $Op^{25'}$, $Op^{35'}$, $Op^{45'}$, $OpFi$), while on the Y axis is reported the average opinion for each experiment. In the Y axis we took as extremes values 0 for the adverse and 100 for the prone. In the graph above, the bold lines (blue and red) represent the trends of the opinion centroids related to two sub-clusters (prone or adverse), the continuous lines (blue and red) describe the subjects who do not change his opinion and dotted lines (blue and red) represent the opinion evolution of the other subjects. In the graph below the black lines describe the trend of the std.dev. of the entire group, the red lines the std.dev. for the cluster of adverse subjects, the blue lines the std.dev. for the cluster of the prone subjects.

It is interesting to observe the evolution of the standard deviation of the entire small group and of the two sub-cluster defined. At the contrary of what suggested by the social influence theories [10–12], the interaction among people within a small group should reduce the differences of opinion, and consequently the standard deviation within the group, or within the sub-cluster should decrease, which does not happen in any experimental session, at least in our experimental setting. The majority of subjects tends to range slightly around their initial values of opinion, and the individuals who change their opinion do it, not always moving towards the interactor's opinion, but sometimes showing a repulsive behaviour (*i.e.* moving away from the others in the opinion space).

To a further exploration of the opinion dynamics, we applied a discriminant function in order to highlight what parameters would allow to discriminate those subjects that move away from their initial opinion. The discriminant function is described by the

TABLE 6.5: Function parameters discriminating the subjects who change their final opinion

Parameters	Weight β
Activity C_M^{NEG} $^{(30')}$	1.125
Centrality PRI_{RADAR} $^{(15')}$	.881
Betweenness C_M^{POS} $^{(45')}$	.683
Betweenness P_M $^{(45')}$	−2.874
Betweenness P_M^{POS} $^{(45')}$	1.840
Betweenness P_M^{NEU} $^{(30')}$	1.534
Betweenness PUB_{RADAR} $^{(15')}$	−.517
Betweenness PUB_{RADAR} $^{(45')}$	.433

parameters in Tab. 6.5, and shows a canonical correlation of the model of 0.8 and a relative reliability of 88%.

Actually the 50% (25 subjects) of the entire sample has not changed opinion after 45' of interaction. Interestingly, as it's shown in Tab. 6.5, only the variables related to the groups interaction are involved in the discriminant function. The parameters related to subjective variables, such as personality factors, anxiety, their opinions or their values/beliefs (*i.e.* trust in science, empathy for animals) aren't involved in such function. This finding seems suggesting the emergence of a group phenomenon, because its independence by the subjective dimensions. We can determine if a person changes or not, albeit slightly, his final opinion basing only on the dynamics of communication, especially in our study considering the frequency of the interactions (activity in community negative messages network), the position of the individuals within the structure of the communication detected (betweenness in community or in private network of messages with positive or neutral mood) and taking into account also the topology of the radars (centrality in private radar, betweenness in public radar), as it shown in Tab. 6.5.

$$O_s = \beta_1 (C_M^{pos})_{Deg}^{45'} + \beta_2 (FF_{fact}5) + \beta_3 (P_M^{neu})_{Act}^{45'} + \beta_4 (C_M)_{Deg}^{15'} + \beta_5 (PUB_{Rad})_{Deg}^{15'} \quad (6.2)$$

Considering the 25 individuals who have changed their opinion, we have defined a linear regression model, putting in relation the amount of the opinion shift with all the observables collected. The best linear regression model explains the 79% of variance of data (Tab. 6.6). Such model involved five parameters (Eq. (6.2), Tab. 6.7), four of which

TABLE 6.6: Summary of the Opinion shift model

r. square	Adj.r	St.Err	S.S Model	S.S. Residual	F
.799	.746	4.96	1856.03	467.73	15.08*

*S.S.: sum of squares; *: p <.01*

TABLE 6.7: Predictors coefficients of Opinion Shift best model

Predictor	Stand.Coefficient	t	Sig
Centrality C_M^{POS} $^{(45')}$	$\beta_1 = -.696$	-5.30	p.$<$ 0.01
5-FasT Factor Co	$\beta_2 = -.473$	-4.44	p.$<$ 0.01
Activity P_M^{NEU} $^{(45')}$	$\beta_3 = -.475$	-4.18	p.$<$ 0.01
Centrality C_M $^{(15')}$	$\beta_4 = -.356$	-2.87	p.$<$ 0.05
Centrality PUB_{RADAR} $^{(15')}$	$\beta_5 = -.285$	-2.75	p.$<$ 0.05

refer to the variables detectable through the study of the interaction (*i.e.* the centrality degree in the community positive messages network at the end of experiment, the activity of the subjects in the private neutral messages network at the end of discussion, the centrality degree in the community messages network and in the public radar within the first 15 minutes of interaction). Only one personality factor, the *5-FasT Co* (β_2), is included in the regression model.

Interestingly, all the coefficients of the parameters involved in the model are negative. The negative sign of the communicative parameters indicates that a greater active participation to the discussion is related to a minor change in opinion. The more a person tends to send and receive messages (how much more one is involved in the discussion), the smaller his shift in opinion is. It is also interesting to note that the parameters involved affect all the areas of communication (*i.e.* community and private chat) for the entire duration of the interaction. Such a finding means that the opinion dynamics are affected both by dyadic communications (*i.e.* private messages) and by social side of the communication (*i.e.* community messages).

Eventually, we describe the behaviour of the subjects who do not change their opinion. We have defined these individuals with a bit of irony “Stubborn people”.

Comparing the stubborn people with the subjects who changed their opinion (Tab. 6.8), we found that the stubbornness effect is affected by a favourable initial opinion to the scientific research. The stubborn individuals posted far fewer negative messages within the community, they less modified their position on the public radar in the first 15’ and they less handled their private radar in the first 15’. The stubbornness effect is also

TABLE 6.8: Mean differences characterizing the Stubborn people

Observables	Mean differences
Initial Opinion	+13.34
Final Opinion	+18.50
Activity C_M^{NEG} $^{(45')}$	−13.2
Activity PUB_{RADAR} $^{(15')}$	−1.44
Centrality PRI_{RADAR} $^{(15')}$	−.22
Betweenness C_M^{NEG} $^{(15')}$	−.04
Betweenness PUB_{RADAR} $^{(15')}$	−.09

related to a lower degree of betweenness in the community negative messages network in the first 15', and to an higher degree of betweenness in the public radar in the first 15'. We not found any significant differences between stubborn people and subjects who changed their opinion for what concern the age, gender, personality structure, anxiety, final absolute opinion, empathy with animals and the trust in science.

6.4 Discussion of results

The sharing of opinions around a topic is a frequent social situation in a context of small group interaction, and it is likely that the discussion brings to the polarization of the group, however temporary. The results of our work indicate that the interactions among individuals engaged into a virtual discussion are affected by different factors.

First of all, we examined the local dynamics, analysing the correlations among the personality factors and the communicative observables. We have observed that the personality factors seem to affect the communicative behaviour of the subjects.

The *neurocitism* negatively correlates with the centrality degree and the betweenness degree in the community positive messages network, exchanged during the first 30 minutes. The subjects with personality traits related to the melancholy, the worry and the dissatisfy appear to be less involved within the community positive discussion.

At the contrary, the *surgency* and the *conscientiousness* positively correlate with the average number of sent messages. The *surgency*, that indicates as much an individual is energetic, active and original, affects the centrality degree of a subject within the private communication space.

The *closeness*, that describe as much a subject is distant, closed, elusive, appears to affects the betweenness within the public radar, and consequently the position assumed by the subjects within the affinity space.

Furthermore, it is interesting to note that no personality factor, neither any individual variables as age, or sex, correlates with the opinions detected. This suggests that there are no correlations between the structure of personality and what was found in the opinion dynamics within a small group interacting into a virtual environment.

We have then explored the opinion dynamics within the local dynamics (*i.e.* dyadic relationships), and we applied a discriminant function in order to distinguish the coherent dyads from the incoherent dyads. We have considered as coherent dyad a couple of subjects that have the same final vote in absolute terms. The parameters of the resulting discriminant function involve the personality factors, some subjective variables and the communicative parameters.

In particular, a coherent dyad can be found observing the exchange of private neutral messages, the distances in the affinity space between two subjects which compose the dyad, in the early stage of the experiments, the differences between two subjects in the *surgency*, in the *agreeableness* and in *closeness*. In addition, even some subjective variables, age difference, a sort of openness to the opinion changing allow to foresee whether a dyad shares the same final opinion or not.

This result suggests that regarding the opinion dynamics within a dyadic relationship, the difference related to the personality structure between two subjects, as well as their distance in affinity, appears to be decisive, while the communication variables appear to less rely; so within the dyadic interaction the subjective variables shown to have much relevance, and it seems to prevail the effect of cognitive dissonance on the opinion dynamics.

Considering the opinion dynamics within the small group, we have examined the evolution of the subjects' opinions, and the standard deviations within the opinion space.

According to the social pressure theories, where it is assumed that more the people interact, the more they influence each other, we expected that the opinion differences among the subjects decreased during the interaction. For this reason, the standard deviations related to the distribution of the opinion within the group, or within the sub-clusters in which the small group has been divided, should show a decreasing trend, which does not happen in any experimental session.

Such finding can be due to the context of interaction and the nature of the task. The virtual interactions, in a context of small group engaged in a common discussion within a virtual environment, does not seem to favour the emergence of complacency or social conformity. Moreover, the separation between the two sub-clusters don't diminish during the interaction.

We applied even a discriminant function analysis to distinguish the best set of variables describing the subjects who changed, and the subjects who changed not their final opinion. It is very interesting to note that the resulting discriminant function suggests that only the parameters related to the interactions within the small group are involved. This it means that no subjective parameter such as age or sex, nor any personality factor, neither state anxiety nor the attitudes toward animal experimentation, the empathy for the animals or the trust in science are necessary to individuate who change his opinion during a small group interaction within a virtual environment.

More interestingly, six parameters are related to the topology of the group, involving the betweenness degree of several dimensions analysed. Such a feature could be related with the concept of "socio-psychological field" topology.

We characterized the behaviour of stubborn people, resulting from the analysis of the mean differences between the two sub-samples of people who changed or not their opinion. Specifically, the stubborn people are more favourable to the animal experimentation, and less involved in negative mood conversation in the community, less central within the affinity space (*i.e.* private radar) and less oriented to modify their position in the public radar. The majority of the features found as defining the stubborn behaviour refers to the first 15 minutes of interaction, therefore within the small group the stubborn individuals are recognisable considering the early stage of a virtual discussion.

Moreover, we brought to light 5 parameters involved into a linear regression model explaining the shift in opinion. Such a model explain the 79% of variance of the data. For what concern the parameters involved, only one is related to the personality, while the other parameters depend by the dynamics of communication among the subjects.

Such result suggest that it is possible to forecast the shift in opinion, once individuated the individuals who have changed their opinion, taking into account the amount of positive messages exchanged in the community side at the end of the session, the messages sent and received in the community, and the centrality degree in the public radar. Also the activity in private messages with neutral mood seems related with the total shift in opinion, as well as the personality trait of *conscientiousness*, which is related to the precision and to the meticulousness of the individuals.

The results of our work suggest that within the small groups engaged into a virtual interaction, facing a structured discussion around a polarizing topic, part of the opinion dynamics is mediated if not dominated by the group structure and its evolution (*i.e.*

topology of the "socio-psychological field"). The stubbornness effect appears as related only to the topology of the network of communication and affinity. In other words, the group seems to require/impose a certain "location" (role) to the individuals, regardless their personal features.

Chapter 7

Opinion and affinity model: the repulsion dynamics

In this chapter, we first summarize the reference model [73] discussed in Chapter 2. We referred to such model for the design of the experimental framework and for the definition of the experimental conditions, as are described in Chapter 3. Successively, an evolution of the opinion and affinity models are proposed, consisting in the introduction of a repulsion mechanism among agents (OAR model).

We describe the rationale behind the introduction of the repulsion process, and the new model in depth. We demonstrate the validity of the new model, comparing it with the opinion and affinity model (OA model) and the Deffuant-Weisbuch model (O model), through the study of the discrepancy of the models, understood as the distance between the model behaviour and the experimental observations. We successively investigate the effects of the variation of the control parameters of the evolved model, in order to explore several scenarios depending on the role of different opinion critical values (ΔO_i^c), and different affinity critical values (α_i^c), for several sizes of the system. We study also the convergence time of the system dynamics and their final configuration. Finally, some psychological interpretations of such scenarios are proposed.

7.1 Reference model

The model from which we started [73] links the dynamics of opinion with the concept of affinity. In such model, the affinity is dynamically coupled with the opinion, and both are updated for every time step t.

The affinity is derived from the mutual representation of the subjects, and evolve taking into account the history of past interactions of agents i as a Markovian process.

In the OA model the affinity is involved also into the mechanism of selection of the interacting agents at every time step t, affecting, together with the difference in opinion between i and j, the social distance, and consequently the probability of the interactions between two agents.

Let us define the social distance $d_{i,j}$ between agents i and j as

$$d_{ij}^t = \Delta O_{ij}^t (1 - \alpha_{ij}^t) + \eta \qquad j = 1, ...N \qquad j \neq i. \tag{7.1}$$

The social distance is defined as the product of the difference of opinion between i and j (ΔO_{ij}^t) and the mutual affinity between i and j $(1 - \alpha_{ij}^t) + \eta$. In such way the distance between two agents depends by their distance in opinion and on their affinity. The constant η corresponds to a noise with Gaussian distribution with zero mean. The experiments were performed extracting random numbers η with a standard deviation of 0.1.

The rule of encounter uses the social distance to select the nearest j to interact with the agent i for every time step t.

The OA model can be synthesized with the following equations. Such equations represent the rules of update of opinion and affinity:

$$O_i^{t+1} = O_i^t - \mu \Delta O_{ij}^t \Gamma_1(\alpha_{ij}^t) \tag{7.2}$$

$$\alpha_i^{t+1} = \alpha_{ij}^t + \alpha_{ij}^t [1 - \alpha_{ij}^t] \Gamma_2(\Delta O_{ij}) \tag{7.3}$$

with the values of Γ_1 and Γ_2 defined as

$$\Gamma_1(\alpha_{ij}^t) = \frac{1}{2} \left[\tanh\left(\beta_1(\alpha_{ij}^t - \alpha_c)\right) + 1\right] \tag{7.4}$$

$$\Gamma_2(\Delta O_{ij}) = -\tanh\left(\beta_2(\left|\Delta O_{ij}^t\right| - \Delta O_c)\right) \tag{7.5}$$

For a detailed description of this model see Chapter 2.

7.2 Opinion, affinity and repulsion

We extend the previous model by including a repulsion process among the opinions of agents. The repulsion mechanism is realized through the modification of the opinion evolution recipe, as follow:

$$O_i^{t+1} = O_i^t - \mu(\Delta O_{ij}^t) \left(\frac{O_i^t}{\max\ O} \right) \left(1 - \frac{O_i^t}{\max\ O} \right) (\tanh(\alpha_{ij}^t - \alpha_i^c)), \tag{7.6}$$

where the opinion of an agent i at time $t+1$ is updated depending by the opinion of the agent i at time t (O_i^t), by the convergence factor μ introduced in the Deffuant-Weisbuch's model (see Chapter 2), by the difference between the critical affinity of the agent i (α_i^c) and by the values that define the relationship (affinity) α_{ij}^t between i and j (*i.e,* the element α_{ij} in the *affinity matrix*).

Comparing the equations for the opinion update in the OA model (Eq. (7.2)) and for the opinion update in OAR model (Eq. (7.6)), the mechanism of the repulsion between the agent's opinion is implemented as an the hyperbolic tangent function. Such function, keeps the values of the difference between α_{ij}^t and α_i^c within the values -1 and $+1$, so that the opinions can both converge or diverge, according to the affinity; while in the OA model, the hyperbolic tangent function is bounded between 0 and 1.

The update rule of affinity works in a similar way. The affinity a_{ij} is updated depending on the affinity between two agents i and j selected at time t and applying an hyperbolic tangent function to the difference between O_i and O_j and the critical opinion O_c.

$$\alpha_{ij}^{t+1} = \alpha_{ij}^t + (\alpha_{ij}^t)(1 - \alpha_{ij}^t)(\tanh(\Delta O_i^c - \Delta O_{ij}^t)). \tag{7.7}$$

In such way, the affinity is dynamically coupled with opinion updating. At every time step t, the element α_{ij} is updated, and the higher value of the vector i is associated to the more reliable agent. The affinity matrix is not symmetric, because the mutual affinity between two agents can have different values for the agent i and for the agent j.

The logistic contribution in the Eqs. (7.6) and (7.7) keeps the opinion values and the affinity values within the range $[0, 1]$.

The encounter dynamics of our model depends on the social distance among agents, Eq. (7.1), similarly to what happens in the OA model. In this way, the affinity and the opinion are coupled not only in the updating dynamics, but also for the selection of the interacting agents. Furthermore, both the opinion and the affinity are subjected to a random variation of amplitude of $\varepsilon = 0.01$ that prevents the collapse of the agents on the extreme values $(0, 1)$ for the opinion and for the affinity.

Such modification of the OA model lead to a better simulation of the experimental data acquired from the opinion modality (see Chapter 6) with respect to other reference models.

The rationale behind the introduction of the repulsion mechanism lies into some theoretical and experimental considerations. The coupling of the affinity and opinion is used to take into account the history of the previous interactions, and moreover for simulating a process inspired by the Festinger's cognitive dissonance theory [23]. Such theory can be summarized as the human tendency to seek a sort of coherence between beliefs and behaviours. In the OA model, the possible inconsistency between beliefs (affinity) and behaviours (opinion) was resolved avoiding the agents with which the affinity is below to the critical threshold α_i^c. Moreover, in such model the evolution of opinion can proceed in only two ways: converge, if $\alpha_{ij}^t > \alpha_c$ or, vice-versa, stay constant. It follows that the affinity critical threshold can stop the opinion updating, implementing the mechanism by which an individual ignores an unreliable interactor.

In the OAR model, the cognitive dissonance is solved by increasing the opinion distance between i and j, if $\alpha_{ij}^t < \alpha_c$. Such implication allows to solve the incongruity both from the beliefs point of view, and from the behavioural point of view. An agent i that "feels" the cognitive dissonance in the encounter with j, can change his affinity in accordance to his opinion (if $\alpha_{ij}^t \to 0$, $\Delta Oij \to 1$), and vice-versa.

Furthermore, all our experiments have shown that within the virtual interaction of a small groups, the network of communication exhibits soon a full-connected network configuration, where everyone interacts with everybody. In a such sense, the mechanism of repulsion can represent a more realistic way by which an individual can manage the cognitive dissonance in the interactions within small group; if it is impossible to avoid the interaction with someone with whom one has a low degree of affinity, it is possible to resolve the inconsistency between beliefs and behaviours with the divergence in opinion.

7.2.1 Discrepancy between simulations and experimental data

We used the real experimental data obtained from the opinion condition described in Chapter 6 to initialize the simulation of OAR model.

The procedure used to feed the model adopts as initial parameters of the simulations:

- the data relating to experimental interactions occurred in the private side of the interface presented in Chapter 3 for the simulation of the encounters,
- the final configurations of the private radar (*affinity space*) defined as the distances between the coordinates of the avatar to initialize the affinity matrix,
- the opinion gathered for each subject before the beginning of the interaction.

We chose to model the interactions of the private part of the chat because the simulation model includes only pair interactions, and because in such way we are sure that the message produced by the subject i is actually directed to the subject j, and not to other recipients. In such a way we exclude the experimental bias due to a possible non-rigorous specification of the recipients in the community, the public side of the chat-room. On the other hand, if we consider only the interactions occurred in the private part of the chat-room, we neglect the public communication, where a considerable part of the communication happens. Under these considerations, the discrepancy between simulations and experimental data can be attributed in part to the accuracy of the model, in part to the finite consistency of data processed.

In order to define the best critical values for the opinion (ΔO_i^c) and for the affinity (α_i^c), we used a iterative approach, consisting into 5 cycles of refinements of the model with a Monte Carlo method. The results of such refinements, with the parameter $\mu = 0.5$, gives a common critical value $\Delta O_i^c = 1$, while α_i^c is found to be different for each subject. The percent mean error of the model for the estimation of the opinions resulted equal to 6.70 ,with a standard deviation of 6.03. The critical value of the opinion ($\Delta O_i^c = 1$ for all the subjects), could be interpreted considering the affinity between the subjects as crucial to change the opinion, in a context of a small group in virtual interaction.

With the aim to assess the relative accuracy of *OAR* model, we applied the same procedure to *O* and *OA* models. For what concern the simulation with *O* model, only the experimental opinion are taken into account, because the affinity is not provided by such model. In addiction, the Heaviside function used in the *O* model (*i.e.*the fact that difference between O_i and O_j must be less than ΔO_i^c for the opinion shifting) has not been considered, because ΔO_i^c is found to be equal to 1.

Specifically, we have developed a statistical analysis to estimate the discrepancy of each simulation starting from the experimental data. Such statistics have been set-up by repeating 5 cycles of refinements for each model, with a fixed parameter $\mu = 0.5$, and then applying the t-test to each paired samples.

We can see in Tab. 7.1 that the model that seems to fit better the experimental data is the *OAR* model.

TABLE 7.1: Paired sample statistics

Models	**Mean**	**Std Deviation**	**Std. Error Mean**
OAR model	6.70	6.03	.85
OA model	9.40	5.49	.78
O model	11.29	9.05	1.28

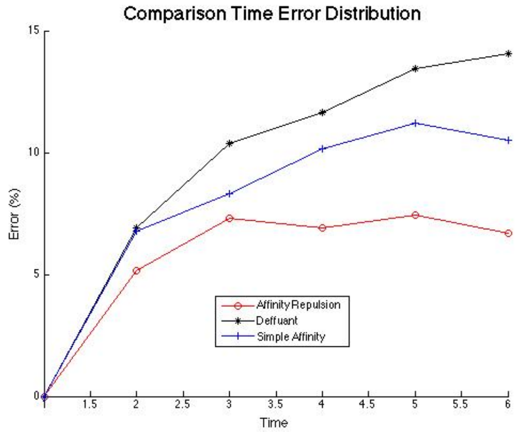
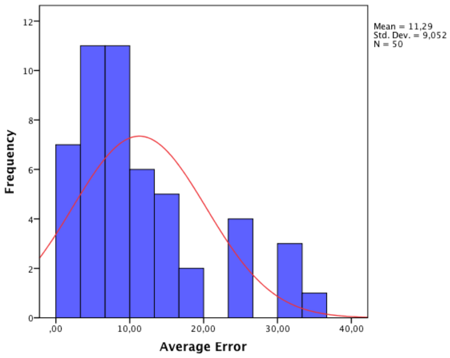


FIGURE 7.1: Comparison between models: percentage error for each experimental opinion. The black line identifies the *O* model, the blue line the *OA* model and the red line the *OAR* model. On the X axis is reported the percentage of the error and on the Y axis the steps of opinion collection

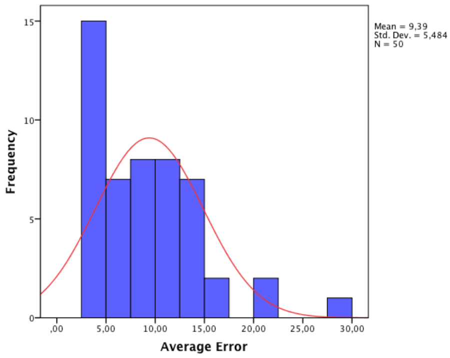
As it also shown in Figs. 7.1 and 7.2, the *OAR* model seems generally more precise, with a large number of small deviations and few high. The most part of the deviations is around 5 and 10 (Fig. 7.2(c)).

The *OA* model exhibits deviations below the value of 5, and an high number over the value of 20 (Fig. 7.2(b)), but the average around 10 make such model less accurate to fit the experimental data. The *O* model (Fig. 7.2(a)), even considering only the opinion dimension, it works pretty well. Such model exhibits many deviations near to the value of 10, but, unlike to *OAR* model and *OA* model, we found also some very high deviations, between the value of 40 and 50 of deviation from the experimental data.

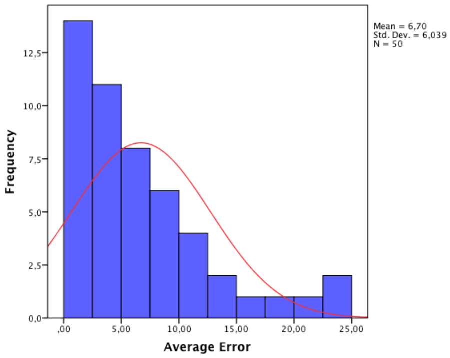
Furthermore, to assess the differences between the models, we adopt a *t-test* for paired samples statistics, since each model started with the same data. It is interesting to note that, as reported in Tab. 7.2, the differences between the averages deviations of the models were found to be significant regarding the comparison between the *OAR* model and *OA* model, as well as between *OAR* model and *O* model, while the difference between the averages of the error between *O* model and *OAR* model was not found to be statistically significant. As the *t-test* for paired samples analysis showed, the addition



(a) Deffuant model



(b) Opinion and affinity model



(c) Opinion, affinity and repulsion model

Figure 7.2: Comparison between models: error distribution. The red lines are the graphical representation of the Gaussian distribution with mean and std. dev. of the error of each model. On the X axis is reported the frequency and on the Y axis the average of the errors

of the mechanism of repulsion regulating the evolution of the opinions into the reference model provides a significant improvement for the simulation of the opinion dynamics in small group, if we consider the experimental data from which we started.

Table 7.2: Paired sample test

Models Comparison	**t**	**Sig.(2-tailed)**
OAR model *vs* *O* model	-4.627	$p. < .01$
OAR model *vs* *OA* model	-2.589	$p. < .05$
OA model *vs* *O* model	1.345	*ns.*

7.2.2 Correlations between α_i^c and ΔO_i^c and the experimental data

Once found the optimum regarding the values of α_i^c and ΔO_i^c, as resulting from the fitting of the experimental data on the *OAR* model (Eqs. 7.6 and 7.7), we performed a correlation analysis between such values, the experimental observables and the data gathered within the Opinion condition (*i.e.* the subjects' opinion (see Tab. 6.2, Chapter 6) and all the communicative dimensions (see Tab 3.1, Chapter 3).

As expected, the value of $\Delta O_i^c = 1$ for every subject does not correlate with any variable taken into account, analogously to the fact that in the experiment the opinion does not correlate with any subjective variable. As it shown in Tab. 7.3, some interesting significant correlations emerge among α_i^c and variables detected. Such correlations involve the local variables, the dynamics of interaction and the global dynamics.

TABLE 7.3: Significant correlations between the critical affinity value and the experimental observables.

Observables	**Critical Affinity Value**
Age	$-.29$*
5-FasT Ne	$-.31$*
Centrality C_M^{POS} $^{(15')}$	.38**
Centrality C_M^{POS} $^{(45')}$	.30*
Centrality P_M^{NEU} $^{(30')}$	.30*
Centrality P_M^{NEU} $^{(45')}$	.29*
Centrality PRI_{RADAR} $^{(15')}$	.29*
Centrality PRI_{RADAR} $^{(45')}$	.35*

***: p. < .01, *: p. < .05*

We found a negative significant correlations with two subjective variables: the age ($\alpha_i^c \to 1$ for the younger subjects) and the score in *5-FasT Ne* ($\alpha_i^c \to 0$ for individuals with personality traits of melancholy, pessimism, anxiety and worry).

On the contrary, we found some positive significant correlations with the communicative variables, specifically with the centrality degree within the different communication networks analysed. Such evidence show that the subjects who are more involved in private discussion with positive mood, and the subject who are more central within the positive community network have an high value of α_i^c. Consistently to the rationale behind the experimental interface and the experimental design, an high value of α_i^c is positively correlated with the centrality in the affinity space (private radar) in the first 15' minutes and at the end of interaction. In such way, the concept of affinity, and the multidimensionality of meanings within it, it is in any case reproduced by the simulation model.

7.3 Different scenario

We provide some numerical simulation exploration of the role of the control parameters on the dynamical characteristics of the system.

The recipe used to initialize the numerical simulations (Eqs. (7.6) and (7.7)) is conceived as follows:

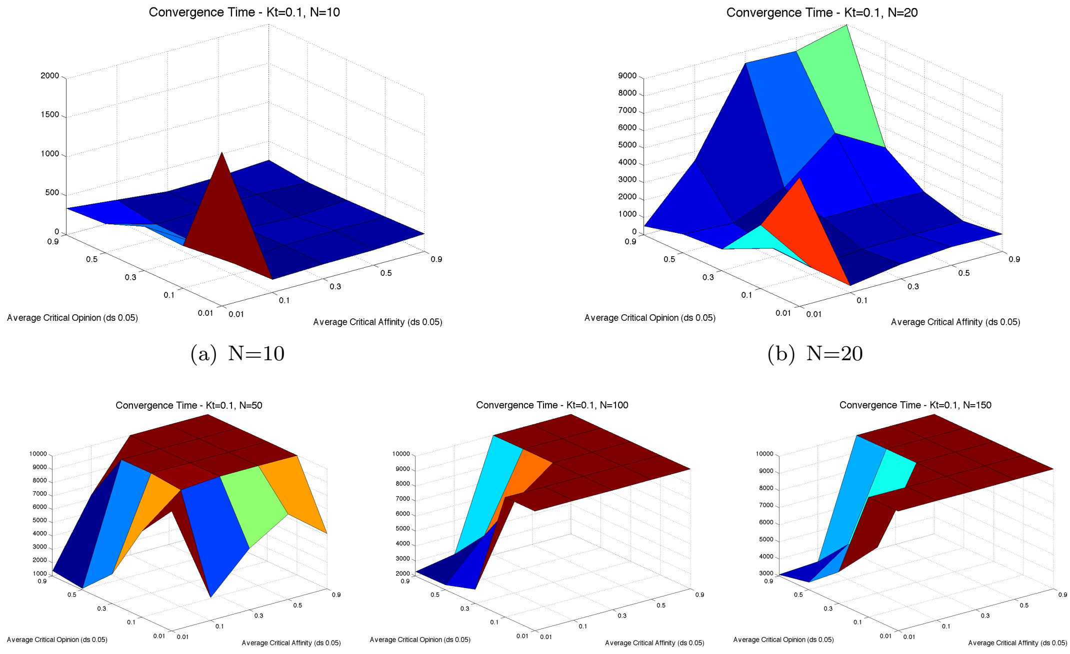
- maximum number of events $t_{max} = 10000$
- the elements of $O_i^{t_0}$ follow an uniform random distribution from 0 to 100,
- $A_i^{t_0}$ with all elements equal to 0.5, considered as the best value to simulate a neutral beginning of interaction, item the elements of $\vec{o}_{ij}$ follow a normal distribution, with std. dev. $= 0.05$ and the average equal to the different critical values used.
- the elements of $\vec{\alpha}_{ij}^t$ follow a normal distribution, with $ds. = 0.05$ and the average equal to the different critical values used.
- $\mu = 0.5$

We investigated several values of the control parameters, several values forα_i^c ($\alpha_i^c =$ 0.01, 0.1, 0.3, 0.5, 0.9), for ΔO_i^c ($\Delta O_i^c = 0.01, 0.1, 0.3, 0.5, 0.9$) and different size of the system ($N = 10, 20, 50, 100, 150$). For every combination of such control parameters, we performed 10 numerical simulations. In the following paragraphs we present and discuss the results of the simulations.

7.3.1 Convergence time

We defined the convergence time through a process of control applied the affinity matrix. According to this criterion, we declare a metastable state of the system and we stop the simulation if, for 20 consecutive events, the matrix A_{ij} shows a change in any of its elements less than 10^{-5}, or, alternatively, the number of events reach the maximum of 10000 events t. We chose this criterion for the convergence time because the temporal evolution of the opinions shown continuous micro-fluctuations (probably due to the mechanism of mutual attraction-repulsion between the opinions), while the affinity was found to be more reliable to define a meta-stable state of the system. We performed a comparison between 5 different scenarios.

As we can see in Fig. 7.3, it seems that the evolution of the simulation is influenced by the size of the system. We can note that the convergence time increases with the



(a) N=10 (b) N=20

(c) N=50 (d) N=100 (e) N=150

FIGURE 7.3: Convergence time for different size of the system

increase of N. The plateau reached by the system with size equal to 50, 100 and 150 is due to the maximum events that we set for our simulations ($t_{max} = 10000$).

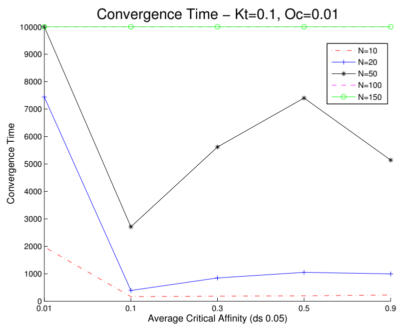
In the small system (Fig. 7.3(a)) the convergence time is around 200/300 events for every critical values of ΔO_i^c, and for $\alpha_i^c \geq 0.1$. For ΔO_i^c and α_i^c equal to 0.01 the convergence time increases, reaching a peak of 2000 events.

Turning from the system with 10 agents (small group) to the system with 20 agents (medium group) (Fig. 7.3(b)) something changes. We can observe the same peak for the convergence time with small values of ΔO_i^c and α_i^c equal to 0.01 or 0.1. For such values the system with 20 agents reaches the convergence time around 7500 events, similarly to what observed in the system with 10 agents. A notable difference with the smaller system emerges for high values of ΔO_i^c and α_i^c, specifically equal to 0.5 and 0.9. In such conditions, the convergence time reaches a peak of 9000 events. We can note that for values of ΔO_i^c equal to 0.1 and 0.3 the convergence time is quickly reached, while for critical values of $\Delta O_i^c \geq 0.5$ the convergence time increases and finally explodes if coupled with $\alpha_i^c \geq 0.3$.

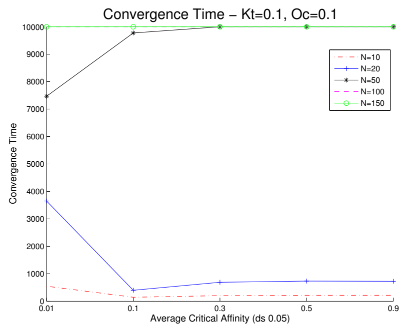
Considering the system with 50 agents, we note that for high values of ΔO_i^c and α_i^c the convergence criterion is not satisfied, and the systems never reach the convergence within the maximum of 10000 events (see the purple plateau in Fig. 7.3(c)). We can still observe a peak for values of $\Delta O_i^c = \alpha_i^c = 0.01$; for such parameters the convergence is not reached within the maximum of 10000 events.

It is interesting to note that a very low value of critical affinity ($\alpha_i^c = 0.01$) drastically reduces the convergence time, if $\Delta O_i^c \to 0.9$. As example, for $\Delta O_i^c = 0.1$, the system reaches the convergence around to the 7500 events, for $\Delta O_i^c = 0.3$ around 3000 events until to reach the 1500 events for $\Delta O_i^c \geq 0.5$.

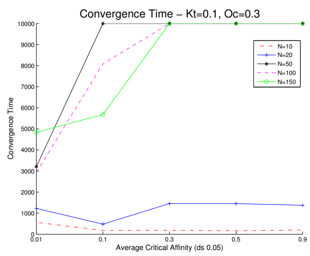
The systems with $N = 100$ and $N = 150$ show a similar behaviour in our simulations, since for such sizes the system show a very similar trend within the 10000 events (Figs. 7.3(d) and 7.3(e)). For such systems is more appreciable the role of very low values of ΔO_i^c, as happens for the systems of size equal to 10, 20 or 50. For what concern the systems with $N = 100$ and $N = 150$, it seems to be necessary a very low value of critical affinity ($\alpha_i^c = 0.01$), combined with $\Delta O_i^c \geq 0.3$, to have a convergence time lesser than 10000 events.



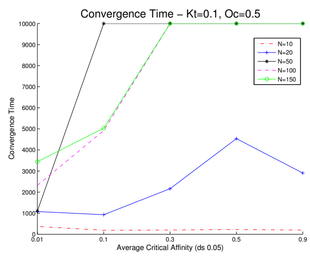
(a) Oc=0,01



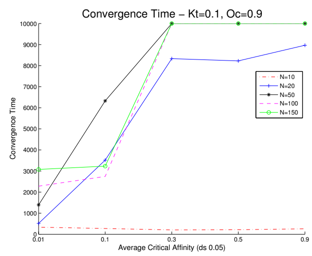
(b) Oc=0,1



(c) Oc=0,3



(d) Oc=0,5



(e) Oc=0,9

FIGURE 7.4: Convergence time for different $\Delta 0_c$

As it shown in Fig. 7.4, the systems with different size behave in a different way. The role of ΔO_i^c and α_i^c changes depending on the size of the system.

The systems with size equal to 10 seem to be more or less robust to the variation of ΔO_i^c and α_i^c, while the systems of 20 agent differently behave for different combinations of ΔO_i^c and α_i^c. As we can see in Fig. 7.4, the convergence time shows a sharp rise for $\alpha_i^c > 0.1$ (Fig. 7.4(d)) and for $\alpha_i^c > 0.01$ (Fig. 7.4(e)).

Regarding the systems with 50 agents, we can note that such systems show a behaviour similar to the smaller system for $\Delta O_i^c = 0.01$ and $\alpha_i^c = 0.1$ (Fig 7.4(a)), while for ΔO_i^c equal to 0.3 and 0.5 (Figs. 7.4(c) and 7.4(d)), the convergence time is reached only for $\alpha_i^c = 0.01$. For $\Delta O_i^c = 0.9$, the behaviour of the systems with 50 agents is similar to the systems with 10 and 150 agents (Fig. 7.4(e)).

Finally, the role of ΔO_i^c and α_i^c seems the same for systems with 100 and 150 agents. For such sizes, the combination of $\Delta O_i^c \geq 0.3$ and $\alpha_i^c \leq 0.1$ (Figs. 7.4(c), 7.4(d) and 7.4(e)) appears crucial to satisfy the convergence criterion.

7.3.2 Number of clusters

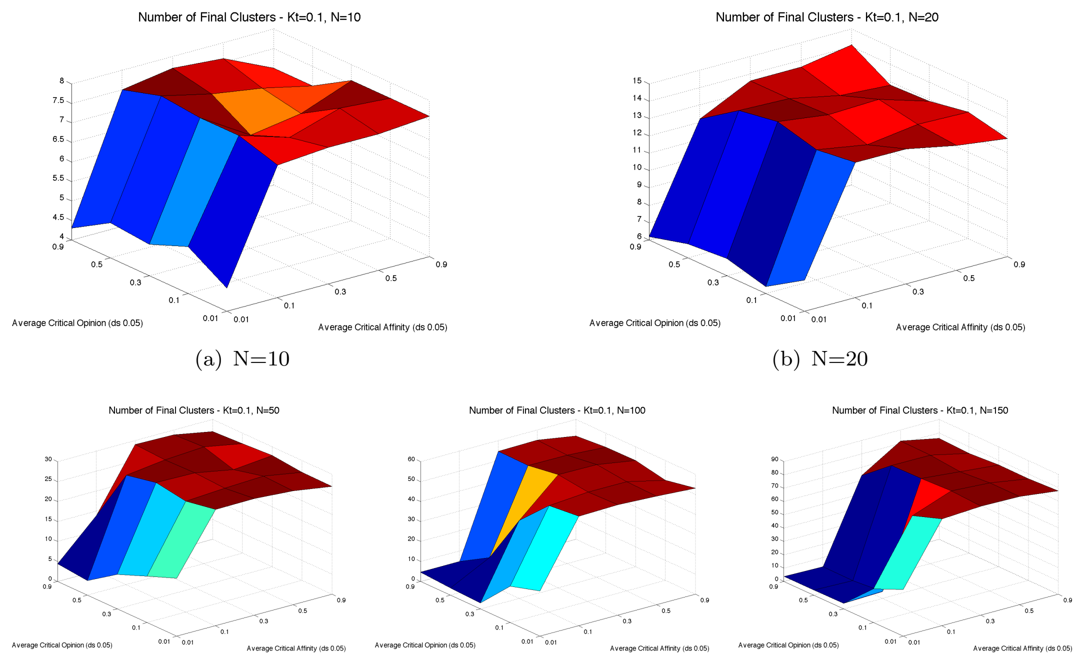
We explored the number of clusters when the simulations reached the convergence time, according to the criterion explained in the previous paragraph. We can observe an increase in the number of clusters if the size of the system increases (Fig. 7.5). Such effect is probably due to the strategy adopted to define the cluster boundaries, basing on the size of the system. As clustering criterion we used the ratio between the maximum value of opinion and the number of agents of the system at issue. In such way, for example, the system with 10 agents may show a maximum of 10 clusters; within each cluster are grouped the agents with $\Delta O_{ij}^t < 0.1$.

Obviously, adopting this method the width of the clusters is affected by the size of the system, whereby for systems with N equal to 100 or 150 we classify the agents with $\Delta O_{ij}^t < 0.01$ for $N = 100$ and $\Delta O_{ij}^t < 0.006$ for $N = 150$ as belonging to a specific cluster, while for $N = 50$ agents with $\Delta O_{ij}^t < 0.02$, and for $N = 20$, $\Delta O_{ij}^t < 0.05$.

On the other hand this procedure, since we treat the opinion as a continuous value, allows us to allocate within a cluster the agents that "exactly" share the same opinion, also for the larger systems, that for particular values of ΔO_i^c and α_i^c have shown a chaotic evolution.

As it shown in Fig. 7.5, the systems with 10 and 20 agents exhibit not many clusters for $\alpha_i^c = 0.01$. Such configuration seems robust with respect to the increase of ΔO_i^c. In the smaller systems ($N = 10$) a value of $\alpha_i^c = 0.01$ keeps the number of clusters around the $4-5$ (Fig. 7.5(a)), while for the systems with 20 agents the number of clusters is around 6 (Fig. 7.5(b)). For $\alpha_i^c > 0.01$ we appreciate a fragmentation for both these systems, with an average number of cluster around $7-8$ for $N = 10$ and around 13 for $N = 20$.

Examining the number of clusters of the systems with of 50 agents, we note that such systems seem to behave in a similar manner to the smaller systems (Fig. 7.5(c)), showing a final number of clusters around $20-30$. However, we point out a first change regarding



(a) N=10 (b) N=20

(c) N=50 (d) N=100 (e) N=150

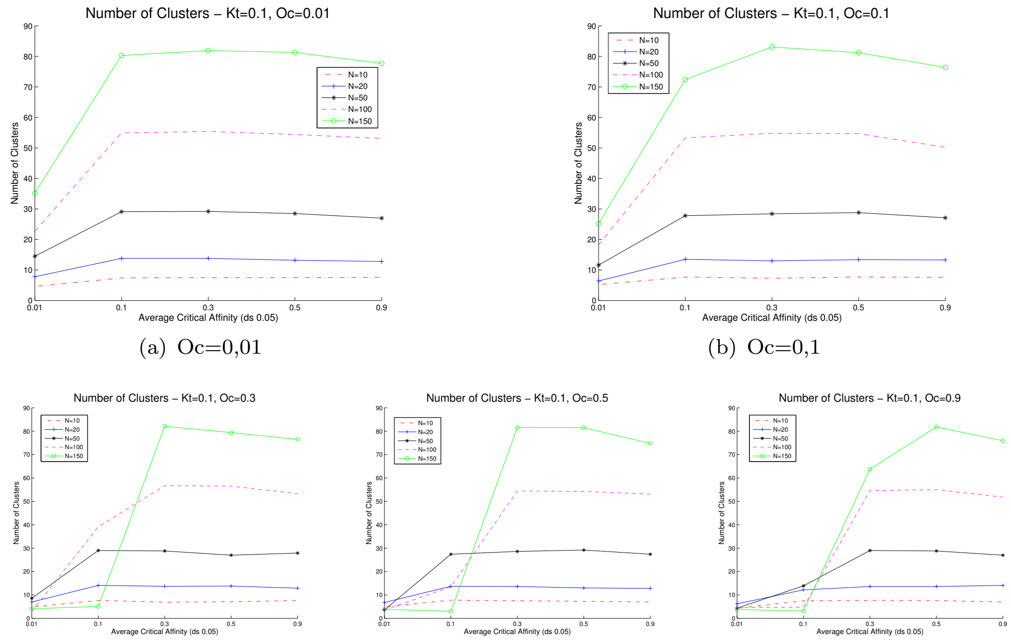
FIGURE 7.5: Final Number of Clusters for different size of the system

the role of ΔO_i^c and α_i^c. If for smaller systems a low number of clusters was mainly dependent by α_i^c, the system with 50 agents seems to be affected also by the values of ΔO_i^c. For example, a value of ΔO_i^c equal to 0.9 keeps the system under a number of 15 final clusters, if coupled to $\alpha_i^c \leq 0.1$.

Concerning the systems with $100 - 150$ agents, the weight of ΔO_i^c still increases, keeping down the number of cluster. As we can see in Figs. 7.5(d) and 7.5(e), the number of the clusters for such systems drastically decreases for $\Delta O_i^c \geq 0.5$ and $\alpha_i^c \leq 0.1$, giving rise to less than 10 clusters.

As we can note in Fig. 7.6, the system with $N = 10, 20, 50$ for each α_i^c and $\Delta O_i^c < 0.9$ show more or less the same trends, in a proportional way to the size of the system. For such systems, the ΔO_i^c seems slightly affect the number of the clusters. A value of $\Delta O_i^c = 0.9$ causes a change on the clusterization of the system with 50 agents, with respect to the smaller ones (Fig. 7.6(e)).

With regard to the larger systems, with 100 and 150 agents, the average final number of clusters is strongly influenced by the different combinations of ΔO_i^c and α_i^c. As we can see in Figs. 7.6(a) and 7.6(b), for values of $\Delta O_i^c \leq 0.1$, such systems behave similarly to the smaller ones.



(a) Oc=0,01 (b) Oc=0,1

(c) Oc=0,3 (d) Oc=0,5 (e) Oc=0,9

FIGURE 7.6: Final Number of Clusters for different $\Delta 0_c$

For $\Delta O_i^c = 0.3$, the bigger systems ($N = 150$) show an huge reduction of the number of clusters for $\alpha_i^c \leq 0.1$ (Fig. 7.6(c)), as well as for the system with 100 agents, for $\Delta O_i^c \geq 0.5$ (Figs. 7.6(d) and 7.6(e)).

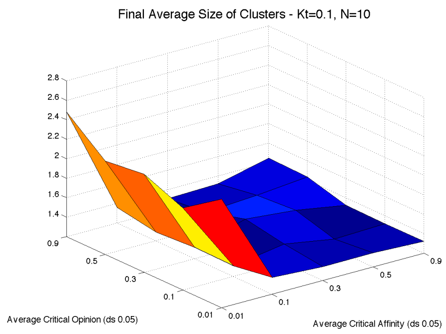
7.3.3 Clusters size

As we could expect, the average size of the clusters (Fig. 7.7) is somehow specular to the number of clusters (Fig. 7.5).

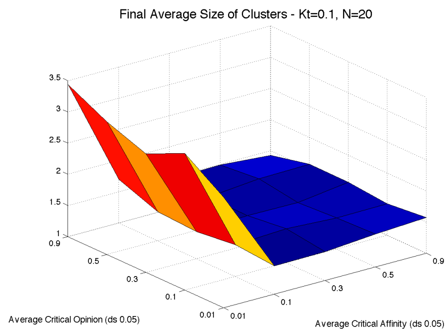
The systems with 10 agents exhibit a final average size of clusters around 2 agents for $\alpha_i^c = 0.01$. An increase of the values of ΔO_i^c and α_i^c brings down the average size of the clusters final to 1.50, so for $\alpha_i^c \neq 0.01$ the system is ever highly fragmented (Fig. 7.7(a)).

In the same way, we can observe that for the systems with 20 agents, for $\alpha_i^c = 0.01$ the average size of the clusters settles around to 3 agents per cluster. Even for such systems, the final average size of clusters does not seem to be particularly influenced by a variation of ΔO_i^c (Fig. 7.7(b)).

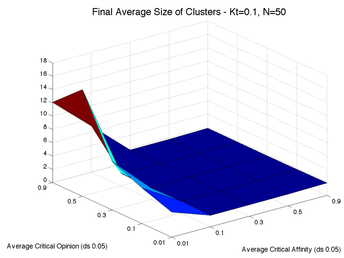
The system with 50 agents shows a final configuration influenced also by ΔO_i^c, although α_i^c seems to be the parameter that more affect the average size of the clusters (Fig. 7.7(c)). The final average size of clusters increases for combinations of $\alpha_i^c = 0.01$ and ΔO_i^c respectively equal to 0.5 (with an average size of the cluster with 16 agents) or



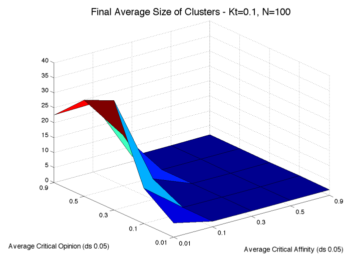
(a) N=10



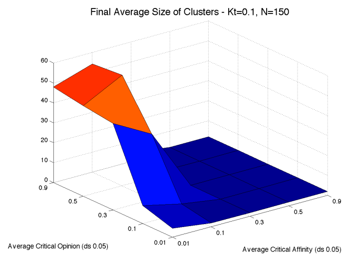
(b) N=20



(c) N=50



(d) N=100



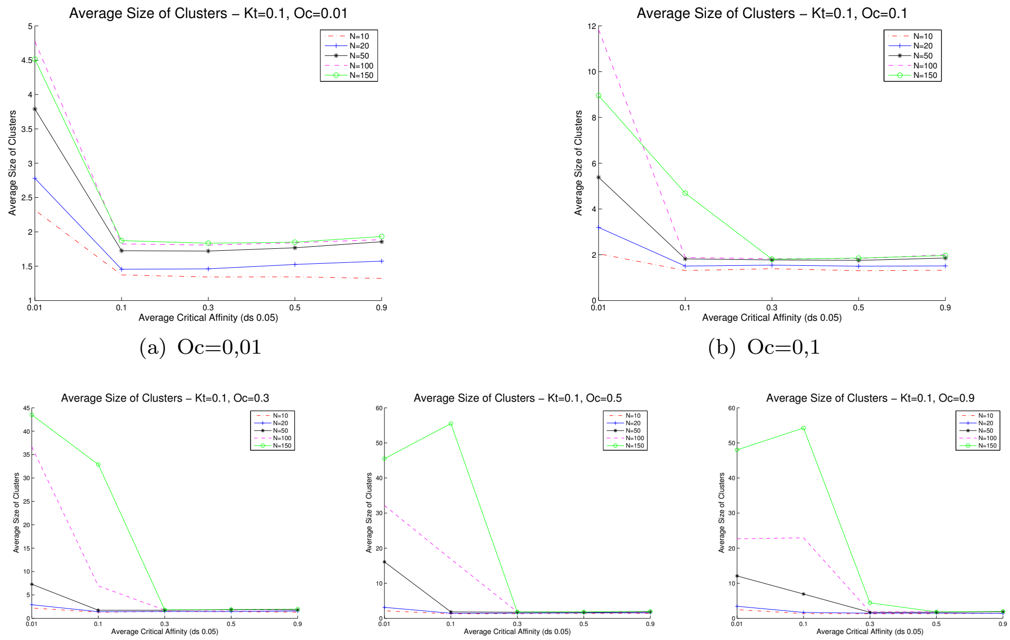
(e) N=150

FIGURE 7.7: Final Size of Clusters for different size of the system

to 0.9 (12 agents); therefore the affinity seems to still have a crucial role. Furthermore, we observed a partial fragmentation of the system for $\alpha_i^c = 0.1$ and $\Delta O_i^c = 0.9$, with clusters of 7 agents.

For what concern the system with 100 agents, we can note that the relevance of ΔO_i^c increases (Fig 7.7(d)). We can observe that clusters of large size are again determined by a very low value of critical affinity ($\alpha_i^c = 0.01$), but only if coupled with the intermediate values of critical opinion ($\Delta O_i^c = 0.3$ or 0.5). For this combinations, the final average size of the clusters is above 30 agents per cluster. Keeping a fixed value of α_i^c equal to 0.01, we can note that the average size of the clusters widely changes depending on the value of ΔO_i^c. For $\Delta O_i^c = 0.9$ we have around 20 agents per cluster, while around 5 or 12 agents per cluster for ΔO_i^c respectively equal to 0.1 or 0.01. For $\alpha_i^c \geq 0.3$, the final average size of the clusters never changes, regardless of the value of ΔO_i^c.

Regarding the systems with 150 agents, we can observe that for $\Delta O_i^c \geq 0.5$ and $\alpha_i^c le 0.1$, the average final size of the clusters settles around to 50 agents per cluster, with a peak of 56 agents for $\Delta O_i^c = 0.5$ coupled with $\alpha_i^c = 0.1$ (Fig. 7.7(e)), while for $\Delta O_i^c = 0.5$ we have around to 43 agents per cluster, if coupled with $\alpha_i^c = 0.1$. If the value of ΔO_i^c drops to 0.1, we appreciate a drastic reduction of the average size of the final clusters (8 agents per cluster), down to around 3 agents for $\Delta O_i^c = 0.01$. The values of critical affinity, if below 0.3 determine few clusters with many agents. If $\alpha_i^c > 0.3$, the system exhibits



(a) Oc=0,01 (b) Oc=0,1

(c) Oc=0,3 (d) Oc=0,5 (e) Oc=0,9

FIGURE 7.8: Final Number of Clusters for different $\Delta 0_c$

many clusters with few agents, around 3 agents per cluster, for each combination of ΔO_i^c and α_i^c.

As we can observe in the graphs in Fig. 7.8, the critical affinity equal to 0.01 causes the formation of clusters with many agents, obviously proportionally with the size of the system simulated. For all the systems, and for $\Delta O_i^c < 0.5$, the higher average size of clusters is reached with $\alpha_i^c = 0.01$ (Figs. 7.8(a), 7.8(b) and 7.8(c)). Regarding the bigger systems ($N \geq 100$), it's interesting to note that for $\Delta O_i^c \geq 0.5$ (Figs. 7.8(d) and 7.8(e)) a value of $\alpha_i^c = 0.1$ gives rise to the emergence of maximum size clusters (Fig. 7.8(e)).

7.4 Discussion of results

With the present study we came back to the sociophysics and to the simulations, starting from the results and the experimental data gathered throughout the experimental sessions discussed in Chapter 6.

Such approach brought us to evolve the opinion and affinity model, from which we started, in order to better simulate the individual processes and the social dynamics emerging within the small group. We introduced a repulsion effect for opinions' dynamics of interacting agents, with the aim to involve and simulate a comprehensive version of the cognitive dissonance within this opinion dynamics model.

The rules that drive the dynamics in the *OAR* model are a good way for simulating the small group behaviour, better fitting the data experimentally collected then the other models. Nevertheless all the models of opinion dynamics taken into account (O, OA, OAR model) behaved pretty well in the approximation of the agent's opinion when feeded with the experimental data.

The repulsion mechanism seems more effective for simulating the cognitive dissonance effects, also from a conceptual point of view. In every experimental session, presented in Chapters 4, 5, and 6, the small groups engaged in discussions within a virtual environment have always shown a full-connected network configuration. If avoiding the interactions with the agents who are not affine, may be economical and adaptive to satisfy the "inconsistency", in cognitive dissonance terms, between affinity and opinion in large groups, in a small group it should not be the case. The repulsion mechanism offers the possibility to restore the coherence between affinity and opinion by increasing the distance from an interacting agent in the opinion space, if such agent is not recognized as affine.

Studying the dynamical characteristics of *OAR* model by changing the values control parameters, we found that such system behaves in a different ways depending by different initial conditions. For different size of the system, and for several values of the control parameters ΔO_i^c and α_i^c, the model gives rise to different scenarios. We have studied the dynamical characteristics through a statistical analysis. Every system behaves in different way depending on the different initial conditions, since the affinity and opinion are coupled in an highly non-linear dependence, giving rise to a complex evolution of the system.

For what concern the impact of ΔO_i^c and α_i^c on the convergence time for the smaller systems ($N = 10$ or $N = 20$), we have to consider that, mathematically, the affinity matrix A_{ij} scales quadratically with the number of agents; therefore for large size of the system, an high value of ΔO_i^c probably affects the meta-stability of the affinity matrix A_{ij}, causing a considerable delay for the satisfaction of the convergence criterion for systems with $N > 20$.

Substantially, the smaller systems with N equal to 10 or 20 seem similarly behave, specially considering the final number and the average size of the clusters. Such order parameters are mainly affected by the value of critical affinity α_i^c, while different values of ΔO_i^c don't perturb in relevant way the final configuration of the system.

Moreover, a very low value of critical affinity increases the amount of the shift in opinion. Such shifting brings the agents closer within the space of opinion, increasing the probability of a later encounter. Higher values of α_i^c slow down such dynamics, increasing the influence of noise η and consequently the probability to meet an agent distant in opinion, or in affinity, increases, leading to a possible fragmentation of the system. The opinion and the affinity are coupled not only into the updating rules, but also into the equation of the social distance (7.1), affecting the probability of encounter between the agents.

On the contrary, we appreciate the crucial role of ΔO_i^c for the clusterization of the systems with N equal to 100 or 150. For the large systems, it seems to be necessary the simultaneous presence of a very low value of critical affinity and an high values of critical opinion, to keep the system clustered, presumably attenuating the effect of η on the probability of encounters.

Furthermore, it's interesting to note that, despite the fact that clusters are quite big for the smaller systems, if compared to the bigger system, (for $N = 10$, the cluster range is equal to 0.1, a and for $N = 20$ equal to 0.05), we have observed an average configuration in pairs for $N = 10$ and in triplets for $N = 20$, while for bigger systems ($N \geq 50$) clusters up to 56 agents emerge.

Such evidence suggests that for the larger groups, for a specific combinations of ΔO_i^c and α_i^c, is easier to collapse on the same opinion, while the smaller systems shown, on average, a more variance of final opinion, and consequently less clusters.

The concept of critical affinity can be translated, from a psychological point of view, into a sort of openness to the listening, or a tendency to be persuaded. In this way, a low value of critical affinity causes a big shift in opinion, because the subject judges the interactor somehow reliable. For the smaller systems (*i.e.*small groups), the affinity seems to be more involved into the opinion change, because it is possible, for the small number of interactors, to "compute" and "manage" the affective relationships with the others. When the size of the group increases, it is more difficult to keep into consideration the complex networks of relationships among the people, and how they relate to each other. Considering that the human cognitive capacities are limited, in a context of a large social group an individual "have to choice" which information to consider in order to represent the social environment in the most satisfying way. In the large group, the opinion of the people is surely more explicit and less complex (maybe complicated) to infer, therefore it offers a sufficient approximation for the interpretation of the social environment and of certain dynamics of the large group.

Concluding, the OAR model seems a good approximation about what happens in a small group for what concern the experimental data forecasting, for the behaviour showed by the model in different simulation scenarios, as well as for the shift observed concerning the role of affinity and opinion on the dynamics of the system when N increases. In this way, putting into relation the cognitive dissonance theory and the social pressure within the same opinion dynamics model, we pointed out the importance of the relationships among people within the small group, and at the same time the relevance of such relationships for the opinion dynamics within small systems.

Chapter 8

Conclusions

The modelization of the dynamics of small groups represents a hard challenge, but at the same time it is also a very interesting field of research, since the small group represents a very common social environment.

In psychology, the researches on the small group dynamics produced many qualitative insights about the emerging phenomena, but from a quantitative point of view they miss many aspects related to the interaction among the members, due to the difficulty to take into consideration and measure the factors that affect the dynamics of relationship.

On the other hand, the sociophysics approach to the study of social dynamics does not adequately consider many qualitative aspects of the individuals in interaction, that in our opinion are essential to correctly simulate the dynamics of a small group. At first, the sociophysics brutally neglected almost the totality of the individual variability. Recent works [73, 89, 105] tried to overcome this lack, implementing some individual factors influencing both the local and global dynamics. This direction reflects the importance of and the interest towards the individual processes, or at least towards the local dynamics, for what concern the study of the social dynamics also from a physical point of view.

So the main purpose of our research was to link the cognitive individual processes and the small group dynamics, exploring in our experiments the communication and affinity networks, in order to provide some quantitative results and qualitative suggestions both for the psychological and sociophysical models.

We faced the study of the small group starting from the conceptual theorization of complex systems. In this way we studied the relations among the elements of the system (*i.e.* individuals) and the influences between these elements and the system (*i.e.* group), focusing on the temporal evolution of the network of interactions and of the relationships among the elements. We believe that the analysis of the communication dynamics is a good approach to interpret the individual processes effects on the group dynamics, since the relations among the members and the topology of the communication structure deeply influence such processes [3, 6, 106]. For these reasons, we focused on the communication and the affinity networks and we used the tools deriving from the complex network analysis and social network analysis to describe the individual behaviours and the group phenomenology in a virtual environment.

In the presented research we refer to the small group as 10 individuals engaged in common discussion within a virtual environment. A key feature of the small groups are the face-to-face interactions between their members, in which everyone directly interacts with each other, influencing each other; so the choice of a chat room as "virtual" experimental setting appears theoretically appropriate for the study of the small groups. Moreover, the large use of new technologies for the communications among people represents a new reality in the context of human relationships, and makes the use of the chat interface in some ways ecological and of a great interest. We designed the experimental set-up in order to keep under control most of the communication aspects, leaving little space to non-controlled communication. The "virtual" environment as experimental setting allowed us to track the relationships evolution in a precise manner, considering their dynamical development from the beginning until the end of any experimental session. The private radar, the sub-environment within the chat interface where the subjects configured their personal affinity space during the interaction, was interpreted as a kind of sociometric measure about the affective relationships among people, and the analysis of such space has been related to the communication patterns. We used a set of analytical tools in order to detect the relevant characteristics of people engaged in virtual discussion. The analysis implemented was independent of the semantic content of the exchanged messages in order to be more context-free as possible, and the chat room interface avoided the hard-to-detect (*i.e.* non-verbal) communications.

The first stage of our research regarded the exploration of the relations between the affinity among individuals and their communication dynamics, focusing mainly on a quantitative investigation of the way in which the subjects create their own cognitive representation of the social space. We designed three different experimental tasks (*i.e.* social problem), with an increasing degree of social complexity, in order to test the impact of different social constraints on the evolution of the affinity network, as well as on the dynamics of communication. Our mainly aim was to define the "cognitive recipes" used by the subjects to solve the required social problems.

We exposed 150 subjects (*i.e.* 15 groups of 10 people) to three experimental conditions. In the *Blank condition*, we proposed the subjects to engage just a free chatting, without any constraint. The only requirement was to accomplish the assessment of their affinity space after the end of the session, reporting it on their "private radar". In the *Topic condition*, we introduced a polarizing subject in the discussion, and we asked the participant to develop their own opinion about the topic. In the *Game condition* we proposed a frustrated minority game based on a voting procedure where only the individuals belonging to the second biggest clusters were the winners.

Our results showed that the complexity of the social problem faced by the group, affects the relation between affinity and communication networks. The betweenness degree in the affinity networks has been used as a measure of the average affinity perceived by the group toward a subject. The affinity among individuals appears to be sensitive to different aspects related to the task, and is apparently assessed by the subjects in different ways. In other words, the subjects appear to adapt their cognitive heuristics used to assess the affinity with the others, depending on the constraints imposed by the task.

A linear regression method has been used to test such hypotheses. The three resulting best models indicate the different strategies adopted by the subjects. In particular, the explained variance of the models is significantly greater for the *Blank* condition (65%), where the affinity dynamics appears related to the number of interaction and to the mood accompanying the textual messages. At the contrary in the *Topic* and in the *Game* conditions the explained variances are respectively of 33% and 43%, where the affinity seems related also to the non-communicative factors, as the configuration of the radars. Noteworthy, in the *Game* condition, the affinity does not appear correlated with any composition of the clusters generated by the three votes. This last result suggest that the affinity dynamics is not correlated or affecting the strategies of votes in the *Game* condition.

Such results shown that in the *Blank* condition it is possible to forecast the final affinity between any two subjects, while this is more difficult in more structured tasks. The interpretation of this result could be that, in the absence of a specific task, people tends to structure their communication space according with their affinity, while for structured tasks other dimensions become more important.

Our results demonstrate how it is possible to realize experiments on small group dynamics using ICT techniques (without considering the semantic content of the messages). We have shown that different tasks elicited different cognitive strategies of the subjects. In particular, in unstructured task the affinity among subjects seems to play a fundamental role, while this is not true for more polarized tasks. The development of the affinity, in unstructured tasks, seems to be consistent with sociophysics models.

As second step, we investigated the relation among the subjective variables (*i.e.* personality, gender, age), the individuals opinion, the affinity network and the communication patterns emerging within the small group in virtual interaction. We focused on the opinion dynamics in a small group discussing about a polarizing topic (*i.e.* the animal experimentation). Within such condition, 50 subjects (5 small groups of 10 people) interacted.

With this study we tried to extend the investigation to the relations between personality and opinion dynamics. We administered a standardized personality test (5-FasT) and a reduced form of a test for the anxiety state (STAI), to gather the data related to the personality of the subjects, and we collected the opinion about the topic at issue before, during and at the end of any experimental session.

We studied the weight of the subjective variables on the dynamics took into account, and we found that the influence of the subjective variables on the opinion dynamics change if we consider the local dynamics (dyadic interactions) or the global dynamics (group dynamics), affecting more the local dynamics with respect to the global ones.

Examining the correlations among the 5-FasT factors (*i.e.* Neuroticism, Surgency, Agreeableness, Closeness, Conscientiousness) and the opinions gathered, we found that no personality factor correlates with the opinions detected, neither with their dynamics. Maybe the personality of the subjects affect the opinion dynamics in an undirected way, influencing their communication behaviour, nevertheless no linear (*i.e.* simple) relations emerges from the analysis. This finding shows that in our experiments it is impossible to forecast the opinion of the subjects considering only their personality.

Furthermore, within our experiments we found a balance between the number of people that changed their opinion during the interaction (25) and of people that remain on their initial position (25). We described the behaviour of the stubborn people (*i.e.* subjects who do not change their opinion) and the difference with respect to the subjects who shift their opinion, pointing out the role of the topology of the communication networks on the behaviour of people in virtual interaction, considering the cognitive and affective aspects. Our results suggested that the dynamics of a small groups of people engaged in virtual discussion about a specific topic is strongly affected by the topology of the communication and affinity network.

Regarding to the sociophysics simulation, in our model 7 we introduced a repulsive mechanism into an affinity and opinion model, considering the affinity among the members both as a memory term and as a mechanism that simulates the affective relationships. given the possibility to affect the opinion dynamics in a repulsive way. Interestingly, we found an unexpected significant correlation with the 5-FasT Ne (*i.e.* Neuroticism) and the critical affinity value, found with the progressive cycles of refinement of our model initialized with the experimental data.

Such value, within a numerical simulation model, reflects in part the personality traits of pessimism, anxiety and worry of real subjects, giving consistency to conceptualization of the affinity and repulsion mechanisms and to the combination of opinion and affinity dynamics used into the sociophysical model.

We demonstrated the validity of the presented model studying the discrepancy of the model in the simulations of the experimental interactions, and comparing it with two existing sociophysical models, and we explored the evolution of the system varying the initial conditions. We found interesting differences in the system behaviours when changing the number of agents involved, due to a different impact of the opinion and affinity critical values on the system evolution. In this way we support the empirical and psychological evidences of the peculiarities behind the collective phenomena characterizing the small groups, with respect to the larger ones.

8.1 Final discussion and future perspectives

The small group dynamics, the communication topology and the individual features and processes are deeply linked. The interplay between the individual dimension and the group dimension dimensions affects the complex evolution of the group dynamics, and vice-versa. The computational models based on the theoretical premises, the experimental evidences and the empirical data may test a wide range of possibilities implied by the theory that would be difficult to test empirically. In this way they could contribute to a better understanding, or maybe to an improvement, of the extant theories. With the purpose to enhance both the psychological and sociophysical models of small groups, it appears necessary to re-think the microscopic level (agents, particles, individuals) and the mesoscopic interactions among the microscopic entities (the interaction dynamics), considering the specific features affecting the interactions among the elements. Regarding the macroscopic level (group dynamics) it seems useful to consider the kind and the topology of the interaction, and its feedbacks on the microscopic and mesoscopic level. The interdependence and the qualities of the interactions among the members of a small group may be addressed combining the *field* theory [18], the *social influence* studies [107] and *cognitive dissonance* theory [23]. The results of our research bring us to suppose that the individuals behaviour within a small groups is determined by the fight for the inner coherence and subjected to the social pressure due to the "position/-role" of an individual within the opinion space and in the communication and affinity networks. Ultimately, our experimental results suggest that a future advisable step will be to consider also the topology of interaction, namely the position on the structure of communication network and of the affective relationships.

The next “required” step, on which we are already working, will be to study the semantics content of the messages related to the communication and relationships structure, exploring then the contribution of the semantic content to certain group dynamics undetectable and especially not interpretable from a viewpoint merely based on the frequency and network messages.

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