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Modelling of reputational dynamics - Applications with telematic environments

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Chapter 1

Introduction

Information and Communication Technologies (ICTs) widely expanded human interaction possibilities. Thanks to technological advances we can interact with people beyond any geographical boundary allowing potentially for wide-scale cooperation between human beings. For instance, Google and Wikipedia can be used by anyone to access a large amount of information and knowledge, as well as to generate and share it all around the world. In this sense, technology enabled people to more deeply exploit what is called Collective Intelligence [181]. Collective Intelligence is a form of intelligence that emerges from the collaboration and coordination of many individuals. Scientific projects like EteRNA [118] and Galaxy Zoo [37], benefitted from crowd collaboration (i.e., crowdsourcing) and reached results unobtainable by experts. Although the potential contribution that ICTs can bring to human progress is evident, the simple extension of the pool of people in interaction does not determine the achievement of the desired results (e.g., production of new knowledge, innovative solutions). As social psychology knows very well, people are greatly affected in their decision-making by others. When people interact in groups several emergent phenomena can occur:

Ringelmann effect / Social loafing: Social loafing is defined by the tendency of individuals to put forth less effort when they are part of a group. To put it simply, individuals contribute less when in group situations compared to when they act alone [105]. Apart from the obvious costs in terms of coordination that can emerge in group dynamics, psychologists individuated some other factors that may affect social loafing. Individuals' motivation, expectations, and responsibility diffusion appeared affected by group size. In small groups, people are more likely to feel that their efforts are more important and will, therefore, contribute more. The larger the group, however, the less individual effort people will undergo.

Free-ridings: In public good/resource situations, people in a group have a strong tendency to contribute little or nothing toward the cost of the good, while enjoying its benefits as fully as any other member of the group [189]. Free-riders heavily hinder cooperation levels and thus the achievement of a common goal and may lead to the tragedy of the commons (i.e., the complete depletion of a common resource) [92]

Sucker effect: Cooperation could be hindered not only by selfish individuals who don't want to cooperate in the first place for the sake of their own self-interest but also by potential cooperators who diminishing their contribution. In other words, some individuals will reduce their individual effort when working in a group due to the fear of becoming or being seen as, a sucker (i.e., someone who contributes more to the group than others but receives the same reward) [173].

These typical group-related effects should be accounted for when investigating social phenomena, nonetheless, in modeling works, this rarely happened thus missing a very important piece of the whole dynamics that is in place.

1.0.1 The role of Virtual Environments

Human beings are social animals. Most of our actions are determined by the environment (especially the social one), or rather by what we perceive as such. In fact, individuals behave differently depending on their awareness of being observed. This phenomenon is clearly dependent on our perception. In particular, we are subject to almost unconscious reactions regarding the presence or absence of a representation of the eyes. A series of recent studies, both in the laboratory and in the field, [17, 69, 91] have shown how a simple image of eyes in front to subjects engaged in situations of social dilemma (even in conditions of anonymity) makes people more cooperative. However, this phenomenon does not happen in other conditions where the possibility of being spied on still exists, such as in the presence of a video

camera with the recording light on. Human beings, therefore, seem to have developed regulatory mechanisms that respond purely to the presence of others. To put it simply, human behavior is strongly influenced by the social environment. Just consider the different elements that give life to small group dynamics. In this case, it is no longer the individual with his specific characteristics that counts, but the complex, circular and interdependent interaction of these characteristics with those of the group, within which the interactions between individuals take place [5]. This complex interaction can be the key mechanism of numerous group phenomena, such as the emergence of different communication topologies, the structuring of social identity, the ingroup-outgroup effects, as well as the processes of social influence [87]. In fact, the relationship between the person and his social environment (i.e group) is so close that already Tajfel and Turner [191] in defining the concept of social identity described it as part of a person's identity. Social identity has also been taken into account in the analysis of economic behavior. Akerlof and Kranton [1] suggest that people in a group internalize the group's behavioral norms. A person who identifies with a group, therefore, links his results to those of the group, thus making his belongings salient. However, membership given externally, when one's interests are accounted, is not enough to make a person cooperate with other members. Subsequent economic studies have shown that greater identification with the group is needed for achieving cooperation (for example through socializing). For example, Eckel and Grossman [64] have shown that only identifying with a team is not enough to overcome personal interest in a public-good game. Instead, by increasing the salience of the group through activities such as group puzzle-solving, the levels of cooperation in the public-good game increase. Moreover, when individuals can choose the group to join, they show higher levels of cooperation than those who are randomly assigned to one of the groups [41].
In the virtual world most of the "automatic" signals to which we are accustomed in real life and through which we adjust our social behavior, do not work or are not present. In fact, on the web, we are literally unaware of how many people can view or access something that we feel as personal. Despite this, the need to understand one's social world persists in human beings, as pointed out by scholars of social cognition. However, it is not obvious that in a virtual environment the processes that regulate actions and the perception of reality are the same as in the real world. In fact, the way in which human

beings acquire information, interpret it and memorize it, as well as their cognitive performance, is influenced by the environment and ICT (Information Communication Technologies) are configured as a new environment in which people can interact. A wide debate has taken place on the effects that these technologies have on human behavior. Indeed, while on the one hand better communication allows us to transcend social boundaries, favoring the standardization of communities, on the other this possibility opens the way for the development of new (virtual) communities and new social identities, thus creating new borders.
The fact of being able to communicate through space and time brings down the need for proximity between communicators, with potentially disadvantageous effects. For example, in computer-mediated communication (CMC) the communicators are connected through a device, which however inevitably eliminates part of the direct feedback available in a normal conversation. This may have the consequence of making CMC less "socially present" [179] and lacking social clues with respect to face-to-face communication [108]. However, this new interaction possibilities (e.g., to make contact with members of other social groups in an easier way), has also been linked to the reduction of intergroup tension and animosity, as well as greater equality [59]. However, some authors (i.e., theories of deindividuation) have underlined the negative effects of CMC. For example, the lack of control, associated with the greater freedom enjoyed by individuals in the CMC, can increase the frequency of antisocial behavior and decrease the regulatory capacity of social norms (eg, [94, 108, 115, 203]). In extreme cases, the communicator can be deprived of the awareness of his and other individual identities (i.e. deindividuation).
This approach to the study of behavior in the CMC is strongly influenced by crowd theories and mass communication. According to these, in fact, the condition of anonymity in the crowd would be responsible for the loss of awareness of people's individual identity. In this condition, social norms would be less effective in regulating and avoiding antisocial behavior. However, Postmes and Spears [158], conducting a meta-analysis on the research concerning deindividuation, found no evidence about the causal link between this and the antinormative behavior. The only true predictor found by the authors turned out to be the situational norm (i.e., what the group values ââas good or bad).
An example of such a rule in the context of the CMC could be a subcul-

ture in which "flaming" (i.e., use of hostile and provocative messages) is seen as good and desirable, while it is considered rude and undesirable outside of that group. Many researchers have tried to ignore the influence of local group norms, and have therefore defined flaming always in terms of antinormative behavior [115]. Furthermore, contrary to the predictions of the deindividuation theory, the meta-analysis of Postmes and Spears [158] revealed how the participants in de-individuation conditions observed and adhered more to the situational norm. Overall, the deindividuation seems to increase individuals' sensitivity to local norms and to those signals coming from the environment, which indicate which behavior is appropriate and desirable in that particular context. This greater reactivity to situational rules could explain the results obtained in previous studies in which the members of the group were anonymous or in which deindividuation had been induced through other means, such as the reduction of self-awareness.
The passage, due to conditions of anonymity, from individual identity to a social one has given impetus to a new line of study of computer interaction, called SIDE model [115, 116, 157]. In the CMC, the visual anonymity associated with the medium offers a context in which the individual differences between group members are less salient. Because of this, the relevance of social identity is likely to be accentuated. However, the lack of information related to individual identity does not configure the medium as a socially poor environment. In fact phenomena such as cyberlove, electronic communities and other examples of virtual solidarity indicate that the CMC is socially engaging and sometimes even intimate.
Based on the evidence previously exposed, the researchers of the SIDE model have highlighted how the local norm influence in computer-mediated communication is strong in the conditions of de-individuation and anonymity (i.e., when individual contributions are difficult to identify).

1.1 The objective

Given the framework offered by the SIDE model for CMC and accounting for the phenomena related to group interaction (i.e., Social loafing, Free-ridings, Sucker effect) the objectives of this Ph.D. Thesis can be summarized in the following points.

First, using an agent-based modeling approach (ABM), we are going to define some insights and conditions to more wisely exploiting large scale cooperation (e.g., crowdsourcing). In particular, group-size and task ergonomy (i.e., difficulty) will be considered.

Secondly and for the major part of the manuscript, we are going to assess the goodness of one of the most employed mechanisms to ensure online cooperation ranging from crowdsourcing projects, Collective Awareness Platforms (CAPs) to e-markets (i.e., reputational systems). The advantages and flaws of reputational systems will be accounted in several empirical studies involving social dilemmas situations. We did that to better represent scenarios in which individuals present different self-interests and thus make selfish conducts more likely to occur. In these studies, particular attention has been given to how reputation can affect people's decision making across different type of behaviors: (a) fairness in bargaining; (b) information seeking; (c) trust-related behaviors; (d) feedback; (e) offers acceptance; (f) donation.

Lastly, we shift our focus from within dynamics (i.e., dynamics that occur between individuals through a virtual environment) to human-device interaction, since problematic behaviors can emerge regarding how people access to virtual environments. By way of example, the behavior of Phubbing (i.e., the habit of snubbing someone in favor of a mobile phone) was selected in order to produce a multivariate and predictive model of this behavior, since it appears to be closely related to addiction conditions.

1.2 Contributions

The contribution of this thesis can be articulated as follows.

First of all, we provided in the first study concerning ABM, useful information regarding task ergonomy and ideal group size, to ease crowdsourced production of knowledge in scenarios when a cost for cooperation is entailed (i.e., modeling typical group emerging phenomena). In particular, our results can be beneficial for defining the optimal number of people that should be involved in performing or solving a given task, which can be more or less difficult to address. Moreover, our work highlighted the need for all those online services and platforms that rely on massive cooperation to estimate cooperation costs, since cooperation trajectories could be very different when different costs for cooperation are considered. Finally, we individuated those most critical situations that ask for additional or dedicated mechanisms to reach cooperation (e.g., small groups facing very difficult tasks and where cooperation costs are high). In these scenarios, strategies to ease task difficulty (e.g., increase task ergonomy, micro-tasking) and cooperation costs are really recommended.

E-markets, CAPs, behavioral-change platforms and potentially all types of online intervention involving interacting people, can exploit the findings provided in this manuscript. In general terms, reputational systems appeared to promote cooperation (in terms of fairness and trust-related behaviors). Nonetheless, when reputation is not conceived as the perfect reproduction of one's behavior (e.g., historical log) and is rather defined through users' feedback, several detrimental dynamics can emerge. Indeed, one established reputation seems to distort users' feedback reliability thus hindering the effectiveness and robustness of the entire system. Our results defined the advantages related to employing a reputational system but at the same time call for new ways of building or assign a reputation within virtual environments or alternatively ways of correcting reputation distortions.

Finally, given the increased availability of ICTs and services that rely on those, we provided a multivariate statistical model for helping to avoid dysfunctional human-device interaction, like phubbing. Online services could rely on these findings and thus proceed in profiling potential phubbers. Based on the presented model, human-device interaction could be opportunely adapted to avoid well-being repercussions for users. Moreover, future intervention aiming to dampen the effects on phubbing on people's well-being can make good use of the identified protection factors (e.g., a more structured virtual sense of community).

Chapter 2

Modeling collective problem-solving and its cost

Collective problem-solving and decision-making, along with other forms of collaboration online, are central phenomena within ICT. There had been several attempts to create a system able to go beyond the passive accumulation of data. However, those systems often neglect important variables such as group size, the difficulty of the tasks, the tendency to cooperate, and the presence of selfish individuals (free riders). Given the complex relations among those variables, numerical simulations could be the ideal tool to explore such relationships. We take into account the cost of cooperation in collaborative problem solving by employing several simulated scenarios. The role of two parameters was explored: the capacity, the group's capability to solve increasingly challenging tasks coupled with the collective knowledge of a group, and the payoff, an individual's own benefit in terms of new knowledge acquired. The final cooperation rate is only affected by the cost of cooperation in the case of simple tasks and small communities. In contrast, the fitness of the community, the difficulty of the task, and the groups sizes interact in a non-trivial way, hence shedding some light on how to improve crowdsourcing when the cost of cooperation is high.

2.1 The importance of crowdsourcing

Crowdsourcing and, more generally, group decision-making and collective problem-solving are central topics in the cognitive computation field [85, 188, 219]. Generally speaking, there have been many attempts to exploit the properties of human information exchange in order to improve collective decision-making [85,188,219]. By means of social and cognitive-inspired simulations based on the sociophysics approach, a numerical simulation framework for crowdsourcing was employed [89] to investigate the role of the cost of cooperation and its interaction with other variables (group-size, difficulty of the task, the presence of selfish individuals, etc.). The conditions when higher costs do not hinder the overall performance were defined.
Engaging a community of experts in solving complex problems or stakeholders in gathering new ideas has become an increasingly common practice. Such types of processes are generally known as crowdsourcing.

For example, in 2009, the mathematician Tim Gowers started the Polymath Project, a collaboration among other mathematicians to solve difficult mathematical problems by coordinating many colleagues. The basic idea was to persuade them to collaborate in order to find the best way to the solution. In just a few weeks, the effort of this community of mathematicians was able not only to solve the proposed problem but to figure out the solution to a more difficult generalized version of it [84].

Moreover, group decision-making and collective intelligence are the core concept of certain crowdsourcing models (e.g., Open Collaboration) [161]. Nowadays, problem-solving is no longer seen as the action of a single individual. Groups and communities have become central in ensuring a distributed, plural and collaborative decision-making process [131]. In such a sense, the crowd proved to have the capability of solving highly complex problems that traditional problem-solving teams can't settle.

Although there are various definitions of crowdsourcing, a feature that seems to be common in many of its definitions [27, 57, 106, 113, 134] is conceiving such dynamics as a widespread problem-solver.

2.1.1 Literature and project's limitations

Given the new opportunities offered by information and communication technologies, collaborative decision-making has become a central topic within many fields, including cognitive computing. For example, CO-WORKER

[188], is a real-time and context-aware system able to exploit information exchange in human interactions going beyond passive data storing. Indeed, the system, inferring contextual information during several different activities (learning, discussion, cooperation, decision-making, and problem-solving) actively engages the participants with respect to communication, meetings, information sharing, and work processes, among other activities. However, CO-WORKER assumes that people will collaborate to the platform: issues such as the number of interacting individuals, the difficulty of the task, and, in particular, the cost of cooperation (i.e., the possibility that some participant will not put enough effort in engaging the system) are neglected. Anyway, those are crucial factors in determining the success of the system. The same applies to other collaborative knowledge building architecture (e.g., TeamWork station, Virtual Math Team, and Dolphin) and, more generally, to systems that employ specific techniques (such as fuzzy logic and aggregation operators) in order to improve group decision-making via the reaching of a certain level of consensus [85]. Also in this case, the above-mentioned variables are usually neglected, but, indeed, they are crucial in solving problems by a community of experts. Another important example could be the problem of the development of semantically structured data and metadata by the annotation of resources [85]. For instance, much effort has been devoted to the development of semantic web-based annotation system able to facilitate the creation of user annotation. However, even in this case, the issue of the cost of cooperation may hinder the entire system. What if the user does not engage in the activity because of laziness, lack of attention, or motivation? Exploring the factors that influence group decision-making and, more generally, online collaboration, may give important information to the extant literature about the development of systems aimed at exploiting collaborative problem-solving. However, those insights would obviously not be applicable to all forms of crowdsourcing since crowdsourcing itself is a broad and complex theme.

2.1.2 Factors Affecting Group Decision-Making: A Numerical Simulation Approach

Many variables affect group decision-making in problem-solving [40] such as cognitive [144], social [14], motivational [29], and evolutive [16] factors. Therefore, it can be assumed that a group needs to solve a problem whose solution may produce benefits for the entire community as well as for single

individuals.
Despite many crowdsourcing projects that include individuals who do not necessarily know each other (i.e., those who do not share a common identity), we have chosen to use the term "community" in order to consider other typologies of crowdsourcing, for instance, those related to organized and online communities [39,208], as it represents our perspective better (i.e., the production of collective knowledge by means of direct interaction among individuals).
Depending on personality factors, motivation, and cognitive variables, an individual may choose to combine his effort with other members or to remain an individualist (the so-called free-rider). In the first case, if the subgroup of people who cooperate finds a positive solution to the problem, such a solution can give benefits to each individual even if their contribution was little to the solution achieved. However, free-riders play an important role from an evolutive point of view, for they have smaller chances of solving the problem, but if they find a solution, the individual learns much more than when the solution is found collectively.
In the real world, as well as in a virtual environment, cooperative individuals live and interact with those who behave selfishly. In this sense, it is important to understand which factors affect the decision to act in a pro-social manner (i.e., cooperate to achieve a common goal). Nonetheless, individual differences in the tendency to cooperate are not only attributable to genetic factors (or in a broader sense to individual aspects), even though these certainly play a significant role. Even the environment, and therefore learning processes, sharply influence cooperation and competition dynamics. For instance, social contexts (e.g., culturally related socialization experiences) appear to predispose individuals to adopt one strategy or another [93]. According to the social heuristics hypothesis [168], people internalize those strategies that are generally advantageous in everyday social interactions, which also lead them into atypical social environments (e.g., virtual environments and laboratory experiments).
Recently, cognitive science has paid special attention to the role of contextual variables that influence cooperation dynamics. Today's technological society has prompted individuals to confront increasingly complex cognitive tasks, and one of the ways in which humans have responded to this complexity is through a group, of which crowdsourcing could be considered the numerically largest possibility [172]. The environment that is created within

a team (e.g., shared and interactive team cognition) can facilitate or hinder the achievement of a cooperative goal [3, 47]. Besides, the interaction with situational variables (e.g., the time available to make a choice, group size, or the complexity of the task) influences in a non-trivial manner the outcome of the decision-making process by making certain strategies of problem-solving more or less salient [103, 213]. Furthermore, computational models [50] and field studies [110] from other disciplines emphasize the role of group size in supporting the level and the quality of interactivity among individuals (i.e., the production of collective knowledge). For instance, experimental literature on social dilemmas suggested that different types of group-size effects on cooperation are possible (negative, positive, and curvilinear), depending on the payoff structure of the game [9, 34].
In a recent study, task complexity was further investigated [143]. Although micro-tasks have become increasingly common within crowdsourcing practices, not all problem-solving situations can be addressed with such an approach. Another factor that can influence the tendency of individuals to cooperate is the cost of cooperation. Every human interaction involves a cost. In the simplest case, these costs concern the communication and the coordination (e.g., Ringelmann effect) among individuals. However, one of the ways in which it is possible to think about the cost of cooperation brings up the concept of reciprocity, which is the risk that our cooperative behavior will not be reciprocated.
With few guarantees that cooperation will not be exploited, the cost (the risk) of the cooperative behavior increases, and this harms cooperation levels [141]. Conversely, a lower exploitation risk (lower cost) positively affects cooperative dynamics. For instance, the possibility to identify effectively [146, 147], to reward or punish our social partners [71, 178], or to spread rumors about them (i.e., to gossip) [155, 185] seems to positively affect the establishment and the maintenance of good levels of cooperation. This phenomenon, which considers the intricate relationship among group dimension, the difficulty of the problem, the tendency to collaborate or not, as well as many other variables, is very complex, and even more so when the results, provided by recent literature and referring to small group situations, are considered.

Contributions in psychology have successfully handled the complexity of such psychological aspects recurring to agent-based modeling (ABM) [183].

An ABM approach proved to account for dynamics characterized by many interdependent individuals that adapt their behavior according to the social environment demands [96, 128, 190]. Moreover, some of the aforementioned psychological aspects that influence cooperation dynamics (e.g., reputation, peer influence, and empathy) have been modeled to replicate human decision-making [200].
As hinted above, this work is based on a recent paper [89] in which the authors proposed a modeling framework for crowdsourcing concerning the level of collectivism that characterizes the community facing the problem. More specifically, the model attempted to investigate the impact of dividing a given population with a fixed number of subjects (called players) into several smaller groups by the ability of these groups to solve problems of variable difficulty (tasks). Several scenarios were explored where everybody was in the same group to a specific scenario in which each player worked alone. The idea was to determine the optimal group size that would allow its players to learn the most. More precisely, the role of two parameters was explored: the capacity, the group's capability to solve increasingly challenging tasks coupled with the collective knowledge of a group, and the payoff, an individual's benefit in terms of new knowledge acquired. The rationale behind these two scores was to model the incremental nature of human advances. It is given that the latest scientific discoveries depend on previous discoveries, as they literally set up the conditions for such an advancement. The famous quote by Isaac Newton, "If I have seen further, it is by standing on the shoulders of giants", clearly describes such dynamics. In other words, we are speaking about a chain of fitness gains, where the total gain is larger than the simple addition of the payoff due to single advancements. Therefore, the framework postulates the two distinct gaining schemes cited before, the capacity and the payoff. In short, the former reflects society's knowledge accumulated over history, whereas the latter reflects the individual knowledge related to skills for daily problem-solving in a given time and context.

2.1.3 Aim of the Study: Protecting Crowdsourcing from the Costs of Cooperation

Previous simulations have shown that, when facing not-so-hard tasks, the tendency to collaborate in a group was and still is inversely proportional to its dimension. Moreover, regardless of the difficulty of the task, there is an optimal group size where collectivism and individualism are balanced by achieving the highest fitness and capacity. However, such simulations did not take into account the cost associated with collaboration. Experimental literature on social dilemmas has stressed that the cost of cooperation greatly impacts the cooperation itself. Indeed, cooperation levels are related negatively to the cost and positively to the benefits of cooperation [36, 68]. As a matter of fact, many studies testified that trying to solve a problem with other people involved many different kinds of costs such as cognitive and [166] communicative ones [133], the need to acquire consensus and deal with relationships among members [214]. Exploiting collective intelligence [215] of a group requires each member to pay a variety of costs. The crucial point is to evaluate the trade-off between such costs and the individual gain associated with collaboration. In this study, we added a cost for cooperation to Guazzini's model. It is trivial to predict that, by adding a cost for cooperation, the rate of cooperation decreases. However, for authors like Rachlin, the capability of acting altruistically (i.e., to pay a cost to benefit someone else) resides in the ability to ignore the short-term benefits of behavioral alternatives and to give greater importance to long-term gains of pro-social actions [164]. If this is true, we might expect a lack of sensitivity towards the magnitude of the cost of cooperation in a whole range of possible scenarios. Furthermore, the presence of a cost cannot certainly motivate "selfish" agents to change their strategies, so the eventual decrease in cooperation levels would presumably be due to the abandonment of their basic strategies by those agents with a greater tendency to cooperate. Nevertheless, these agents may offer some resistance to changing their strategies in relation to the increase of the cost. In addition, given the complex interaction among the variables at stake, we can expect that this decrement will interact with the size of the group and difficulty of the task.

2.2 The Model: Settings and Simulations

Modern sociophysics and cognitive modeling frequently merge their approaches and languages, developing hybrid methods and models' architectures [78]. Such a trend allowed sociocognitive sciences to go beyond the limitations characterizing the "classic" approach based on game theory (e.g., public goods games), sometimes capturing the minimal complexity required to "understand" the dynamics of human social systems [123]. The complexity of our approach actually refers mainly to the way we implemented the collective dynamics of the agents. Despite such complexity, the computational model describing the cognitive dynamics of the agents is very simple and represents a standard in the "computational modeling of cognition" [107,122]. From the other side, the "toy sociophysical model" we propose is devoted to bridging the agents' dynamics with the study of the collective competition between groups. Such a model has been already validated in a previous publication and represents the first attempt to capture the concurrent interplay between group competition and agent cooperation within the groups [88]. Moreover, in order to mimic the "indirect reciprocity" effect [146], we introduced an explicit representation of the "group knowledge", defined as the result of the amount of past altruistic behaviours of its agents. In this way, the "basic" tendency to free-ride the others at the level of the agent is dynamically moderated by the evolutionary selection of the agents based even on its "groups knowledge". Finally, such an interplay, merging cognitive and psychosocial modeling, has been implemented as follows.

We divided a population of N players into n groups with the same size S, so that $S = \frac{N}{n}$. We took $N = 64$, and seven values of $S = 1, 2, 4, 8, 16, 32, 64$ ($N = 64$ remained fixed). The algorithm assigned a value of p_i (chosen uniformly between 0 and 1) to each player i in each group. The value p_i was characterized for each player, which remained the same over time, and measured the player's tendency to collaborate with other group members when solving a certain task (i.e., the propensity to work collectively as opposed to individually). More precisely, a small value of p_i (close to 0) indicated a tendency towards individualism, while large values (close to 1) indicated a propensity towards collaboration. We stress the fact that such p_i are in all respects the strategies of player i: therefore, it must be considered as an innate feature of each individual and independent from other quantities. As usual in most game-theoretic models, see for example [95], by means of the evolution rule individuals with higher fitness will be more likely to reproduce, so that their strategies will survive to the detriment of the other ones. Indeed, our goal is to understand what are the best strategies depending on the values of the model parameters.

In a subsequent phase, a task was assigned to a group. The task was represented by the value R, which indicated the simplicity of the task and it was chosen randomly from six values ($R = 0.01, 0.1, 0.3, 0.5, 0.7, 0.9$). Values

of R close to 0 indicated a hard task, while values close to 1 indicated easy tasks. Each of n groups worked in parallel to solve a task with the same simplicity R. For size group S and for task simplicity R value, we ran a sequence of games. Each iteration of the game was divided into three steps: (1) first, we determined if a player in a group was a collectivist or an individualist. Each player i had a probability p_i of being a collectivist, so the player collaborated with other collectivists in the group to solve the problem; if not, the player was an individualist, who still benefited from the group but tried to solve the task alone. (2) Second, if the player i belonging to group j was a collectivist, the expected gain (G_i) was fixed at $G_i = C_j + 1$, with C_j representing the cardinality of group j, which is described in detail below, as well as the level of knowledge reached by the group during the previous turns (i.e., experience). On the contrary, if the player i decided to adopt an individualistic strategy, the desired gain G_i^* was chosen uniformly at random (between 1 and 10). Larger G_i^* meant smaller probability to solve the task but with a potentially greater gain if there was a positive resolution of the task. This result reflected the more effort that the individualist needed to solve the task, but a greater reward was not shared with the group.
The choice to let the individualists' gain be extracted at random, differently from the collectivists' case, is a conservative selection: indeed, while collectivists work together for a common goal, an individualist struggles for a given objective, which is harder or easier according to the specific instance. More precisely, we could have set the model so that individualists could select the possible gain following a given rule; however, since on average individualists face every kind of task, for simplicity we preferred to extract it at random.
(3) Third, the algorithm determined if the task was actually solved (or not) by each player. The collectivist player solved it with a probability of R, whereas the individualist player solved it with a probability of $R^{G_i^*}$. Obviously, since $R \leq 1$, a larger desired gain G_i^* meant a smaller chance of solving the problem. As a consequence, the advantage of being collectivist is to have always the opportunity to gain a fitness equal to her group knowledge plus one ($C_j + 1$), with a probability of R, while the individualists always gain a certain amount of fitness (F), with a probability of R^F.

The expected gain used to study free-riding dynamics cannot always be known at the beginning. Indeed, the success (and thus the expected gain) of crowdsourcing application and platforms rely massively on users' adoption and participation [204]. In this sense, this first phase of the crowdsourcing projects resembles a social dilemma [197]. The gain resulting from crowdsourcing is unpredictable and depends on the use that others do of such platforms. Choosing not to tie the decision to cooperate or compete to the expected earnings could be considered a conservative solution that reflects this first phase of crowdsourcing projects.

Each group, regardless of its iteration-dependent divisions into collectivists and individualists, was indexed with j in order to differentiate from i, which indicated the players within a group. Regarding the players who solved the task for a given iteration, the algorithm assigned to the scores was as follows:

- Cardinality C_j equaled the group's capacity to solve increasingly more challenging tasks (e.g., the collective knowledge of a group) and thus, it was also an integer parameter that was equal to the number of iterations in which one collectivist solved the task, regardless of R. At the beginning of this experiment, it was set at the value of $C_j = 0$ for all groups and then updated to $C_j \to C_j + 1$ each time one collectivist player solved the task.
- The player's fitness or payoff π_i represented a player's own benefit in terms of new knowledge acquired. If a collectivist (C) or an individualist (I) failed to solve the task, their fitness increased only because the others' contribution of $\pi_i = \frac{C_j}{S}\sum_j^C$, with $\sum_j^C$ equal to the number of cooperators belonging to the group j of player i who solved the task in the game turn. However, if a collectivist solved the task, it contributed an additional fitness of $\frac{C_j+1}{S}$, with $C_j^* = C_j + 1$ becoming the updated cardinality of the group, so having $\pi_i^C = \frac{C_j+1}{S} + \frac{C_j}{S}\sum_j^C$. In addition to the gain shared by the collectivists in the group, an individualist who solved the task gained an additional fitness of G_i (i.e., $G_i = R^{G_i^*}$), so having $\pi_i^I = G_i R^{G_i^*} + \frac{C_j}{S}$.
- Furthermore, the cooperative players in the group needed to coordinate and synchronize the cooperation of solving the problem among each other. On the contrary, individualists did not have to pay this so-called cost for the very fact that they acted alone. To represent this difference, the collectivist player fitness always is computed as $\pi_i^C = \frac{C_j}{S} - (\frac{C_j}{S}\delta^c)$, where the term δ^c represented an additional cost

of cooperation, which was the cost that every collectivist is assumed to pay in order to synchronize his effort with the group. On the contrary, the individualists are not affected by such cost directly. Such a model of payoff aims to represent the idea that collectivists distribute new knowledge both to themselves and to all the others, while individualists keep it for themselves. However, collectivists solved tasks more easily since they worked together, but with potentially less new knowledge (fitness) for each of them separately. In contrast, by working alone, individualists solving harder tasks learned much more since they avoided sharing this new knowledge with the others.

Summarizing, the dynamics of the system implemented by our model, is ruled by two linked equations (Equations (2.1)–(2.4)), respectively, determining the agent's personal gain (i.e., the gain coming from its game turn), and the payoff of an agent which depends even from the possible cooperators' contribution. The average gain ($\overline{\gamma_i}$) is the direct contribution to the own fitness of each player in a single turn of the game, and it can be expressed as

$$\overline{\gamma_i} = p_i R \frac{C_j + 1}{S} + (1 - p_i) R^{G_i^*} G_i^*, \tag{2.1}$$

or separately for Collectivists (C) and Individualists (I), as in the Equations (2.2) and (2.3):

$$\overline{\gamma_i^C} = R \frac{C_j + 1}{S} \tag{2.2}$$

and

$$\overline{\gamma_i^I} = R^{G_i^*} G_i^*. \tag{2.3}$$

The fitness of each player in a turn of the game π_i is then defined as the total gain of each player at the end of such a turn, deriving both form its contribution (γ_i) and from the contribution due to the number of cooperators k, which solved the task during the turn within the same group of i.

π_i can be expressed by Equations (2.4), (2.5), (2.6), (2.7).

$$\overline{\pi_i} = \overline{\gamma_i} + \sum_k^N p_k R \frac{C_j + 1}{S} \tag{2.4}$$

with $k \neq i$.

Again we can express the π_i separately for Collectivist (π_i^C) and Individualist (π_i^I), as follows in Equations (2.5) and (2.6):

$$\overline{\pi_i^C} = R\frac{C_j + 1}{S} + \sum_k^N p_k R \frac{C_j + 1}{S} \tag{2.5}$$

$$\overline{\pi_i^I} = R^{G_i^*} G_i^{*\tau} + \sum_k^N p_k R \frac{C_j + 1}{S}. \tag{2.6}$$

Finally, if we introduce the cost of cooperation (δ_c), and we consider the time, we have that the expected fitness of an agent i at a certain time t becomes:

$$\overline{\pi_i^t} = \sum_{\tau=1}^{t} \left[p_i \left(R\frac{C_j^\tau}{S} + \sum_k^N p_k R \left(\frac{C_j^\tau}{S} - \frac{C_j^\tau}{S}\delta_c \right) \right) + (1 - p_i) \left(R^{G_i^{*\tau}} G_i^{*\tau} + \sum_k^N p_k R \frac{C_j^\tau}{S} \right) \right] \tag{2.7}$$

where the first term of the summatory argument represents the contribution of the cooperative actions, while the second term represents those of the individualistic actions.

The simulations involved n groups of a size of S simultaneously for a given R. Since an entire game consisted of 2000 rounds, a round was interrupted after 1000 iterations in order to check the fitness of the players. The average fitness $\overline{\pi}$ of all players, regardless of the group they belonged to, was computed. At random, 20% of players whose fitness was below $\overline{\pi}$ were removed and replaced by new ones, whose p_i was drawn anew, so that the groups' sizes S were preserved. From one round to another, all group capacities $sumC_j$ and all players' fitnesses π_i were reset to 0, where the value R remained the same, only changing the structure of groups in terms of players p_i, and the distribution of p_i within each group, from one round to another. The fitter players were kept in the game as well as 80% of lesser fit players. It is the player's p_i and his relationship with the other players' p_i-s that dictated the player's overall performance in any game. The system evolved over 2000 rounds, with an evolutionary selection being applied at the beginning of each round and then after a number of iterations, and these rounds were sufficient in reaching a stable configuration. Finally, a different series of simulations were run in order to test the effect of the cost of cooperation

(δ^c). The control parameter δ^c varied during the testing of six different values, respectively, $\delta^c = 0, 10\%, 30\%, 50\%, 70\%, 90\%$ of the collectivist players' expected gain.

2.3 Results

According to the effect of the Cost of Cooperation on Problem Simplicity (Figure 2.1 Left),

the simpler the tasks (from $r = 0.9$ to $r = 0.1$), the lesser the difference on the final agent fitness. Moreover, the difference increases from 15 to 55% in conjunction to the cooperation costs. On the contrary, for a difficult task ($r = 0.01$), the relationship between the cost of cooperation and the difference in the fitness is almost linear. The main reason for such behavior is that the cost of cooperation influences the reduction of the fitness measure in two ways: (i) directly, where the agent has to pay a cost to cooperate, and (ii) indirectly, where fewer agents want to cooperate because of the direct cost, and, thus, the cooperation is infrequent and the agents have fewer advantages. However, from the point of view of the community size (Figure 2.2 Right), the cost of cooperation affects the smaller group more than the larger ones. As for the smallest community size (i.e., $s = 1$), as well as for the smallest problem simplicity (i.e., $R = 0.01$), the final difference on the fitness is greater than 100%. Such an effect is due to the fact that, especially for very difficult tasks (i.e., $R = 0.01$), the cost of cooperation is frequently paid without any subsequent payoff, therefore producing a negative final fitness for the agent.

For what concerns the maximum group capacity reached by the system at the equilibrium (Figure 2.1), a general decrease is revealed as related to the cost of cooperation. The effect is caused by the reduction of collectivists' behavior within the system. Nevertheless, its magnitude is largely affected by the two control parameters of the system (i.e., problem simplicity and the size of the group). In particular, as shown in the left plot of Figure 2.1, the greatest reduction affects the systems facing the hardest problem (i.e., simplicity of the task = 0.01), quite independently to the cost parameters (δ^c), always reducing the final group capacity at about 40% in comparison to the zero cost condition. On the contrary, the systems facing the easiest problems (i.e., simplicity of the $task = 0.9$ and 0.7) appear not to be affected greatly by the cost, always reaching a reduction of the final group

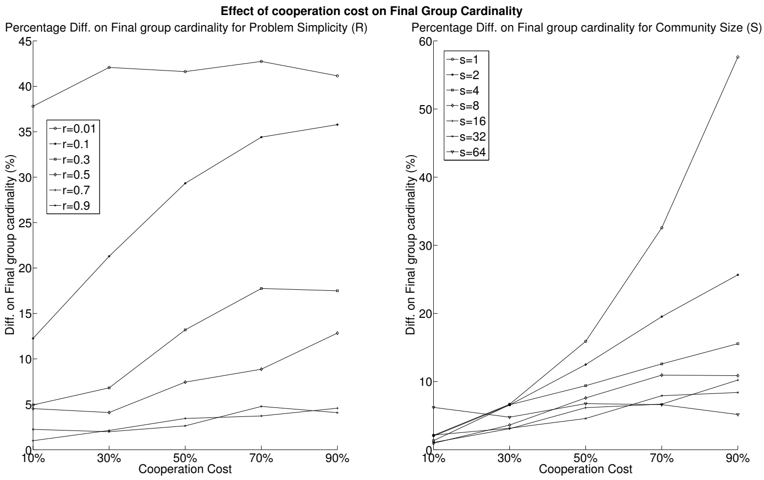


Figure 2.1: Percentage differences of the final group cardinality (i.e., the maximum complexity of the problem-solved in the past) in comparison to the cost of cooperation, for each problem simplicity (**left** plot) and for each group size (**right** plot).

capacity below 5% quite independently from the cost of cooperation. Interestingly, the systems that faced problems of intermediate complexity (i.e., $R = 0.1, 0.3, 0.5$) are revealed to be the most sensitive to the cost of cooperation. For instance, a group challenged by a problem simplicity of $R = 0.1$ demonstrated a loss of around 13% when the cost of cooperation was equal to 10% of the expected gain, reaching a loss of 35% for a cooperation cost of 90%. By the same token, the results show an effect contributed by the community size (the right plot of Figure 2.1). The larger the community, the smaller it appears to be both in the magnitude of the capacity reduction and the sensitivity to the cost of cooperation. In particular, in the extreme case represented by individuals alone, the group capacity reduction ranges between the 2%, for a cooperation cost of 10%, to 60% for a cooperation cost of 90%.

In general, when the cost of cooperation is zero, there is an inversely proportional relation between the average probability of cooperation and the size of the group (Figure 2.3 Left). Moreover, this relation is common de-

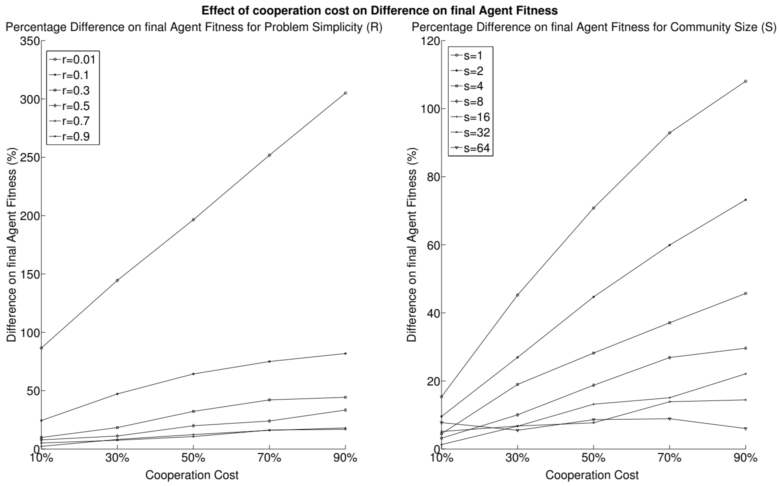


Figure 2.2: Percentage differences of the final agent fitness in comparison to the cost of cooperation, for each problem simplicity (**left** plot) and for each group size (**right** plot).

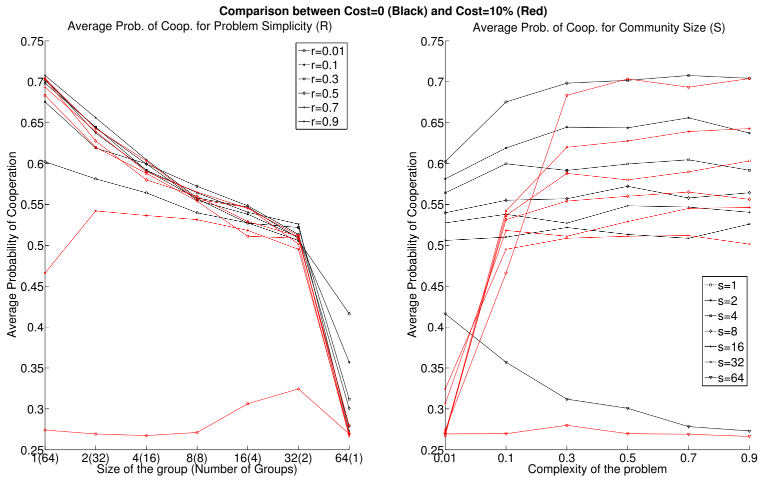


Figure 2.3: Comparison of the final average probability of cooperation for the condition with the cost of cooperation equal to 0 (dark lines) and the cost of cooperation equal to 10% (red lines), compared to the problem simplicity (**left** plot), and to the group sizes (**right** plot).

spite the different difficulty of the task. Another important aspect is that the optimal equilibrium is reached when there are 2 groups of size 32, respectively. In fact, for smaller groups, more competition is required because an agent has no interest in splitting the gain equally with the others. This aspect is stressed when a cost of cooperation is needed. Actually, the average probability of cooperation significantly decreases for the harder tasks ($r = 0.1$ and $r = 0.01$), in particular for smaller size groups. Similarly, considering the complexity of the problem in Figure 2.3 (right) without the cost of cooperation, the average probability of cooperation is stable when the size is between 1 and 32, while it directly decreases with more complex tasks from $s = 64$. With the cooperation cost, the tendency in larger groups ($s = 64$) is to defect regardless of the complexity of the problem. For smaller size groups, this effect is clear for harder tasks (complexity < 0.3), while for simpler tasks (complexity 0.9) the average probability of cooperation converges to similar values reached without any cooperation cost.

In Figure 2.4, the final average probability of cooperation compared to the problem simplicity (left subfigure) and to the community size (right subfigure) are presented. In both plots, the case of a cooperation cost of 90% is represented in red and compared to the baseline condition (i.e., cooperation cost of 10%) in black. Conversely to the case of cooperation cost of 10%, the effects of the payment to cooperate change dramatically in the final configuration of the system. It is worth noting, as is shown in the right subfigure, that the cost appears to be similar in the two extreme conditions $S = 1$ and $S = 64$. In other words, in both extreme cases, the introduction of a cooperation cost reduces the average probability of collectivist behavior quite independently from the complexity of the problem faced. The remaining system sizes (i.e., $S = 32, 16, 8, 4, 2$) also appear to be strongly affected by the cost, which presents a noticeable increase of the average cooperation probability only for very simple tasks (i.e., $R = 0.7, 0.9$). Finally, the left subfigure shows another qualitative shift with respect to the cooperation cost of 10% for what concerns the relation between the frequency of collectivist behavior and the community size. With the hardest tasks ($R = 0.01, 0.1$), there is a collapse of the cooperation tendency for all the community sizes, because the final values are always below 30%. On the other hand, for less challenging tasks ($R = 0.9, 0.7, 0.5, 0.3$), we observe a maximum of the functions for intermediate values of the community size. A relation between this maximum and the size of the group, in the case a cooperation cost of 90%, can be also observed. In particular, it appears that the greater the simplicity of the task is, the smaller the fragmentation of the most cooperative system is.

2.4 Conclusions

The simulations presented here allowed us to investigate the complex relationship among the tendency to cooperate, group sizes, the cost of cooperation, as well as the difficulty of the task. Our results indicate that, when an agent has to pay a cost, sucha price reduces the fitness both directly and indirectly (cooperation is less frequent and implies fewer advantages). These dynamics are modulated by the difficulty of the task, i.e., increasing the cooperation cost has a greater impact on the fitness of the agents in the case of very difficult problems.

The reduction of cooperation due to the cost is mitigated by task simplicity and group size. To sum up, the larger the community is, the smaller the

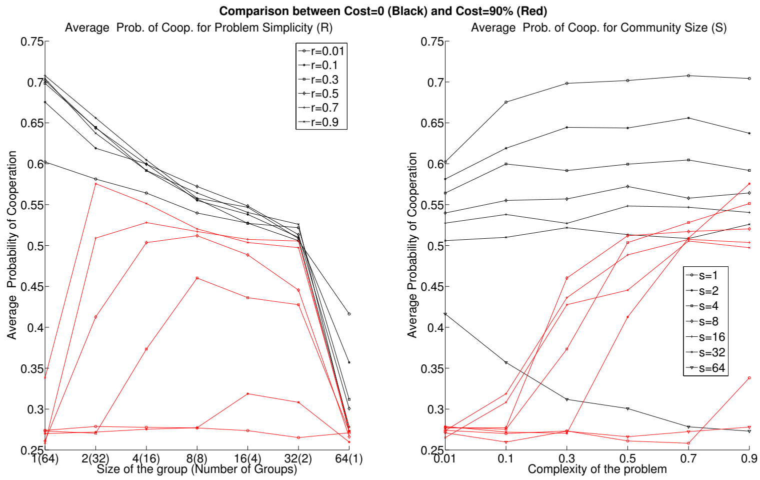


Figure 2.4: Final average probability of cooperation for the condition with the cooperation cost equal to 0 (dark lines) and the cooperation cost equal to 90% (red lines), compared to the problem simplicity (**left** plot) and to the group sizes (**right** plot).

decrease of the capacity is, which leads to less sensitivity to the cost of cooperation. Such results indicate that, when dealing with small groups and hard tasks in concrete applications, it is better to control and reduce the cost of cooperation with ad hoc interventions. However, at the same time, we have to consider the effects already emerged in the work of [89], which is confirmed by our numerical simulations. In fact, beyond a certain size of a given interacting group, we registered a collapse in their performance (i.e., the production of collective knowledge). In its entirety, our findings could provide valuable insights into structured virtual environments and for the psychosocial ergonomics of web-based systems in relation to scientific and laboratory widespread problem-solving. These results also underline the importance of the design of crowdsourcing tasks. Complex problems do not need to be divided into smaller parts to be solved. Sometimes simple tasks are better than little (or micro) tasks. An effective design allows people, whose experience or knowledge is limited, to perform like expert individuals, i.e., to produce a qualitatively better knowledge than expected [212]. Therefore, as our simulations also seem to suggest, making complex problems simpler (i.e., easily understandable, executable, and with the least possible degree of inherent uncertainty) helps to establish a higher level of cooperation within the group. Furthermore, it is possible to observe another possible effect due to the complexity reduction obtainable through task design, concerning the cost of cooperation. Despite the fact that in our model, the cost of cooperation and the complexity of the task are treated as two separate parameters, in reality there is an area, albeit limited, of an overlap. In fact, difficult tasks involve intrinsically higher costs related to the task. Therefore, it is reasonable to expect that a reduction of complexity also affects indirectly the levels of cooperation through the reduction of costs linked to the task. As demonstrated above, one of the ways in which it is possible to conceive the cost of cooperation is through the concept of reciprocity. Signs indicating a lower risk of exploitation of cooperation could reduce the cost of cooperation itself and facilitate the collaboration process [146,155,198] by means of an accurate modeling of task ergonomics.

Clearly, our results appear to be strictly applicable only to certain types of crowdsourcing. For instance, interactions within groups need to be not episodic. Therefore, our indications seem not to greatly benefit virtual labor marketplaces (e.g., Amazon's M-Turk and Crowdflower) and those activities known as tournament crowdsourcing, while open collaboration projects appear more prone to exploit our findings [161].

However, it is necessary to stress that the observed results are based on a simulation study. Given the difficulty and the cost of performing empirical investigations about similar scenarios, it is better to start with numerical simulations under reasonable assumptions and then perform empirical investigations. Therefore, it is necessary to complete these studies with a direct empirical test of the observed results. Such empirical investigation could also be obtained employing an architecture such as CO-WORKER.

In conclusion, the cost of cooperation can affect the tendency to cooperate in a non-trivial way, so future simulations and empirical research should further investigate this point as well as take this point into account in concrete applications.

Chapter 3

Reputation effects on Fairness and Trust in virtual environments

Since large-scale cooperation suffers from group-related dynamics (e.g., social loafing, free-ridings, sucker effect) and group-size and task difficulty as well, we focused our attention on how currently cooperation is enforced. Reputation supports pro-social behaviors in a variety of social settings and across different ages. When re-encounters are possible, developing a positive reputation can be a valuable asset that will result in better outcomes. Nonetheless, reputation systems are used also in those situations where encountering again the same person is unlikely. In real life scenrios cooperative acts are ambiguous and happen in noisy environments in which individuals can have multiple goals, visibility is reduced, and reputation systems may differ. This study examined how reputation within a virtual environment affects fairness in material allocations and trust in information exchange, in a three-actors interaction game in which each player had an incentive to deceive the others. We compared the results of two experimental conditions, one in which informers could be evaluated, and one without reputational opportunities. In otherwords, in one condition players could rely on reputation, while in the other it was absent. A reputational system appeared to enhance both trust and

fairness even within a virtual environment under anonymous condition. We tested adolescents and adults finding that they were consistently more generous when visibility was increased, but they showed significantly different patterns in resources allocation and information exchange. Male and female participants, across ages, showed other interesting differences. These findings suggest that reputational effects increase fairness and trust even in a noisy, ambiguous and uncertain environment, but this effect is modulated by age and gender.

3.1 Introduction

Fairness, trust and social influence dynamics have received an increasing attention in relation to virtual environments in latest years. In fact, these constructs appear to play a fundamental role in a plethora of virtual social interactions, e.g., e-market, virtual workgroups, crowdsourcing [127] [153]. In virtual environments reputational systems have been widely adopted because of their capability to positively impact the aforementioned psychosocial dynamics. Nevertheless, a model explaining the potential impact of such systems in affecting online human dynamics, for instance within a social dilemma situation (i.e., where individuals have conflicting interests), is still missing.
Our study shown that in a virtual environment the introduction of a reputational system, structured to be independent and not affecting the goal given to the subjects, has a significant impact on the decision dynamics (i.e., the problem solving strategies) adopted by the players. In particular, when the reputational system was present we observed an increasing in the fairness and trust levels, as well as in the players' average social influence on the others. We also found age-related differences in reputation usage (i.e., adolescents avoided asking information to bad and ambiguous reputed individuals), and management (i.e., adolescents obtained a lower level of reputation overall), while gender effects appeared quite small.

3.1.1 Reputation effects on prosocial behaviors between real and virtual environment

Fairness and trust are two important aspects of social interactions. A concern for relative payoffs between oneself and another individual, and the willingness to rely on someone's help or suggestion are important aspects of social exchanges [51, 73]. Understanding why and how humans act prosocially is a challenging question, and several mechanisms have been proposed among which reputation has gained important recognition in the last decade [46, 132, 140, 194]. Computational models [146, 199], and laboratory experiments [19, 141, 155], emphasize the role of reputation as a motive supporting pro-social behaviours through indirect reciprocity [145]. Indeed, reputation allows to discriminate between pro-social and selfish individuals through informal and inexpensive social control [81, 82, 147], and thanks to gossip cheaters can be identified, and their selfish choices punished [65].Interestingly, reputation still influences people's decision making even when it comes from a complete unknown source and it is earned from an obscure situation [35]. Analogously, in online markets information sharing is a powerful means to build trust and enforce norms [56], and reputation systems based on online feedback mechanisms [54] make possible to have large scale interactions between complete strangers living in faraway places. Moreover, the information and communication technologies (ICT) revolution introduced brand new factors affecting trust and reputation dynamics impacting on both cyber communities as well as real ones [52, 75, 99, 195]. In particular, very recent research highlights how a transaction could be completed in virtual environments because of reputation, even in the absence of any other enforcement [162].

Reputation can be considered as a collective phenomenon and a product of social processes [66], that goes well beyond single beliefs of impressions in the mind of any single individual. We can think of reputation as a product of natural evolution that equips human groups with a higher collective intelligence potential. In such sense, reputation is an evolutionarily stable strategy [147] that fosters the emergence and maintenance of pro-social behaviours. Notably, humans learn very early how to handle reputation during their development. The progressive achievement of a complete Theory of Mind [4, 15], and the maturation of the reward system [149] might provide the bases for the development of a capacity to track others' reputation and to manage one's own. During ontogeny reputation management develops and

people learn to use reputation in a more structured and strategic way [70]. For instance, adolescents unlike adults reported high levels of trust but low reciprocity [90]. Moreover, reputation is a mechanism that acts on a pre-existing social structure characterized by roles and status. For this reason, men and women, could be influenced differently by reputation [63, 101]. Previous literature about human interactions in virtual environment, that we mentioned early in the introduction section, highlighted even how anonymity, physical isolation, low identifiability and group salience could affect social influence dynamics [159, 186]. The interaction between these factors could lead to different outcomes, among which, when the social identity is salient, a greater adherence to local norms. Reputation represents a proxy for local norms [18]. In other words, reputation stands for the local norm and you earn or lose reputation based on how much you follow the norm. Therefore, according to the Social Identity Model of Deindividuation Effects (SIDE model), anonymous individuals could be influenced more by reputation if the reference group's importance is stressed. Under these circumstances reputation's social influence should appear to foster more pro-social behaviours in virtual environment.
In the present work, we tested whether the introduction of a reputation system increased fairness in resource allocation, and whether there was an effect on trustworthiness and trust dynamics during the process of information provision, within adolescents and young adults. We did this to provide empirical evidence of the benefits connected with reputational systems built upon users' feedback. We developed a novel experimental paradigm, modifying a previous experiment by Feinberg et al. [74], in which reputation was implemented as the opportunity to like or dislike an Observer who could provide Receivers with suggestions about a deal proposed by a Donor. Receivers had only partial information about the deal (i.e., they knew the offer amount without be acknowledged about the requested amount), therefore a truthful suggestion from the Observer could help them make a more accurate/safety decision. An important detail of the game was that Observers do not get any direct or indirect benefits from providing wrong or good suggestions, even because they didn't were acknowledged about the Receivers identity. In the experimental condition, we introduced the opportunity for Receivers to punish Observers by giving them bad evaluations as well as to reward them with positive feedback. Both the presence of a reputational mechanism within the game/setting, as well as the reputation level of the

Observes should enhance the fairness and the trust within an anonymous virtual/cyber community.

Overall, the following are the main hypotheses tested in the present study:

- **H1:** The introduction of a "Reputational System" affects Donors' pro-social behaviour (i.e., fairness) in our web-based multiplayer social dilemma game.

- **H2:** A positive reputation have a greater social influence upon the others than the other types of reputational status (i.e., negative, ambiguous) exerting more frequently trust-related behaviours (i.e., suggestion request, suggestion following).

- **H3:** The age of the participants elicits different behavioural patterns about reputation management and usage.

- **H4:** Men and women differ in reputation management skills.

3.2 Experiment

3.2.1 Sampling

The research was conducted in accordance with the guidelines for the ethical treatment of human participants of the Italian Psychological Association (AIP). The participants were recruited with the snowball sampling strategy. All participants signed an informed consent and could withdraw from participation at any time.
The participants were 226 (108 female). All participants were volunteers and their anonymity was preserved through the use of nicknames during the game. All the participants completed the experiment. At the end of each experiment a debriefing session took place to give participants more information about the aims of the study, clarify their doubts and to identify participants who were able to guess the research hypothesis. Since none of

the participants succeeded to identify the aims of the experiments, none of them has been excluded from the subsequent analysis.

3.2.2 Study 1

Participants (N= 154, 70 women; M = 15.7 years, SD = 1.3) recruited in a high school in the city of Prato (Italy) completed the study on a voluntarily basis with no monetary incentives. The testing sessions were conducted in the computer lab inside the school. Instructions were read aloud by the experimenter and also shown on the participants screens. Participants played in groups of six and each session lasted a maximum of 30 minutes.

3.2.3 Study 2

Participants (N= 72, 38 women; M= 22 years, SD = 3.7) recruited from the University of Florence completed the testing sessions in the computer lab of the Faculty of Psychology. Not differently from the study 1 participants, the subjects of the second study did not have monetary incentives. Instructions were read aloud by the experimenter and also shown on the participants' screens. Participants played in groups of six and each session lasted a maximum of 30 minutes.

The subjects' distribution across the two conditions is reported in Table 5.1.

Table 3.1: *Number of participants in each condition divided according their sample type.*

	Experimental Design			
	Reputation Treatment		**Control Condition**	
	Adolescents	Adults	Adolescents	Adults
Number of participants	78	36	78	36

3.3 Materials and Methods

All measures and manipulations of the studies are disclosed in the following section.

The **bargaining game**. The game consisted of 45 independent rounds, in which a Donor interacted with a Receiver and an Observer. Participants were anonymous and identified through nicknames. Participants played in groups of six, and each participant played all the roles of the game for fifteen times in a certain sequence determined by a computer program. The initial role for all the player was random. However, to minimize and standardize the influence of the tasks order upon players' problem solving we balanced the turn shifting (i.e., the same kind of action occurred after three turns). Overall, each participant interacted three times with every other group member in each role. We selected three matches to guarantee that two participants in each role could interact more than once, while maintaining the duration of the game sessions within 30 minutes. At the beginning of the game, each player was endowed with three kinds of resources, labelled Gold, Power, and Happiness, which were functionally equivalent. Among these resources, one was set equal to 50 units and the other two were set at a minimal level of 5 units each. According to this rule, resources were randomly distributed by the software at the beginning of the session, and the player with the highest amount of the minimum resource at the end of the game was the winner. So, if Player A had at the end of the 45 rounds 25 Gold, 13 Power and 17 Happiness and Player B had 10 Gold, 30 Power and 25 Happiness, Player A score will be represented by his amount of Power while for Player B the score will be calculated upon his quantity of Gold.

The players could see both their score and those of their opponents for the whole duration of the game. In order to prevent any influence upon participants' decision making resulting from the previous turns memories with a certain individual, players were not aware of which player they were interacting. In the game screens, the nicknames of the other players were omitted apart from the general ranking board. Thus, for instance, the Player A interacted with the Player B without knowing anything about him except his role. The only additional information about another player (i.e., the Observer) was constituted by his reputation in the Reputation Treatment condition. Not further information in both condition was permitted. We specify that once the players were appointed to one condition (i.e., Reputation Treatment or Control Condition) no shifting was allowed. Therefore,

the players in the Reputation Treatment had always at their disposal the Observers' reputation, while the individuals in the Control condition never experienced this additional information.
Furthermore, to avoid any sort of "end game" effect participants in all conditions were unaware of the game session duration (i.e., number of rounds).
The players in each role had different tasks and goals (see Table 4.1).

Table 3.2: *Summary of the actions played in the two conditions.*

	Reputation	
Roles	ON	OFF
Donor	Offers her maximum resource and asks the Receiver her minimum resource	Offers her maximum resource and asks the Receiver her minimum resource
Observer	Has the opportunity to make a suggestion (accept or to decline) about the Donor's offer and can receive a like or a dislike from the Receiver	Has the opportunity to make a suggestion (accept or to decline) about the Donor's offer
Receiver	Accepts or declines the Donor's deal with no additional information or asks for the Observer suggestion. Once the deal is completed the Receiver can rank the Observer's suggestion with a like or a dislike.	Accepts or declines the Donor's deal with no additional information or asks for the Observer suggestion.

The Donor's task was to make an offer and a request to the Receiver. The Donor offers some amount of her greatest resource, among the three at her disposal, and asks in return some amount of her minimum resource to the receiver. Actual quantities were adjusted by means of sliders. The Receiver could only see the amount and type of the resource offered by the Donor, but was unaware of what and how much the Donor had asked in return. The Receiver could "accept" or "reject" the donor's deal right away, or could require the Observer's suggestion (by clicking on the "ask suggestion" button). The Observer had the opportunity to evaluate the Donor's offer and request, knowing both the amount and the type of resources involved in the deal. In accordance with that information, the Observer could provide a hint to the Receiver, clicking on the button "suggest to accept", "no hint" or "suggest to refuse". The Observer had 10 seconds to make her choice. When the reputation system was active (in the so-called Reputation Treatment), the Receiver had access to the rating (i.e., the number of like and dislike accumulated) of the Observer. Once the offer is accepted or rejected,

the Receiver becomes aware of the Donor request (i.e., deal information was shown on the player's screen). If the Receiver accepted the deal than the resources were transferred otherwise were not. In the Reputation Treatment, if the Receiver had asked for the suggestion, she had the opportunity to give a like or a dislike to the Observer. Observers were not aware of the single evaluations received, nor of their overall reputation. The receiver had 18 seconds to make her decisions. More time was given to the Receivers as they could potentially perform more actions than the other roles (i.e., ask for a suggestion, decide on the deal, feedback Observers). For all the roles, if a decision was not made within the available time frame, default options were set by the computer.
The bargaining game was developed as a multiplayer virtual game implemented through Google Apps, using the Google Script programming language.
For clarity reasons, we combine the presentation of the results of the two studies.

3.4 Results

3.4.1 Data Analysis

The preconditions necessary to inferential analyses were verified on the data produced by the experiments. For all the continuous variables that were under investigation, the normality of the distribution was assessed through the analysis of asymmetry and kurtosis values. When the distribution was not quasi Gaussian (i.e., skewness and kurtosis ranging between -1 and +1), a logarithmic transformation was applied. On continuous variables that do not respect the preconditions a discretization were made, using the median as a reference, and thus defining two levels for each variable. Because of the repeated measures structure of the experimental data, the inferential analyses were conducted using a general linear mixed model (GLMM) approach [136]. The difference in sample size has always been offset by either the type of data analysis or by random resampling through bootstrap method.

Table 3.3: *Descriptive statistics of all the game variables.*

	Study 1		Study 2	
	Female	Male	Female	Male
	Average(s.d.)	Average (s.d)	Average (s.d)	Average (s.d)
Amount offered	4.02(2.0)	4.83(2.1)	5.12(2.2)	5.12(2.2)
Amount requested	6.26(4.1)	6.80(3.9)	4.77(1.7)	5.68(3.6)
Diff. offered-requested	-2.3(8.60)	-1.86(9.11)	-0.04(5.09)	-0.58(7.56)
Suggestion (-1, 0, +1)	0.19(0.84)	0.00(0.88)	0.23(0.88)	-0.15(0.90)
Suggestion required (0, 1)	0.41(0.49)	0.53(0.40)	0.58(0.49)	0.64(0.48)
Acceptance (-1, 0, +1)	0.15(0.94)	0.02(0.94)	0.03(0.98)	-0.27(0.92)
Suggestion coherence (-1, +1)	0.19(0.71)	0.23(0.85)	0.27(0.86)	0.27(0.86)
Score	10.45(8.39)	10.5(3.62)	11.52(7.16)	13.52(8.80)
Variables related to the activation of the reputation system (Rep. On)				
Final reputation	-1.06(2.55)	-0.56(2.53)	2.54(6.49)	1.86(6.10)
Dislike/Like (-1, 0, +1)	10.7%/10.5%	15.7%/12.2%	9.7%/16.2%	18.5%/22.2%
Mean Like received	2.05(1.0)	2.17(1.3)	3.59(1.8)	4.59(2.9)
Mean Dislike riceived	2.29(1.4)	2.27(1.4)	2.11(1.2)	3.62(2.1)
Suggestion request coherence	46.5%(+)	41.5%(+)	46.8%(+)	57.7%(+)
Acceptance coherence	44.4%(+)	42.9%(+)	54.7%(+)	49.2%(+)
Feedback coherence	10.9%(+)	13.4%(+)	15.1%(+)	22.2%(+)

Amount offered*: Quantity of the resource offered;* ***Amount requested:*** *Quantity of the resource requested;* ***Diff. offered-requested:*** *difference between the amount offered and requested in return by the Donors;* ***Suggestion:*** *to refuse (-1), no suggestion provided (0), to accept (1);* ***Suggestion required:*** *the Receiver did not request the Observer's suggestion (0), the Receiver benefited of the Observer's advice (1);* ***Acceptance:*** *The Receiver accepted the deal (1), refused the deal (-1) or did not take any action within the time limit (0);* ***Suggestion coherence:*** *The Observer provided a "good" suggestion (1) (i.e., suggested to accept a deal when the variable "Diff. offered-requested" is major or equal to 0, and to refuse a deal when "Diff. offered-requested" is smaller than 0), or a "bad" suggestion (-1);* ***Score:*** *The quantity of the minimum resource for each player;* ***Final reputation:*** *Difference between the number of the positive feedbacks (i.e., like) and the negative ones (i.e., dislikes);* ***Dislike/Like:*** *The Receiver rated with a like (1), a dislike (-1) or did not take any action within the time limit (0);* ***Mean Like received:*** *Average of the likes received by the players;* ***Mean Dislike received:*** *Average of the dislikes received by the players;* ***Suggestion request coherence:*** *The Receiver requested the suggestion when paired with a good rated Observer (+);* ***Acceptance coherence:*** *The Receiver followed the suggestion received by a good rated Observer (+);* ***Feedback coherence:*** *The Receiver rated positively an Observer who provided a "good" suggestion and negatively an Observer who gave a "bad" advice (+).*

Descriptive statistics

In Table 3.3 the descriptive statistics for both studies are presented, and they are visualized according to gender. The upper part of the table presents those variables that have been measured in both condition (i.e., Reputation Treatment and Control Condition), while the bottom part reports those that have been recorded in the Reputation Treatment.

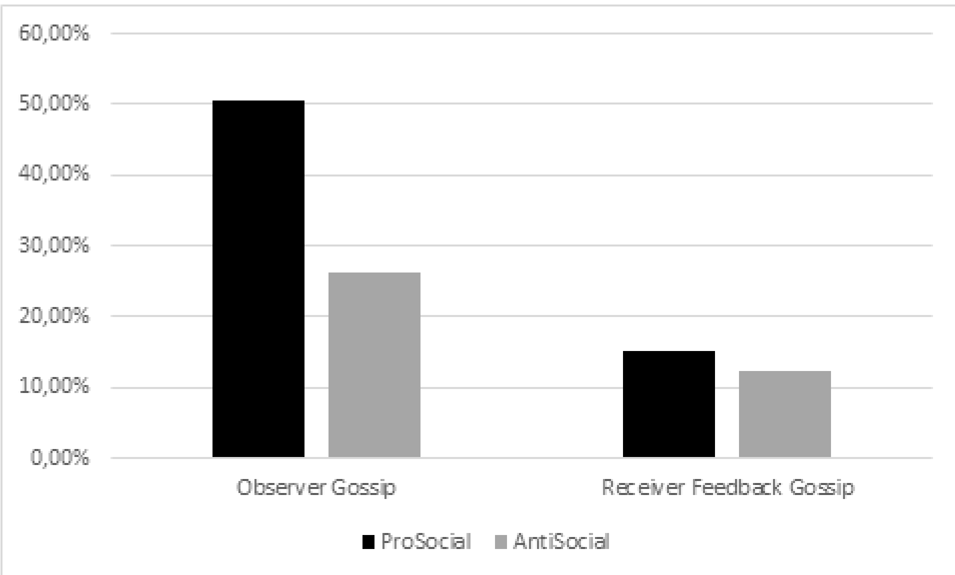
3.4.2 Manipulation check

We operationalized fairness as the difference between offers and requests and we asked whether introducing an evaluation of the Observer, as a proxy for reputation, could affect participants' behaviors. The answer is yes, and this happened both in the resource exchange part of the game, and in the information exchange (i.e., feedback actions). When reputation was on, Donors' offers were characterized by a larger positive difference between the donation and the request (Table 3.4). In order to evaluate information sharing, we termed "prosocial" a useful suggestion from the Observer and the consequent like by the Receiver, and "antisocial" a wrong suggestion. Receivers can be antisocial in two ways: either they dislike a correct suggestion (thus decreasing the Observer's reputation), or they like a wrong one. Figure 3.1 shows that during the game, and regardless of the presence of reputation mechanisms, the Observers were prosocial 50.6% of the times. Also, 15.2% of the likes received by the Observers were justified (i.e., prosocial), showing a cooperative use of this tool. The number of participants who did not provide an observation was marginal (23.3%), and not too different from the percentage of those giving antisocial suggestions (26.1%). Subjects did not provide a feedback to the observer's reputation in 72.4% of the interactions, while 12.4% of the times Receivers provided wrong feedbacks (giving a like to an Observer who suggested an unfair deal or the other way around). Overall, the introduction of reputation changed Donors' and Receivers' behaviors, even if only one player, the Observer, was subject to peers' evaluation.

Hypothesis 1

Table 3.4 reports the results of the Generalized Linear Mixed Models (GLMM) analysis for the Donor role. Regarding the offers, we found a significant effect

Figure 3.1: Distribution of the informative behaviors for both treatments. Percentage of pro-social and antisocial feedback for the Observers' advice and for the Receivers' feedback.



of Age and Gender, but also two interaction effects (i.e., Age*Gender, Condition*Gender). In general, the adolescents offered lower amounts than the undergraduates. Gender also played a role, with the females offering more than the males. Interestingly however, the males offered more without the reputation system and adolescent females appeared to offer less than their adult counterpart. Instead, no gender effects were found for the Donors' resource request behaviour, which was affected by Age and Condition. In particular, the adolescents demanded a larger amount of resources and the overall level of asked resources was higher when reputation was absent. However, when the reputation system was absent the adolescents reduced their demands.
Also, the analysis for the fairness of the deals (i.e., difference between the amount offered and the amount requested in return), did not show any gender effects. The average level of fairness seemed to be higher in the Reputation Treatment and among young adults. Surprisingly, the adolescents have sent unfair offers more frequently when the reputation system was present.

Hypothesis 2

In order to understand whether Receivers' behaviors changed after the introduction of an evaluation on Observers, we carried out a Generalized Linear Mixed Models (GLMM) analysis. The final models about the reputation capability to influence the Receiver's decision making are reported in Table 3.5.

The decision about asking for a suggestion resulted influenced by the interaction between the Reputation score and the Age of the participants. The adolescents payed more attention to the reputation of their partners avoiding asking untrustworthy Observers. As regards the use of the reputational information to decide about the Donor's deals (i.e., coherence of acceptance) we observed different patterns of compliance. Our participants relied on their partners' reputation more often if this was positive, whereas when interacting with a ill reputed Observer our participants trusted his/her suggestions significantly less. Finally, the tendency to leave a feedback resulted influenced by the Reputation level and by Gender. Observer with an ambiguous reputation were less frequently being evaluated. Furthermore, the males showed themselves more inclined to feedback their partner.

Table 3.4: *GLMM â Donor's behaviours: Donation and Requested amounts and Fairness of the deals (CC: Control condition; RT: Reputation treatment; A: Adolescent; U: University Student; M: Male)*

General Models					
Target	Akaike[1]	F	df(1)	df(2)	Precision
Donation[d]	65,002	52,01***	5	3151	55,7%
Requested[d]	66,209	4,11***	5	3155	54,3%
Fairness[d]	65,658	6,63***	5	3155	54,0%
Fixed Effects and Parameters - Donation[d]					
Parameter			F	B[2]	Student t
Age (A)			109,5***	-0,601	-10,64***
Gender (M)			42,94***	-0,273	-4,41***
Age(A)*Gender (M)			28,99***	0,639	9,71***
Condition(CC)*Gender (M)			42,94***	0,337	5,38***
Fixed Effects and Parameters - Requested[d]					
Parameter			F	B[2]	Student t
Age (A)			3,43*	0,356	2,32*
Condition (CC)			4,52**	0,526	3,18***
Condition(CC)*Age (A)			11,46***	-0,601	-3,38***
Fixed Effects and Parameters - Fairness[d]					
Parameter			F	B[2]	Student t
Age (U)			15,97***	0,662	4,66***
Condition (RT)			19,70**	0,670	4,38***
Condition(RT)*Age (A)			13,32***	-0,599	-3,65***

[d]*:Discretized with respect to the median;* [1]*:Correct Akaike coefficient;* [2]*: Standardized coefficient;*

****: p. ¡ 0.001*; **:*p.* ¡ 0.01; *:*p.* ¡ 0.05

Table 3.5: *Reputation (i.e., number of Like â number of Dislikes) influence final model. Suggestion required (Requested), Coherence on Acceptance (Coh. Acc.), Feedback (Feedback) e Suggestion Followed (Followed) (0: Ambiguous reputation; - : Negative reputation; A: Adolescents; M: Male).*

General Models					
Target	Akaike[1]	F	df(1)	df(2)	Precision
Requested[d]	47,359	12,99***	5	1598	58,3%
Coh. Acc.[d]	14,985	29,18***	1	473	77,1%
Feedback[d]	40,708	19,53***	3	798	60,6%
Followed[d]	22,580	14,66***	2	619	71,1%
Fixed Effects and Parameters - Requested[d]					
Parameter			F	B[2]	Student t
Reputation (0)*Age (A)			7,83***	-1,036	-4,36***
Reputation (-)*Age (A)			7,45***	-0,360	-1,85*
Fixed Effects and Parameters - Coh. Acc.[d]					
Parameter			F	B[2]	Student t
Reputation (-)			29,18***	-1,258	-5,40***
Fixed Effects and Parameters - Feedback[d]					
Parameter			F	B[2]	Student t
Reputation (0)			22,13***	-0,848	-5,41***
Gender (M)			13,82***	0,432	7,72***
Fixed Effects and Parameters - Followed[d]					
Parameter			F	B[2]	Student t
Reputation (0)			14,66***	-1,064	-4,35***
Reputation (-)			14,66***	-1,039	-4,94***

[d]*:Discretized with respect to the median;* [1]*:Correct Akaike coefficient;* [2]*: Standardized coefficient;*

****: p. ¡ 0.001*; **:*p.* ¡ 0.01; *:*p.* ¡ 0.05

Hypotheses 3 and 4

To test the effects of age and gender in relation to reputation management and usage we carried out new GLMM analyses. Obviously, such analyzes considered only the game sessions in the Reputation Treatment condition. The results are presented in the Table 3.6.

Table 3.6: *GLMM â Reputation (i.e., number of Like â number of Dislikes) and Age influence upon Suggestion request and Feedback behaviours (0: Ambiguous reputation; - : Negative reputation; A: Adolescents)*

General Models					
Target	Akaike[1]	F	df(1)	df(2)	Precision
Requested[d]	47,359	12,99***	5	1598	58,3%
Feedback[d]	45,874	18,60***	5	1598	72,4%
Fixed Effects and Parameters - Requested[d]					
Parameter			F	B[2]	Student t
Reputation(0)*Age (A)			7,83***	-1,036	-4,36***
Reputation(-)*Age (A)			7,45***	-0,360	-1,85*
Fixed Effects and Parameters - Feedback[d]					
Parameter			F	B[2]	Student t
Reputation(-)			19,33*	0,407	1,95*
Age(A)*Reputation(-)			4,52***	-0,386	1,95*
Age(A)*Reputation(0)			4,52***	-0,929	-3,12***

[d]*:Discretized with respect to the median;* [1]*:Correct Akaike coefficient;* [2]*: Standardized coefficient;*

****: p. ¡ 0.001*; **:*p.* ¡ 0.01; *:*p.* ¡ 0.05

Deciding whether to ask for a suggestion appeared influenced by the interaction between the reputation level of the Observer and the Age. The adolescents preferred not to ask Observers with a bad or an ambiguous (e.g., number of Like â number of Dislikes = 0) reputation, but were less inclined to provide a dislike to Observer who had already several, irrespective of their direct experience. Indeed, the adolescents tended to refrain from providing a feedback to Observers who already had a bad or an ambiguous level of reputation.

In order to take into account the effect of gender differences within and between the two samples and among the two conditions (i.e., Reputation Treatment and Control Condition)., we run a set of GLMM. However, for those behaviours present only in the Reputation Treatment (i.e., Reputation level, Acceptance Coherence, Feedback) the GLMM considered only Gender, Age and their possible interaction effects as predictors.

The average level of reputation obtained by the Observers within the Reputation Treatment condition resulted to be affected directly by both Gender and Age and no interaction effects were found. The adolescents achieved a lower level of reputation while the females succeeded to obtain a higher reputation degree compared to the males (Table 3.7).

Table 3.7: *GLMM â Observer's behaviour: Reputation (i.e., number of Like â number of Dislikes) (A: Adolescent; M: Male)*

General Models					
Target	Akaike[1]	F	df(1)	df(2)	Precision
Reputation[d]	33,184	52,01***	2	1600	65,0%
Fixed Effects and Parameters - Reputation[d]					
Parameter			F	B^2	Student t
Age (A)			76,41***	-1,126	-7,29***
Gender (M)			4,56*	-0,398	-2,26*

[d]*:Discretized with respect to the median;* [1]*:Correct Akaike coefficient;* [2]*: Standardized coefficient;*
****: p. ¡ 0.001*; **:*p.* ¡ 0.01; *:*p.* ¡ 0.05

Participants' gender and age affected the Receivers' search for information (Table 3.8), with the adolescents and the females less likely to ask Observers for suggestions. The tendency to trust the suggestion (i.e., decide to accept the deal if the Observers suggest to the Receivers to accept it and to refuse the Donors' offer if the hint received was to decline it) was also connected to Gender (both directly than by the interaction Gender*Condition) and Age: the adolescents trusted (called "Suggestion Followed") the Observer's suggestions less frequently while the females seemed to be more sensitive about the suggestion. Furthermore, when reputation was not present the males trusted the Observer's information even less.
Nevertheless, trust in the reputation of the Observer to decide whether to accept or decline the offers (called "Acceptance Coherence") did not result

connected to Gender and only seemed to vary as a function of Age. The adolescents appeared to rely less on the Observer's reputation when deciding about the Donor's deal. Receivers could also leave feedbacks about Observers' trustworthiness, deciding between no feedback, a positive one and a negative one. The males were more inclined to feedback the Observer with which they had interact compared to the females, while the adolescents were less prone to leave a feedback.

3.5 Conclusion

When individuals experience "deindividuation" in an anonymous virtual group interaction, they rely more on reputation to orientate their own behaviors. In line with the previsions based on the SIDE model, individuals appeared to be greatly influenced by the opponent's reputation (i.e., under such psychological state reputation appears to exert a greater social influence). In such sense, reputation seems able to promote pro-social behaviors (i.e., fairness), as well as to discriminate between social partners, exerting more trust-related behaviours (i.e., suggestion request, suggestion following) towards good-rated individuals. Differently from previous works on Prisoner's Dilemma, in our game reputation levels (i.e., high, low and ambiguous) were treated differently by participants for orienting their choices [35]
Overall, our work contributes to the literature on the role of reputation in supporting fairness and trust-related behaviors by showing that reputational dynamics have a broad impact, changing individuals' behaviors both directly and indirectly. Furthermore, some trends seem to suggest that adolescents and undergraduates could have and rely on different behavioral patterns with regard to reputational concerns and usage.
Even in a competitive environment in which information can be strategically manipulated in order to increase one's scores, we observed a predominance of reliable suggestions from Observers, with and without reputational opportunities.
As pointed out by previous research Donors in a social dilemma situation appear to be very sensitive to some game-related features and adjust their behavior consequentially [31, 121]. In our case, even if the Donors were not identified by any reputational score, they adjusted their behavior when facing a virtual environment characterized by reputational mechanisms. Indeed, we

Table 3.8: *GLMM â Receivers' behaviours: Suggestion required (Requested), Coherence on acceptance (Cohe. Acc.), Feedback (Feedback), Suggestion Followed (Followed) (A: Adolescent; M: Male; CC: Control condition).*

General Models					
Target	Akaike[1]	F	df(1)	df(2)	Precision
Requested[d]	36,122	25,70***	2	3158	57,4%
Coh. Acc.[d]	33,161	2,64*	1	1455	52,9%
Feedback[d]	32,647	9,82***	2	1598	72,4%
Followed[d]	59,884	32,48***	5	1653	57,6%

Fixed Effects and Parameters - Requested[d]			
Parameter	F	B^2	Student t
Age (A)	52,32***	-0,664	-6,15***
Gender (M)	20,41***	0,245	1,98*
Fixed Effects and Parameters - Coh. Acc.[d]			
Parameter	F	B^2	Student t
Age (A)	6,63**	-0,376	-2,41*
Fixed Effects and Parameters - Feedback[d]			
Parameter	F	B^2	Student t
Age (A)	11,50***	-0,226	-1,97*
Gender (M)	17,99**	0,676	3,59***
Fixed Effects and Parameters - Followed[d]			
Parameter	F	B^2	Student t
Age (A)	40,02***	-0,237	-3,62***
Gender (M)	95,28***	-0,264	-3,87***
Condition(CC)*Gender (M)	17,25***	-0,297	-4,15***

[d]*:Discretized with respect to the median;* [1]*:Correct Akaike coefficient;* [2]*: Standardized coefficient;*

***: *p. ¡ 0.001*; **:*p.* ¡ 0.01; *:*p.* ¡ 0.05

observed how the Donors raised the number of resources offered while they decrease their demands, thus increasing the fairness of the proposed deals.
Furthermore, the level of the acquired reputation (i.e., positive, negative, ambiguous) influenced the level of trust-related behaviors shown by Receivers. Reliable partners were more often required for a suggestion and their prescriptions were more frequently followed, thus underlying the great persuasive potential of having a good reputation. While generally, Observers with an ambiguous or a negative reputation had less influence on the Receivers' decisions.
Moreover, the reputation capability to exert an influence on trust behaviors within an anonymous virtual group appeared almost entirely disconnected from gender, age, and psychological features. This phenomenon could be account for by the psychological state of "de-individuation" [158]. Indeed, the anonymity and the physical isolation of our virtual setting could have triggered such a state, and thus induced subjects to rely less on their individual characteristics, and more onto the set of local norms (i.e., reputation) to adjust their behavior.
One striking aspect of our results is that reputational concerns worked even indirectly, through players' expectations. Donors became more generous because they plausibly expected Observers to be more reliable in the Reputation Treatment, even if Observers were not aware of their reputation and could not strategically increase or decrease it. This is a very interesting result which adds to the fairness literature on the effects of reputational concerns. When playing as Observers, participants did not care about their reputation, probably because they had no access to this information and thus did not behave differently (i.e., their suggestion coherence remained the same)
Although in the last few years the importance of reputation in supporting fairness and trust has been widely acknowledged (see [140, 217] for two recently published reviews on the topic), the importance of individual characteristics, like age and gender, in reputation-mediated social interactions deserves more attention. The ontogeny of fairness and trust has received growing attention in the last years [20, 205], and reputation management abilities appear relatively early in ontogeny [120], but less is known about the transition from adolescence into adulthood. During this period, two elements become characteristics in adolescents' behavior: the susceptibility to peer influence and the sensitivity to peer rejection, both mediated by reputation. Social approval and positive reputation might affect the development

of self-processes, and perceived support from others can protect adolescents from stress and anxiety [206]. As we have seen, having a negative or ambiguous reputation could lead to being ostracized. In our game setting individuals characterized by these types of reputation were avoided (i.e., suggestion less likely requested) and less followed. Thus, reputation management appears fundamental for avoiding, for instance, the fear of missing out [163]. A growing body of research shows the existence of a link between reputation management and delinquency in adolescence [38], with adolescents actively engaging in the acquisition of a non-conforming social reputation. The search for social approval could explain why adolescents became unfairer when playing as Donors in the Reputation Treatment, but it could also explain why they were cautious with reputational information. Reputation, as we explained earlier, is a safeguard against ostracism [211] but it also functions as a way of attaining higher status within the peer group [38]. Adolescent behavior is motivated by social goals and purposeful reputation-enhancing strategies [67] because acquiring a reputation has also implications for how an adolescent regards herself. In such a context, adolescents in our game paid more attention to their partners' reputations, consistently avoiding asking untrustworthy Observers, but they also achieved a lower level of reputation overall. Our results highlight the importance of reputation and status during adolescence, showing that these concerns orient individuals' behaviors also in the laboratory. Further research is needed to understand the extent to which age interacts with the virtual environment (both denied as competitive and cooperative), and with self-presentation issues which were ruled out by anonymity in the experimental setting.
Another promising direction of research is on gender differences in fairness and trust-related behaviors, as in our study. The evidence on the topic is inconclusive, partially because different kinds of social preferences can explain it. Some studies suggested that women are more prosocial than men (e.g., [138, 210], but in a review paper by Croson and Gneezy [48] the inconsistencies between studies reporting opposite effects, or even no gender effects are revealed. The emergence of gender differences in social dilemmas could be mediated by a set of contextual factors [6], like mixed-sex vs. same-sex dilemmas. Recent works reignited the debate by suggesting that women are more altruistic than men in the Dictator game [28, 167]. Women are expected to behave more pro-socially than men and this may drive their allocation behavior. Nevertheless, in our work, no gender effect was detected

regarding fairness. In our study, women were more inclined to follow the Observers' suggestions, thus showing higher levels of trust (i.e., following the presciption). However, such women's behavior could be interpreted in other ways, for example, by a lack of self-confidence or a greater tendency to pay more attention to the others' suggestions culturally promoted. Interestingly, women seemed to show better reputation management skills, gaining a more positive reputation during the game, even if previous research had reported different results [101]. In any case, the effect of gender does not seem to be too strong in our experiments. This is not surprising since, as we stated before, the deindividuation psychological state can make individual identity influences less strong.
To conclude, our results illustrate that reputational concerns may promote pro-social choices even indirectly, and in ambiguous and noisy (i.e., virtual) environments. Moreover, fairness and trust are appeared mediated within virtual environments and social dilemmas games by reputation. As in Shakespeare's words: *Reputation, reputation, reputation! Oh, I have lost my reputation! I have lost the immortal part of myself, and what remains is bestial. My reputation, Iago, my reputation!*

Chapter 4

The Reputation Inertia Effect

"Reputation systems" are widely used in a high number of web-based services to enhance cooperation among users, as well as to ensure they function well. With the previous work, we reported how reputation systems could be beneficial in terms of trust and fairness. However, the acquired reputation within such systems does not always reflect people's actual behavior and this could be one of the major flaws connected with reputation employment. This bias can reduce the effectiveness and robustness of a web-based system. The present study investigates the mechanisms underlying reputation building in an online multiplayer game. We observed that the reputation, once acquired, seems to be maintained over time (i.e., Reputation Inertia Effect) despite the actual behavior of its owner. Moreover, if the players are asked to pay to suggest to the other players, the Reputation Inertia Effect decreases. Nevertheless, even if reduced in frequency, "Reputation Inertia" persists under this condition.

4.1 The importance of reputation

In today's world, having a good reputation confers undoubtedly some advantages. Companies, firms, and freelancers know it well and commit energy and resources to reputation management practices [58, 98, 202]. Such costs would not be expended without the belief that having a good reputation entails considerable strategic benefits. In other words, they conceive a good reputation as an asset. Besides, the existence of such practices would not make sense if the reputation were not self-preserving to some extent over time [196].

The expansion of communication possibilities introduced by Information and Communication Technologies (ICTs) has facilitated the development and proliferation of systems based on online feedbacks [54]. The very existence of the e-markets and recommendation systems (e.g., Trip Advisor) is based on the goodness of users' feedback. The literature already explored Trust and Reputation construct, and refined method of assessments designed and validated [24, 43].

However, despite many online services relying on reputation systems for their functioning, our knowledge is still limited about how reputation is attributed and its time course inside the cyber world, especially during the first stages of interaction, and with partial or incomplete information.
Scientific studies confirm the benefits of having a good reputation [146, 147, 185]. In fact, by using the indirect reciprocity mechanisms offered by reputation, an individual can minimize the risks of being cheated.

However, the indirect reciprocity mechanisms offered by reputation generally assume subjects' rationality as an axiom (i.e., leaving positive feedback for those who have helped me and negative feedback for those who have harmed me). On the contrary, experimental evidence shows how, through their behavior, humans often violate the principle of rationality by using different behavioral and decision-making rules (e.g., social norms, heuristics) [25, 168].

Therefore, it is of fundamental interest to understand whether humans adhere to the principle of rationality in attributing a reputation or whether they rely on different rules and norms. Interestingly, [177] study has suggested that humans consider the past behavior of others (i.e., their reputation) more than their direct interaction with these partners. Reputation was able to exert a social influence in directing rewards and to overcome individuals' personal experience.

Despite the undoubted interest of this study, we do not know if the social influence of reputation (i.e., rewarding those who have good reputation regardless of their own experience) may also occur in relation to informative behavior, and within environments in which individuals present conflicting interests, and have no personal incentive to provide feedback or evaluation (e.g., e-commerce sites). Moreover, in [177] public good game, the reputation was strictly bounded to the behavior (historical log of the decision to cooperate for the public good) and it was not possible to let the reputation evolve on its own (e.g., build it based on individualsâ feedbacks).

Differently, in more ecological scenarios like those offered by e-markets, the reputation is not definable as a historical log but it is rather built based on users' impressions. This means that a lot of other factors are plausibly playing a role in defining users' evaluation. At this point, it becomes crucial to understand whether this persistence of the reputation remains when passing through a conceptualization of the reputation as the strict transposition of one's partner behavior, to an assignment conferred by others which may be more or less tied to a specific type of action (e.g., cooperation). Besides, social psychology studies have denoted that groups do not always allocate status fairly [174], and this could lead to some "irrational" behavior, both in reputation building and in reputation maintenance processes. For instance, give positive feedback to a partner that did not cooperate but have a high reputation status. For clarity, from now on we will refer to a "rational agent" as that agent that rewards (positive feedback) his partner when he receives an advantage and punishes (negative feedback) him when he gets damage from him, disregarding his reputation.

For this reason, particular attention should be paid to those factors capable of bringing "rationality" back to the reputation building process, in all those situations in which the reputation evolves in a way that is too disconnected from the behavior which it should serve.

In order to investigate the "ecological reputation dynamics" in virtual environments, unlike the setting proposed by [177] in which the reputation served as an honest indicator of past cooperative conducts, we adopted a "widespread reputation building system" (i.e., in which reputation is built from the feedback of other individuals and not on the basis of the actual behavior). In this way, we determined in our system a higher degree of uncertainty and a more ecological measure of the subjects' reputation dynamics.

To study a possible solution to the "irrationality bias" affecting the reputation dynamics is required to consider the Costly Signaling Theory used in economics, evolutionary biology, and evolutionary psychology, that presents other possible ways of building and managing reputation [11]. For instance, when individuals pay a cost to help they receive some benefits, including a reputational gain. People who pay for a prosocial act are seen as more trustworthy [2, 10], and the payment conveys an informational value about the giver. Therefore, excited by the payment of others, the cognitive process involved in the construction of another's reputation appears becoming more data-driven (i.e., more focus is paid on the social partner's current behavior), so promising to be effective in reducing possible schema-driven biases. As a consequence, we introduced in our study even the opportunity to pay to have the possibility to advise another player, a very disadvantaging condition within the game, to study the effect of such condition on the social partners' behavior, and on the reputation dynamics itself.

Given the tendency of humans to use the internalized rules of conduct in new contexts and issues that have a certain degree of similarity [168], the following are the main hypotheses of the present study about the reputation dynamics within virtual environments:

H1: Changes in reputation are affected by the level of reputation already achieved.
H2: Good reputation subjects tend to attract other positive feedback, regardless of personal/actual "experience." Conversely, bad reputation subjects are more likely to attract negative evaluations.
H3: Once acquired, reputation tends to be maintained/enhanced over time (i.e., it demonstrates inertia) in a way disconnected, at least in part, from the actual dynamics of the interactions.
H4: Paying a personal cost to provide information to others reduces the ability of the reputation to maintain itself in case of unreliable behaviors.

To verify our hypotheses, we developed a social dilemma game called the Bargaining Game. It involved a widespread feedback system among the players in a competitive scenario. In some circumstances (i.e., game sessions), to evaluate other players' behaviors, an individual had to pay a personal cost, while in others did not. For further details about the game, please refer to the game section.

4.2 Methods

4.2.1 Materials

- **Sociodemographic survey:** Participants were profiled according to their gender and age.
- **Five-Factor Adjective Short Test (5-FasT):** Developed by [80] the 5-FasT investigates the five-factor model of personality traits: Neuroticism, Surgency, Agreeableness, Closeness, and Conscientiousness. Using a 5-point Likert scale (ranging from "Not at all" to "Very much"), participants had to indicate how much the 26 adjectives described their personality (example items: Anxious, Active, Calm, Closed, Confused, Brave, Distant).
- **Self-efficacy scale:** Developed by [100], this scale investigated the perception of self-efficacy of the participants through 10 items. For each assertion, participants had to indicate their level of agreement through a 4-point Likert scale (ranging from "Not true at all " to "Totally true"). Examples of items are: "I can always manage to solve difficult problems if I try hard enough", "I am confident that I could deal efficiently with unexpected events".
- **Classroom Community scale:** Developed by [171], this scale examined the sense of community about the participants' reference network. The scale consisted of 20 items and two subscales (social community and community learning); 10 items measured each of the subscales. For each statement contained, participants had to indicate their degree of agreement using a 5-point Likert scale (ranging from "Strongly disagree" to "Strongly agree").Examples of items are: "I feel that I can rely on others in this course" (Social community), "I feel that this course does not promote a desire to learn" (Learning community).

4.2.2 The "New" Bargaining Game

The game consisted of 45 independent rounds in which a Donor interacted with a Receiver and an Observer. Participants were anonymous and identified only through nicknames. Participants played in groups of six, and each participant played all the roles of the game fifteen times in a sequence randomly determined by a computer program. This game-dynamic resulted in each participant interacting three times in each role with each other group member. At the beginning of the game, each player was endowed with three kinds of resources, labeled Gold, Power, and Happiness, which were functionally equivalent. Among these resources, one was set equal to 50 units, and the other two were set at a minimal level of 5 units each. The software randomly distributed resources at the beginning of the session, and the player with the highest amount of the minimum resource at the end of the game was the winner. For the sake of clarity, we specify that for each player the type of the minimum resource dynamically varied during the game session according to his actions. In other words, if a player started with 50 Gold, 5 Power, and 5 Happiness and ended up with 10 Gold, 15 Power, and 20 Happiness, his final score is defined by the Gold resource disregarding the fact that was the maximum resource at the beginning. The players could see both their score and those of their opponents for the whole duration of the game. The players in each role had different tasks and goals (see Table 4.1).

Table 4.1: *Roles.* Summary of the actions to fulfill within the game for each role

ROLES ACTIONS RECAP	
Roles	**Actions**
Donor	Offers his/her maximum resource and asks the *Receiver* his/her minimum resource.
Observer	Makes suggestions to the *Receiver* about the *Donor*âs offer and can receive a like or a dislike from the *Receiver*.
Receiver	Accepts or declines the *Donor*âs deal with no additional information or asks for the *Observer*'s suggestion. Can feedback on the *Observer*âs suggestion with a like/dislike.

The Donor's task was to make an offer to and a request of the Receiver. The Donor offered a given amount of his greatest resource, among the three at her disposal, and in return asked for a certain amount of the Receiver's minimum resources. Actual quantities were adjusted using sliders. The Receiver could only see the amount and type of the resource offered by the Donor but was unaware of what and how much the Donor had asked in return. The Receiver could "accept" or "reject" the Donor's deal right away, or could request the Observer's suggestion (by clicking on the "ask suggestion" button).

The Observer had the opportunity to evaluate the Donor's offer and request, knowing both the amount and the type of resources involved in the deal. The Observer could provide a hint to the Receiver, clicking on the button "suggest to accept," "no hint" or "suggest refusing." In the Payment On condition, providing a suggestion (i.e., to accept or to refuse) determined a payment equal to 1 of the Observer's highest resource, while selecting "no hint" meant that the Observer did not undergo any cost. Instead, in the Payment Off condition, none of the Observer's available action were charged a fee. The Observer had 10 seconds to make her choice.

To decide whether to ask for the Observer's suggestion, the Receiver also had access to the rating (i.e., the number of likes and dislikes accumulated) of the Observer. When the game started all the Observers had a neutral reputation score (i.e., 0), and at each time step the Observer's reputation is updated following the equations 4.1 and 4.2, where L_O^{t+1} and D_O^{t+1} represent respectively the number of likes and dislikes (i.e., L_R and D_R) accumulated by the Observer from the Receivers, before the time $t+1$.

$$L_O^{t+1} = \sum_{t^*=1}^{t} L_R^{t^*} \tag{4.1}$$

$$D_O^{t+1} = \sum_{t^*=1}^{t} D_R^{t^*} \tag{4.2}$$

We did that to better simulate and study the reputation evolution in the early stages of a virtual setting with no prior information about its users. Once the offer is accepted or refused, the Receiver becomes aware of the Donor's request, and the resources are transferred. At this point, if the Receiver had asked for a suggestion, he/she would have the opportunity to give a like or a dislike to the Observer. We specify that even if the Receiver asked for a suggestion and obtained a "no hint" from the Observer, the latter still resulted eligible by our system to be evaluated by Receivers. Observers were not aware of the single evaluations received, nor of their overall reputation, but were informed at the very beginning that the Receivers would judge them and that the Receiver's feedback actions would determinate their reputation within the game. The Receiver had 18 seconds to make his decisions.

For all the roles, if a decision was not made within the available time frame, default options were set by the computer. In general, for each role, none of the possible actions were "externally" incentivized. For instance, provide reliable and coherent feedback was neither reward nor punished by our system. Even winning the game did not involve monetary rewards or prizes. In the Payment On condition, the only action to provide a suggestion was charged by a fee (on game resources) and thus disincentivized.

The bargaining game was developed as a multiplayer virtual game implemented through Google Apps, using the Google Script programming language.

4.2.3 Sampling

The research was conducted following the guidelines for the ethical treatment of human participants of the Italian Psychological Association (i.e., AIP). The participants were recruited through a completely voluntary census and had no monetary incentives to take part in the experiments. All participants (or their legal guardians) signed an informed consent form and could withdraw from the experimental session at any time.

Overall, 203 participants (121 females) took part in our experiments. The sample size for our work has been determined using the work of [177] as the reference point. A brief presentation of the various samples will be described here, while their game-related descriptive statistics are presented in the results section.

Seventy-seven adolescent volunteers (36 females) with an average age of 16 (s.d. 1.28) were recruited and carried out the experiment entirely in the Payment Off condition. Also, 36 adult volunteers (19 females) with an average age of 21 (s.d. 1.88) completed the experiment in the Payment Off condition. Ninety adult volunteers (66 females) with an average age of 22 (s.d. 3.45) underwent our experiment in the Payment On condition.

4.2.4 Procedures

The experimental sessions that involved adolescents were conducted in the computer lab inside the high school. The experiments concerning the adults were carried out in the computer lab of the Faculty of Psychology. Upon their arrival, the experimenter seated the participants at their designated computers and gave them a brief speech about the fact that their anonymity was assured. Moreover, to preserve the playerâs anonymity, all participants were separated by partitions. After providing the necessary demographic information (age, gender, years of education) and completing the psychological survey, the participants received instructions about the game that were read aloud and shown on the participants' monitors.

4.2.5 Data Analysis

In the first step, we verified the preconditions necessary for the inferential analyses on the experiment's data. For the continuous observables that were under investigation, the normality of the distribution was assessed through the analysis of asymmetry and kurtosis values. Then, due to the repeated measures structure of the experimental data, the inferential analyses were conducted using a general linear mixed model (GLMM) approach [136].

4.3 Results

4.3.1 Descriptive Statistics

Table 4.2 reports the descriptive statistics for the game-related variables, already divided according to the sample type and game condition played. The descriptive statistics for the psychological and psychosocial observables are presented in (Table 4.3).

Table 4.2: *Descriptive Statistics.* Game observables descriptive statistics for each sample involved

Game Observables Descriptive Statistics			
	Samples		
Variables	**Adolescents Payment Off**	**Adults Payment Off**	**Adults Payment On**
	Mean (s.d.)	Mean (s.d.)	Mean (s.d.)
Like	2.11 (1.13)	4.00 (2.42)	3.82 (1.56)
Dislike	2.28 (1.38)	2.82 (1.85)	3.30 (1.27)
Reputation	-1.65 (1.18)	1.23 (2.74)	0.53 (1.80)
Goodness of Suggestion[1]	65.5%	66.7%	70.1%

[1]*: Percentage of good suggestions*

Table 4.3: *Descriptive Statistics.* Psychological and Psychosocial descriptive statistics for each sample involved

Psychological and Psychosocial descriptive statistics			
	Samples		
Variables	**Adolescents Payment Off**	**Adults Payment Off**	**Adults Payment On**
	Mean (s.d.)	Mean (s.d.)	Mean (s.d.)
Neuroticism	7.18 (3.78)	8.06 (3.77)	8.33 (4.10)
Surgency	11.17 (3.68)	10.44 (3.51)	10.41 (2.90)
Agreeableness	10.55 (3.90)	12.36 (3.07)	11.96 (3.29)
Closeness	5.31 (3.76)	5.75 (4.53)	5.42 (3.64)
Conscientiousness	7.87 (3.98)	8.33 (4.50)	9.61 (4.05)
Self-efficacy	17.52 (4.23)	19.31 (4.46)	18.33 (4.03)
Sense of Community	22.04 (5.40)	26.31 (4.02)	22.18 (4.67)

4.3.2 Evaluation Dynamics: How Reputation is "Made"

To better understand how the reputation was built and handled within our game, we focused our attention on the feedback actions (i.e., give a like or a dislike) of the Receivers. Indeed, it was through the feedback that the Observer's reputation was built and shown to other players as the difference between the number of likes received minus the number of dislikes got in the Observer role. First, we investigated age-related differences regarding our observables through generalized linear mixed models.

As we can gather from Table 4.4, adolescents provided less frequently feedback (i.e., both likes and dislikes) and achieved on average a lower reputation despite showing a similar suggestion behavior compared to adults. Given this evidence, we performed further generalized linear mixed models that considered as parameters the reputation score of the Observer and the goodness of the suggestion given by the Observer (defined as it follows: The Observer provided a "good" suggestion when he suggested to accept a deal when the Donor's offer was greater than or equal to his request and to refuse if that difference was lower than 0). Otherwise, the Observer's suggestion was classified as a "bad" suggestion), the genders of the participants playing

Table 4.4: *Generalized Linear Mixed Models.* Game Observables differences between Adolescents and Adults

Game Observables Age differences			
Variables	**F**	**Coefficient (β)**	**Student t**
Like	182.702***	-2.062	-13.517^{***}
Dislike	15.389***	-0.557	-3.923^{***}
Reputation	105.580***	-1.505	10.275***
Goodness of Suggestion[1]	$0.158^{n.s}$	0.050	$0.397^{n.s}$

$^{***} = p < 0.001$; $^{n.s.}$= *not significant;* [1]*: Percentage of good suggestions*

as Receivers as well as their ages (i.e., adolescents and young adults). Furthermore, we took into account for the young adults' sample (adolescents played only one game scenario) the two different game settings offered by the presence or the absence of a costly transmission of information for the Observer. The final model is reported in Table 4.5.

Table 4.5: *Generalized Linear Mixed Models. Factors that influence the feedback behavior of the Receivers*

GLMM Best Model LIKE				
	Model Precision	*Akaike**	**F**	**Df-1(2)**
Best Model	77.1%	64.246	50.27***	6(752)
Fixed Effects				
Factor			**F**	**Df-1(2)**
Reputation			159.74***	1(752)
Goodness of Suggestion			80.14***	2(752)
Payment*Goodness of Suggestion			3.96***	3(752)
Parameter			**Coefficient (β)**	**Student t**
Reputation(-)			-2.117	-12.64^{***}
Goodness of Suggestion(-)			-1.878	-6.65^{***}
Goodness of Suggestion(0)[1]			-2.813	-10.38^{***}
Payment(1)*Goodness of Suggestion(0)[1]			-1.064	-3.05^{***}

$^{***} = p < 0.001$; [1] : Suggestion not present

Age and gender did not appear to affect the feedback behavior of the Receiver either directly or through interaction effects in any of the subsequent models. In particular, the fact that adolescents gave less feedback did not appear to affect the way they give them, which was similar to the adults' behavior. Interestingly, only two factors contributed to forming the reputation of each participant in the Observer role: the goodness of the suggestion and the level of the reputation achieved. In other words, good suggestions and positive reputations more frequently attracted positive feedback from the others. Moreover, as we could appreciate from the standardized β in the Receivers' decision making, the reputation level of the partner seemed to outweigh the goodness of the hint received. Besides, refraining from providing a suggestion usually led more frequently to negative feedback. Furthermore, the game setting (i.e., Payment On/Off) seemed to influence the construction of the Observer's reputation marginally. Indeed, in the Payment On condition, the Observers who did not provide a hint to the Receivers were evaluated even worse.

4.3.3 Evaluation Coherence: How Reputation Alters Decision Making

As we have seen, reputation seemed a crucial factor in building and determining itself. Thus, we investigated whether this tendency to feedback to our social partners by relying on their previously acquired reputation is influenced by sociodemographic, psychological, or game-related factors. The results of our GLMM between the two game settings (i.e., Payment On/Off) are reported in Table 4.6.

As we could appreciate from the model, neither the sociodemographic nor the psychological variables entertained a significant relationship with the tendency to use the reputational information to provide feedback. However, the game-related factors such as Payment condition, Goodness of the Suggestion and Reputation played a role in defining the condition under which such a behavioral rule is more or less used. In both game settings (Payment On/Off), we observed how a negative reputation determined a lower use of the reputational criterion. In other words, in their feedback decision making, participants appeared to rely more on the reputation of their partner when the Observer's reputational score was positive compared to when it was negative. In the same way, and in both game settings, bad suggestions seemed to undermine the adoption of the reputation criterion to

Table 4.6: *Generalized Linear Mixed Models. Factors that promote the use of the reputation criterion across both conditions*

GLMM Best Model "Reputation Inertia"				
	Model Precision	*Akaike**	**F**	**Df-1(2)**
Best Model	75.0%	49.38	5.44^{***}	6(565)
Fixed Effects				
Factor		**F**		**Df-1(2)**
Reputation*Goodness of Suggestion		27.32^{***}		1(565)
Parameter		**Coefficient (β)**		**Student *t***
Payment(0)*Reputation(-)		-1.157		-2.89^{***}
Payment(1)*Reputation(-)		-1.486		-2.66^{***}
Payment(0)*Goodness of Suggestion(-)		-1.918		-3.87^{***}
Payment(1)*Goodness of Suggestion(-)		-1.517		-3.23^{***}
Goodness of Suggestion(-)*Reputation(-)		3.326		5.23^{***}

$^{***} = p < 0.001$

feedback, while in the case of bad suggestions provided by negatively rated Observers, we registered an increase in such use. Interestingly, the Receivers did not use the reputation criterion differently, only in relation to the type of reputation, as we could see from the insert in Figure 4.1. Indeed, reputation revealed complex relationships both with the Payment and the Goodness of the Suggestion and thus affected the use of the reputation criterion through the interaction effects.

4.3.4 Reputation Inertia as Deviation from Rationality

The type of suggestion received (i.e., good or bad) influenced the feedback tendency to rely on the reputational information in both game settings (Fig.4.1). However, the probability of providing feedback in line with the previous reputation of the Observer was higher in those cases in which the Goodness of the Suggestion and the Reputation score were concordant. Instead, when these two observables were discordant (i.e., positive reputation-bad suggestion, negative reputation-good suggestion), the probability of adhering to the reputational criterion was lower.

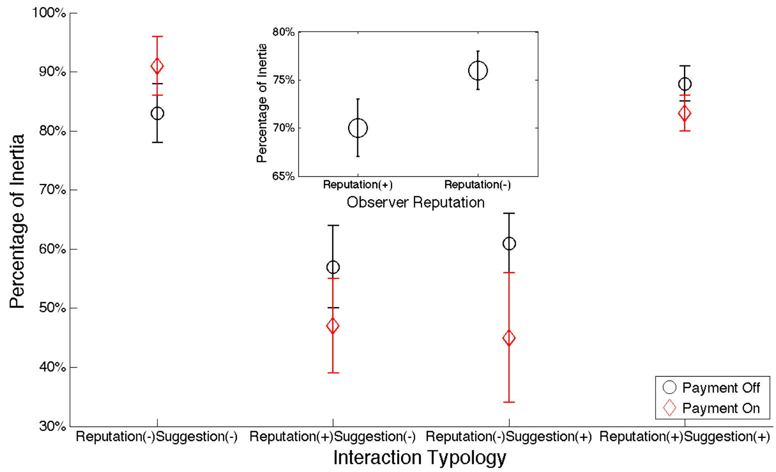


Figure 4.1: In the figure, the percentage of "Inertia" is presented with respect of: the experimental condition related to the payment (i.e., red and black bars), and the four possible "Interaction Typologies" (i.e., the combination between the observer's reputation and the fairness of her suggestion. The error bars report the standard error of the mean. The insert figure highlights the relation between Inertia and the Observers' reputation.

In the first cases, the use of information based on reputation was not different (and diversifiable from a behavioral point of view) from what a rational agent would have done (i.e., give feedback based on the behavior of the interactor). Instead, in the latter cases in which the observation goodness and the reputation scores were discordant, feedback that maintained and confirmed the reputation of the Observer breached the principle of rationality. To better represent this irrational component that we could call properly "reputation inertia" we subtracted the probability of feedback that we would expect from a rational agent $p_I(R)$ from the probability of feedback based on reputation registered within our sample $p_I(S)$ (Table 4.7). Since in our game the participants were asked to provide a feedback only after becoming aware of the actual behavior of their interactor (i.e., when the participants had all the information about the specific event they have to evaluate), we considered "irrational" those participants which relied on the reputation of their interactor when reputation score and behavior were discordant (e.g., the Receiver provided a positive feedback to an Observer with a positive reputation immediately after having received a damage from him).

Table 4.7: *Inertia Table.* In the table the average values of the variable Inertia where $I \in (0, 1)$ in both game settings and the probability of using the reputational criterion that would be expected from a rational agent are reported

	Experimental Inertia		
Condition	**Payment Off**	**Payment On**	**Rational Agents**
Reputation(-)*Coherence(-)	0.83	0.91	1
Reputation(+)*Coherence(-)	0.57	0.47	0
Reputation(-)*Coherence(+)	0.61	0.45	0
Reputation(+)*Coherence(+)	0.88	0.83	1

Irrational feedback model

The subtraction ($p_I(S)$ - $p_I(R)$) allowed us to represent the irrationality for all the cases considered. Indeed, two types of irrationality were derived. For the concordant cases, the irrationality manifested itself when the Receiver did not follow Reputation criterion when he should have done it. Thus, for instance, the Receiver gave a dislike to an Observer with a good reputation that helped him. This type of irrational feedback does not contribute in any way to the "reputation inertia" and actually hurt the maintenance of the Receiver's reputation. For the concordant cases, the irrationality reflected, as already pointed out, the reputation inertia phenomenon.

Figure 4.2 shows the degree of deviation from rationality due to the Irrational Inertia in every condition and for both game settings.

In Table 4.8, the best model for the Receiver's irrationality is presented. Three interaction effects involving Reputation, Goodness of Suggestion, and Payment determined the levels of Irrational Inertia within our game. As expected, the payment condition reduced the levels of irrationality both in relation to a negative reputation and to a bad suggestion. In general, when disjointed, these two factors seemed to increase the Irrational Inertia fre-

Table 4.8: *Best Generalized Linear Mixed Model (GLMM) predicting the "Irrational Inertia" behaviour.*

GLMM Best Model "Irrational Inertia"				
	Model Precision	*Akaike**	**F**	**Df-1(2)**
Best Model	75.7%	47.763	34.16^{***}	6(565)
Fixed Effects				
Factor		**F**		**Df-1(2)**
Payment*Reputation		5.28^{*}		1(565)
Payment*Goodness of Suggestion		2.91^{*}		1(565)
Reputation*Goodness of Suggestion		153.01^{***}		1(565)
Parameter		**Coefficient (β)**		**Student t**
Payment(0)*Reputation(-)		2.078		9.88^{***}
Payment(1)*Reputation(-)		1.585		5.36^{***}
Payment(0)*Goodness of Suggestion(-)		2.168		8.54^{***}
Payment(1)*Goodness of Suggestion(-)		1.613		6.51^{***}
Reputation(-)*Goodness of Suggestion(-)		-4.122		-12.37^{***}

$^{***} = p < 0.001$; $^{**} = p < 0.01$; $^{*} = p < 0.05$; [1] : Suggestion not present

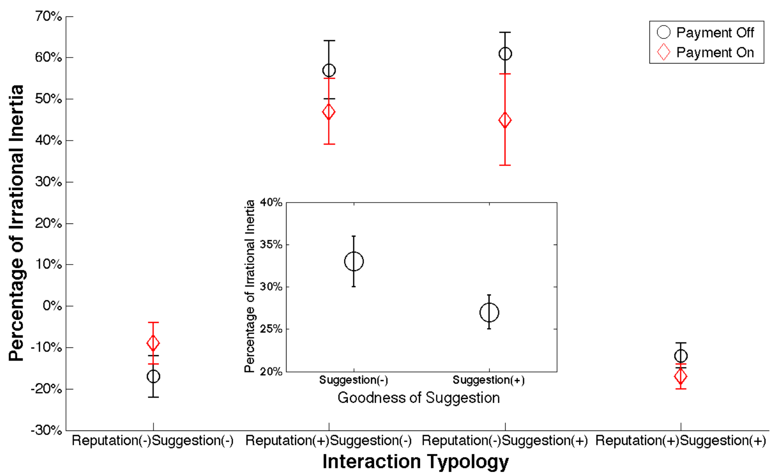


Figure 4.2: In the figure is reported the dynamics of "Irrational Inertia", defined as those events in which the receiver rated the observer just following her/his reputation, but against the "rational" evaluation that should be derived from the real behavior of the observer itself. Again, in red and black are reported the average values and standard error of the mean, and the percentage of "Irrational Inertia" is reported separately for the four possible interaction typologies. In the insert figure, the average "Irrational Inertia" is reported with respect to the goodness of the observer's suggestion.

quency as well as (as seen already in Table 4.6) the use of the reputational criterion (see also the insert in Figure 4.2). Hence, the increase in irrationality due to these factors is attributable to those cases in which the Receivers did not consider either Reputation or Personal Experience (i.e., concordant cases irrationality). However, when a negative reputation and a bad suggestion were joined, this combination of events led to a decrease in the feedback irrationality.

Irrationality among the different typologies of interaction

To better present the same phenomenon from another point of view (i.e., concordant vs. discordant cases), we produced a new model (Table 4.9) involving the Typology of Interaction as a parameter. We did not consider Goodness of the Suggestion and Reputation in this new model since the variable Interaction is a linear composition of them. We observed how the degree of irrationality was lower in the concordant cases when the game setting did not involve a cost to make a suggestion. Moreover, the payment reduced the irrationality in the discordant cases and thus hindered the irrational reputation inertia. However, this cost also increased the irrationality in the concordant cases (and specifically for a positive reputation and good suggestion combination as we can appreciate from Figure 4.2).

Moreover, we analyzed the relationship between the reputation values achieved by the Observer and the degree of irrational inertia shown by the Receivers (Figure 4.3).

Observers' experimental reputation values ranged from -10 to +10. These values were matched in couples (e.g., -10 and -9 values defined the -5 reputation level) to obtain five levels for each typology of reputation (i.e., positive and negative). We registered a non-linear relationship between the Observers' reputation level and the tendency to feedback according to reputation in the discordant cases. Such non-linear relation can be approximated to a quadratic or a complex function. In general, we observed the existence of two plateaux in correspondence to the reputation limit values (i.e., -5 and +5) and of a minimum point for those levels proximate to zero (i.e., -1 and +1). Notably, our participants gave a bad evaluation to a very badly rated Observer who provided a good suggestion nearly the 85% of the time. The same level of irrationality happened with a very good rated Observer who gave a bad hint to the Receiver. In both of these cases, the high level of

Table 4.9: *Best Generalized Linear Mixed Model (GLMM) predicting the "Irrational Inertia" behaviour with respect to the "Typology of Interaction". The typologies of interaction can be concordant if the action of the observer is congruent with her reputation (e.g., a fair advice from an observer with good reputation), and discordant otherwise.*

Best Generalized Linear Mixed Model (GLMM)				
	Model Precision	*Akaike**	**F**	**Df-1(2)**
Best Model	75.7%	27.948	33.12***	3(568)
Fixed Effects				
Factor			**F**	**Df-1(2)**
Typology of Interaction			80.74***	1(568)
Payment*Typology of Interaction			2.61*	2(568)
Parameter			**Coefficient (β)**	**Student t**
Payment(0)*Concordant			-1.730	-5.15^{***}
Payment(0)*Discordant			0.529	1.94*
Payment(1)*Discordant			-1.585	-4.88^{***}

$^{***} = p < 0.001$; $^{**} = p < 0.01$; $^{*} = p < 0.05$; (0): Payment not present

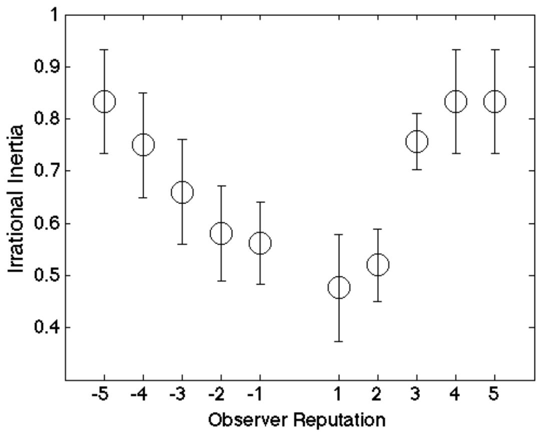


Figure 4.3: In the figure the Irrational Inertia (II) is reported as a probability (i.e., a normalized frequency of occurrance) in relation with the observer reputation. The magnitude of the II appears as clearly related with the magnitude of the observer's reputation.

reputation triggered irrational feedback from the Receiver.

4.4 Conclusion

Overall, our work contributes to clarifying, which mechanisms are involved in reputation building and maintenance.
We showed how reputation is really "made" within a widespread feedback system (e.g., e-commerce sites). As predicted by Hypothesis 1, individuals did not behave like rational agents. In their feedback, they considered not only the direct behavior of their social partner (i.e., the goodness of his/her suggestion) but also they were significantly influenced by the previously acquired reputation of their interactor. In line with the work of [177], we discovered how reputation could exert a social influence by also directing social rewards (i.e., the reputation itself) in a manner disconnected from personal experience. A good reputation attracted other positive feedback, and surprisingly, this happened even when the Observer's behavior damaged (bad suggestion) the Receiver. The opposite also appeared true. A nega-

tive reputation attracted other negative feedback more frequently, and this occurred even when the "bad" Observer provided a good suggestion.

The fact that this effect persisted even when the observation goodness and the reputation score were discordant makes reputation resistant to change. In particular, since the likelihood to follow the reputation in the discordant cases is approximately higher than 50Therefore, our results supported Hypotheses 2 and 3.

Furthermore, the tendency to use the reputational information as one criterion for the feedback action resulted independent from sociodemographic and psychological factors, while the game scenario (i.e., Payment On/Off) influenced its use. When the information transmission (i.e., the Observer suggestion) was free, the tendency to feedback according to the previous reputation was not different for positive and negative reputations. Whereas, if the passage of information from the Observer to the Receiver entailed a cost, we observed a new way of using the reputation to adjust feedback. In this latter game scenario, Receivers seemed to be more influenced by a positive reputation in their feedback action and less by a negative one. This result appeared in line with the one presented in the previous study in which trust-related behaviors were more affected by a positive reputation and negative and ambiguous reputations had less impact. In other words, in this condition, a good-rated Observer seemed more able to exert an influence on the Receivers' feedback behavior, whereas badly-rated Observers were less likely to be evaluated by Receivers using the reputation rule (i.e., give a dislike disregarding personal experience). However, the analysis of the irrational component of the reputation inertia phenomenon (i.e., the proper reputation inertia) showed that there was no difference between the positive and the negative reputation limit values. In the discordant cases, higher reputation values determined a higher probability of engaging in irrational feedback. This probability decreased for lower levels of reputation.

Moreover, the payment allowed real behavior to be considered more within the context of the Receivers' decision making. In other words, as predicted by the costly signaling theory [11], the cost involved to provide data activated in the Receivers a more data-driven (i.e., more focus on the social partner's behavior) cognitive evaluation process. Indeed, willingness to pay provides useful information to others both when the interactor helped [2] and when he damaged others [93]. This additional data-driven information contributed to determining the reputation of the Observers. Indeed, the payment action seemed to establish a new pattern of reputation influence, conferring importance to personal experiences as well.

We analyzed the effect of the payment on those cases in which the observation goodness and the reputation score were discordant (i.e., those that maintained the reputation against the real behavior). We observed a reduction in the usage of the reputation criterion by our participants. In a sense, the payment made individuals more rational in their general feedback. However, even if reduced in frequency, the reputation inertia persisted. Again, since discordant cases presented the reputation inertia likelihood around 50Such a result fits with some novel findings of reputation side-effects [76]. As pointed out by the two authors, reputation exhibits a sort of cumulative advantage that is disconnected from the trustworthiness of the interactors, and this simply led to strongly preferring the individuals with a good reputation. Similarly, we provided evidence of a similar cumulative effect (i.e., reputation inertia effect) in the reputation building. In our game, the interactions were scheduled and were not based on personal preferences, but still, individuals frequently chose to build the reputation of their social partner according to their previously acquired reputation and not in response to the actual behavior, even if this conduct ended up damaging the Receiver.
To conclude, people appear to rely significantly on the previously acquired reputation once they have to "rate" a partner during online social interactions. i.e., the probability of receiving a like within an online reputation system appears as positively (even if not linearly) related to the previous amount of likes obtained by the target (e.g., her/his reputation). Such a tendency (or heuristics) seems to be very pervasive in virtual environments, probably because of the lack of information affecting the decision making processing [77], and produces a bias that we labeled as "Reputation Inertia". The absence of any effect referable to age, gender, and psychological variables can be explained by the Social Identity Model of Deindividuation Effects [158]. Indeed, as emerged in a recent work, when people experience the psychological state defined as "deindividuation" in response to anonymous virtual group interaction, they seem to be more influenced by reputation than by their individual characteristics [62].
Since "Reputation Inertia" appears to be able to distort the reputation dynamics of a web-based social system, so reducing its effectiveness and robustness, the modeling of the virtual human dynamics underlying this phenomenon could proceed to exploit the preliminary findings of this paper.

Indeed, virtual environments that can take into account the impact of the reputation on individuals' social judgment could foster citizens public reason and social coordination capabilities [45] as well as benefiting all those projects that use reputation systems to cope with free-riding and social loafing dynamics (e.g., Collective Awareness Platforms, crowdsourcing projects).

Chapter 5

Virtual Social Influence: The effect of "reputation" in an online ultimatum game.

"Reputation systems" are widely used within web-based platforms and projects. However, recent works stressed the main limitations of such systems due to the reputation capability to distort people's decision making. Using a modified version of the Ultimatum Game we tested if people within a virtual environment modified their behavior when their interactor was connotated by a reputation both in donation and reception phases. We discover that reputation in virtual environments exerted a pervasive social influence. In particular, reputation significantly affected the donation size, the acceptance rate and the feedback decision making as well.

5.1 Introduction

Reputation has been widely analyzed as a tool to foster social interaction and cooperation mechanisms [176], as well as in relation with social influence. In particular, the social influence effect can be found in a higher tendency to evaluate favorably a person with an already high reputation [61]. The majority of the studies aiming to analyze these dynamics has been conducted using face-to-face interaction, however nowadays a great portion of human interaction takes place online, where several environmental factors affect the dynamics of social exchange and communication. In fact, due to the possibility to collect and be exposed to several informational sources and great amounts of data, reputation has become a fundamental meter to judge the trustworthiness or quality of sources. Several online platforms provide information on their users' reputation, guiding the choice to engage or not in interaction and social or economic exchanges with them. The most famous examples are carpooling platforms as BlaBlaCar, housing platforms as Airbnb or Couchsurfing and travelling and restaurant platforms as TripAdvisor. In all the aforementioned platforms, reputation is the element that determines the success of the offered services. However, despite the possibility to contribute to the building of one's reputation on the basis of personal experience, social influence can mediate this process, influencing the interplay between a person's reputation and their actions. In our study, we analyze the relation between social influence and reputation, and in particular, in what measure reputation exercises social influence, affecting people's choices and judgments. To observe these dynamics, we proposed to our subjects an Ultimatum Game, with the reputation visible in some trials and invisible in others, and with the possibility to express a judgment on the exchange (so to influence the other's reputation). From the study emerged that in both in donation and reception phases, the subjects behavior was influenced by the other person's reputation, as well as their judgment. In particular, the donors' reputation affect the propensity to accept their offer and they are judged coherently according to their reputation. We also noticed that, in the donation phase, when reputation is absent, subjects tend to behave positively and donate the same amount of money that they would give to someone with a positive reputation.

5.1.1 Social influence and reputation

The fact that anonymity affects the way human beings interact has been a central element, guiding research that focuses on social influence in online environments. Several authors, argued whether anonymity diminishes the effects of social influence within computer-mediated-communication, linking this factor to the so-called "deindividuation effect". The conceptualization of deindividuation has changed throughout time, and the most up-to-date definitions frame it within the self-categorization processes, in which individuals experience a group-level perception of the self, weakening the awareness concerning their own individual characteristics [159,186]. Several authors argued that deindividuation weakens the effects of social influence, mainly because of the lack of proximity, both physical and perceived [55,114,126,179]. However, recent findings within the theoretical frameworks of the Social Identity Model of Deindividuation Effects [159, 186], provide a better understanding of how anonymity, deindividuation and group saliency result entwined and produce different effects on social influence. The Social Identity Model of Deindividuation Effects, shows how deindividuation caused by anonymity can actually enhance the effects of social influence, as long as the importance of the reference group is stressed. In this case, conformist behaviors can result even more frequent and anonymity becomes a central element in producing social influence, to the extent that providing visual cues about members of the reference group can cause a decrease in conformity [117]. On the other hand, deindividuation alone, so without any type of group engagement, tends to decrease the effects of social influence.

Reputation has been often considered a tool to foster and maintain cooperation [216]. Traditionally, the prosocial effect due to reputation has been explained referring to "gossip dynamics" and "reciprocity mechanisms" [155]. However, reputation could be conceived also as a proxy for social norms [18]. In such terms, reputation serves as a fundamental cue to understand which behaviors are accepted, desired and encouraged within one group or environment. For instance, the emergence of a "reputational system" within a typical e-market interaction (i.e., exchange of resources between buyers and vendors), deeply influence the vendors' behavior (Frey, 2017). Obviously, we can assume that vendors adjust their behavior to respond to the shift of system's equilibrium (i.e., mistrust the buyers is no more the "best" strategy) and to maximize their income. Despite that, reputation still represents in an economic and in a perceptively ergonomic way, the new system local norm (i.e.,to be a trustworthy vendor).

Reputation seems also capable to exert an influence towards those individuals who are not directly identifiable by reputation, but they use such cue to direct their behavior. Indeed, in e-markets equally trustworthy individuals (i.e., individuals with the same behavior) realize different exchange volumes according to their reputation [76]. Thus, individuals appear to rely on a great basis on reputation to select the people they want to interact with.

Interestingly, reputation's influence upon people's decision making some-

times originates some apparently "irrational" outcomes (e.g., behaviors disconnected from the personal experience). For example, people continue to prefer high-rated partners even despite they charged the same good with a much higher price [162]. In other words, people seem willing to accept a worse offer if it comes from a high reputed member. This fact suggests that reputation could have a great influence upon people's acceptance rating. Similarly, it has been reported the people's tendency to give a positive feedback to an individual with a good reputation in an online social dilemma situation disregarding his/her actual behavior [60, 61]. To conclude, we have seen how these works highlight how in a widespread feedback system, good-rated individuals acquire more easily further positive feedback whatever their behavior actually is.
In all these cases, individuals facing a "reputational system" appear more prone to neglect their personal outcome to adjust their actions in order to adhere to the local norm. Also, it was appreciable how people actively reinforced the social evaluation that was constructed and defined by the totality of the interacting users.

5.1.2 Hypotheses

Given the main findings presented by literature, we created an experimental framework aiming to analyze how the social influence exerted by reputation affects human behavior in an Ultimatum Game, so in the reception and in the donation phases. Generally, we expect reputation to influence behavior in the reception phase, with higher reputation broadening the acceptance range and conversely, lower reputation narrowing it. In the same way, the level of reputation should affect the expression of judgment, namely, subjects will feel more inclined to value positively a subject with an already high reputation, and viceversa. The social influence effect, in these cases, should appear when subjects, engaging in an exchange with a counterpart with high reputation, accept amounts of money below the average threshold (around 40% of the endowment) indicated by literature [192], and evaluate the interaction positively in the feedback phase. These behavioral patterns, would indeed bring benefits in terms of social exchange and interactions [177]. Similarly, we expect reputation to affect also the donation phase, namely, subject should feel inclined to donate more generously to a counterpart with high reputation, rather than to someone with a negative reputation. In the conditions with no reputation, given that the social influence effect will be nullified, we expect subjects to generally accept on the basis of the average threshold. However, in the donation phase, we could expect social heuristics oriented towards cooperation to take place, so the experimental subject could feel inclined to donate more even if they have no information on the counterpart's reputation [168]. In fact, this strategy could be implicitly seen as beneficial for future interactions [165].

5.2 Methods and Procedures

5.2.1 Sampling

The research was conducted in accordance with the guidelines for the ethical treatment of human participants of the Italian Psychological Association (AIP). The participants were recruited through a completely voluntary census. All participants (or their legal guardians) signed an informed consent form and could withdraw from the experimental session at any time. The participants were 444 (76 males) with an average age of 15.82 (s.d. 1.30). The ratio between males and females has been kept constant in all the experimental conditions. All the participants completed the experiment.

5.2.2 The conditions and the game

In order to verify our hypotheses, we developed four different conditions (two for each phase of our game) that concerned the presence or the absence of a reputational system (see Table 5.1).

Table 5.1: *Experimental Design. Number of subjects for each condition*

Experimental Design			
		Reception Phase	
		Reputation ON	Reputation OFF
Donation Phase	Reputation ON	111	111
	Reputation OFF	111	111

Once attributed to one condition subjects would stick to that role. As the original ultimatum game, our game included two phases: donation and reception. Furthermore, the order of the phases was constant, namely the players played as donors in the first phase, and as receivers in the second. Although the participants knew that they were interacting with other players, in reality subjects interacted only with our system, which was programmed in order to record the proposals made during the donation phase, and to generate offers using an uniform distribution (ranging from 0 to 10 euros) in the reception phase. The system also recorded the players' decisions when they acted as Receivers, and generated a random reputation ranking when necessary for the succession of the different experimental conditions. The probability distribution of reputation was uniform as well (i.e., each reputational level had the same probability of being selected).

In the donation phase participants had to decide how much of their stack (from 0 to 10 euros) they wanted to offer to their counterparts, and this phase lasted 15 times. This action could be performed by sliding a bar throughout the 0 to 10 euros range. The Donors also knew that the Receivers' decision would determine their gain. Indeed, if the Receivers accepted their offers the resources were split among them according to the Donors' will, while nobody got nothing if the Receiver refused the deal. We specified to the subjects that in our game the exchanges were asynchronous and delayed in time. In the reception phase, players displayed their interactor as anonymous (as they were themselves), so, players could not know if they had interacted with them or not before. Our participants also knew that they could interact with players (i.e., those who had already complete our experimental sessions or people that will play our game in the future sessions) who were different from those that were performing with them in the same game session. The participants were also told that their actual gaining would be revealed in a second time when the Receiver players had taken their decisions. In the sessions in which the reputation system was present, Donors could see the reputation (expressed as coloured circles and ranging from +5 to -5) acquired by their counterparts. The participants were instructed to consider the reputation level as the result of the previous conduct of that particular player when he acted as Donor. On the contrary, in the sessions in which reputation was not displayed, the Donors simply did not have any information about the Receivers. In the reception phase, the players had to evaluate the offers for 15 times. Their gain in this phase followed the same rule of the previous one, so if they refused the offer, both donor and receiver would gain zero, while if they accepted it, they would gain what the Donor offered to them and the Donor would keep for himself the remaining resources. Like in the donation phase, two reputational conditions were present, so reputation could or could not be visible, and in the case in which reputation was present, we explained to the participants that the level of reputation depended on an evaluation given during previous exchanges. After each decision (i.e., accept or refuse) Receivers had to decide about the Donors behavior by rating them with a plus or a minus.

5.2.3 Procedures

The experiments took place inside the computer lab of the "Giovanni da San Giovanni" high-school in San Giovanni Valdarno (Italy). Before the experimental session started, the experimenters presented the game to the participants. Instruction were read aloud and explained using a power point presentation. Once the explanation phase ended, the experimenter led the participants to their designated computers. After completing a brief demographic survey (age, gender, years of education) the participants obtained the permission to run the game. The experiments lasted a maximum of 30 minutes.

5.2.4 Data Analysis

First, we verified the preconditions necessary for the inferential analyses on the experiment's data. For the continuous variables that were used, the normality of the distribution was assessed through the analysis of asymmetry and kurtosis values. Then, we proceeded to the inferential analyses using a general linear mixed model (GLMM) approach [136] due to the repeated measures structure of the experimental data.

5.3 Results

In Table 5.2 the descriptive statistics of the game-related variables are presented.

Table 5.2: *Descriptive statistics*

Descriptive statistics		
Variables	**Mean**	**s.d.**
Amount offered	3.48	1.24
"Plus" feedback rate	0.59	0.19
Feedback Coherence rate	0.78	0.11
Acceptance rate	0.67	0.17

Amount offered: *The quantity of the endowment offered per turn;* ***Plus feedback rate:*** *The Receivers' rate of positive feedbacks;* ***Feedback Coherence rate:*** *The rate of positive feedbacks towards Donors who offered higher or equal to 41% of their endowment and of negative feedbacks to those proposals under this threshold;* ***Acceptance rate:*** *Ratio between the times the Receivers accepted (1) and refused (0) the offer.*

Donors' Reputation affect the propensity to accept.

We analysed through a Generalized Linear Mixed Model the players' propensity to accept or to reject the Donors' resource allocation. As we could imagine, higher offers were more likely accepted by the Receivers. However, also allocations that came from good-rated Donors were accepted more often respect to those that have been made by bad-rated Donors. In general, our participants after receiving the same amount of the Donor's endowment, more frequently decided to accept such offer if it came from a Donor characterized by a positive reputation, while no effect of the receiving condition has been found in relation to the acceptance behaviour (Table 5.3 and Figure 5.1).

How do people evaluate the Donors' behaviour?

Generally, in Ultimatum Games a "fair" offer is around 40% (i.e., average of 41, 01%) of the amount to share [192]. We use this evidence to define the feedback coherence as it follows:

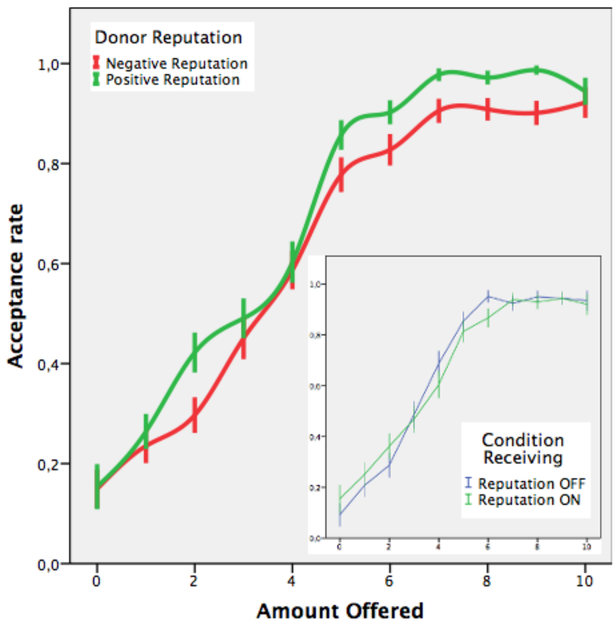
- The Receiver provide a coherent feedback when he gives a plus to Donors' offers higher or equal to 41% and a minus to those proposals under this threshold. Conversely, the Receiver acts incoherently when he gives a

Table 5.3: *Generalized Linear Mixed Models 1. Acceptance Dynamics*

GLMM best model for Acceptance Dynamics				
	Model Precision	*Akaike**	**F**	**Df-1(2)**
Best Model	78.5%	517.077	219.215***	2(3356)
Fixed effects				
Factor	**F**	**Df-1(2)**	**Coefficient (β)**	**Student t**
Reputation	11.174***	1(3356)	0.067	3.343***
Amount offered	436.218***	1(3356)	0.546	20.886***

$^{***} = p. < 0.001;$

Figure 5.1: Acceptance dynamics respect to positive and negative reputation of the interactor. In the insert the acceptance rate trend related to the receiving conditions is represented.



plus to Donors' offers below the 41% or a minus to those allocations higher or equal to 41%.

At this point we investigated which factors could affect the feedback behaviour in terms of coherence. In other words, we were interested to assess whether a change in what is considered "fair" was possible. Results obtained with a GLMM approach are reported in Table 5.4

Table 5.4: *Generalized Linear Mixed Models 4. Coherence Dynamics*

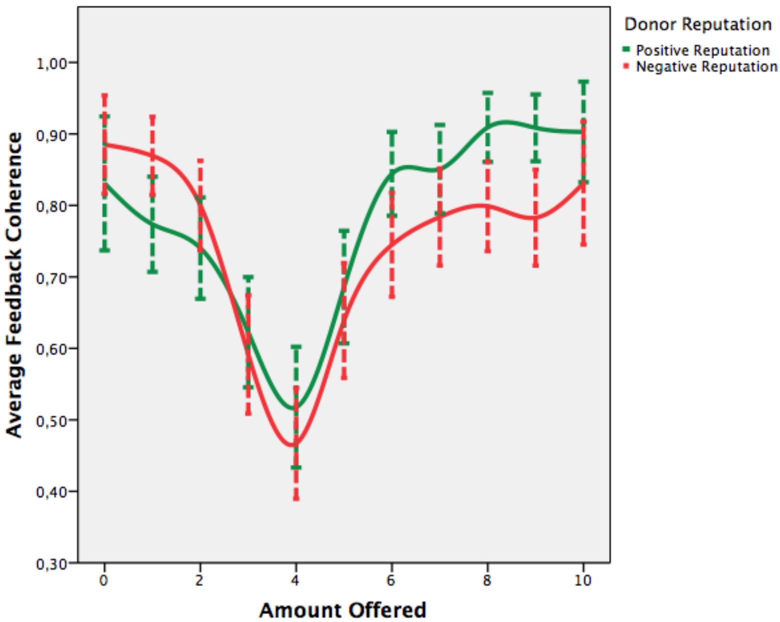
GLMM best model for Coherence Dynamics				
	Model Precision	*Akaike**	**F**	**Df-1(2)**
Best Model	75.3%	704.833	5.365***	3(3355)
Fixed effects				
Factor	**F**	**Df-1(2)**	**Coefficient (β)**	**Student t**
Reputation * Amount Offered	7.760***	1(3355)	0.021	2.786***
Amount offered	8.857***	1(3355)	0.067	2.976***

$^{***} = p. < 0.001$;

Receivers' feedback coherence was influenced by the amount offered by their counterparts. A higher offer more often was considered fair by the Receivers (i.e., coherent feedback), while lower allocations resulted in a fuzzier (i.e., incoherent) feedback behaviour. In other words, high offers seem to elicit a greater evaluation similarity (i.e., a positive feedbacks). Instead, a greater difference in judgments between individuals was observed towards lower offers, with a portion of individuals acting incoherently (i.e., positively feedbacking offers under the 41% threshold). Furthermore, there is an interaction effect between the amount offered by Donors and their own reputation in relation to the Receivers' feedback coherence. The Receivers were most coherent in that situation with higher offers made by good-rated individuals, while the lowest coherence has been found with those offers near the the 41% threshold provided by negatively connotated interactors (Figure 5.2).

Notably, equal offers were treated differently in terms of coherence according to reputation, with those made good-rated individuals more frequently feedbacked coherently.

Figure 5.2: Feedback Coherence trend in relation to Donors' reputation levels.



Players' feedback behaviour appears to be affected by opponent's reputation

To investigate the players' tendency to provide a positive feedback (i.e., a plus), we proceeded with a GLMM for repeated measures. The results are presented in Table 5.5.

Table 5.5: *Generalized Linear Mixed Models 3. Plus Dynamics*

GLMM best model for Plus Dynamics				
	Model Precision	*Akaike**	**F**	**Df-1(2)**
Best Model	75.5%	557.493	244.047***	2(3356)
Fixed effects				
Factor	**F**	**Df-1(2)**	**Coefficient (β)**	**Student *t***
Reputation	15.497***	1(3356)	0.068	3.937***
Amount offered	484.375***	1(3356)	0.446	22.009***

*** $= p. < 0.001$;

More generous allocations were more frequently rewarded with a like from the Receivers. Moreover, the Donor's reputation showed a positive association with Receiver's probability to feedback with a like independently from the amount offered. Good-rated opponents more easily acquired further positive feedbacks, while negatively connotated opponents were more frequently evaluated by our participants with a dislike. Therefore, equally "generous" Donors are treated differently in terms of Receivers' positive feedbacks.

Donation differences between conditions.

Differences in donation behaviour were assessed by means of a GLMM.
As we can see from Table 5.6 and from Figure 5.3 alike, the average donation in those sessions where the reputation system was enabled was lower. Overall, more "generous" allocations were performed by our subjects in those situations in which Receivers were not identified by their reputation. Specifically, when reputation was absent (i.e., totally anonymous interactions), our participants tended to donate the same amount as with an opponent characterized by a good reputation (i.e., +3 reputational score in a scale ranging between -5 and +5).

Figure 5.3: Differences in the average amount offered in the two donation experimental condition.

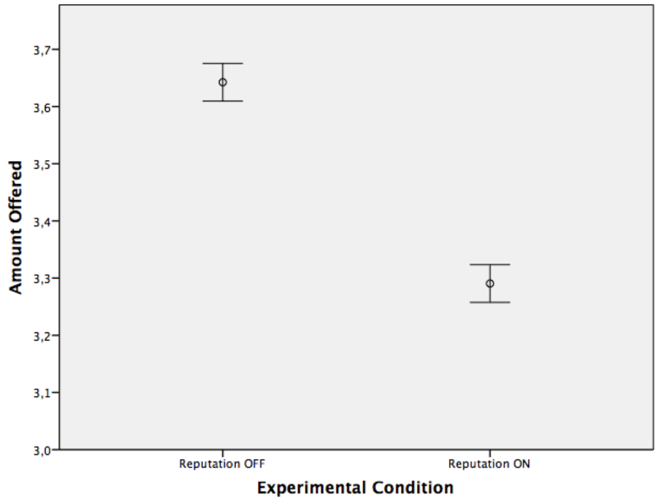


Table 5.6: *Generalized Linear Mixed Models 3. Effect of the Introduction of a Reputation System on the donation*

GLMM best model for Donation Dynamics VS Reputation System				
	*Akaike**		**F**	**Df-1(2)**
Best Model	27604.197		57.050^{***}	1(6685)
		Fixed effects		
Factor	**F**	**Df-1(2)**	**Coefficient (β)**	**Student t**
Reputation System (Off)	57.050^{***}	1(6685)	0.352	7.553^{***}

$^{***} = p. < 0.001$;

Opponent's reputation affects the amount of donation.

The reputation's influence upon donation decision making has been further investigated considering only the donation phases in which the reputation system was provided to our participants.

Figure 5.4: Comparison between the average donation trend respect to Receivers' reputation score (green dots) and the amount offered without the reputation system (red dashed line).

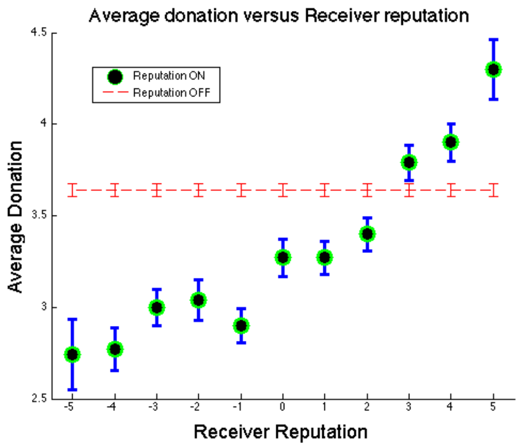


Figure 5.4 underline the existence of a positive relationship between the average participants' donation and the Receivers' reputation. Good-rated Receivers received on average a greater portion of the Donor's endowment, while peoples' donation towards bad-rated opponents resulted smaller. To assess the statistical strength of the result, a GLMM was conducted. The results presented in Table 5.7 seemed to confirm the previous statement.

5.4 Conclusion

Individuals facing "deindividuation" within an anonymous social dilemma situation are greatly affected by reputation. Indeed, under such psychological state reputation appears to exert a pervasive social influence towards different behaviors. On the one hand, reputation allows individuals to recognize more generous social partners by means of a positive reputational

Table 5.7: *Generalized Linear Mixed Models 5. Average donation*

GLMM best model for Average Donation Dynamics				
	*Akaike**		**F**	**Df-1(2)**
Best Model	13745.669		154.387***	1(3357)
Fixed effects				
Factor	**F**	**Df-1(2)**	**Coefficient (β)**	**Student *t***
Receiver Reputation	154.387***	1(3357)	0.140	14.425***

*** = $p. < 0.001$;

score. On the other, reputation-related social influence appears to push individuals to neglect their personal experience (i.e., feedback) and individual preferences (i.e., acceptance) and to adhere to a emerging group standard. As pointed out by [177] having a good reputation implies benefits in future interactions even outside one's own group. In our work we verified that donation, feedback and acceptance behaviors are all adjusted preferentially towards good rated interactors. Moreover, we observed how individuals were susceptible to reputation's influence even when reputation was not built by a real evaluation process but rather extracted from a uniform distribution and assigned randomly to "fake" interactors. Overall, our work contributes to define the potential aspects and biases due to reputation dynamics in virtual environments [76]. Independently from its size, allocations coming from good-rated interactors were always preferred (i.e., accepted more often) to those proposed by negative evaluated individuals. In other words, individuals facing the same proposal are more inclined to accept it if the social partner's reputation is positive and conversely, to reject it if it comes from a negative evaluated partner. In this sense, reputation affects people's acceptance threshold. Furthermore, as emerged from our experiments, people are available to accept less from individuals with good reputation [162].

For what concerns the feedback-related behavior, our results are in line with the previous studies involving widespread feedback systems [61]. Independently from the amount offered to the subjects, good rated individuals had more probability to receive a positive evaluation compared to those interactors that instead where presented by the system as bad rated. Notably, also for extreme low offers (from 0 to 2) the probability of good-rated Donors to receive a negative feedback is inferior to the one of negative reputed partners. Reputation affects not only acceptance ratings but also feedback decision-making conferring to reputation some sort of inertia. In other words, one acquired reputation appears to maintain itself or even to increase. Neuroscientific evidence suggest that prior social evaluation and perceptions of an individual can diminish reliance on neural feedback mechanisms deputed to trial-and-error reward learning [53]. Thus, reputation maintenance against personal experience could be, at least in part, rooted in our own neural circuits.

Finally, when individuals have to decide how much of their endowment give to someone else, the reputation of their partner matters. However, when no reputational information was provided by the system (i.e., Reputation Off condition), people interacted more generously as Donors (i.e., proposed more on average). Several explanations are accountable for this result. Without any additional information about their interactor, individuals seem to rely on that automated predisposition towards cooperation individuated by social heuristics hypothesis' scholars [168]. In this sense, since there are no clues about the partners' trustworthiness that could be used to outweigh this heuristic decision-making process, allocations are made more indiscriminately. Instead, when indirect reciprocity mechanisms are in check, cooperation (i.e., resources) could be direct preferentially towards those individuals that the interacting group "apparently" selected (i.e., conferred a positive reputation) as "valuable" members. Give to an unknown individual the same amount of resources of a good-rated person may seem strange, however this behaviour could be far from being a sort of "mismatch" between humans' evolved psychology and the environment we lived in [72]. Indeed, being generous with unrated individuals could be a successful method to identify other cooperative individuals and possibly turn them into interaction partners for the future [165]. In our work we appreciate how this "social seduction tendency" persists in virtual environment.

To conclude, reputation social influence appears able to distort the dynamics of a web based social system. On the one hand reputation could reduce the effectiveness and robustness of such systems due to potential cascade effects. On the other, reputation capability to foster cooperation under certain circumstances results confirmed. In particular, reputation's persuasiveness could be useful to cope with the typical free-riding and social loafing dynamics of social virtual systems (e.g., Collective Awareness Platforms, crowdsourcing projects), in a more implicit way respect to the simple reputation loss threat.

Chapter 6

An explorative model to assess individuals' Phubbing risk

As proven in the last two chapters, reputation once established influences people's decision making interacting online. In this chapter, we will investigate instead the emergence of "problematic" behaviors concerning human-machine interaction, given the current and future ICTs pervasivity in our lives. Phubbing could be defined as a new form of addiction, however checking the phone ignoring the speaker could also be linked to the increased availability of virtual social environments. We developed a multidimensional model for Phubbing considering psychological dimensions and information and communication technology-related habits. We collected data through online questionnaires and surveys. The best model obtained from our data was constituted by Information and Communication Technologies (ICTs) usage behaviors, Trait Anxiety, Virtual Sense of Community and Neuroticism. Finally, our study confirmed a strong connection between Phubbing and online addiction behaviors. Nonetheless, it also individuated protective factors.

6.1 Introduction

The impact of Information and Communication Technologies (ICTs) (e.g., smartphone, tablet, kindle, smartwatch) on people's everyday life is very noticeable [111, 125]. Indeed, for instance, millions of people all over the world are having relationships of any kind with others simply by using their phone [139]. Despite from merely remain updated about who contacted us, smartphones and other ICTs devices also permit us to handle our own virtual social identity and to keep in touch with relevant virtual social communities [142]. In such a sense, virtual environments have strong social attractiveness. Consequently, brand new psychological questions and issues emerged. Indeed, while the world is becoming more and more connected, with obvious repercussions on the potential for cooperation as we have seen, people can develop addictions in response to this wider possibility of virtual contacts and thus becoming more disconnected from reality [112].
Despite recent studies highlighted a positive influence of smartphones in professional environments such as health care coordination [209], infrastructure monitoring [207], and in promoting socialization with geographically distant individuals [182], in other cases, smartphone usage could be detrimental for individualsâ well-being [13, 32, 119].
Phubbing behavior (i.e., the habit of snubbing someone in favor of a mobile phone) has recently received growing attention among those psychological issues and consequences related to smartphone usage [7, 44, 49, 104]. Phubbing is derived from the union of the words "phone" and "snubbing", and describes the action of ignoring someone in a social environment by looking at the phone instead of paying attention to the other person [170]. Phubbing is also prominent during intimate social interactions. For instance, a large number of couples interrupt repeatedly their meal while eating together to check their phone for messages or missed calls [79].
Phubbing is considered by the scientific literature as a new form of addiction [49,169], a compulsive behavior realized to temporarily escape and avoid a particularly stressful situation or negative thoughts and emotions. Since more and more people are becoming addicted to their smartphones [21] web-based platforms and online services relying on mobile phones should rapidly find a solution to avoid addiction-related taxes (similarly to cigarette use) and to meet well-being required standards [150]. Indeed, it not conceivable to use enhanced crowdsourcing capability relying on addicted people or at the expense of individuals' well-being. In such sense, having defined the cir-

cumstances in which large-cooperation can occur and be maintained, it is not viable per se. One possible way to achieve this goal relies on understanding which individual characteristics are linked to smartphone addiction and thus profiling the user according to these parameters to assess their phubbing-related risk. However, the current literature is a little bit scarce, there are only a few studies that investigate the phubbing's possible predictors and they certainly did not give us the full picture of this complex phenomenon. For instance, psychological constructs like anxiety, self-efficacy, and personality were not fully taken into consideration and several studies demonstrated that all these observables can trigger compulsive behavior [8, 135, 220]. In particular, neuroticism, trait anxiety, as well as social involvement, appeared very related to online addiction behaviors [97, 137].

On the one hand, Phubbing could be defined as a form of addiction, in which the compulsive component appears to be preeminent. On the other, checking the phone ignoring the speaker could also be linked to the increased availability of virtual social environments. In the latter case, the attention could simply be directed towards the social group perceived at that moment as more salient. Smartphones and virtual environments' great availability potentially increased the number of social identities to be managed at the same time. For instance, people often use more than a social network [201]. Furthermore, people try to re-create their offline self online. However, individuals spend efforts in editing self's facets to project a given identity online [30]. Thus, virtual identities managing process could be very time consuming and can lead to privilege virtual environments even to the detriment of face-to-face interactions. Phubbing could be determined by both an online identity management process and an avoidance necessity. The analysis of the interactions between these dynamics will allow us to build a first and exploratory multivariate model to assess Phubbing risk extending the previous work of [86]

6.1.1 Aims of the study

Overall, our work aims to explore the determinants of Phubbing (ranging from a mere interruption of the face to face interaction to a phone obsession) developing a multidimensional model considering all dimensions that the scientific literature has shown to be related to this behavior (e.g., so-

ciodemographic and psychological variables). Given the previous works several hypotheses have been formulated.
First, we expect Phubbing to be positive related with phone related addiction (e.g., use of SMS) and with Internet and social media addiction [44,104]. Indeed, in the first case the phone is a medium through which addiction is substantiated, while surfing on the Internet and social network attendance could be thought as the objects to which addiction is directed.
We also expect that ICT pervasivity measure would be associated with Phubbing. Indeed, the more connected devices people have, the more are the possibility for them to engage in Phubbing [139]. However, we hypothesize that the simple number of social networks used by a person will not necessarily imply a need to check the phone, while could affect the communication disturbance component of Phubbing [112]. Again, the more social networks a person uses, the more are the occasions in which could be reach by a notification or be incentivized to check the phone during a face-to-face interaction.
Finally, we expect that psychological dimension like Neuroticism, Trait Anxiety, as well as Virtual Sense of Community could affect Phubbing obsession component [8, 97, 135, 137, 220].

6.2 Methods and Procedures

6.2.1 Sampling and Participants

The research has been conducted on a sample of 394 individuals. The data obtained from some people, who gave the same score to all items and who were believed to have responded dishonestly, affecting the validity of this research negatively, were removed before the analysis. Thus, data from 361 participants were used in the research. The sample responded to an online questionnaire, design ad hoc, in total anonymity. Since the real identity of the subjects wasn't collected, we didn't proceed in asking the informed consent. The sample was recruited through personal contact and online posts on the major Social Network Sites. All the participants were volunteers. Of the participants, 306 were female (84,8%) and 55 male (15,2%) with an age from 15 until 68 (M: 24,16; DS: 8,14). The sample turn out to be composed for the majority of Italian people (98,6%), except for 5 individuals (1,4%) and most of them were full time students (71,7%). The 98,1% of the participants owns a smartphone.

6.2.2 Procedures

The data were collected thanks to the use of google modules that allowed us to create an online version of our questionnaire and to easily send it through email and social network sites. We decided to proceed with an online somministration, rather than face to face, because from literature it has been found that online, indiviuals are more inclined to give sensitive informations (i.e. more real self disclosure) and to give more honest answers [193]. The final questionnaire asked for data of the sociodemographic beckground, of the ICTs and Social Network Sites usage, and used different scales to investigate the phubbing behaviour and personal characteristic. For most of the scales, we used the validated italian version but for a few of them, like the phubbing and partner phubbing scales, not available in italian, we proceed with a forward and back translation. The instruments that we used are several:

The Phubbing Scale [104] consists in 10 items diveded in 2 factors: *Communication disturbances* (high scores indicate that the person often disturb the communication using the smarphone in a face to face envoiroment) and *Phone Obsession* (high scores indicate that the persone feel the constant need of his/her smartphone in envaroiment where there's a lack of face to face communications.

The *Partner Phubbing Scale* was developed by Roberts and David (2016) and investigate the extention of the smartphone usage when someone is in company of his/her own partner.

The *Mobile Phone Usage Addiction Scale* [104] evaluate the mobile phone usage addiction, the *SMS Addiction Scale* [104] investigates the extent of the sms addiction while the *Game Addiction Scale* [104] is used to establish the addiction to games. The *Social Media Addiction Scale* [104] was developed to investigate the addiction specificaly to social media and the *Internet Addiction Scale* [104] is measuring the internet addiction.

We investigated the ICTs pervasivity asking in which contexts and environments the participants use the online services giving the possibility of multiple choice. We chose as indicators contexts like *at school/university*, *in the free time*, *with family*, *with friends*, *in case of emergency*, *while shopping* and *at work*. The more ICTs contexts are selected, the more participants' ICTs pervasivity results high.

In order to investigate the personality we used the *I-TIPI Scale* in the validated italian version of [42] developed from the original scale of [83]. To measure anxiety we used the *Stai scale* of [187] in its Italian version developed by [152] divided in two scales that focus on how people feel generally (trait anxiety) or on how they feel in that particular moment (state anxiety). In our questionnaire we used only the trait anxiety scale. The *Self-Efficacy Scale* was developed by [100] (here in the Italian version of [180]) and was used to investigate the perception of self-efficacy. The *Self-Esteem Scale* measure the self-esteem of one person considering the positive and negative feelings towards one's self. The *Sense of Virtual Community Scale* developed by [26] investigate the sense of virtual community, meaning the sense of belonging and attachment that one person feel towards a comunity, in this case in virtual envairoment. The *Perceived Social Self-Efficacy Scale* wants to investigate the ability of negotiation in social envairoment and of producing social interaction. The *Social Interaction Anxiety Scale* investigates the distress that an individual lives when meet or talk to other people.

6.2.3 Data Analysis

The statistical procedures adopted to treat and analyze the data have been divided along three phases. In the first phase the data were collected, cleaned, and the outliers were eliminated. Therefore, the preliminary conditions required by the inferential analysis planned by the study were verified (i.e., minimal sample sizes, balance and normality of continuous variable distributions by means of skweness and kurtosis). In the second phase the descriptive statistics were produced, and in the third phase the inferential analysis were carried out. In order to answer to the main hyphotheses of the paper, we adopted the Pearson *r.* correlation to explore the relation between continuous variables, and the multiple linear regression modeling in order to model the multiple effects acting on the Social Media usage (i.e., Social Media Addiction Scale score). Finally, a multivariate analysis of variance and covariance (MANCOVA) has been adopted to develop the best model explaining the Phubbing network of relations with the observables considered by our study.

6.3 Results

The results of the study are organized along four subsections. Each subsection answers to a subset of preliminary hyphotheses regarding the same “family” of theorethical constructs and relations. In the first section the descriptive statistics are provided for all the variables considered by the study. In the second section we provided the univariate statistics describing the complex network of relations between the operative variables (i.e., phubbing factors) and the ICTs’ usage dimensions, as well as the psychological dimensions. In the third section a multivariate modeling of Social Media usage is presented, and in the four and last section, a multivariate analysis of variance and covariance (MANCOVA) is provided to understand the complex network of relations associated with the Phubbing phenomena.

6.3.1 Descritpive Statistics

Descriptive statistics of the psychological and digital life dimensions considered in our study are shown in Table6.1. These dimensions, for which we reported the average with standard error and standard deviation, skweness and kurtosis in the table below, represents in general how our subjects responded to our questionnaire and the data show the normality of distribution.

In Table 6.1 are reported the descriptive statistics and it shows that the subjects who responded to our questionnaire use the ICT (predominantly smartphone and computer) at least one time a day for more than one hour. They use them to access Social Network Sites (SNSs) more than one time a day for one to four hours. On avarage, each persone owns at least 3 different social networks that they use for various activites like discuss different topics and be in touch sometimes with their contacts.

Table 6.2 illustrates the average with standard error and standard deviation, skweness and kurtosis for the operative variables. The experimental data reports both for Personal Phubbing Scale and Partner Phubbing Scale an avarage behaviour very close to those reported in literature. In particular we found an avarage for Personal Phubbing Scale of 2.74, in line with Karadag et al. which reported an avarage of 2.76 [104]. For what concern the Partner Phubbing Scale, the data reports an avarage of 2.54 accordingly with Roberts & David that, in their study, found an avarage of 2.64 [170].

all the operative variables show a accetable normal distribution (i.e. the

Table 6.1: Descriptive Statistics of psychological and digital life dimensions. [1]:ICT Usage frequency avarage is between often (one time a day) and always (more than one hour a day). [2]: SNSs daily accesses between 1 and 50 times a day . [3]: SNSs daily duration of connection is between 1 and 4 hours a day. [4]: Frequency of contacts on SNSs is around rarely and sometimes

Descriptive Statistics				
Psychological Dimensions				
Variable	**Average (SE)**	**Std. Dev.**	**Skweness**	**Kurtosis**
Neuroticism	6.12(0.11)	8.11	−0.17	−0.70
Trait Anxiety (STAI)	47.78(0.56)	10.61	0.24	−0.02
Sense of Virtual Community (SVC)	27.01(0.40)	7.58	0.15	0.05
General Self Efficacy (GSE)	28.17(0.28)	5.38	−0.09	0.01
Social Anxiety (SIAS)	48.09(0.80)	15.19	0.38	−0.35
Digital Life Dimensions				
Variable	**Average (SE)**	**Std. Dev.**	**Skweness**	**Kurtosis**
Mobile Phone Usage Scale	40.15(0.49)	9.33	0.27	0.45
SMS Usage Scale	15.10(0.21)	4.07	0.26	0.43
Games Usage Scale	13.17(0.29)	5.63	1.14	0.54
Social Media Usage Scale	26.81(0.39)	7.41	0.12	0.16
Internet Usage Scale	13.51(0.27)	5.18	0.70	−0.14
ICT Usage frequency[1]	4.78(0.03)	0.50	−0.35	0.53
Number of ICT Services owned	5.29(0.08)	1.61	0.05	−0.10
ICT Social Pervasiveness	3.96(0.78)	1.47	0.23	−0.57
Number of SNSs	3.31(0.07)	1.37	0.72	1.22
SNSs daily accesses[2]	2.53(0.04)	0.76	0.56	0.78
SNSs daily duration of connections[3]	2.17(0.05)	0.93	0.53	−0.07
Number of Activities on SNSs	3.35(0.08)	1.54	0.96	1.15
Number of Topics on SNSs	3.57(0.10)	1.97	0.62	−0.04
Frequency of contacts on SNSs[4]	2.63(0.05)	0.92	0.64	0.26

values of skewness e curtosis ranged between -1 + 1

Table 6.2: Descriptive Statistics of Operative Variables. [1] ratio between score and number of items

Operative Descriptive Statistics					
Variable	**Score (SE)**	*Avarage*[1]	**Std. Dev.**	**Skweness**	**Kurtosis**
Personal Phubbing Scale (PePS)	27.41(0.31)	2.76	5.97	0.06	−0.20
PePS Factor: Communication Disturbances	11.89(0.17)	2.38	3.18	0.30	0.10
PePS Factor: Phone Obsession	15.52(0.19)	3.10	3.58	−0.12	−0.43
Partner Phubbing Scale (PaPS)	22.91(0.35)	2.64	6.67	0.31	−0.22

6.3.2 Psychological and sociodemographical effects

In Table 6.3 are illustrated the correlation between the operative and the psychological and sociodemographic variables. As shown in the table, age and self-efficacy have a negative significant correlation with both personal phubbing and partner phubbing pointing out that younger people report to do and to suffer more phubbing than elder people. Medium-low positive correlation emerge with psychological variables like anxiety, social anxiety and neuroticism.

Table 6.3: Pearson $r.$ correlations between personal and partner phubbing and sociodemgraphic (age) and psychological variables, like anxiety and self-efficacy. $^{***} = p\ 0.001$, $^{**} = p\ 0.01$, $^{*} = p\ 0.05$

Observable	**Social Anxiety**	**STAI (Trait)**	**General Self Efficacy**	**Neuroticism**	**Age**
Phubbing Factor: Communication disturbance	0.282^{***}	0.281^{***}	-0.183^{***}	0.233^{***}	-0.251^{***}
Phubbing Factor: Phone obsession	0.160^{***}	0.157^{***}	-0.112^{*}	0.214^{***}	-0.195^{***}
Personal Phubbing (Total)	0.246^{***}	0.244^{***}	-0.165^{***}	0.252^{***}	-0.250^{***}
Partner Phubbing	0.057	0.151^{**}	−0.038	*ns*	*ns*

6.3.3 ICT and Social Media effects

Overall, the social media effects (i.e., social media and ICT usage and related addiction scales), have been previously assessed by research. Following literature we explored the general correlation structure emerging from those observables of our study that fit with the literature evidences (Table 6.4). In particular, in accordance with literature the Mobile Phone Usage appears to be the best predictor, within the ICT related features, of all the Phubbing factors scores, as well as of the partner phubbing score. A strong relation is evident also, as predictable, with the other scales. The only exception is represented by the Games Usage Addiction Scale (GUAs). Nevertheless, the strength of relations with the Partner Phubbing appear in general to be weaker.

Table 6.4: Pearson $r.$ correlations between personal and partner phubbing and the ICT usage addiction. $^{***} = p\ 0.001$, $^{**} = p\ 0.01$, $^{*} = p\ 0.05$

Observable	**Phubbing Factor 1**	**Phubbing Factor 2**	**Total Phubbing**	**Partner Phubbing**
Mobile Phone Usage	0.524***	0.597***	0.636***	0.294***
SMS Usage/Addiction	0.441***	0.460***	0.510***	0.228***
Games Usage/Addiction	0.162***	0.130**	0.164***	0.154***
Social Media Usage/Addiction	0.499***	0.498***	0.564***	0.293***
Internet Usage/Addiction	0.493***	0.413***	0.510***	0.254***

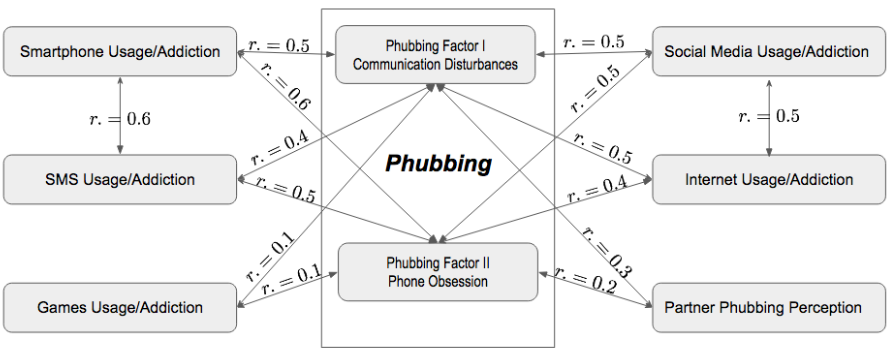


Figure 6.1: Summary of correlations between Phubbing and ICT based predictors. Pearson $r.$ correlation between phubbing and ICT usage addiction features

The Figure 6.1 is a recap of the results explained in details above. As we can see in this picture there are strong positive correlations between both factor of phubbing and the addiction investigated in our study. The strongest one is with the mobile phone/smartphone usage addiction. A good relation is present also between phubbing and partner phubbing, highlighting how do phubbing is correlated to our perception on how much one's partner does phubbing in his/her presence and so on how much someone feels being phubbed. All correlations are reported in Table 6.4.

6.3.4 Phubbing Multivariate Modeling

MANCOVA analysis allows us to study the effects of our factors of interest, on a centroid variable merging different and correlated observables representing the complexity of a certain phenomenon. In this way is it possible to appreciate (i.e., estimate and validate) the single and combined effects of the model factors, on both the single dimensions composing the centroid (i.e., Phubbing Factor 1 &, as well as on the centroid itself (i.e., general model). In upper part of the table 6.5 the best general model refined by the analysis is presented. The model explains the 36% of the variance of the centroid, and the factors maintained by the model are 8. The power of test is always greater than 0.7, and the η^2 tells the percentage of explained variance by every factor. The factor which explains the greater quantity of variance is Social Media Usage (i.e., 7.2%), with the SMS usage explaining the 5.4%, and the Internet Usage the 5.9%. A moderate effect ranging around the 3% is played by the ICT pervasivity, the number of SNSs owned, the Neuroticism, the Anxiety and the Virtual Sense of Community of the subject.

The principal effects, i.e., the effects of the factors on the single components of the centroid, are reported on the lower part of the table 6.5. While the Phone Obsession (PO) Factor appears to be very sensitive to all the model factors with the only exception of the Number of SNS, even if with effects always moderated ranging between the 2 and the 5%, the Communication Disturbance (CD) Factor shows a sensitiveness only toward ICT Pervasivity, Number of SNS, SMS, Social Media, and Internet usage addiction scales. The psychological features of the model seem to affect only the PO Factor.

Table 6.5: Multivariate model $^{***} = p\ 0.001$, $^{**} = p\ 0.01$, $^{*} = p\ 0.05$

MANCOVA General Model (r^2: 0.36)				
Factor	**Wilks' λ**	**F**	**Power (β)**	η^2
ICT Pervasitvity	0.969	$5.616(2,351)^{***}$	0.857	3.1%
Number of SNSs	0.969	$5.639(2,351)^{***}$	0.859	3.1%
SMS usage	0.946	$10.114(2,351)^{***}$	0.985	5.4%
Social media usage	0.928	$13.639(2,351)^{***}$	0.998	7.2%
Internet usage	0.941	$10.961(2,351)^{***}$	0.991	5.9%
Neuroticism	0.977	$4.211(2,351)^{**}$	0.737	2.3%
STAI (Trait)	0.969	$5.620(2,351)^{***}$	0.857	3.1%
Virtual Sense of Community	0.977	$4.160(2,351)^{**}$	0.732	2.3%

Principal effects and Parameters						
Parameter	**Phubbing Factor**	**F**(Df)	β	**Student *t***	**Power (β)**	η^2
ICT Pervasivity	Phubbing^{CD}	$9.430(1)^{***}$	0.307	3.071^{***}	0.865	2.6%
	Phubbing^{PO}	$5.613(1)^{*}$	0.266	2.369^{*}	0.656	1.6%
Number of SNSs	Phubbing^{CD}	$3.820(1)^{*}$	-0.210	-1.954^{*}	0.496	1.5%
	Phubbing^{PO}	ns	-	-	-	-
SMS usage addiction	Phubbing^{CD}	$7.473(1)^{***}$	0.116	2.734^{***}	0.778	2.1%
	Phubbing^{PO}	$18.696(1)^{***}$	0.207	4.324^{***}	0.991	5%
Social Media usage addiction	Phubbing^{CD}	$18.902(1)^{***}$	0.106	4.348^{***}	0.991	5.1%
	Phubbing^{PO}	$18.303(1)^{***}$	0.118	4.278^{***}	0.989	4.9%
Internet usage addiction	Phubbing^{CD}	$20.147(1)^{***}$	0.158	4.489^{***}	0.994	5.4%
	Phubbing^{PO}	$8.299(1)^{***}$	0.114	2.881^{***}	0.819	2.3%
Neuroticism	Phubbing^{CD}	ns	-	-	-	-
	Phubbing^{PO}	$8.179(1)^{***}$	0.263	2.861^{***}	0.814	2.3%
STAI (Trait)	Phubbing^{CD}	ns	-	-	-	-
	Phubbing^{PO}	$9.531(1)^{***}$	-0.060	-3.087^{***}	0.868	2.6%
Virtual Sense of Community	Phubbing^{CD}	ns	-	-	-	-
	Phubbing^{PO}	$7.881(1)^{***}$	-0.059	-2.808^{***}	0.800	2.2%

^{CD}- Phubbing factor: Communication disturbance; ^{PO}- Phubbing factor: Phone Obsession; ns: not significant;

6.4 Conclusion

This study was driven by the desire to better understand Phubbing phenomenon that is still new and, despite all, not exhaustively investigated. Overall, our paper provides a multidimensional model of Phubbing. Having a clear set of factors related to Phubbing will be useful for all those web platforms and online services that can be reached via mobile devices. Indeed, it would be possible for them to evaluate usersâ Phubbing risk using a pretty economic profiling phase.
Phubbing does not appear to be exclusively related to addiction behaviors. Nevertheless, our results highlighted a strong connection of Phubbing with online addiction behaviors (e.g., Social media addiction, Internet addiction) as well as with psychological and psychosocial determinants of online compulsive behaviors (i.e., Trait and Social Anxiety). Our findings appear in line with the previous literature that defined Phubbing as a compulsive behavior put in place to reduce anxiety and discomfort due to social interactions [49, 169]. For instance, we reported a positive correlation between phubbing and both trait anxiety and social anxiety, confirming that those with a higher level of anxiety are those who do more phubbing. However, our results suggest that Phubbing could be related also with constructs not directly linked to addiction behaviors (e.g., ICT Pervasivity, Virtual Sense of Community). Indeed, when addiction variables were already considered within the multivariate model other factors still contributed to explaining Phubbingâs variance. Mobile devices seem to be "habit-forming" but these new habits (e.g., checking habit) do not imply necessarily an addiction. Repetitively inspect the content accessible through smartphones could be experienced more as a diversion (sometimes even as an annoyance) than an addiction [148]. Thus, Phubbing appears to be a complex phenomenon not only definable and predictable by its addiction component.
Interestingly, a greater number of social networks seemed to push individuals to interrupt face-to-face interaction to check their phones less often. They also experience a lesser need to check their phones. Probably, those individuals who have many social networks do not give great importance to them, or they could already have a more structured self. In either case, they may not need to interrupt the conversation to check their phone so often.
Moreover, Virtual Sense of Community seems to act as a protective factor in our model reducing the phone obsession component. This result may suggest how the successful development of social identity through virtual

environments could reduce the perceived need to engage in Phubbing. Consequently, employing resources to structure a proper virtual self and developing individuals' virtual sense of community, can be the bulwark against the negative effects of a close bond between people and ICTs. Plausibly, this may be achieved also by using appropriate reputational systems, that as we have seen arethe representation of a local norm. When addiction-related observables were considered within our model also Trait Anxiety appeared to reduce the phone obsession component of Phubbing (probably because the variance that increased phubbing was already captured in our model by the addiction-related variables), while Neuroticism seemed to increase it.
ICTs availability (i.e., pervasivity) increases the overall Phubbing frequency. Usually, the more people are exposed to ICTs and online services in their daily activities, the more their digital media literacy rise [151]. So, it is not a surprise that the individuals more used to ICT could also be the one that more often use smartphones and engage in Phubbing. Whether their use can be read as an addition or a simple interruption of face-to-face communication, the "confidence" with ICTs appear to be a promoting factor for Phubbing.
We also registered how digital native subjects (i.e., individuals under the age of 26) were more likely to engage in phubbing than digital immigrants. Younger individuals were born and raised in the age of new ICTs [160]. Their use of smartphones is quite different from people who experience ICT revolution in adulthood. Indeed, digital natives use of smartphones is pervasive in their lives. Not only their use is more frequent with obvious effects on both Phubbing components, but it is also more socially connoted. Indeed, digital native individuals use smartphones also to signal their social affiliation as well as to build social relationships [12, 109]. While, digital immigrants, especially seniors, use smartphone mainly for their utility as phones [22]. Therefore, the difference between digital natives and digital immigrants in ICTs social importance and pervasivity could be a possible explanation for age effect on Phubbing. Preliminary data on a still ongoing data-collection on the relationship between virtual social influence and well-being (that is not presented in this thesis) throws a new light on this aspect. In particular, the relationship between virtual sense of community and well-being seems to exist and be strong for the younger (age under 28) while no relationship emerged for older peope. This could mean that digital natives are those who can benefit from a stronger sense of belonging to a virtual community, since

this aspect is a major predictor of their well-being.
The social environment defined by dyadic-couple interactions also seemed to have a role in shaping Phubbing behavior. Indeed, individual Phubbing is associated with the perceived level of partner's Phubbing. Which could mean that seeing a significant other engage in Phubbing could influence the acceptability of such behavior and possibly reinforce Phubbing dynamics [79]. Significant others' influence affects a broad variety of behaviors, among which addiction conducts [175]. Indeed, what others do (i.e., empirical expectations) influences the likely to engage in a behavior, thus defining a norm within a social system [23].

However, our measurement of partners' Phubbing is based on a person's perception of what another person does and thus, could be biased. Future works should investigate the possible role of Phubbing as a shared and self-reinforcing norm.
Lastly, we verified the effects of gender and psychological and psychosocial observables on Phubbing. Differently from the previous literature [44, 104] gender did not appear neither to impact the Phubbing level nor to mediate the relationship between the smartphone addiction, internet addiction and phubbing behavior. The relationship between Self-efficacy and anxiety is well known in the scientific literature [8]. Nevertheless, the relation between self-efficacy and Phubbing appears quite weak, probably indicating a more complex dynamic between the observables than a simple linear relation.

Overall, our work could be exploited in line with primary prevention approach [33]. Indeed, future online services should aim at avoiding the emergence of psychological detrimental issues like Phubbing and therefore promoting well-being among Internet users. On the one hand, having a clearer picture of Phubbing antecedents could be very useful in assess usersâ Phubbing potential risk and consequently adapt service-user communication via smartphone. On the other, our results could be used for dedicated mobile device settings to help reducing ICTs pervasivity for potential phubbers (e.g., managing appropriately the number and the timing of smartphone notifications) [129, 156].

Chapter 7

Conclusion

This chapter summarizes the contribution of the thesis and discusses avenues for future research.

7.1 Summary of contribution

Reputation can identify what a virtual community thinks of a certain person. As we have seen in the several empirical studies presented, reputation is built based on users' past actions in a given context. Nevertheless, once established fully, reputation seems to show some limitations in guaranteeing online systems and services' effectiveness and robustness (i.e., to have inertia to change in response to opposite behaviors). Currently, reputation systems are widely used on the Internet assuming that reputation could be a reliable indicator of individuals' future behavior. Users are affected by reputation and show more trust-related behaviors towards individuals characterized by a positive reputation. In other words, people decide how to behave with online interactors based on their reputation [184], which, however, under certain circumstances, is not so reliable.

In general, this thesis highlighted even more how reputation could be a strategic asset for all those people, entities and projects whose core is the social online activity. Referring in particular to Chapter 5, having a positive reputation implies a higher persuasive potential that can compensate for a qualitatively inferior behavior (e.g., an offer, a good). This appears particularly important in a context like e-markets where consumers often do not have complete information on what they are buying [102]. Apart from these not marginal aspects, our results showed how reputation could foster fairness among online interacting individuals (see Chapter 3 for instance). Interestingly, this effect has been captured in experimental circumstances in which the users who were called to be more or less fair were not definable by a reputational score. Third-Party users, whose role was to give suggestions, were instead evaluated. In this scenario, the presence of a reputational system appeared sufficient to modify users' behavior in the direction of promoting fairness. One possible explanation of this indirect effect of reputation can be rooted in users' expectations of fairness. In other words, if a reputation system is in place users may expect other individuals to be more prone to fulfill their role and thus less feasible to exploit the system for self-interest purposes. In reality, the third-party members didn't act differently based on the presence of a reputational system. In any case, reputation appeared a useful feature to promote desirable outcomes (e.g., fairness, generosity). Therefore, the critical aspects of reputation did not involve what reputation conveys or is capable of, but rather how this social signal is built. The ascendancy that reputation has over people emerged clearly in our studies. People greatly rely on reputation for their decision making and even more when they interact online.

Reputation could be also a viable and sustainable strategy to achieve participation in a wider large-scale interaction scenario. Indeed, participation could be what reputation stands for (or represents) in a given virtual community. For instance, reputation is gained by researchers active in academic online groups [130]. As we have seen in Chapter 2, large-scale cooperation and problem-solving are affected by group-related dynamics such as social loafing, free-ridings and others, and encounter some threshold in which they decline pretty fast. In particular, after a group-size of 64 and even when the problematic group dynamics were not yet modeled, cooperation could not be achieved. Thus, social and public indicators that convey what is the desired behavior (i.e., participation), like reputation, could dampen this decline. Further indications emerging from the presented results encompass other critical circumstances that should be addressed to achieve large-scale results, like those considered by EU Societal Challenges objectives and UN Sustainable Development Goals.

Small groups facing difficult tasks are particularly exposed to the effects of a costly interaction. Interestingly, as emerged in Chapter 4, reputation still functioning (i.e., is built) when a cost is applied thus suggesting that a

reputational system could be viable also in situations of high-costly interaction. Moreover, the building process of reputation in costly circumstances appeared to be more rational (i.e., more adherent to the actual behavior of the interactor). Overall, our work contributed to the understanding of reputational dynamics in virtual environments [76], defining the best scenarios of application of a reputational system and underling when they could fail.
Finally, the focus of the Ph.D. thesis shifted towards human-device interaction accounting for the phubbing behavior, which is usually linked to psychological and well-being issues. Our work supported the connection between phubbing and addiction-related outcomes, nonetheless also individuated protection factors. In particular, the virtual sense of community seems particularly promising in dampening the problematic outcomes on the well-being of intense human-device interaction. Enhancing the young-individuals' virtual sense of community could be useful in defining well-being especially if we consider IoT technology [154], which is going to be widely adopted soon enough with a huge impact on people's lives.

7.2 Directions for future work

The most conspicuous part of this Ph.D. thesis focused on how people are affected by others' reputations. Nevertheless, much less is know about how assigning a given reputation to an individual (positive or negative) influences his behavior. In virtual environments, identification processes are in place. For instance, the creation or selection of an avatar is generally the first step in a video game. The term avatar refers to a perceptible digital self-representation [218].
Currently, people on the Internet are not present as physical entities, but only as a virtual representation that, usually, has been considered as a one-way process (i.e., we deliberately choose how we want to be perceived and represented in a virtual environment). However, scientific literature highlighted that also the opposite can be true. For instance, several studies [124], showed that online role-playing games' players incorporate the avatar features into their self concept. Interestingly, some players seemed to identify more with their avatar than their real selves. This identification appears to have direct repercussions on people's emotions and perceptions: indeed, individuals may infer their own attitudes and mood by observing the appearance of their own avatar. As an example, it has been observed that users who were assigned

black-dressed avatars expressed a greater desire to commit antisocial acts than those who had been assigned with white-dressed avatars (Yee, 2009). The effect that the avatar has on individuals' behavior is called the Proteus effect. Since we are affected by both our own self-representation and the group's local norm (see SIDE model), assign a socially constructed representation of a person (like reputation), can make certain desired behaviors more likely. Future research should investigate if this influence occurs as well as the direction of this effect (i.e., which behaviors are impacted by a type of reputation and to what extent).

Online interactors are not only other human beings. From the appearance of the first chat-bots to the most recent artificial assistants (e.g., Amazon Alexa, Google Home), people are becoming more used to interface with non-human entities. Preliminary findings not included in this manuscript seem to suggest that human beings make an assumption about how Artificial Intelligence evaluates them. For instance, individuals behaved differently according to their assigned reputation when interacting with an A.I. In general, it must be shown in which circumstances individuals treat artificial entities like human beings and in which other peculiar behavioral patterns emerge. In any case, further effort should be made to address this point, since as expected from the increasingly rapid development of the Internet of Things (IoT) technologies, humans will be connected more and more frequently with artificial interactors.
ICTs' pervasivity in our lives should also be investigated further. Indeed, different online settings, services, and environments are accessible using modalities with a different degree of immersiveness (e.g., voice command, HMD visor). Understanding how people stand before the technology is fundamental to assess not only if something will be used but also to define the circumstances in which a given technology is enabling and when it is not. As we have seen with phubbing a great availability of ICTs could be detrimental for certain people. For this reason, it seems mandatory for future research to be able to profile users, assess their wellbeing and adapt communication in case of need.

Appendix A

Publications

This research activity has led to several publications in international journals and conferences. These are summarized below.[1]

International Journals

1. **M. Duradoni**, M. Paolucci, F. Bagnoli, A. Guazzini. "Fairness and trust in virtual environments: the effects of reputation", *Future Internet*, vol. 10, iss. 6, pp. 50, 2018. [DOI: 10.3390/fi10060050] *4 citations*

2. A. Guazzini, **M. Duradoni**, A. Lazzeri, G. Gronchi. "Simulating the Cost of Cooperation: A Recipe for Collaborative Problem-Solving", *Future Internet*, vol. 10, iss. 6, pp. 55, 2018. [DOI: 10.3390/fi10060055] *2 citations*

3. S. Collodi, S. Panerati, E. Imbimbo, F. Stefanelli, **M. Duradoni**, A. Guazzini. "Personality and Reputation: A Complex Relationship in Virtual Environments", *Future Internet*, vol. 10, iss. 12, pp. 120, 2018. [DOI: 10.3390/fi10120120] *3 citations*

4. A. Guazzini, **M. Duradoni**, A. Capelli, P. Meringolo. "An Explorative Model to Assess Individualsâ Phubbing Risk", *Future Internet*, vol. 11, iss. 1, pp. 21, 2019. [DOI: 10.3390/fi11010021] *4 citations*

5. **M. Duradoni**, G. Gronchi, L. Bocchi, A. Guazzini. "Reputation matters the most: The reputation inertia effect", *Human Behavior and Emerging Technologies*, 2019. [DOI: 110.1002/hbe2.170]

[1]The author's bibliometric indices are the following: H-index = 3, total number of citations = 21 (source: Google Scholar on Month 10, 2019).

International Conferences and Workshops

1. A. Guazzini. **M. Duradoni**, G. Gronchi, "The selfish vaccine Recipe: A simple mechanism for avoiding free-riding", in *Winter Simulation Conference (WSC 2016)*, Washington (USA), 2016.
2. **M. Duradoni**, F. Bagnoli, A. Guazzini. "Reputational Heuristics Violate Rationality: New Empirical Evidence in an Online Multiplayer Game", in *International Conference on Internet Science (INSCI 2017)*, Thessaloniki (Greece), 2017.

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