

Networks dynamics and information sharing: an agent-based simulation approach for the sharing economy

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Abstract

The widespread availability of digital ecosystems and networking tools have supported the emergence of the sharing economy, and in particular, social support networks that enable collaborative consumption. This paper proposes an agent-based simulation to shed light on how information sharing dynamics can affect the decision-making process and outcomes of asset sharing online communities. The model considers the online community as a complex system of cognitive and tangible networks, and provides a platform to evaluate architectural choices in the design process of digital platforms. It is grounded on a cognitive model of dependence networks and provides a means for modeling the dynamics of collaborative consumption in digital social support networks. The results of four simulation runs are analyzed and discussed, providing insights regarding the potentiality of this approach and the effect of behavioral rules on agents' outcomes and decision-making patterns.

1. Introduction

Digital platforms are having a significant impact on businesses as they reduce transaction costs, diminish distances and increase network effects [48]. Not surprisingly, the diffusion of ubiquitous digital ecosystems [12] has facilitated the emergence of many sharing services, particularly Customer to Customer platforms [6, 10].

These networking tools [50] have provided a fruitful ground for the emergence of the sharing economy (also referred as “collaborative economy”) [4, 39]. The sharing economy essentially aims to create market efficiencies by developing new as well as reframing established products and services that generate sustainable economic growth [10]. The sharing economy can be seen also as a form of open collaboration, where members of online communities share resources for achieving a common goal, creating products and services with an economic value [36, 41]. From a different perspective, it could also represent a social support network that provides members access to tangible assets.

The disruptive potential of the sharing economy has recently drawn the attention of entrepreneurs, researchers, policy makers as well as the media [19, 46]. While the behavior of open collaboration and online (virtual) communities has been exhaustively researched in terms of community members' motivation and institutional aspects [37, 55], the emerging characteristics of asset sharing dynamics of social networks still require further investigation [51]. As the information shared in an online community is originated from various sources and can be used for different goals [45], it is particularly important, in an asset sharing dynamic context, to understand how the information shared among participants could affect the outcomes of the community.

A suitable approach to investigate this issue is through the use of simulation techniques [15, 49]. Simulation has been adopted in many disciplines as a means for understanding the behavior of a system by imitating it through an artificial object that exhibits a nearly identical or partial behavior [49, 62]. It can help to understand the relationships among objects, and subjects and their environment, by providing a means for reproducing the system behavior in a controlled environment. It represents a powerful tool for decision makers [62]. Indeed, simulation studies are considered particularly useful for building a place in which it is easy to explore new concepts, ideas, boundaries and limitations [14]. It is frequently used for building and validating explanatory and predictive theories in Information Systems research as well as its reference disciplines such as Operational Research, Management Science, and Computer Science [5, 25, 61].

As a result, the aim of this paper is to develop an agent-based simulation to help understand how information sharing dynamics may affect the outcome of an online community focused on asset sharing. The simulation model is founded on a cognitive model of dependence networks and provides a means for modeling the dynamics of collaborative consumption, considering social support networks as a particular instance. These specific communities are represented by small sets of agents that interact with each other and whose behavior is mainly driven by their needs (to reach a specific goal), capabilities (possible actions and available resources), belief systems (perception of the reality) and

environmental constraints. By conducting several rounds of “what-if” analyses, the proposed simulation model considers the online community a complex system and aims to assist decision and policy makers to evaluate some key architectural choices [23] in the design process of digital platforms.

The paper is structured as follows. Firstly, a brief literature review is presented. Then, the theoretical constructs from socio-epidemiological studies and cognitive models that provide the grounding for the proposed simulation model are discussed. Section three introduces the simulation approach, as a means for studying information sharing dynamics in social support networks and describes the proposed simulation architecture. Section four presents and discusses the experiments’ results. Finally, the conclusion and suggestions for further empirical research closes the paper.

2. Background literature

There are four pillars to the proposed framework: (1) sharing economy and collaborative consumption, (2) sharing economy as a social support network, (3) information sharing and the digital platforms that enable the flow of information among members, and (4) cognitive models that guide members’ behavior in the network. This section presents a review of the literature in those areas and provides the theoretical background of the paper.

2.1. Sharing economy and collaborative consumption

Although the term “sharing economy” emerged more than 25 years ago [8], the debate around it has significantly intensified in recent years due to a growing need for environmental and economic sustainability, the diffusion of ubiquitous information systems as well as peer-to-peer digital platforms [4, 34]. As most emerging and evolving phenomena, the literature still lacks a convergent and homogenous definition for the term sharing economy [46]. It is quite common to see terms such as “collaborative consumption”, “sharing economy” [39, 50] as well as “collaborative economy” [20] used interchangeably across the literature. On the other hand, a stream of authors seems to provide some indication of a conceptual distinctiveness among the terms. Sharing economy could be considered as a broad concept umbrella for the phenomenon [19, 20, 54] while collaborative consumption is a specific business model within the sharing economy that can be defined as “peer-to-peer-based activity of obtaining, giving, or sharing access to goods and services, coordinated through community-based online services” [33].

Examples of these online communities are neighborgoods.net, www.freecycle.org, and buynothingproject.org.

Collaborative consumption enables a cultural shift from “asset ownership” to “sharing asset access” [10]. This cluster of community-based online services is fostered by digital (peer-to-peer) platforms that connect consumers, enabling them to make more efficient use of underutilized assets [46]. Most importantly, it empowers individuals to obtain, give and share access to goods and services in a coordinated manner [33].

From a pragmatic perspective, actions of individuals that engage in collaborative consumption are often based on rational reasoning, seeking the maximization of utility and cost savings or the minimization of transaction costs [48]. The exchanges among the members of a community could be based on direct or indirect reciprocity. In the former, there is usually a high level of uncertainty because participants rely on the norm of reciprocity (comparable benefits) instead of explicit agreements (negotiation). In the latter, participants provide valued resources to others without any expectation directly from the same person [60]. In social exchange terms, indirect reciprocity is called “generalized exchange” where people give benefits in response to needs or to demonstrate a general concern for the other person [17]. This results in the development of social support networks, where the members of the online community aim to reach a common goal. In the case of collaborative consumption this is achieved by “offering” and “requesting” goods through a digital platform [33, 39]. The next section presents a brief review of social networks and social support.

2.2. Social support networks and information sharing in online communities

Social exchange theory [29] emphasizes that social interactions are normally based on a trade-off analysis of the costs and rewards associated with transactions. Rewards can be easily associated to the possibility of sharing contacts and obtaining resources through the network which then becomes a resource underpinned by social capital [2]. On the opposite, costs can be related for instance to potential issues derived from social interactions such as disagreements, bashfulness, jealousy and invasion of privacy [52]. Social ties are constructed based on the individual perception of the capacity to obtain rewards in comparison to sustain costs among the possible alternatives. This perception can be misleading due to bounded rationality that can limit the individual’s capability to choose people with whom a positive interaction takes place [3]. Many other contextual factors can affect the capability of a social support network to provide the needed help. These are related for instance to

culture, rapid social change, industrialization, and urbanization [7]. Although these upstream factors influencing social network structures are important, this research focuses on the micro-level factors (e.g. common goals, resources needed) leading individuals to exchange resources and information through their personal networks.

Social support has been considered a key value that online users can obtain from social network platforms [42]. Social networks are formed by interactions among people, providing a “give and take” of assistance and protection [32]. In this sense, the social network can be seen as the structure of this interactive process, while social support is the actual function [40]. Support is given and received through structured relationships described in networks. Consequently, social support research has begun to deploy social network analyses as a more formalized way to understand the concept of social support [1]. Although related to social networks, social support has its emphasis on the subjective nature of exchange rather than on the structural aspects of the network. Its function is to provide information or resources to an individual [3]. As a result, social support networks concepts can be useful for understanding both the subjective and the structural value of social support networks which is essential to sustain sharing economy initiatives.

The exchanges among the members of the social support network (community) relies on their ability to share information [16, 45]. The information produced and shared by people acting in the same online community creates a knowledge base that is defined as community memory [45]. The online community memory is not only useful but, often, crucial for accomplishing the tasks needed to achieve individual as well as collective goals (*ibid*).

In addition to the information produced by the community members [26], the digital platform may also generate and broadcast information in the network. For example, some platforms allow users to see which members are currently online or when was the last time they logged in. The use of such features usually improve the sense of co-presence among the community members [43]. Another example could be the possibility to see the information regarding transactions among members (e.g. exchanging goods). This type of feature is often referred as “transaction transparency” and is argued to increase the levels of trust among members of the community [58]. In the case of this study, the information taken into consideration is both produced directly by the members as well as the digital platform.

2.3. Cognitive models of dependence networks

In order to understand how information sharing dynamics may affect the outcome of an online community focused on asset sharing, it is relevant to also understand the cognitive model guiding the behavior of the members in the network. In the dependence network theory proposed by Conte and Castelfranchi [21], it is assumed that agents are members of a network based on social relationships and these relationships are a result of agents’ mental states. Thus, social networks are based on networks of goals. Among these relationships, social dependence represents one of the most important kind of relationship as agents need each other to reach their individual goals. In collaborative consumption members are tied by the assets that they can offer and receive from the community, but also by their beliefs or perceptions about those ties. There are two dependence networks: (1) a real dependence network (RDN) based on asset needs and haves; and (2) a believed dependence network (BDN) based on imperfect beliefs about those needs and haves.

This research extends previous developments in agent-based simulation of dependence network [47] and provides a tool for improving coordination in multi-agent systems [22]. It assumes there is an objective reality that agents could or could not effectively know as it is; hence, various levels of divergence between the real and BDN could exist among the members of the network. The model of dependence networks described in this paper is based mainly on Conte and Sichman’s formal theory of social dependence [13, 22]. The concepts of external description, dependence relationship and dependence situation from the original model are extended. Moreover, the proposed model adopts the concept of cognitive dissonance, which can be defined as the distance between an individual’s believed dependence (subjective point of view) and her real dependence (objective point of view). This is used to investigate how this distance may influence agents’ behaviors in the network. For this reason, the theoretical framework of the cognitive model includes the objective dependence network (built on the real dependence relationships between agents in the network) and several BDNs (reflecting each agent in the network).

The proposed model is conceived as composed by an exogenously defined environment in which there are different dependence relationships, and a given number of agents. These agents are goal oriented and autonomous in making decisions but dependent on others for reaching their individual goals. Based on their personal BDN, agents proceed by trial and error (updating and correcting their beliefs about their perception of the dependence relationships in the environment) or by broadcast requests (revealing their needs and relying on the support network for a response).

3. Methodology

This section introduces the simulation approach as a means for studying information sharing dynamics (in a broad sense) in social support networks. This is followed by the description of the proposed simulation architecture as well as the agent's mind and the environment configuration.

3.1. Simulation models in social support networks research

Social support networks have been studied through a variety of approaches and research methods [35]. Simulation approaches have been largely adopted in social support networks research, especially in the context of healthcare. The most commonly used simulation methods are discrete event simulation (DES), system dynamics (SD) and agent-based models (ABM). For instance, some studies have focused on economic aspects by developing a computational model based on DES of population and healthcare delivery [30]. Such studies are unit specific and seldom provide a holistic representation of the problem domain. Some attempts to overcome this limitation have been based on SD simulations. For instance, some studies developed a dynamic simulation model of poverty incidence, linking transitions into and out of poverty to various events, such as increased earnings, or having a child as a teenager, and linking these events to policy [24]. Through such simulation approach additional complexity can be embedded in the computational model, though the relations among system variables is assumed to be fixed. This makes such models poorly representative of the complexity of the system in which social support services are provided.

This research is based on the assumption that collaborative consumption relies on the existence of a social network [57]. This is a complex process where individuals, groups, organizations interact by exchanging resources and information in a dynamic environment. Such settings can be modeled as dynamic networks made by a mix of human subjects that can exchange information through digital channels. The possibility to simulate the behavior of such complex settings can provide powerful means for exploring “what-might-be” scenarios in which sustainability is addressed from an economic, social, and environmental perspective [62].

Therefore, the main premise in this study is that ABM and Multi-Agent Simulations (MAS) have the potential to yield insights on the mechanisms that drive information sharing dynamics in an online community focused on asset sharing. Agent-based modeling creates artificial worlds that model real-world environments. Automated agents are used to populate these worlds and simulate the behavior of their real world counterparts,

usually for testing theoretical and empirical constructs [27]. The development and implementation of MAS attempt to attack more complex, realistic, and large-scale problems which are beyond the capabilities of an individual agent [56]. In MAS, the agents can solve a particular aspect of the problem (e.g. provide a specific resource or performing a given action), and they are able to interoperate and coordinate with one another in peer-to-peer interactions [53]. Such models must specify the characteristics of the agents, the connections among them and the mechanisms of their interactions [44]. Meanwhile, the dynamics of social support networks emerge from the behaviors of heterogeneous individuals and their interactions that mediate social production of support [28]. As a result, MAS is a suitable tool for modeling agents' interactions in these environments and to study agents' achievements in terms of resources and information as well as their decision-making processes and strategic actions (based on models of other agents and the environment).

3.2. Simulation architecture

As previously mentioned, agent-based modeling and simulation is an approach for modeling complex systems composed by autonomous and interacting agents. Their behavior, is described by rules, and their interactions with other agents influences the behavior itself [9]. Modeling the agents individually (micro-level) the effects of their interaction can be observed at a macro-level and allows exploring the behavior of the whole system. Indeed macro-level patterns, structures, and behaviors emerge from the interactions, without the need of being explicitly programmed within models [28, 44]. Furthermore according with Bousquet and Le Page [11], looking at a complex system as an ecosystem, it is possible to study the individual agents, their interactions, and their organization across various scales.

In the proposed architecture, each agent (based on her own beliefs) has a subjective representation of the environment and the relationships among other agents. She is aware of her available resources and possible actions, and she aims at reaching some goals by performing actions and using her own resources and/or asking some other agents for actions or resources. On the basis of their needs, each agent interacts with each other mainly for exchanging resources or for involving other agents in performing needed actions. The interaction is influenced by the BDN that may equate (or not) to the corresponding RDN. The agent can have one or more BDNs as each goal generates a corresponding dependence network. Each agent updates their BDNs after every interaction, considering the information exchanged. The period of time regulating the interactions among the agents is called “round” and it is a rule of the

environment. In each round, every agent randomly gets a turn to perform one action based on her needs.

The simulation design defines that when an agent needs a resource or an action, based on her beliefs (e.g. if she knows who can assist her), she will contact one or more agents in the network until she receives a positive response, or she will broadcast message with a request to the environment. In the latter case, each agent receives the request and can decide to broadcast the answer or contact only the requester. Based on these interactions, each agent is able to gain new information about the dependence relationships among the agents in the environment. First, each agent involved in the interactions learns what the requesting agent needs, creating in some cases a new belief dependence link with an agent for the specific resource or action or a new link in general. Second, if the answer was broadcasted, any agent can collect additional information (learning the existence of new agent and/or new dependence link). Finally, each agent stores all new information in their minds using them for updating her BDNs.

Following the overall structure of the Soar cognitive architecture [38], the agent's mind is composed Long Term Memory (LTM) and the Working Memory (WM). The information stored in the LTM corresponds to the agent's perception of the reality, her capability, her needs and objectives, it includes goals, actions, plans, resources, BDN. On the other hand, the Working Memory, hosts the specific step of each plan that needs to be accomplished and concomitantly stores the information collected during the interaction.

Moreover, in the agent's mind architecture there is a set of rules - Rules for Updating (RU) – that regulates the extent to which the information gathered in the Working Memory is considered useful and reliable for updating the BDNs in the Long Term Memory.

4. Implementation, experiments and results

As an initial step of this study, a basic and general scenario of a social support network simulation was considered with the following assumptions:

- Endowment of Resources: each agent is allotted with a starting set of resources out of a sorted array of possibilities (such as a set of numbers).
- Goal: all the agents have the same goal, which is to consume once all the possible resources in a circular order; every agent can start consuming any resource in the sequence, on the basis of her initial allocation of resources, and reaches her goal when the cycle is complete (e.g. 4,5,1,2,3).
- Actions: at each round agents can perform one of the following actions, defining the elements of the

set $A=\{\text{ALL}, \text{CON}, \text{ARA}, \text{ARB}, \text{SRA}, \text{WAIT}\}$ as summarized in Table 1:

Action	Description
$A_i(\text{ALL})$	agent A_i allocates her resources
$A_i(\text{CON}(R_j))$	agent A_i consumes resource R_j
$A_i(\text{ARA}(R_j, A_k))$	agent A_i directly ask for R_j to A_k
$A_i(\text{ARB}(R_j))$	agent A_i broadcasts a request for R_j
$A_i(\text{BRA}(R_j))$	agent A_i broadcasts her answer about the availability of R_j
$A_j(\text{SRA}(R_j, A_i))$	agent A_j answers directly to A_i about the availability of R_j
$A_i(\text{WAIT})$	agent A_i wait for the answer

Table 1. The set of actions

- Each agent has one BDN since they have only one goal to achieve.
- Regarding the Rules for Updating (RU), each agent has only the following:
 1. The new information collected (via broadcasted communications) in each round updates the BDN for the following round.
 2. Transparency allows agents to observe transactions (of resources) between agents in the environment and update their beliefs in real time.
- Moreover, the set of environmental assumptions, constraints and rules that govern agents' actions and interactions conform to these guidelines:
 1. An agent must give away requested resources when they are not needed by the owner (otherwise, they should be pre-allocated and consumed in the specific rounds).
 2. In each round, every agent can perform only one action.
 3. During a round the order in which agents act is random.
 4. Answering to broadcasted requests prevails over waiting. An agent can answer to one or more broadcasted requests while waiting to a response to her own broadcasted request.
 5. Each agent owns an amount of resources that is at least equal (or higher) to the number of resources needed for reaching the goal.
 6. The total number of resources in the environment is sufficient to allow all agents to achieve their goals.
 7. The set of priority rules refers only to the sequence of the resources to consume.
 8. Every agent has her individual BDN, driving her interactions.
 9. BDNs are consistent and based on believed endowment of resources. Agents know with certainty their own inventory of resources.

4.1. Experiment settings

The environmental constraints can determine how agents interact. In this experiment, four digitally-enabled scenarios are recognized out of eight potential scenarios presented below. The actual reality can be often a mix of these scenarios, which are a result of the combination of the following aspects:

- Whether agents can perform a broadcasting request when they do not know who to ask for a specific resource.
- Whether agents reply to a broadcasted request via an individual response to the requester or via broadcasting.
- Whether information about the resources exchanged in the network is shared among the agents (transparency).

The simulation developed in this study concentrates in Scenarios 3 through 6, as these scenarios are enabled by digital technology and constitute the catalytic force behind sharing economy and collaborative consumption. Broadcasting of responses and transparency are features that can be adopted by digital platforms in the inception phase. For example, listserv groups like Freecycle (<https://www.freecycle.org/>) impose rules on its members such as respond directly to requesters but notify the group when a request is fulfilled. However, little is known regarding the effect of these design decisions on the performance of the network and on the agents' ability to achieve their goals within them. For example, when transactions are not transparent in the network, agents are not able to maintain their BDNs updated and coherent with the RDN during the time (simulation run).

Broadcasting responses (as opposed to respond to requester) can also reduce friction in the social network by disseminating information and unveiling dependency links to third party agents. In this case, broadcasted requests and broadcasted responses can lead to positive externalities.

Lastly, agents can differ in terms of their knowledge about the resources in the network, who has them and who needs them. Agents with better information can benefit from such information as opposed to agents with poor information or no information. In that sense, for each scenario an agent can have her BDN equal to the real one (perfect information) or not (cognitive dissonance). The divergence degree quantifies cognitive dissonance and measures the distance between the BDN and the real one as the number of incorrect links in the BDN.

In summary, the simulation experiment seeks to understand if transparency and broadcasting responses

could have a positive effect on the average amount of time required by agents to achieve their goals, and if there is a correlation between the cognitive dissonance and the time required by an agent to achieve her goal.

Scenario	Transparency	Broadcasting request	Broadcasting answer
1	Disable	Disable	Disable
2	Enable	Disable	Disable
3	Disable	Enable	Disable
4	Enable	Enable	Disable
5	Disable	Enable	Enable
6	Enable	Enable	Enable
7	Disable	Disable	Enable
8	Enable	Disable	Enable

Table 2. Simulation scenarios

The complete simulation environment and agents were coded in Matlab R2016a. For the four simulation runs, a population of thirty agents was generated. Each agent was given an initial inventory of resources as well as beliefs about the initial inventory of every other agent in the population. In addition, each agent has a random degree of cognitive dissonance that spreads from perfect information (ten agents) to significant cognitive dissonance. The initial real and believed inventories were used to derive the real and BDNs for each agent. The total number of agents represent a convenient number of actors of a social support network acting in a local area [59] as well as it provides an adequate sample size for statistical analysis [18]. The same population of agents interacted under each scenario and the divergence degree path over the simulation rounds and the number of rounds required to achieve their goals were tracked. In the next section, the simulation results are described and contrasted.

4.2. Experiment results

Table 3 shows the average number of rounds that took agents to achieve their goals, the average final divergence degree (DD) and the correlation between the initial divergence degree and the number of rounds that took agents to complete their goals under each scenario. The average number of rounds seems to be different depending on whether responses are broadcasted or not but remains stable regardless of the transparency level. Computational times were marginal for all scenarios (under 20 seconds). A repeated measures ANOVA test [31] confirmed at the 0.01 significance level that broadcasted responses had a significant effect on the number of rounds that took agents to complete their goals while transparency was found to be insignificant.

Transparency decreases the average divergence degree in the population while the broadcasting of

responses has the opposite effect. A possible explanation for this behavior is that the final divergence degree is measured at the time that all agents complete their goal, which with no transparency went from 27 to 18 rounds when there was broadcasting of responses. Figure 1 shows the trajectory of agents' divergence degree as the rounds progress. Agents start at the same level for the four scenarios. In Scenarios 3 and 5 (with no transparency) the agents that start with perfect information (zero divergence degree) quickly start losing that benefit and their divergence degree increases almost monotonously. On the contrary, in Scenarios 4 and 6 agents with perfect information retain their advantage throughout the simulation and the divergence degree for all other agents shows a decreasing trend at each step of the simulation. A comparison side-by-side of the divergence degree trajectory without and with transparency indicates that transparency helps agents align their BDN with the RDN; although, such alignment does not correlate with an improvement on the number of rounds to completion of their goals.

Scenario	Average rounds to goal	Average final DD	Correlation DD vs. rounds to goal
3	13.867	1969.867	0.773
4	13.267	716.233	0.799
5	11.267	2466.933	0.703
6	11.567	1050.667	0.810

Table 3. Contrast of simulation results

A third aspect is the quality of the initial beliefs of each agent. The correlation between an agent's initial divergence degree and the number of round to complete her goal is significant at the 0.01 significance level under the four scenarios. The correlation is strong and positive in all cases indicating that the greater the cognitive dissonance, the longer it took the agent to complete her goal. The highest correlation was observed with transparency and broadcasted responses. Interestingly, the lowest correlation was observed with no transparency and broadcasted responses. A possible explanation is that no transparency removes the initial advantage of agents with perfect information while broadcasted response benefits more agents with great initial cognitive dissonance than agents with perfect information. In other words, it reduces (mildly) the advantage of agents with perfect information over agent with poor information.

5. Conclusions and future work

The public perception towards shared services and goods has changed substantially in the past few years

[19]. Cities are becoming breeding grounds for the sharing economy that is driven by emerging and long-standing collaboration activities as well as the widespread availability of ubiquitous information and communication technologies [20]. Social support networks represent a specific instance of collaborative consumption. This paper focused on the information sharing dynamics governing the interactions among the actors in the network, fostered (totally or partially) by the use of digital technologies.

Based on the dependence network theory [21], this research proposed an agent-based simulation model architecture. It also instantiated the model aiming to simulate the information sharing dynamics of a collaborative consumption social support network. Four digital-enabled ideal types of scenarios were defined reflecting the quality and quantity of information that is shared among the agents. The simulation results from each scenario showed that information has a significant impact on the average of rounds that took agents to achieve their goals.

However, not all types of information had the same effect. Transparency is a type of information that did not show a significant effect on the average number of rounds. Nevertheless, it allowed agents with perfect information to retain the quality of their information and other agents to align their beliefs with reality. It was surprising though that reducing the collective cognitive divergence did not improve the wellness of the community measured as the aggregate number of rounds necessary to achieve their goals. On the other hand, broadcasting of responses showed a significant effect on the average time it took agents to complete their goals. An agent's initial quality of information (perfect information versus cognitive dissonance) was highly correlated with the time it took her to complete her goal. The better the information, the faster the agent completed her goal. Broadcasting of responses mildly reduced the correlation between quality of information and time to complete the agent's goal, reducing initial disparities among agents and potentially acting as a social equalizer.

From a practical perspective, the simulation architecture herein proposed could be used for modeling social support networks (e.g. neighborgoods.net and www.freecycle.org), endowing agents with different actions and resources. This allows developing simulations for understanding emerging dynamics and how these complex systems could evolve. This could be also useful for developing sustainable policies as well as for supporting the design process of a specific digital platform. For example, it could be possible to plan and use the simulation model to test the outcome of possible social support policy interventions as well as the requirements for implementing a specific digital platform.

From a theoretical point of view, this paper provides an ABM architecture exploiting dependence network principles. It could be used for describing social support networks as well as the interaction among users in a collaborative consumption scenario. It also could be used for testing and validating an evolutionary model of a network (based on certain set of characteristics) and for building theoretical models of how these networks develop and evolve.

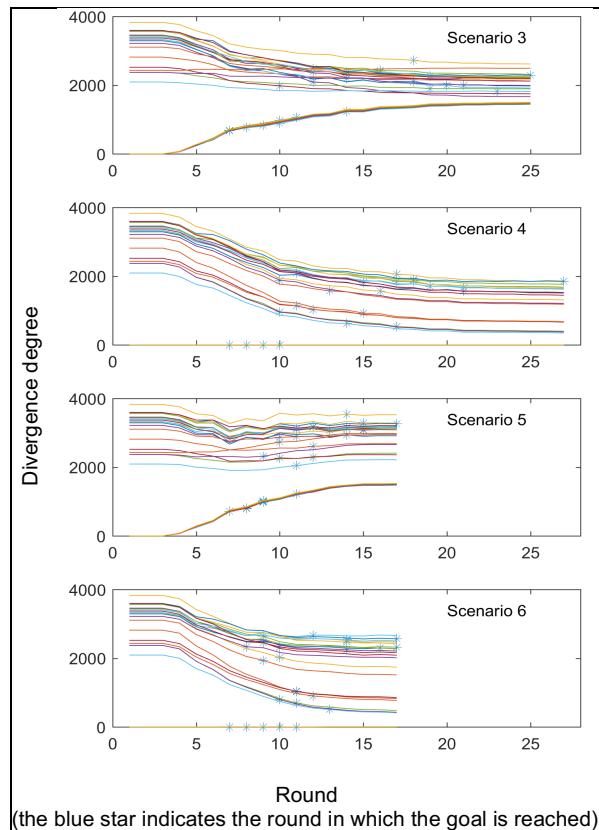


Figure 1. Divergence degree trajectory

While this paper makes a positive contribution to understanding how agent-based simulation can be used to investigate the information sharing dynamics of a social support network for collaborative consumption, it is appropriate to note the existence of limitations in the experiment results due to the parsimonious nature of the simulation instantiation of a small social support network. There is a natural trade-off between the complexity of the simulation experiment and the generalizability of its results. In this case, only a few characteristics (i.e., generic physical assets; no digital resources; one single goal equal for all agents; small set of actions; few agents; etc.) were taken into account for the agents and the environmental settings.

Future research could consider different trajectories for increasing the complexity of the scenario as well as

considering more aspects depicting reality. For example, it could be possible for an agent to provide useful information if she does not have the requested resource, or to distribute the agents into different sub preferred groups based on their likelihood to share information and/or resources (considering aspects as trust and reliability). Another direction for future research could be to allow an agent to learn further actions by other agents. Finally, it could be useful to compare the simulation run of a specific instance of the model with a human based experiment, to explore and analyze behavioral differences.

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