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INVESTIGATING THE EFFECTS OF SOCIAL AND ORGANIZATIONAL STRUCTURES ON INFORMATION SPREAD: A SIMULATION-BASED APPROACH

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Research in Progress

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Abstract

Organizations rely on access to information to deal with environmental uncertainty and to support their decision making processes. Consequently, they implement structural mechanisms and information processing capabilities to enhance the information flow, such as integrated information systems and formal hierarchies. Particularly in environments that are strongly influenced by information and communication technology, the ability of an organization to provide decision makers with useful and trusted information is also dependent on social interactions outside of the organizational hierarchy. This research therefore jointly analyses the effects of social and organizational network structures on information spread for archetypical organizational configurations. Drawing upon literature on information diffusion in social networks and on organizational design, a conceptual model of information spread in organizations is developed. Based on this model, a simulation is built, validated, and a series of simulation experiments is performed. First, the simulation is able to replicate observations from other studies. Second, the results indicate that information spreading patterns in organizations differ significantly, depending on the organizational configuration, the position of a person within this configuration, and the employed communication strategy. Implications and next steps for further, more detailed analyses are eventually discussed.

Keywords: Information flow, Information spread, Social network, Organizational structure, Simulation, Connectivism.

1 Introduction

In today's fast-paced environments, it is increasingly important for organizations to provide decision makers with quick access to trusted information in order to cope with environmental uncertainty and to support their decision making processes (Premkumar et al., 2005). This necessitates structural mechanisms and information processing capabilities that enhance information flow, such as integrated IS that improve information sharing within and across organizational subunits (Trier and Bobrik, 2009). While large-scale statistical studies have long focussed the macro phenomena, such as overall community structures or information diffusion (Bakshy et al., 2012), more recently a better understanding of the underlying micro-level mechanisms has been gained. The propagation of information can be understood as a sequence of interactions between the agents that make up the system (Agliari et al., 2006). Since these interactions are, to a large extent, social processes, an analysis of information spread in organizations should not only take into account organizational structures, but also include informal communities and non-professional social interactions that may affect information behaviour (Trier, 2008). For both types of network, the trust between the agents that exchange information is an important factor for analysing organizational information spread (Droege et al., 2003).

The purpose of this research is to study how information spreading patterns in organizations differ, depending on the organizational configuration, the position of a person within this configuration, and the employed communication strategy. To this end, it draws upon literature on information spread in social networks, a topic that has extensively been studied in the context of online communities. Existing models of information spread in social networks are adapted to the organizational context. The resulting conceptual model is combined with organizational archetypes to derive models of information spread in typical organizations. Based on this, a simulation is developed, validated, and a first series of simulation experiments is performed. The results show that the simulation is able to replicate observations from other studies and provide a promising starting point for further analyses.

2 Related Work

This research takes a connectivist perspective on information behaviour, in the sense that information acquisition, for example in the context of decision making processes, cannot be understood in isolation, but needs to include the surrounding information network of the decision making entity (Siemens, 2005). In contexts that are heavily influenced by communication and information technology, the information that is used by people is not only the knowledge that has been previously acquired and internalized, but also information that can be accessed from other sources during the course of the decision making process. Besides retrieving externalized information from technology artefacts, such as databases, or digital documents, individuals increasingly rely on their social and professional network for obtaining and evaluating information (Puranam et al., 2012). A bounded-rationality perspective helps to explain this phenomenon (Simon, 1991): since, for example, an abundance of information is now available to any individual with access to the internet, the time and effort that is spent on “gathering, interpreting and synthesis of information in the context of organizational decision making” (Tushman and Nadler, 1978 p.614) comes into focus (Puranam et al., 2012). Short deadlines and other constraints prevent decision-makers from exhaustively studying and evaluating all potentially relevant data, thus their ability to make a completely rational decision is bounded by their limited ability to process all available information correctly. Individuals therefore rely on other people to interpret and judge the reliability of information artefacts: ”Since we cannot experience everything, other people’s experiences, and hence other people, become the surrogate for knowledge” (Stephenson, 1998 p.1).

Following DeCanio and Watkins (1998), an understanding of these activities can be achieved by studying the organizational network structure of a firm in combination with the information-processing capabilities of its workers. In addition to the organizational structure, which has been directly linked to information flow in organizations (e.g., DeCanio and Watkins, 1998; Gupta and Govindarajan, 1991; Braha and Bar-Yam, 2004), social networks outside the organizational hierarchy have also been found to significantly influence information flow (Leonardi, 2015). Thus, both social network theory and organizational structure is discussed in this section and reflected in the conceptual simulation model.

2.1 Models of social communities and information spread

Social networks are commonly modelled as graphs, in which each node represents a person and each pair of nodes can be connected by an edge that signifies any type of social interaction or tie between them, including friendship, collaboration, business relationships, information exchange, among others (Newman, 2012; Porter et al., 2009; Agliari et al., 2006). The number of edges originating from a node is referred to as the degree of this node. Research in the field of network science has found that many complex real-world informational and social systems follow network structures that are characterized by power law distributions (Girvan and Newman, 2002; Barabási, 2009; Andriani and McKelvey, 2009). This also holds true for many technology-enabled communication networks so that the behaviour of the participants of such networks has extensively been studied in the context of online communities (e.g., Johnson et al., 2014).

Of particular interest for the analysis of social network graphs are community structures, referring to well-connected subnetworks within a larger network, as this structural property influences information dissemination (Chierichetti et al., 2009). Power laws also describe the distribution of sizes and interconnections of communities in many real-world cases (Girvan and Newman, 2002; Leskovec et al., 2008). A commonly used benchmark was proposed by Lancichinetti et al. (2008), termed LFR benchmark after the authors’ initials, which creates social network graphs that closely resemble real-world networks.

The trust of the person receiving information in the person who is propagating this information plays an important role for influencing the behaviour of the informed individual (De Clercq et al., 2013; Ziegler and Lausen, 2004). Thus, including measures of trust is crucial for correctly capturing the influence of information on decisions (Ziegler and Lausen, 2004). When modelling the dynamics of information spread, i.e., the actual propagation of information over time, many models rely on Susceptible-Infected-Resistant (SIR) models from epidemic spread analysis (Borgatti and Halgin, 2011; Wu et al., 2004). However, in Borgatti's (2005) typology of network flow processes, the spread of attitudes is considered different to the spread of viral infection: a person may continue to influence people who have already received a piece of information (Borgatti, 2005). Thus, models that include trust often consider the state of a node and the interactions between nodes as continuous rather than discrete phenomena.

2.2 Organizational structure

The ability of an organization to provide decision makers with useful information is closely related with the topology of the network of its workers (López et al., 2002). Thus, the study of organizational configurations in general, meaning "any multidimensional constellation of conceptually distinct characteristics that commonly occur together" (Meyer et al., 1993 p.1175), and of organizational hierarchies in particular, has played an important role in organization theory (Fiss, 2007). The formal structure of an organization shapes the formation of knowledge, as, for a given structure, the information processing interactions between members of certain groups are emphasized over interactions with other people (Puranam et al., 2012). De Clercq et al. (2013) find the relationship between trust and internal knowledge sharing within organizations to be negatively moderated by the level of formalization. Lopez (2002), by studying information propagation in tree-like network structures, argues that the traditional hierarchical topologies often found in organizations are poorly designed in terms of information efficiency. Exerting increased control over information flow might, however, have both negative and positive effects, such as a lower cost for information seekers in identifying potential information sources and, at the same time, a lower fit of the acquired information to the information needs (Ariely, 2000).

Instead of exhaustively analysing the potential space of all organizational configurations, this research employs archetypical organizational configurations, following the argument that "organizational structuring can better be understood through the combination of groups of elements into ideal or pure types, which we call configurations" (Mintzberg, 1980 p.323). To this end Mintzberg (1980) proposes five organizational archetypes – *Simple Structure*, *Machine Bureaucracy*, *Professional Bureaucracy*, *Divisionalized Form*, and *Adhocracy* – which have since become an established cornerstone of organization theory (e.g., Dess and Davis, 1984; Doty and Glick, 1994; Fiss, 2007; Miller, 1986).

3 Research Method and Simulation Model

The simulated scenario is that of a new piece of information being introduced into a given organization by a single person. The goal of the simulation is to describe how this information spreads in this organization, including trust, i.e., the extent to which people believe the information to be true and accurate.

Network structures are modelled as directed graphs. Each node P_i is assigned a number T_{P_i} between 0 and 1, signifying the extent of trust of the person represented by P_i in the spread information. If a person has either never received the information or does not trust it at all, then $T_{P_i} = 0$. Links represent directed information sharing between two individuals, i.e. one person provides the other person with the new information or tries to further convince this person. Links are weighted, described by two numbers between zero and one. The first number describes the trust of person P_1 receiving the information in person P_2 propagating the information, denoted as t_{P_1,P_2}. The second number signifies the chance that information is shared by person P_1 with person P_2 within a given time step, denoted as w_{P_1,P_2}. During each time step, the new trust for each node P_i is calculated based on t_{P_i,P_j} and w_{P_i,P_j} for all interacting nodes P_j.

3.1 Social network structure

The LFR benchmarks (Lancichinetti et al., 2008) are employed to generate realistic community structures outside the organizational hierarchy. Table 1 shows the parameters that define the community structure of social networks for this research. A default value indicates that commonly recommended values are employed, which are not varied depending on the organizational archetype, whereas the other parameters will be chosen accordingly. The parameter choices for the experiments presented in this paper are based on the author's interpretation of case descriptions (e.g., Kotlarsky et al., 2008; Becker and Zirpoli, 2003) using the framework of Mintzberg (1980), similar to the process employed by Nan (2011). In addition, parameter variability-sensitivity tests were performed.

The topological mixing parameter μ_t describes the fraction of links of a node that is shared with nodes outside of its community. The lower this parameter is, the tighter will be the communities and the less interaction will take place between different communities. Similarly, μ_w describes the trust towards people from the same community as compared to people from another community. Initially, the community sizes are taken from a power law distribution with exponent β, so that the sum of all community sizes is equal to n and the size constraints $c_{\min}$ and c_{max} hold. In addition, the parameters o_n and o_m are used to randomly select o_n people, which will be members of o_m communities, instead of only a single community.

symbol	Parameter	default
n	Number of nodes	-
k	Average in-degree	-
k_{max}	Maximum in-degree	-
μ_t	Mixing parameter for the topology	μ_w
μ_w	Mixing parameter for the weights	-
β	Exponent for the weight distribution	1.5
t_1	Negative exponent for the degree sequence	2
t_2	Negative exponent for the community size distribution	1
c_{min}	Minimum community size	*(1)
c_{max}	Maximum community size	*(1)
o_n	Number of overlapping nodes	-
o_m	Number of memberships of the overlapping nodes	-

(1): $\boldsymbol{c_{min}}$ and $\boldsymbol{c_{\max}}$ are chosen close to the degree sequence extremes

Table 1. Parameters defining the social network structure

3.2 Organizational structure

Following Mintzberg (1979), organizations consist of five basic parts:

- the *operating core (OC)*, i.e., the employees who produce the basic products and services
- the *strategic apex (SA)*, containing the top general managers and their personal staff
- the *middle line (ML)*, comprising the hierarchy between strategic apex and operating core
- the *technostructure (TS)*, consisting of analysts who maintain and adapt the organization's structure
- the *support staff (SS)*, including people who provide indirect support to the organization

A tree-like hierarchical structure, similar to Lopez (2002), is used to model the internal hierarchical structure of the basic components (see Figure 1). The parameters that characterize this internal structure are listed in Table 2. In addition, a similar set of parameters for upwards and downwards interaction is employed in order to describe the interactions between the different basic parts for each organizational archetype.

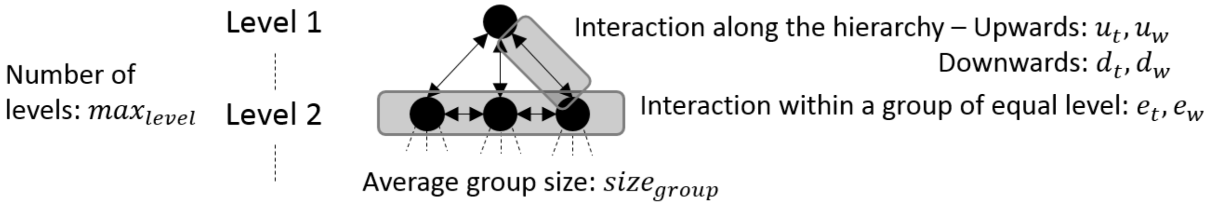

Figure 1. Hierarchical model of internal structure of basic organizational parts

Each organizational archetype is technically described by the parameters shown in Table 2, where ID signifies one of the basic parts. The basic structure is characterized by the number of levels max_{level}^{ID} and the average group size $size_{group}^{ID}$. Usually, information propagated from higher ranks has a stronger impact on lower ranks than vice versa, thus interaction is split into upwards, u_t^{ID} and u_w^{ID}, and downwards, d_t^{ID} and d_w^{ID}. In addition to interacting with their direct superiors and inferiors, people are assumed to interact with all members of the same organizational group at an equal level, e_t^{ID} and e_w^{ID}.

Symbol	Parameter	Symbol	Parameter
n^{ID}	Size of ID	u_t^{ID}	Avg. trust of upwards communication in ID
max_{level}^{ID}	Maximum level in ID	u_w^{ID}	Avg. probability of upwards interaction in ID
$size_{group}^{ID}$	Avg. size of groups in ID	d_t^{ID}	Avg. trust of downwards communication in ID
k^{ID_1,ID_2}	Number of links between ID1 and ID2	d_w^{ID}	Avg. probability of downwards interaction in ID
t^{ID_1,ID_2}	Avg. trust for links between ID1 and ID2	e_t^{ID}	Avg. trust of within group communication in ID
w^{ID_1,ID_2}	Avg. interaction probability between ID1 and ID2	e_w^{ID}	Avg. probability of within group interaction in ID

Table 2: Parameters defining the internal structure of the basic parts

To illustrate this, the two organizational archetypes, *Simple Structure* and *Machine Bureaucracy*, which are used in the results section, are now described. The S*imple Structure,* often found in young and small organizations, has little technostructure and few support staff. Coordination is usually happening via direct supervision and decision-making power is centralized in a small strategic apex. The organizational environment is generally open and dynamic, so the social network of people tends to be strong.

The M*achine Bureaucracy* is characterized as a highly specialized organization, with "routine operating tasks, very formalized procedures and large-sized units in the operating core" (Mintzberg, 1980 p.332). The technostructure is large and influential in this setting, and communication along the line is highly formalized and directed bottom-up.

Table 3 provides an overview of the simulation model parameter choices for this paper. Scaling factors σ and τ are used to describe the influence of the social and organizational networks in an organizational configuration. Parameter choices are based on an in-depth review of the described organizational archetypes, on existing models of social networks from literature and on several test runs.

	Parameter	**Simple Structure**	**Machine Bureaucracy**
Social Network	Scaling factor σ	0.3	0.1
	n	100	1000
	k	10	15
	k_{max}	20	25
	μ_w	0.1	0.1
	o_n	30	100
	o_m	2	2
Organizational Structure	Scaling factor τ	0.3	0.5
	n^{OC} , max_{level}^{OC}, $size_{group}^{OC}$	80,2,9	700,3,15
	n^{SA} , max_{level}^{SA}, $size_{group}^{SA}$	5,1,5	20,2,5
	n^{ML} , max_{level}^{ML}, $size_{group}^{ML}$	5,1,5	80,3,6
	n^{TS} , max_{level}^{TS}, $size_{group}^{TS}$	0,0,0	150,3,6
	n^{SS} , max_{level}^{SS}, $size_{group}^{SS}$	10,1,10	50,2,8
	u_t^{OC}, u_w^{OC}	0.5, 0.5	0.2, 0.2
	d_t^{OC}, d_w^{OC}	0.8, 0.3	0.5, 0.1
	e_t^{OC}, e_w^{OC}	0.5, 0.6	0.3, 0.3
	u_t^{SA}, u_w^{SA}	--(1)	0.2, 0.3
	d_t^{SA}, d_w^{SA}	--(1)	0.5, 0.2
	e_t^{SA}, e_w^{SA}	0.7, 0.7	0.4, 0.6
	u_t^{ML}, u_w^{ML}	--(1)	0.2, 0.3
	d_t^{ML}, d_w^{ML}	--(1)	0.5, 0.1
	e_t^{ML}, e_w^{ML}	0.7, 0.7	0.3, 0.3
	u_t^{TS}, u_w^{TS}	--(1)	0.3, 0.3
	d_t^{TS}, d_w^{TS}	--(1)	0.4, 0.3
	e_t^{TS}, e_w^{TS}	--(1)	0.4, 0.7
	u_t^{SS}, u_w^{SS}	--(1)	0.2, 0.1
	d_t^{SS}, d_w^{SS}	--(1)	0.3, 0.1
	e_t^{SS}, e_w^{SS}	0.4, 0.5	0.3, 0.3

(1): Not applicable, since no hierarchical structure is present

Table 3. Parameter choices for the examples in the results section

4 Results

While experiments for all of Mintzberg's proposed organizational archetypes have been performed, this section is limited to a discussion of *Simple Structure* and *Machine Bureaucracy* type organizations, as these are very different in structure and behaviour, and nicely illustrate the discussed mechanisms. Figure 2 shows the organizational network structures for a *Simple Structure* and a *Machine Bureaucracy*, as well as the social network structure for the same *Machine Bureaucracy* organization – the social network of the *Simple Structure* looks very similar in structure, albeit smaller and slightly less connected.

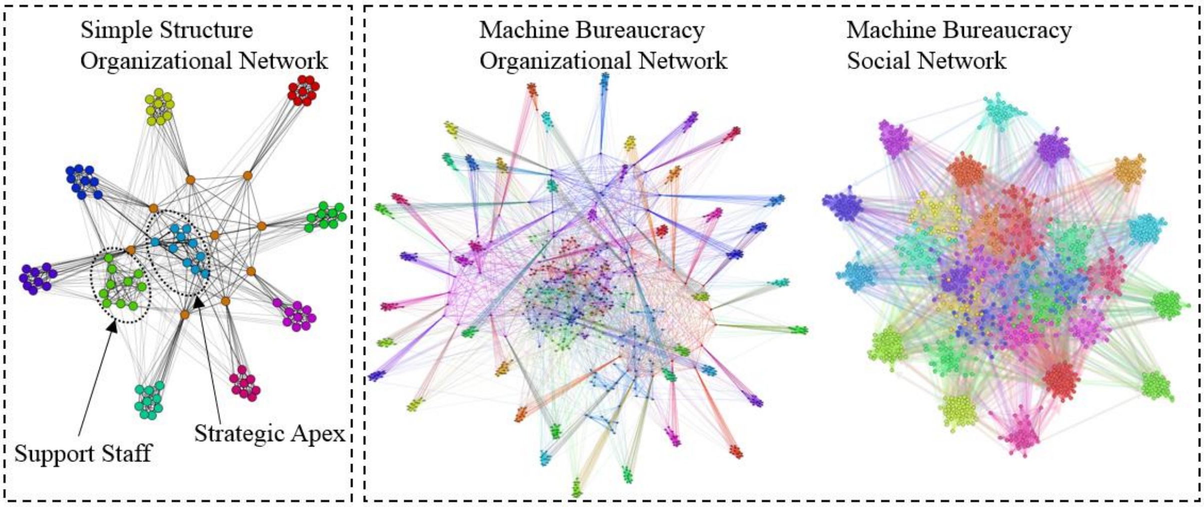

Figure 2. Organizational networks of the Simple Structure and the Machine Bureaucracy, and the social network of the Machine Bureaucracy

A simple visual inspection already shows that these structures are quite different. In the *Simple Structure*, the strategic apex can easily be identified in the centre, surrounded by the first level of the operating core. On the outside are the second level operating core departments and the support staff. The *Machine Bureaucracy* is ten times bigger (n = 1000), more complex and exhibits strong hierarchical structures, with the strategic apex and the technostructure being in the centre. Compared with the corresponding social network structure, the organizational structure displays clearer hierarchies and less interaction between different communities.

4.1 Effects of social networks

In order to adequately recreate information sharing behaviour in organizations, both, the organizational network and the social network of people within this organization should be jointly analysed. Figure 3 shows the results of a series of simulation experiments, in which the social network scaling factor σ was varied. The interpretation of this type of figure is as follows: Figure 3 depicts seven simulation runs, from top to bottom. For each run, the vertical axis describes time steps, the horizontal axis describes different people P_i in the organization (i.e., each bar represents a person) and the colour indicates the amount of trust put in the information that is spread, with blue being zero trust, and red being complete trust ($T_{P_i} = 1$). Thus, the first row of each run resembles the state in which only one person, the initial seed, has the information, and the last row is the final information spread for the simulation run. All simulation runs analyse 30 time steps.

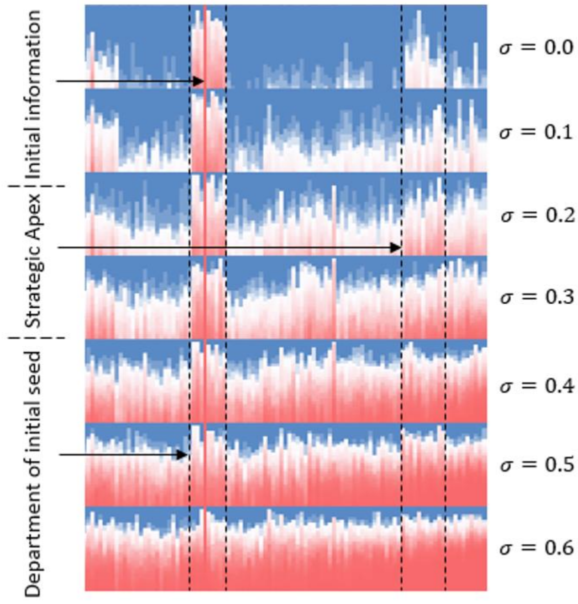

Figure 3. Effects of social network strength in the Simple Structure

In the first row of Figure 3, the social network is completely ignored ($\sigma = 0$). Therefore, we only see the information spread within the department of the original seed, the first-level department managers (leftmost part of Figure 3), and the strategic apex. When gradually increasing the influence of the social network, information spreading better fits the expected behaviour for a *Simple Structure*; the dynamic interaction across departmental boundaries can be seen. If σ is increased to very high levels, the organizational structure plays nearly no role for information spread, which is again an unlikely scenario for real-world organizations. Consequently, a correct analysis of information spread in organizations requires a carefully constructed joint analysis of both social and organizational structures.

4.2 Different organizational structures and initial seeds

Different organizational structures should show different patterns of information spread. Furthermore, these patterns should depend on the position of the initial seed: if the person is in an influential position, the spread is expected to be greater. Figure 4 illustrates this for the M*achine Bureaucracy*: the first two rows show simulation runs, in which the initial seed is in a low-level department of the operational core. The third and fourth rows show the case, in which the initial seed is part of the technostructure, a highly influential part of *Machine Bureaucracies*.

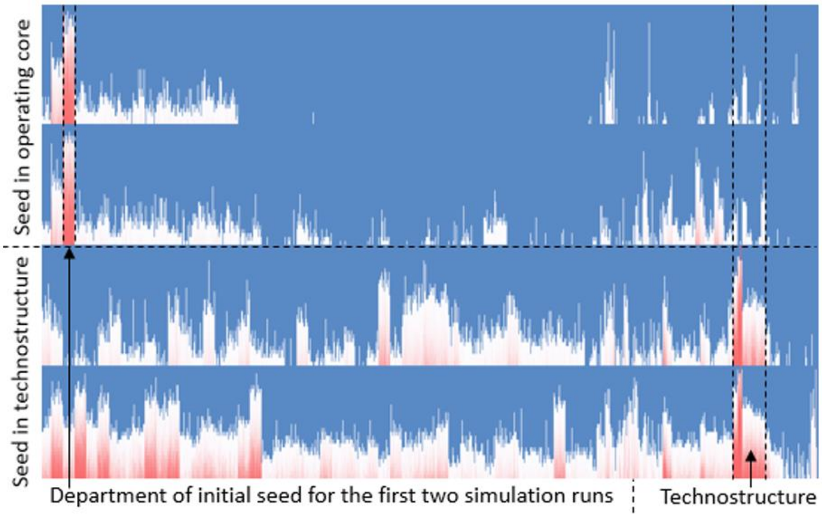

Figure 4. Effect of position of initial seed in the Machine Bureaucracy

First, note that the information spread pattern in *Machine Bureaucracies* is quite different from the *Simple Structure* (compare Figure 4 with Figure 3). As expected, the more rigorous, formal structures prevent information spread outside of the department of the initial seed (Puranam et al., 2012). Second, we can see that an individual in a more powerful position will have a stronger influence on spreading information: the lower two simulation runs of Figure 4 have a significantly higher spread of information than the upper two simulation runs.

4.3 Comparing different communication strategies

In Figure 4 there is a noticeable difference between the last two simulation runs, which in this case can be attributed to randomness. If influential people receive the information early, propagation does noticeably increase. To better understand this effect, a series of simulation experiments, in which the initial seed uses different communication strategies, was performed. The right side of Figure 5 shows the results: the upper three rows are simulation runs, in which the initial seed randomly spreads information, thus results are similar to the fourth row of Figure 3. In the lower three rows, the initial seed targets high degree nodes, which do not yet trust the information, first.

Note that the overall spread of information is significantly higher for the targeted maximum degree strategy. Additionally, a different department gets targeted; instead of the own department of the initial seed, the highly influential strategic apex of the simple structure shows a strong initial increase in information spread. The left side of Figure 5 illustrates this by plotting the average trust in the information over all three simulation runs for each timestep for the entire organization (upper part) and for the strategic apex (lower part): not only does the maximum degree strategy lead to an overall higher information spread in the organization, this effect is also significantly stronger for the strategic apex, being the centre of power in a *Simple Structure*.

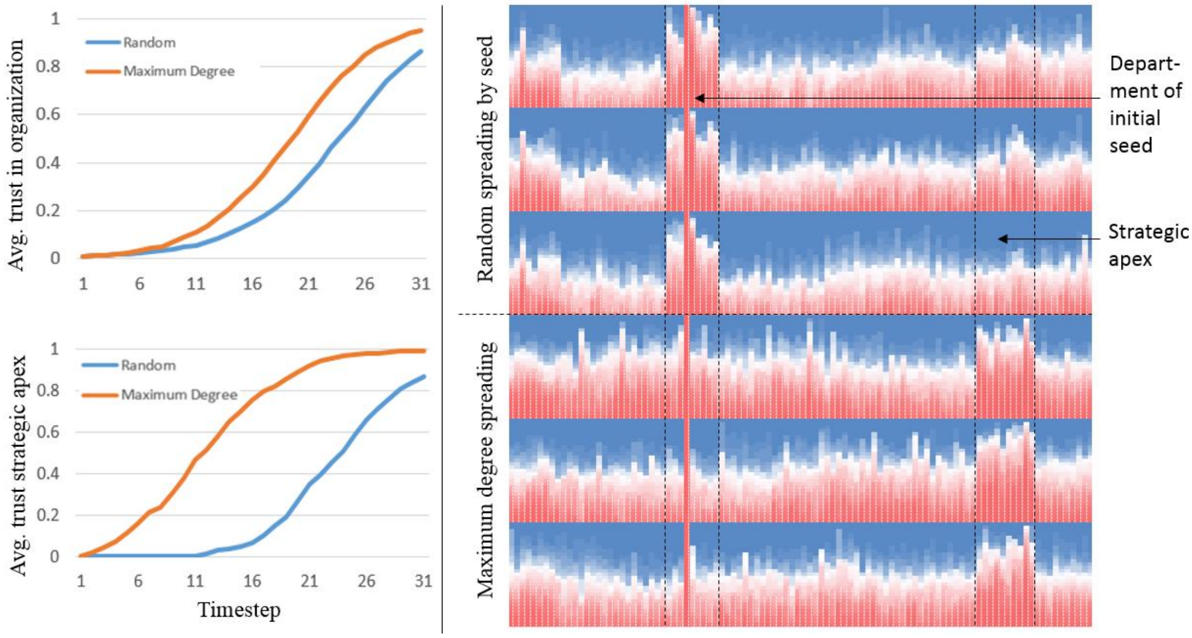

Figure 5. Comparison of communication strategies in the Simple Structure

5 Discussion

This research in progress presents a simulation model, which is based on commonly employed models of information sharing in informal social networks and established organizational archetypes and structures. The results show that the simulation model is able to reproduce findings and hypotheses from previous research: the positive relationship between trust and information sharing is negatively moderated by the level of formalization (De Clercq et al., 2013) – see Figure 3 and Figure 4. Formal organizational structures prioritize information sharing between some agents, over interactions with other agents (Puranam et al., 2012) – see Figure 3 in comparison with Figure 4. Different information spreading strategies differ significantly in performance (Hinz et al., 2011) – see Figure 5. This initial set of simulation experiments thus confirms that information spreading patterns in organizations differ significantly, depending on the organizational configuration, the position of the initial seed within this configuration, and the employed spreading strategy.

The proposed conceptual model of the simulation studies organizations by looking at “patterns of information exchange among the agents […] corresponding to different organizational structures” (DeCanio and Watkins, 1998, p.) in combination with effects from social networks outside the organizational hierarchy. According to Davis et al. (2007, p. 485), “these interactions are often difficult to study with traditional statistical methods or to anticipate with thought processes. In contrast, these processes usually can be computationally represented, verified, and then explored […] using simulation”.

Following recent evaluations of simulation-based research in IS, the conceptual model and the corresponding simulation tool are expected to provide researchers with a useful tool for analysing, understanding, and/or predicting collective decision-making behaviour in organizations (e.g., Beese et al., 2015; Zhang and Gable, 2014; Burton and Obel, 2011). The simulation allows for cross-level and multi-level analyses (Rosseau, 1985), as the multi-level nature of organizations (Klein et al., 1994) is inherently included in the simulation model via the organizational structure: aspects of individuals (e.g., the bars in Figure 5), aspects of groups (see the description of groups in Figure 1), and aspects of the overall organization can be observed in relation to each other. This provides researchers with a valuable tool for studying emergent phenomena in the context of information spread and collaborative decision making, such as the overall effects of specific governance or institutionalization mechanisms in organizations.

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