Promoting organisational emergence in business social networks

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***Abstract*— In this paper complex adaptive systems theory (CAS) and social autopoiesis have been interpreted with the aim to identify factors realising emergent properties in organisations structured as social networks. Understanding the complex dynamics of such communities requires a view of their infrastructure as a network of interacting agents involving both goals and constraints. We analyze the network structure, showing that it defines a complex weighted network with scaling laws at different levels. We also present a simple model of network growth involving non-local rules.**

Keywords - Social Networks; Self – organization; Complex Adaptive Systems; Organisational emergence; Social autopoiesis

I. INTRODUCTION

Looking back there have been a few distinctive technological innovations that have radically changed the way society operates and is able to interact. Johannes Gutenberg's printing press is the earliest example. For the first time knowledge could be shared to a wider population and what this did was take away the control of knowledge from the nobility and transfer it to the general population, this was the first step towards the democracy of knowledge. Radio and television and the Internet are more recent examples but the most exciting step, social networking has just arrived and will once again have a major impact on all elements of society.

The Internet has been around for almost 20 years and has made drastic changes in the way we run our lives and the manner in which we conduct our business. The internet has provided us with a platform to exchange information and create knowledge in exponential quantities. We are however only now beginning to truly collaborate globally in how we exchange and create knowledge.

One place that we are beginning to see this kind of global collaboration and knowledge creation is in social networks. It took radio 28 years to reach a market audience 50 million, 13 years for TV, 4 years for the internet and only 2 years for FaceBook.

More and more of our personal data are making it onto the web every day. From applications as pedestrian as word processing to social networking tools such as Loopt, which allow one to share their GPS location with friends, the web is supplanting the classic Personal Computing paradigm. The smart phone is accelerating this trend. Users expect to be able to view data produced on the desktop while on the go.

Centralized application services have many positive properties. They are easy to use. They make it easy to share. It is fun and easy to discover new friends, to discover who your friends have as friends or to reconnect with old friends. Users do not need to worry about software upgrades as the application provider automatically updates the software as needed. Third party application developers have, through independent development, made these platforms more useful and fun than ever before.

All of this freedom does come at a cost however. The risks created by centralized service providers is worthy of concern, and one can consider that in less than five years a network like Facebook is worth more as a direct mail marketing service than it is as a social networking application. Even worse seems to be the freedom in social networks communication for businesses. With a digitally connected social world in which the line between personal and corporate lives is increasingly blurred, potential risks to businesses also rise. It's clear that businesses need a proactive— and powerfully persuasive—communications plan to educate their user community about social media risks, personal and company impacts, and expected behaviors.

On the other hand, despite the risks, many companies are ill-prepared. To safeguard critical data, mitigate data leakage, and control intellectual property, one must adopt a strategy that leverages the experience and leadership of the business and technology sides of the companies. As an alternate solution, we propose to use in social network management a distributed platform that retains the core functionalities of a centralized service with the additional advantage of returning ownership of the data to the user. The existence of a distributed solution offers consumer choice and puts pressure on centralized services to treat our data with the care and discretion we desire.

II. THE POLICIES AND PROCESSES FOR SUCCESSFUL SOCIAL NETWORKS

As with any policy implementation, the first step concerning social media is to form a business strategy that includes a long-term adoption plan for policies, procedures, and solutions.

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It is essential that the business classify data so that employees understand precisely what is—and is not—sensitive information. This process also should define who is authorized to access and share corporate content, and it should lay out procedures that delineate how employees may use sensitive data. As part of data classification, the business should also establish a data-retention policy for information created on social media.

Policy also must clearly specify who is responsible for particular types of communications; these operational roles typically fall within the marketing and customer service departments. The company also should establish management oversight for social media—both a chief strategist and a community manager, for instance.

When developing roles and policies, the business should include a strategy for employee separation to maintain ownership of intellectual property and social identities.

Establishing these policies is only the beginning, however. The real work lies in behavioral changes of employees. Businesses must educate employees on the need to protect intellectual property and sensitive information, and they should fully detail the consequences of noncompliance for both the company and the individual.

Typically, technology incubated by Computer Science professionals in universities and companies eventually make its way to consumers. Distributed systems have not made this leap. Consumers have the same need to share media with friends over the Internet. We envision that personal servers of tomorrow may become as prevalent as today's personal computers. Obviously we still have a long way to go before today's social applications. The key is to create open high-level distributed programming interfaces and frameworks that enable independent software vendors to create distributed applications that run across these servers.

Privacy, the key factor in our new design, must make possible a new class of viral applications and preserve and even enhance the ability of advertisers to make a profit. Without privacy, an entire class of financial and medical applications will not be accepted. In fact, privacy is also useful for applications involving interpersonal relationships, a particularly viral category. While it is generally accepted that the younger generation has less qualms over making personal information public, few would be willing to make public their negative feelings about other individuals.

Concluding that in turbulent business environments organisations need to react quickly and creatively to make the most of new opportunities and business models, in this paper we consider as a possible solution to reach these new imperatives which require organisations to become more flexible to handle change, the model of complex self-organizing systems, where of key importance in responding successfully to change is the concept of emergence. Complexity science is a way of addressing and improving such capabilities in organisations, as it is concerned with the role of chance, emergence and contingency in the face of frequent and continuous change [1].

In our work factors facilitating organisational emergence have been identified by interpreting complex adaptive systems (CAS) and social autopoiesis theories with the aim of identifying mechanisms or strategies that raise the emergent properties of social business enterprises [2]. Social autopoiesis was chosen as it focuses on social elements of emergence, such as communication, collaboration, morale, trust, etc., whereas CAS theory concentrates more on adaptive mechanisms that make a CAS produce emergent order, such as inter-relations, interconnectivity, edge of chaos, feedback, etc. Based on this a framework has been derived that summarises the so-called factors that facilitate organisational emergence. The framework classifies factors as tangible and intangible, and it differentiates between dynamics, enabling infrastructure and controls, amongst emergence factors. By enforcing factors facilitating emergence and avoiding factors prohibiting emergence, it is argued that organisational emergence will be leveraged leaving space to project teams to innovate and continuously evolve appropriate solutions in order to adapt to an ever-changing business environment.

III. CHARACTERIZATION OF THE SOCIAL NETWORKS AS COMPLEX ADAPTIVE SYSTEMS

Self-organization has been subject of discussions concerning the question of the interrelationship between a system and its environment in various disciplines, apart from DAI (Distributed Artificial Intelligence). The different theoretical approaches have in common that they call any kind of system self-organizing if it is able to determine its internal structure by itself as the environment changes. The boundaries of a self-organizing system and its structure (i.e. the relation between its elements) are not determined by environmental factors. Rather, these systems generate, change and adapt their internal organization within their own logic in a dynamic process to cope with environmental changes. As a result of more recent social theories, the notion of self-organization has become a primitive in sociology when it comes to describe social entities (groups, networks, organizations). In particular in MAS (Multiagent Systems) literature the concept of self-organising MASs has been partially considered by researchers interested in designing the best match among task, environment, structure and performance. A prevalent opinion is that sociological theory can help overcoming difficulties in modeling MAS. In this spirit it is to mention a new sociological concept to the study of self-organization in MAS, the habitus-field theory of Pierre Bourdieu which describe organizations as self-organizing social entities ("autonomous fields") [3].

Most of the work on complexity and the development of complexity theories have been undertaken in the context of the natural sciences and there has been relatively little work on developing or applying such theories in the social sciences. A thorough review of complexity and social autopoiesis literatures is undertaken in this section, based on the work of Alaa [4], with special focus on management-related contributions to extract mechanisms or groupings of factors that are argued will facilitate emergence in social and management contexts. The analysis resulted in a classification into several groupings; dynamics (social construction factors/intangible dynamics and adaptive factors/tangible dynamics), enabling infrastructure (tangible & intangible), and control factors (tangible & intangible). Dynamics are factors that realise emergent properties, the enabling infrastructure include elements that enable the dynamics to become effective, whereas controlling factors attempt to ensure balance of dynamics to prevent descent into chaos.

A. Social Construction Factors/Intangible Dynamics

The social drivers and stimulators that have been suggested as important in facilitating emergent social behaviour are presented as follows:

- The development of autopoietic society requires communication, meaning and consciousness that form an essential driver of emergent behaviour.
- Facilitation of interaction in the development of social organisations put co-operative interaction and relationships at the centre of organisational emergence, which can be achieved through participation, collaboration and team working.
- Local interactions are responsible for new order creation and emergence of global structures.
- The quality of interactions between human agents is a function of the diversity, density, and intensity of those relations. These may be formal or informal, designed or un-designed, implicit or explicit
- Individual motives or intentions and individual emotions and morale act as driving forces for social autopoietic systems influenced by interests, social context and forms of co-operation and collective behaviour towards achieving a specific goal.

Thus, the important social construction factors are communication, collaboration, interaction, trust and morale. These appear to be the important elements of complex social systems as they are responsible for social interactions and stimulation of creative thinking that will lead to human empowerment and leveraging self-organisation.

B. Adaptive Factors/Tangible Dynamics

The dynamic of an evolving social entity is determined by inter-component relationships that outline its form and internal arrangements. Adaptive factors are required to improve the ability of the social system to re-arrange, re-form its structure and quickly respond to change; they include the following elements:

- In a social context each individual belongs to many groups and different contexts and the contribution depends partially on the other individuals within that group and the way they interact.
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- Propagation of influence through social system depends on the degree of connectivity, interdependence and strength of coupling.
- In human systems, connectivity between individuals or groups is not a constant or uniform relationship, but varies over time.
- Complexity thinking is about wholes and complex inter-relationships.
- Difficulties created by the unpredictability of complex human processes and interdependencies are problematic, therefore short-term orientation and simple solutions (simplicity) are likely to result in better outcomes.
- Conditions for experimentation and exploration of possibilities implies small-scale orientation in order to quickly try out various options and get quick feedback without requiring large scale resources and time.

Thus, the adaptive factors reflect the degree of interdependence, connectivity, structural coupling and quick re-formation of internal arrangements. These elements help facilitate fast response and quick, internal adaptation and re-formation of system components.

C. Enabling Infrastructure

Aspects of an enabling infrastructure that facilitates emergence in social contexts include:

- Hierarchy and structure are pre-conditions that enable or inhibit the emergence of new behaviours and working ways.
- Action of organisation members is shaped to a high degree by the existence of specific organisational form and structures.
- Conditions that facilitate the day-to-day management of an organisation, for example management style, are necessary for learning and emergence to occur.
- Analysis of the influence of external factors like power, money and control regulations like contracts and conventions act as constraints that limit social dynamics in complex situations.

D. Control Factors

Complexity theory in social contexts is designed to enable creativity, spontaneity and emergence but it also requires some kind of moderating or control mechanisms, which seeks to balance excessive change with stability, possibilities with constraints, innovation with tradition, etc.

- Change and stability are balanced and the edge of chaos is a critical point of the system, where a small change can either push the system into chaotic behaviour or tip the system back into a stable state.
- Edge of chaos is controlled by equilibrium models which attempt to bound a system to ensure that the system is always pushed back to stable conditions.
- The mechanisms by which complex systems maintain control and achieve certain goals is by feedback, learning and frequent small adjustments to counteract any excessive tendencies to change.
- Continuous reflection, learning and circular causality mutually reinforce social relationships and interactions.
- Simple high-level rules are a way to achieve a balance between dictation and freedom enabling

team members to interact with each other guided by these rules

Based on the above analysis we identify the first grouping of factors facilitating emergence, i.e. dynamics that include those factors that operationalise the emergent behaviour. The factors of a complex social system are also classified into intangibles and tangibles. Intangibles represent the social factors that uniquely characterise social human systems, as opposed to natural systems, whereas tangibles represent the mechanistic/adaptive factors, those elements responsible for the internal connectivity of system components.

The second grouping is the enabling infrastructure that enables or allows the social and adaptive elements to either be effective or inhibited. This includes organisational structure, hierarchies, management style, work culture, leadership, etc. These elements can also be tangible, such as structures, hierarchies and external factors or intangible, such as culture, management style and leadership. The third grouping is control, as in order to facilitate emergent behaviour without complete chaos or anarchy, controls need to be in place and maintained, but they need not to be too restrictive. The different groups and elements of each category are illustrated in Fig. 1 that collates the various factors. It is argued that this forms a useful framework for identifying and understanding factors that facilitate organisational emergence.

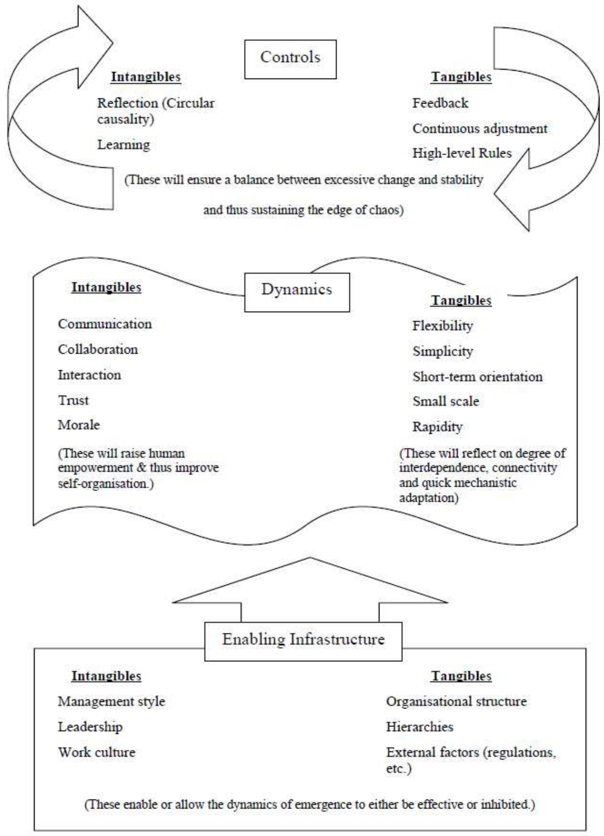

Figure 1. Framework of Factors Facilitating Organisational Emergence

IV. An infrastructure model for social networks

Social network analysis represents agent relationships with nodes and links. Every node i represents an actor *i* within the network and links (*i, j*) denote social ties between agents *i* and *j*. More representative models of social networks decorate each link (i, j) with the strength of the social tie or the amount of information flowing through it, hereafter called link weight $w_{i,j}$. The statistical analysis of link weights $w_{i,j}$ between pairs of vertices in the social network indicates an heterogeneous pattern of interactions, typically following a power law: $P(w_{i,j}) \sim w_{i,j}^{-\lambda}$. In addition, the heterogeneous distribution of link weights might be related to the hierarchical organization of the social network.

We have chosen as specific example for which it is possible to reconstruct the social network, the social network of open source software communities (OSS). This system define a network of interacting agents with very similar features in common, reflecting the presence of limitations in the information shared by agents. It has been argued that decentralization leads to a distinctive organization that solves the communication bottleneck associated to large software projects [5]. The amount of submitted e-mails from one programmer to other members is a good indicator of his social position in the software community. However, not every e-mail message has the same influence in the process of software development. In order to reduce the amount of noise, here we will consider only e-mail traffic associated to bug-fixes and bug reporting. The rest of e-mails are discarded from any further consideration. From this subset of e-mails we can reconstruct the social network of the software community as shown in [6].

Nodes and links (i, j) of the OSS social network represent members and e-mail communication from *i* to *j*, respectively. At any time, a new software bug is discovered by the member i who sends a notification e-mail. Then, other expert members investigate the origin of the bug and eventually reply with the solution. Typically, several messages are required to solve the problem. Here, we define $E_{i,j}(t)=1$ if developer *i* replies to developer *j* at time *t*, or $E_{i,j}(t)=0$ otherwise. We also define link weight $w_{i,j}$ as the amount of e-mail traffic flowing from member *i* to member *j*, $w_{i,j} = \sum_{t=0}^{T} D_{i,j}(t)$ where *T* is the timespan of software development.

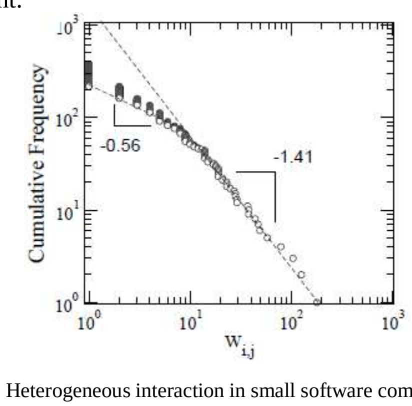

Figure 2. Heterogeneous interaction in small software communities

In fig.2 we put an emphasis in the link weight distributions $P(w_{i,j})$. Here $P_>(w_{i,j})$ is defined as the probability of having a link with weight $w_{i,j}$. In order to reduce the noise in the statistical data, we make use of the cumulative distribution $P_>(w_{i,j})$, defined as $P_>(w_{i,j}) \cong \int_{w_{i,j}}^{\infty} P(\omega)d\omega$. For the standard case where a scaling behaviour $P(w_{i,j}) \sim w_{i,j}^{-\lambda}$ is observed, we have $P_>(w_{i,j}) \sim w_{i,j}^{-\lambda+1}$.

There is a characteristic pattern of asymmetric interaction, where a few strong units dominate the activity of the whole OSS. Interestingly, the distribution of link weights in large software communities also follows a power-law; with an exponent consistent with the observed in the small software communities. Most real networks typically contain parts in which the nodes (units) are more highly connected to each other than to the rest of the network. The sets of such nodes are usually called clusters, communities, cohesive groups, or modules having no widely accepted, unique definition.

In general, each node i of a network can be characterised by a membership number m_i, which is the number of communities the node belongs to. In turn, any two communities α and β can share $s_{\alpha,\beta}^{ov}$ nodes, which we define as the overlap size between these communities. Naturally, the communities also constitute a network with the overlaps being their links. The number of such links of community α can be called as its community degree, d_{α}^{com}. Finally, the size of any community α can most naturally be defined as the number of its nodes. To characterise the community structure of a large network we introduce the distributions of these four basic quantities. In particular, we will focus on their cumulative distribution functions denoted by $P(s^{com})$, $P(d^{com})$, $P(s^{ov})$, and $P(m)$, respectively.

The basic observation on which our community definition relies is that a typical community consists of several complete (fully connected) subgraphs that tend to share many of their nodes. Thus, we define a community, or more precisely, a *k*-clique-community as a union of all *k*-cliques (complete subgraphs of size *k*) that can be reached from each other through a series of adjacent *k*-cliques (where adjacency means sharing $k-1$ nodes). This definition is aimed at representing the fact that it is an essential feature of a community that its members can be reached through well connected subsets of nodes. There are other parts of the whole network that are not reachable from a particular *k*-clique, but they potentially contain further *k*-clique-communities. In turn, a single node can belong to several communities. All these can be explored systematically and can result in a large number of overlapping communities. Notice that in most cases relaxing this definition (e.g., by allowing incomplete *k*-cliques) is practically equivalent to lowering the value of *k*. In the same time any *k*-clique (complete subgraph of size *k*) can be reached only from the k-cliques of the same community through a series of adjacent *k*-cliques (two k-cliques are adjacent if they share $k-1$ nodes) [7].

The algorithm for numerical determination of the full set of *k*-clique-communities is based on first locating all cliques (maximal complete subgraphs) of the network and then identifying the communities by carrying out a standard component analysis of the clique-clique overlap matrix [8]. We use our method for binary networks (i.e., with undirected and unweighted links). An arbitrary network can always be transformed into a binary one by ignoring any directionality in the links and keeping only those that are stronger than a threshold weight w^*. Changing the threshold is like changing the resolution with which the community structure is investigated: by increasing w^* the communities start to shrink and fall apart. A very similar effect can be observed by changing the value of *k* as well: increasing *k* makes the communities smaller and more disintegrated, but at the same time, also more cohesive.

The extent to which different communities overlap is also a relevant property of a network. Although the range of overlap sizes is limited, the behaviour of the cumulative overlap size distribution $P(s^{ov})$ is close to a power law for each network, with a rather large exponent. This remark leaded us to consider that the most suitable topology of a social network is that of a scale free network [9].

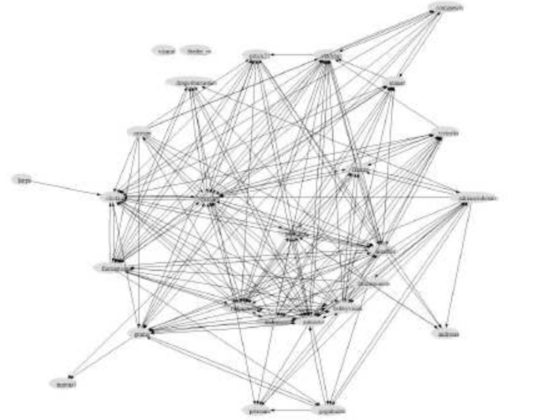

Figure 3. The network of the most influent 27 blogger profiles on Twitter

In order to establish whether sociak networks are indeed scalefree, we determined the degree distribution $P(k)$, which is the probability of finding a node with a degree k in the Romanian Blogosphere (the interconnected network of romanian bloggers). The obtained distribution is indeed scale-free and satisfies the power law with the exponential: $\lambda=2.65$ which satisfies the condition to be between 2 and 3 for a scale-free topology. As expected, the most influent persons in the Romanian Blogosphere will also have accounts on a large social network as Twitter and will keep their superiority there also. From the first 100 blogs, in July 2008, already 27 were also on Twitter. Figure 3 shows the interconnection between these most influent blogger profiles which are also interconnected on Twitter. The scale-free topology following the preferential attachment law is easy to observe.

To determine the connectivity degree of such a network, we have made simulations using Ns2 simulator [910] and the Nam animation tool [11]. Fig.4 illustrates the topology of a free scale network with 128 nodes that started from an initial core of 4 nodes; in the connection of other nodes we have applied the law of the preferential attachment. In fig. 5 is represented the distribution of the connectivity degree from the most connected node till the less connected one, for 4 scale free networks with nodes from 100 to 100000, the similarity being evident.

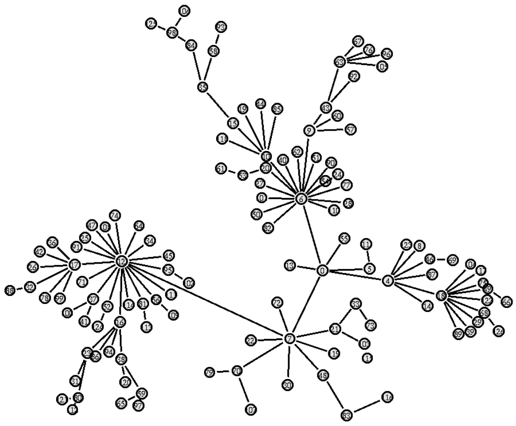

Figure 4. A scale free network with 128 nodes having 5 hubs

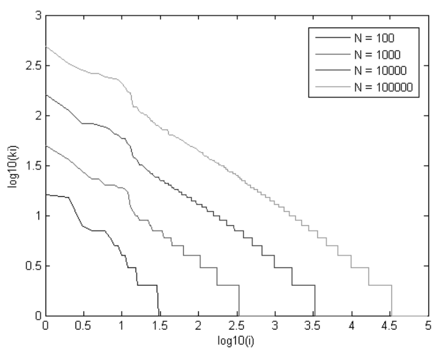

Figure 5. The evolution of the node conectivity for 4 free-scale networks

The specific scaling of the community degree distribution is a novel signature of the hierarchical nature of the systems we study. We find that if we consider the network of communities instead of the nodes themselves, we still observe a degree distribution with a fat tail, but a characteristic scale appears, below which the distribution is exponential [12].

CONCLUSION

In this paper complex adaptive systems theory (CAS) and social autopoiesis have been interpreted with the aim to identify factors realising emergent properties in organisations defined as social networks. Social construction elements, such as communication, collaboration, interaction, trust, etc. are argued to be critical drivers of human empowerment and thus self-organisation, whereas mechanistic, adaptive dynamics like flexibility, short-term orientation, small scale approaches, simplicity and rapidity will ensure fast response and quick adaptation to the problem situation. However, emergence cannot be fully realised without the necessary enabling infrastructure that will allow the dynamics of emergence to become effective, e.g. management style, work culture, organisational structure etc. The elements or factors in each category have been identified and related in a framework, to help understand and analyse the phenomenon of emergence in social organisations.

This framework can be seen as a significant improvement on generic complexity principles suggested in literature, such as diversity, large number of agents, interactions, edge of chaos, etc. that refer to emergence characteristics but without providing a clue on how to realise these concepts in action.

Especially, it is important to notice that the framework represents a holistic approach where the various identified factors are intertwined and some of them may produce counteracting effect. Future research will focus on further validation of the framework through other empirical applications. Especially of interest is to test if the framework does help better understand and manage the emergence phenomenon and put forth intentionally factors that raise the emergence of new work arrangements. Generality and completeness of the framework are also important to test in future work.

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