Mining Sociotechnical Patterns of Enterprise Systems with Complex Networks: A Guiding Framework

ABSTRACT

Organizations worldwide are supporting their processes and decisions with enterprise systems (ES). Large amounts of data are produced and reproduced in these increasingly complex sociotechnical systems, opening new opportunities for the adoption of self-supervised learning techniques. Complex networks are viable solutions to create models that learn from data. This chapter presents (1) a review on the possibilities of networks for self-supervised learning, (2) three cases illustrating the potential of complex networks to address the autopoietic nature of ES: adoption of enterprise resource planning, web portal development, and healthcare data analytics, and (3) a framework to mine sociotechnical patters uncovering the entanglement of human practice and information technologies. For theory, this chapter explains the potential of complex networks to assess enterprise systems dynamics. For practice, the proposed framework can assist managers in establishing a strategy to continuously learn from their data to support decision-making in self-adapting scenarios.

Keywords: Self-Supervised Learning, Complex Networks, Sociotechnical Patterns, Enterprise Systems, Enterprise Resource Planning, Semantic Knowledge, Complex Adaptive System, Autopoiesis Visualization

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INTRODUCTION

Complexity and autopoiesis are inseparable concepts to understand organizational enterprise systems. According to Gershenson (2015) "[a]*utopoiesis can be defined as the ratio between the complexity of a system and the complexity of its environment*" but its measurement and visualization are challenging.

Big data has provided a fundamental ingredient for automatic learning: context data. This new strategic resource for organizations (Yin & Kaynak, 2015) is produced by a diversity of information technologies (IT). For example, enterprise systems (Markus, Petrie, & Axline, 2000; Pollock, Williams, & Procter, 2003), have evolved at an accelerated pace from simple local applications to complex platforms offering proactive support to interplay networks (Panetto et al., 2016). Artificial intelligence (AI) is also developing very fast to create new systems that autonomously learn from large volumes of data and extract behavioural patterns. This semantic knowledge mimics human learning processes and is useful for IT developers, for example, to identify the different dimensions of information systems (Barata & Cunha, 2013) that are more relevant to the organization but also for companies with a need to develop the full potential of their sociotechnical resources (Baxter & Sommerville, 2011).

Sociotechnical complex adaptive system (Vespignani, 2009) describes systems acquiring their form and attributes only from the evolving interdependence. These systems are able to develop adaptability in emergent and self-organizing behaviour within a self-supervised learning process (Sermanet, Lynch, Hsu, & Levine, 2017). Modelling such a complex system comprises the capability to learn from system own data (self-data) and visualize its significance interdependences. However, even with the capability of exploring "all the data" it is virtually impossible to remove uncertainty on learning. Managing uncertainty and the capacity of self-organizing are crucial on any decision-making process.

Complex networks are one of the predominant approaches to learn from data and deal with uncertainty (Mitchell, 2006), providing insights about the self-organization characteristics of a system (Prokopenko & Gershenson, 2014). The two fundamental properties of emergent behaviour and self-organization has demonstrated to be important on complexity modelling and structure understanding. Having its foundations in the field of physics, a complex network is a system of connected (linked) elements (nodes) that allows "*true predictive power of the behaviour of techno-social systems*" (Vespignani, 2009). The nodes that are significant to a complex network and its interrelations can be measured using different techniques such as information entropy (Guo et al., 2020), opening new opportunities to (1) learn from the complex system data, (2) measure its autopoiesis, and (3) graphically visualize its characteristics.

Drawing on the fundamental concepts of sociotechnical complex adaptive system (Vespignani, 2009), this chapter aims to uncover the potential of complex networks to understand and visualize an enterprise system autopoiesis.

The remainder of this chapter is presented as follows. The next section explains the research approach. Afterwards, background concepts to our research are introduced, namely (1) enterprise systems, (2) complex adaptive systems, and (3) complex networks supported in statistical based learning techniques. Subsequently, three cases of complex networks modelling are presented. Based on the literature review and the design process, a framework to measure autopoiesis in enterprise systems is proposed. The chapter closes stating the main conclusions, the limitations, and future work opportunities.

METHOD

Design science research (DSR) has its roots in the sciences of the artificial (Simon, 1996), aiming to simultaneously design innovative artifacts and contribute to scientific advances (Hevner, March, Park, & Ram, 2004). An information systems artifact may "*refers to a system, itself consisting of subsystems that* *are (1) a technology artifact, (2) an information artifact and (3) a social artifact, where the whole (the IS artifact) is greater than the sum of its parts (the three constituent artifacts as subsystems), where the IT artifact (if one exists at all) does not necessarily predominate in considerations of design and where the IS itself is something that people create*" (Lee, Thomas, & Baskerville, 2015). Theory and artifact production must be balanced during the research lifecycle (Baskerville, Baiyere, Gregor, Hevner, & Rossi, 2018; Deng & Ji, 2018).

Our work aims to propose a framework and its development is inspired by the six main dimensions of DSR projects (vom Brocke & Maedche, 2019): problem description; input knowledge; research process; key concepts; solution description; and output knowledge. Figure 1 summarizes the design science research approach following the structure proposed by vom Brocke and Maedche (2019).

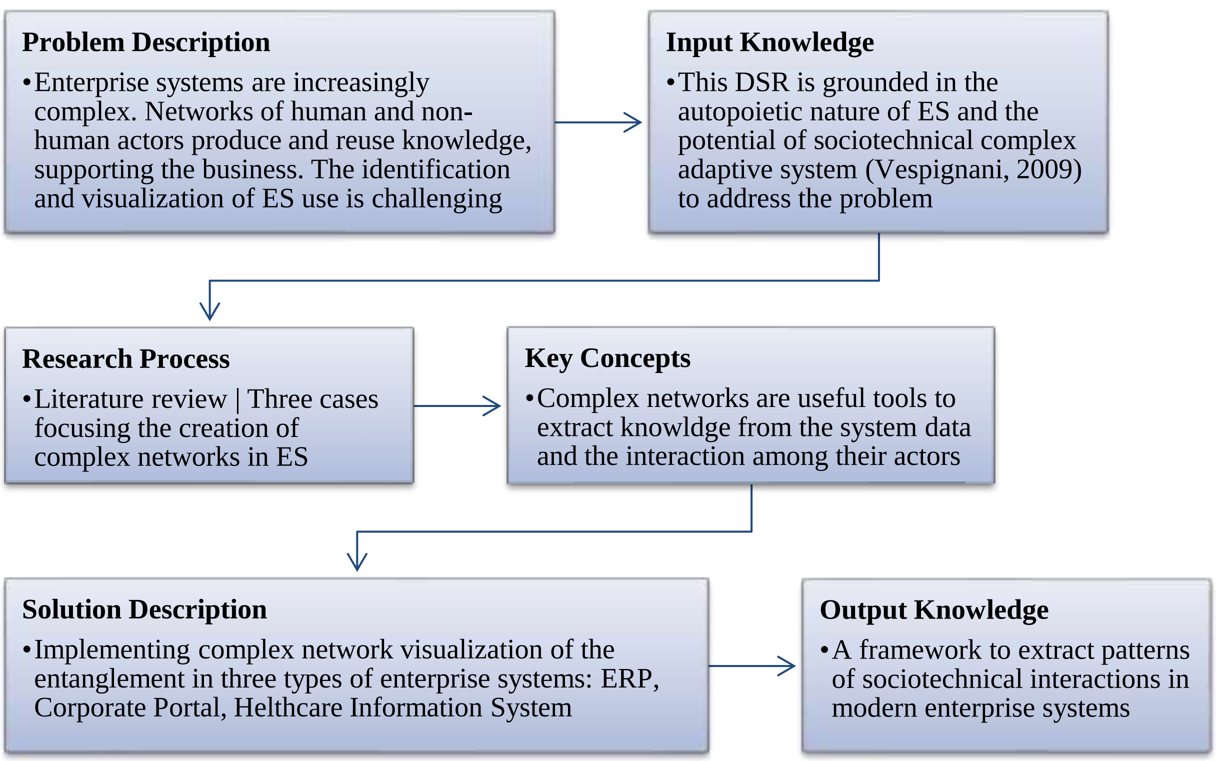

Figure 1. Planning and communicating the design science research approach (Source: Own elaboration following vom Brocke and Maedche (2019)).

The artifacts that are relevant to this research were created and deployed in a major European Healthcare Research Institute. The next section presents relevant literature to guide our DSR.

BACKGROUND

This section starts with an introduction to the importance of enterprise systems in modern organizations and its conceptualization as complex systems. Next, the foundations of complex networks are presented, followed by the techniques to create them.

The Changing Role of Enterprise Systems in Organizations

Enterprise information systems can be seen as a combination of human (e.g. users, assessors, IT staff) and non-human (e.g. packages, services, databases) actors, that interact in "*a network of heterogeneous Subsystems that are continuously changing. Every EIS* [enterprise information system] *is unique to its enterprise. However, it is not the individual subsystems (e.g. standard software applications) but rather a unique network. To be able to connect existing subsystems, an infrastructure that supports a learning, sensing, adaptive and complex network of information systems is required*" (Weichhart, Guédria, & Naudet, 2016).

Traditional enterprise systems such as Enterprise Resource Planning (ERP) systems are common in organizations worldwide. Its integration capacities, interoperability, and the comprehensive offer of modules (e.g. finance, production, sales, planning, human resources) soon captured the attention of managers to support their processes and the decision-making process. However, the capacity to constantly adapt was never an easy task in systems that were sometimes considered monolithic and rigid

(Romero & Vernadat, 2016). On the one hand, companies want to implement standard processes and practices that adhere to the imposed (e.g. legal requirements) or voluntary (e.g. policies, procedures, guides) regulations. On the other hand, companies are constantly changing and also the human and non-human actors of their network are requiring adaptability. This duality is well presented in the work of Marabelli and Galliers (2017) who point to the importance of performative power of actors in transformations enabled by ES.

More recently, some authors point to the "[n]*ext Generation EIS (NG EIS) which is federated, omnipresent, model- driven, open, reconfigurable and aware*" (Panetto et al., 2016). Therefore, it is increasingly difficult to identify the complex interactions that emerge in systems of people and information technologies. On the technology side, for example, it is important to understand which parts of the system are more important to practice and the role in the necessary cooperation between the organizational users. How the use of ES packages evolves over time and how technologies support knowledge creation in the teams? Examples of questions on the social side of enterprise may include (1) how people use the technology to cooperate with colleagues, (2) how the ES "formal" components support the tasks in the organization or changes practices, or (3) what type of knowledge is being generated by the network of human and non-human actors.

The next section presents a theoretical foundation to understand the complex and adaptive nature of ES in organizations.

Enterprise Systems as Complex Adaptive Systems

Multiple non-linear interactions occur within organizational settings and with their environment, producing complex networks of agents that use and produce relevant knowledge, evolving and self-organizing (Anderson, 1999). There are "*four key elements: agents with schemata, self-organizing* *networks sustained by importing energy, coevolution to the edge of chaos, and system evolution based on recombination*" (Anderson, 1999).

Complexity is inherent to enterprise systems that include subsystems linked with several functional areas and organizational users (Schoenherr, Hilpert, Soni, Venkataramanan, & Mabert, 2010). Applying the lens of complexity to ERP systems, Menon, Muchnick, Butler, and Pizur (2019) identified a comprehensive lists of challenges to this type of ES according to the human behaviour, system behaviour, and what the authors named as ambiguity "*which contains emergence and uncertainty*". A previous study focusing ERP complexity over SaaS pointed to the importance of network complexity and its models trying "*to capture the essence of interaction among the many elements in a system, by modelling large numbers of nodes connected by simple logical rules*" (Spiteri, Luca, Reynolds, & Wilson, 2012).

Enterprise systems can mediate individual and collective action similarly to the devices that according to Michel Callon (Callon, 2002) "*lie at the heart of the organization in action and that without them the organization would not exist, as it does, in a location between knowing and acting*". The same author highlight that previous studies "*have paradoxically paid very little attention to the tools used by actors as they organize themselves*", but, more recently, (Fernandes & Tribolet, 2019) also point to the persisting "*lack of artifacts to handle the enterprise self, and consequently with its dynamic self-governing system, responsible for continuously assuring its viability and sustainability, in a fast changing environment* (…) *to better model enterprises as self-observing systems, and not merely as observed systems*".

New models are necessary to extract knowledge from data and understand how enterprise systems are constantly evolving its patterns of action. The work presented by Mansouri and Mostashari (2010) highlights four crucial theories that can be adopted, namely, complexity theories, social sciences theories, systems theories, and network theories. The next section explains the importance of networks in this process.

Complex Networks

Complex networks offer one possible solution to extract knowledge from data produced by the techno-social systems (Vespignani, 2009). This type of network is capable to identify relations between important elements of the system. Each element is a node, which significance is measured through betweenness (the bigger the node more significant it is) (Albert, Jeong, & Barabási, 1999; M. Newman, Barabási, & Watts, 2006; M. E. J. Newman, 2001; Pincus, 1991). Nodes are linked and its interdependency can be modelled by measuring the weight of each connected pair of nodes (the thicker the line more significant it is) (Mitchell, 2006). Finally, a community is represented by colours, each one pointing to groups of nodes that share a common pattern.

An example of a type of complex network is presented in Figure 2, created with the VOSViewer (van Eck & Waltman, 2010), a popular tool for bibliometric analysis.

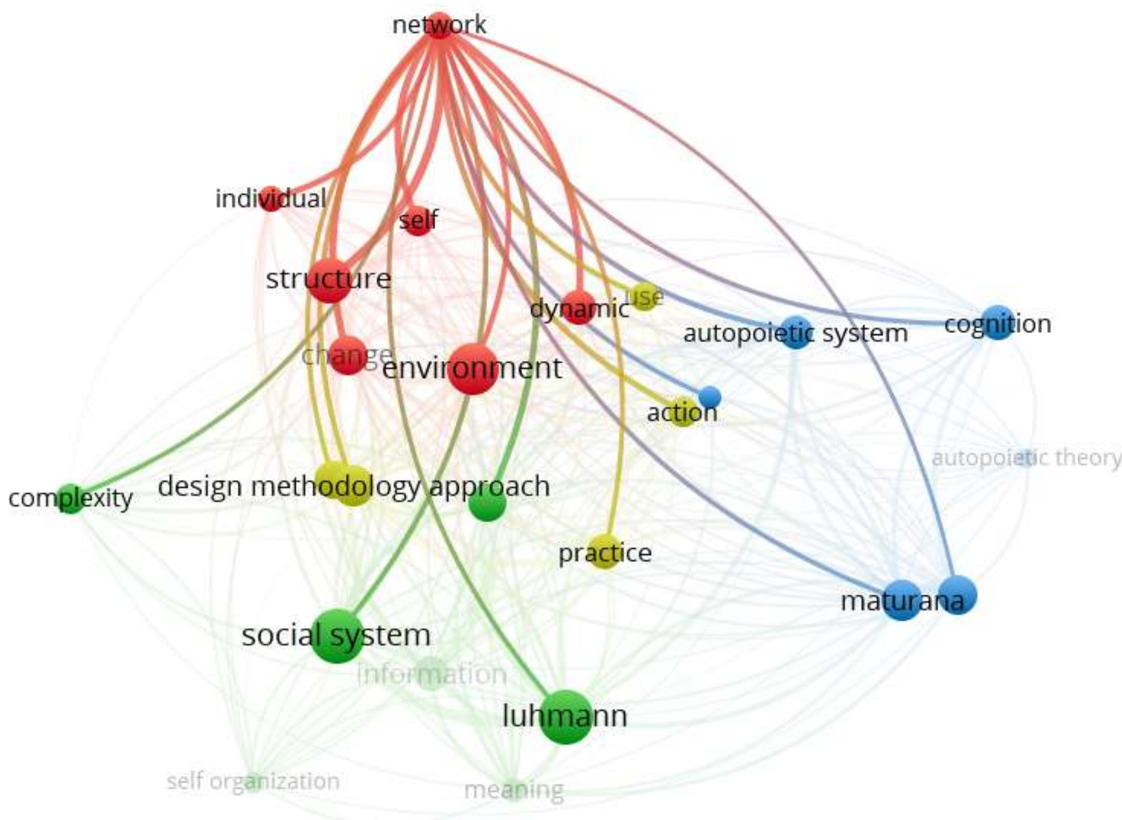

Figure 2. Autopoiesis in management and computing areas – Analysis in Web of Science (Source: Own elaboration using VOSViewer).

Figure 2 was obtained with publications indexed in Web of Science related with the keyword "autopoiesis OR autopoiese", no time restriction, filtering areas related with management and computing (e.g. information systems, computer science). The network presents the most relevant words found in title and abstract (the nodes), according to four clusters or communities. The word "network" appears in the red cluster, with closer connections (links) with the word environment, structure, or dynamic. It is also linked with the word "complexity" (leftmost word on the green cluster). Important authors in the field are also emerging in this network, as well as the main keywords that are related to them. The network includes human (e.g. authors) and non-human (e.g. concepts, approaches) actants and provides an interesting visualization of the literature and how it is reproduced by the knowledge generated in the field.

The same concept can be adopted to data emerging from enterprise systems (e.g. log files, database searches) that consist of large-scale structures of people, and IT infrastructures embedded in a dense network of communications and computing infrastructures, whose enactment defines systems dynamics and evolution (Leonardi & Barley, 2010). To understand the enactment of complex systems is indispensable to characterize its patterns. Resulting knowledge can be used to anticipate, evaluate risks, and eventually manage future developments. Moreover, they allow the conceptualization of the system ought-to-be and the visualization of the emergent and unpredicted interactions that may occur.

Complex network analysis had its origin in the mathematical study of networks, known as the graph theory. However, the complex network analysis, unlike the graph theory, deals with complex real-life networks. Complex network analysis can describe significant properties of complex systems by statistically quantifying and modelling the emergent network topology. Complex network concepts are applied on situations from biology to human creations (enterprises), and social interactions. Some researchers study the individual components while others study the nature of the interactions. However, there is another aspect of the interacting systems, sometimes neglected, but crucial to the understanding of the emergence, which is the anatomy of the connectivity enactment (Barabási, 2016; M. Newman et al., 2006).

Developing Complex Networks

Networks studies started to seize networks as Poisson distributions, resulting in simple random graphs. Moreover, by definition, random graphs in graph theory are graphs with Poisson distribution of connections (Dorogovtsev & Mendes, 2002). At first stage, all networks seemed random, but along the development of the network analysis, some different and fundamental key characteristics are found. Firstly, that form characterizes networks. A network reduces the reality of interactions to a simplified representation through an abstract structure capturing only the basic patterns. Secondly, that statistics such as degree distribution, average path length between pairs of nodes and clustering degree are able to characterize the nature of the interaction (Dorogovtsev & Mendes, 2002).

Knowing the structural or functional model of a complex network has strong implication in the way the complex network behaves. Scale-free networks are an example classified regarding its degree distribution: distribution of the frequencies of the different degrees of all nodes (Albert et al., 1999; Dorogovtsev & Mendes, 2002; Mitchell, 2006). This type of network is used in examples such as the one presented in Figure 2 for citation analysis or in the world wide web (Albert et al., 1999).

Complex networks emerged as a tool for the characterization of structural and functional connectivity (Dorogovtsev & Mendes, 2002). There are different ways of representing, through mathematical notation, such networks, quantifying the nodes importance, structural or functional patterns and the resilience to change of the complex network. For example, the adjacency matrix of a network with elements A_{ij} when A_{ij} is defined, considering 1 if there is a link between the nodes i and j and 0 otherwise. One of the most used network metrics is the degree. The degree of a single node is the number of links of that node. In practice, it is equal to the number of neighbours of the node. Viewed separately, the degree value reflects the importance of the nodes. Viewed globally, the degree represents the degree distribution of the network, determining its topology, which is a central pointer of network expansion and resilience. These basic complex network characteristics greatly influence the complex network models.

Figure 3 illustrates key complex networks metrics (in italics). These metrics are based on the fundamental complex network connectivity properties (bold).

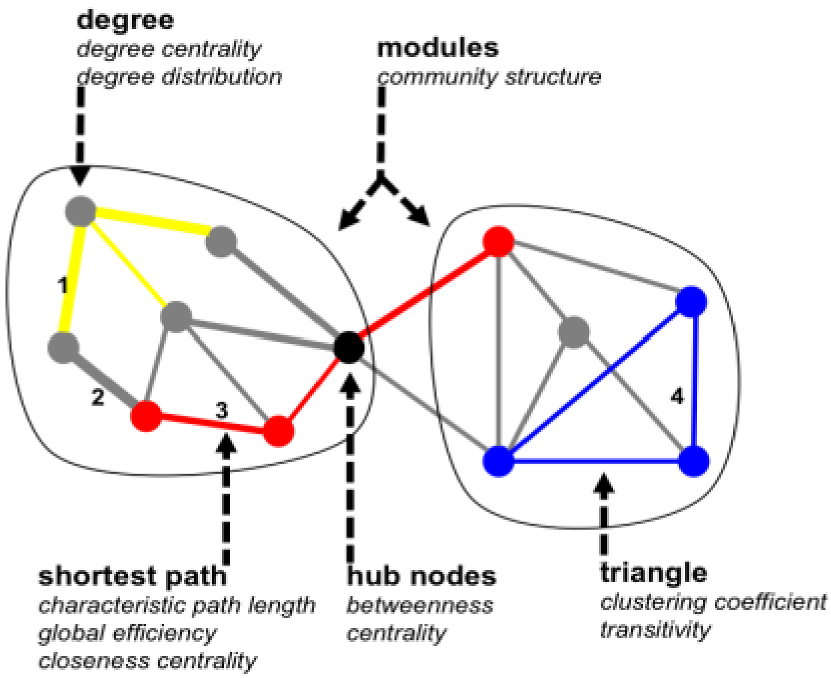

Figure 3. Complex network measurements (Source: Adapted from Rubinov and Sporns (2010)).

The integration base metrics are the shortest path lengths (red)(3). Moreover, the detachment bases it metric on clustering (blue)(4). Detachment can also include more sophisticated patterns metric, such as communities (ovals). The degree illustrates the number of connections of a node (yellow)(1). The degree metric enables the discovery of central nodes in the information flow (hub nodes). Additionally, the length of the path metric determines the global efficiency of the information flow. Measures of centrality are based on the node degree (black) and in the length and number of the shortest paths between nodes (red)(3)(grey)(2). Hub nodes (black) often exist on a high number of shortest paths and consequently often have high betweenness centrality. To illustrate the different representations and variants of a complex network measure is typical to consider a basic and a main metric known as the degree (Dorogovtsev & Mendes, 2002).

The nature of connectivity can be described by metrics:

- To understand how the functional enactment result from structural connectivity;
- To understand the emergent enactment;
- To understand the structural or functional resilience;
- To uncover functional communities and their structural relation.

Moreover, they reveal elements and patterns that play a hidden role in the enterprise system (communities, each one with a particular colour), and at the same time confirming important roles of central elements (hub nodes).

The clustering develops in a process that "a friend of a friend is also my friend", where if the node u connects to the node v, and v connects to w, then u also connects to w. A high number of such triangles imply segregation. The fraction of triangles around an individual node is known as the clustering coefficient (C) (Dorogovtsev & Mendes, 2002; M. Newman, 2010). The clustering (C) is the probability that if a triple of nodes in a network is connected by at least two links, then the third link is also present. Its quantification is illustrated on the equation 1.1 that is the most common way of defining the clustering coefficient (M. Newman, 2010).

$$\boldsymbol{C} = \frac{(\boldsymbol{number\ of\ triangles}) \times \mathbf{3}}{(\boldsymbol{number\ of\ conneted\ triples})} \qquad \textit{(Equation 1. 1)}$$

The numerator factor of 3, in the equation 1.1, arises because each triangle gets counted three times when counting the connected triples of the network. The average clustering coefficient for the complex network determines the prevalence of clustered connectivity around individual nodes. Subdividing the network into such groups of nodes reveals the complex network community structure. The community is defined by the appearance of densely connected groups of nodes (patterns or motifs), with only lighter connections between groups. This represents the maximal possible number of within-group links, and a minimal possible number of between-group links.

The average shortest-path length (li) (closeness centrality) between all pairs of nodes in the network is known as the characteristic path length of the complex network. The equation 1.2 describes the average shortest-path (l_i) for a network of dimension n supposing that d_{ij} is the length of the path from i to j (M. Newman, 2010).

$$\boldsymbol{l_i = \frac{1}{n}\sum_j d_{ij}} \qquad \textit{(Equation 1. 2)}$$

The closeness centrality of a node in a network is the inverse of the average shortest-path distance from the node to any other node in the network. It can be viewed as the efficiency of each node (individual) in flowing information to all other nodes. The larger the closeness centrality of a node, the shorter the average distance from the vertex to any other node, and thus the better positioned the node is in flowing information to other nodes (M. Newman, 2010).

Centrality describes the extent to which a given node connects or can connect to others in a network. It relates with power, influence in decision-making and innovation. Key hub nodes often interact with many other nodes, facilitating functional enactment. Measures of node centrality evaluate the importance of nodes in the above criteria. There are many measures of centrality, however, the degree, is one of the most common (M. Newman, 2010; M. E. J. Newman, 2001). The degree, k, of a node is the total number of its links (Dorogovtsev & Mendes, 2002). The degree has a straightforward interpretation that is: nodes with a high degree, structurally or functionally actively link, in the complex network. The degree is a sensitive measure of centrality in complex networks. The mathematical notation of equation 1.3 represents the degree (k_i), where A_{ij} characterizes the adjacency matrix of a network with n nodes.

$$\boldsymbol{k_i = \sum_{j=1}^{n} A_{ij}} \qquad \textit{(Equation 1. 3)}$$

Metrics of centrality focus on the idea that central nodes participate in many short paths within a complex network topology and consequently acts as important controls of network flow. A related metric is betweenness centrality, defined as the extent to which geodesic paths (shortest-paths) in a complex network pass through a given node. It can be formally expressed, for a general network, through Equation 1.4. The n_{st}^{i} represents the number of geodesic paths from s to t through i, and g_{st} represents the total number of geodesic paths from s to t.

$$\boldsymbol{x_i = \sum_{st} \frac{n_{st}^{i}}{g_{st}}} \qquad \textit{(Equation 1. 4)}$$

It can be used to detect important structural or functional topology through the links that fall between nodes, rather than those nodes that are well-connected. In fact, a node can have a high betweenness centrality and a low degree. Nodes in these characteristics, known as brokers (hub nodes) (M. Newman, 2010), often connect disparate parts of the complex network. Moreover, betweenness centrality as yet another relevant property: its values are typically distributed over a wide range (M. Newman, 2010).

This section provides an overview of fundamental concepts in complex network creation. Although far from extensive, it aims to provide the foundations of visualizing complex networks and the rationale for the nodes and the links involved in the system. Networks are a vibrant field of research with continuous development in techniques and tools for network production. The subsequent section presents real examples of using complex networks to understand the autopoietic nature of enterprise systems and the visualization potential of the tools previously described.

MODELING ENTERPRISE SYSTEMS: LESSONS FROM PRACTICE

Three design cases are introduced in this section. The first case reports to ERP adoption in a major healthcare institute and the complex network development. The nodes include humans (users) and packages of the ERP. The second case explores the front office dimension of the organization with a web portal implementation and the differences between the planned functionalities of the web portal and the surprising adaptations emerging from the effective use in the organization. Finally, a healthcare analytics scenario is used to illustrate the explanatory power and support to decision-making enabled by complex networks of data.

The three situations illustrate different autopoietic observations of enterprise systems phenomena, where the interaction of sociotechnical systems elements is emergent, many times unplanned and unexpected.

Self-Monitoring and Self-Organization in ERP Adoption Scenario

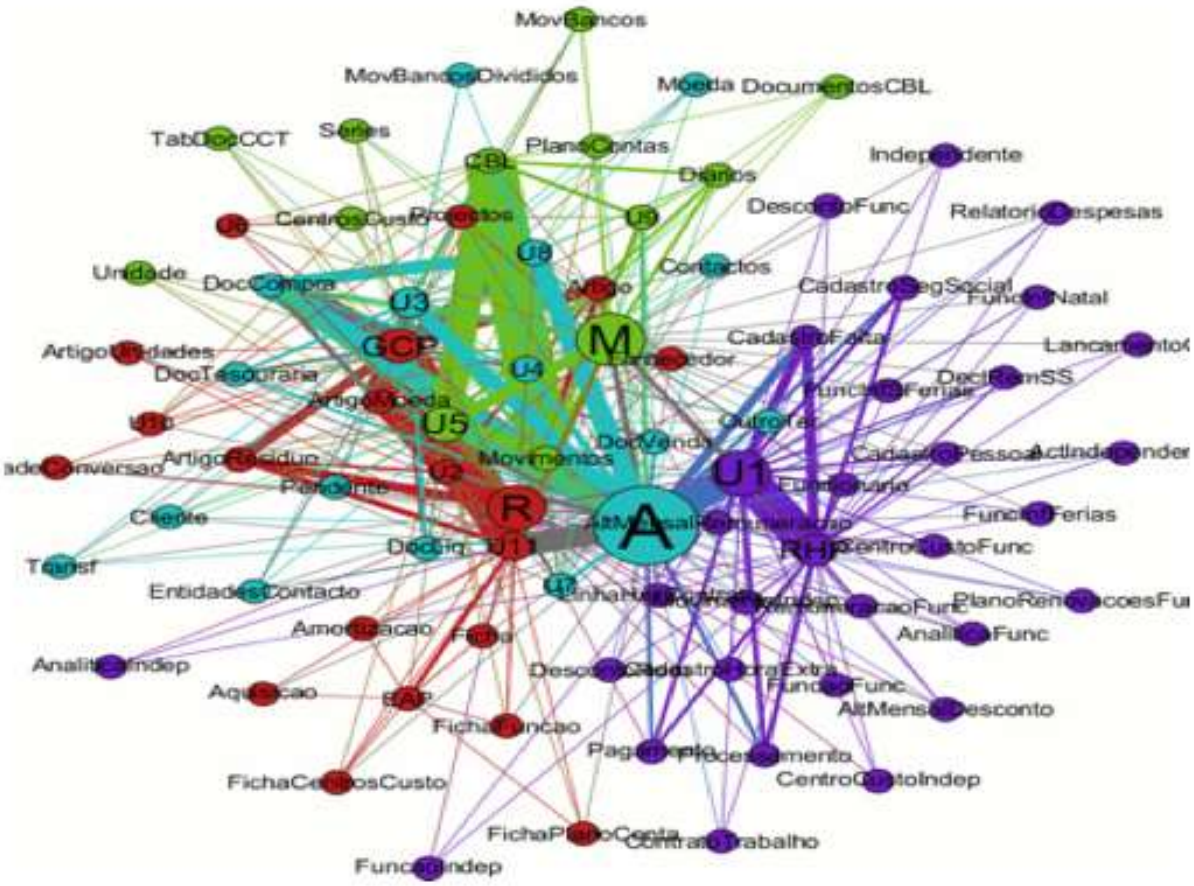

Figure 4. ERP sociotechnical interaction (U labels are users and the other labels are the technological packages) (Source: Own).

The shakedown phase of ERP implementation is one of the most critical for learning and adaptation (Haddara & Hetlevik, 2016). The U labels presented in Figure 4 are human workers, for example U1; the other labels are the ERP technological packages, for example, human resources – RH and its different features).

The nodes presented in Figure 4 reveal the complex interactions between humans (U) and ERP packages that emerge from log file data. The network is generated with machine learning techniques that extract patterns from data produced in daily practice, revealing important interactions for systems development. The interactions revealed an understanding of how and for what the ERP solution was being used for in the organization, as the ERP aimed to be transversal and supportive to all the daily activities. It also allowed understanding of how certain activities were dependant from a specific user, to unfolding bottlenecks on people management and turnover (Sousa & Machado, 2013). One of these cases is the strong interdependence between user 1 (U1) and RH (the human resources package of the ERP).

How people use and adapt ERP packages can change over time. Some potential indications emerging from ERP networks include (1) the most used packages, (2) interactions between the organizational workers using the system, (3) the need of additional hardware resources (most used modules), (4) the opportunities to improve less used packages of the ERP. Monitoring the self-adjustment dynamics over time proved to be an efficient technique to assist ERP adoption and improvement.

The Web Portal Case

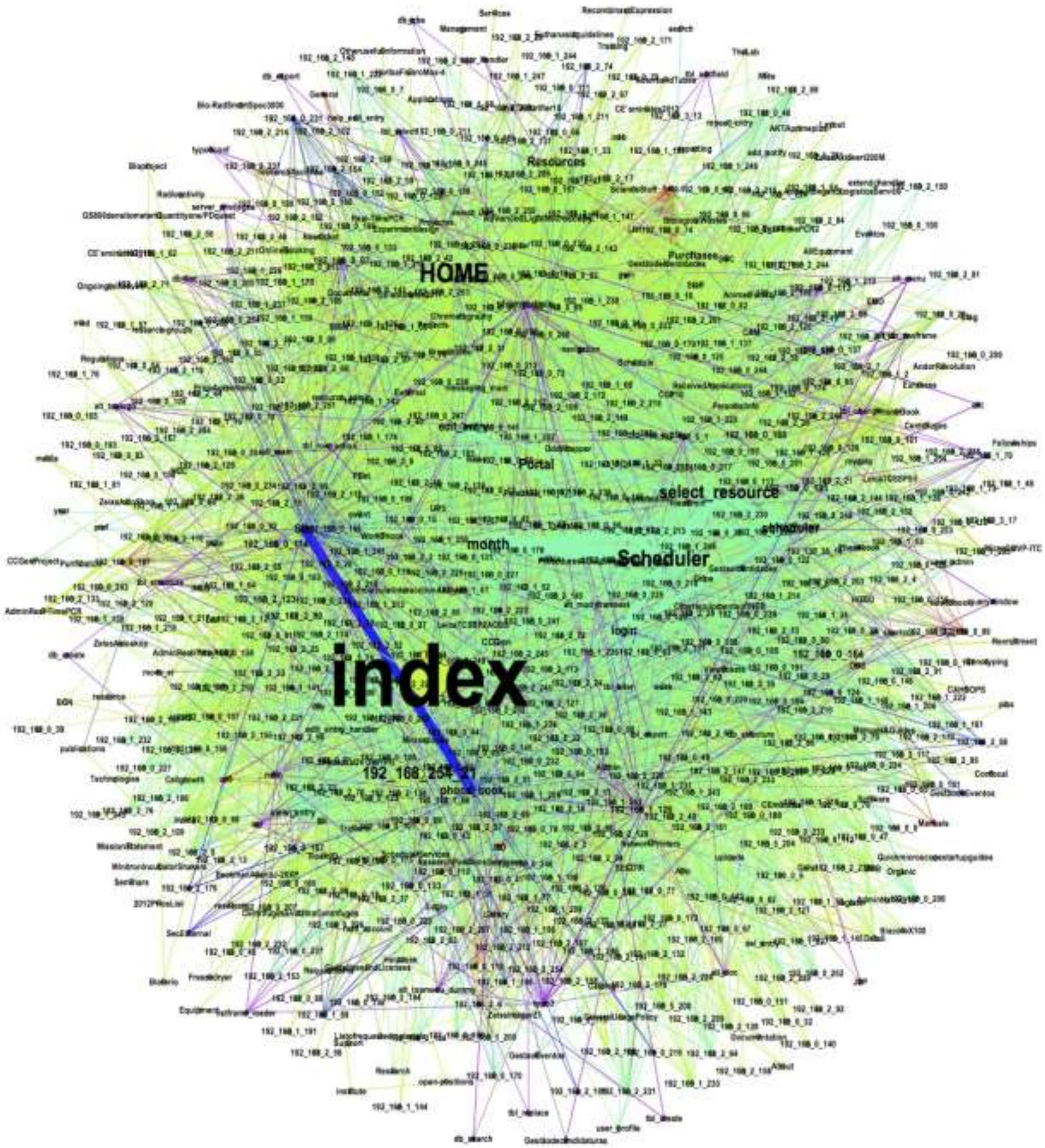

Figure 5. Web Portal sociotechnical interaction (Source: Own)

The Web portal development is another example on how certain tasks are overtaken by others that were considered to be more important at the beginning of the project. The web portal was developed as a structure to schedule the internal use of the available research resources, visible in the figure as Scheduler (node in the middle), however, as the web solution evolved, one of the mostly interdependent functionalities came to be the Phone Book, in relation to the secretariat (Sec node, with the link in blue). The adaptation of IT and business processes by its users (Paul, 2007) can be surprising, as we found in this case. This network reveals that the main investment (schedule) was not achieved in practice, despite the numerous users of the platform (IP addresses are also included as nodes), dispersed by different areas of the portal – and most of them revealing low interaction (thickness of the links) with the different web portal areas.

Healthcare Analytics with Complex Networks

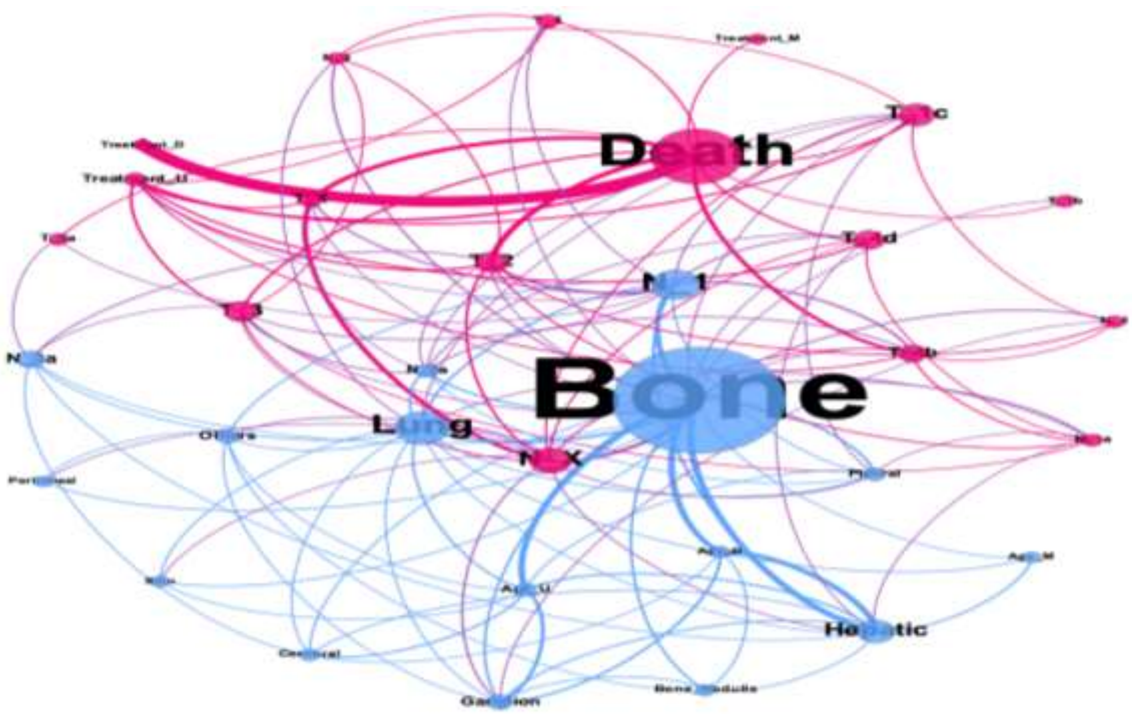

Figure 6. Treatment and metastasis progression in lung cancer (Source: Own).

Complex network analysis in healthcare data has been widely studied (Zhou & Liu, 2009). Figure 6 presents the modelling of the metastasis progression in lung cancer when applying a prescribed treatment procedure. The modelling clearly demonstrates a statistically significant progression effect on bone with the outcome of death relevant in relation to treatment D (when a reduction in the treatment is applied). Some other comorbidities are also identified such as hepatic failures. This visualization of interactions between system elements of diverse nature (behaviour, causes, consequences) can assist decision-making in multiple scenarios.

The three cases presented in this section are representative of the extremely rich and emergent networks in enterprise systems: entanglement of people, technology, and information/data. Being able to understand and visualize the autopoietic nature of organizational systems with complex networks requires a structured approach, as we present in the next section.

A FRAMEWORK TO MINE SOCIOTECHNICAL PATTERNS IN ENTERPRISE SYSTEMS USING COMPLEX NETWORKS

Complex network knowledge structures open the way to discovery and understanding of the dynamics and emergent behaviour in enterprise systems. These tools can provide a rationale for understanding the emerging tipping points and non-linear properties that often underpin the most interesting characteristics of enterprise systems, namely, the interactions of human and non-human actors that produce and reuse information to support the organizational processes and decision-support. We confirmed that these type of systems "*produce and reproduce information and knowledge, and they interact in such a way that the interactions become bound with the continued autopoiesis of the components*" (Pankowska, 2015). Additionally, the visual representation of actors and interactions in clusters may reveal dynamic patterns of action.

Enterprise systems are faced with a need for managing the information flow through space and time in order to support enterprise needs. Modern users are now challenging old fashioned software and technological ubiquity. The attachment enactment modelling through complex networks can contribute to this emergent self-understanding of enterprise systems.

The cases reported in this chapter have a common characteristic: learning from systems data about its human and non-human elements. The framework summarizing the lessons learned in the three DSR cycles is presented in Figure 5. The four steps of the process are inspired in the work of Mansouri and Mostashari (2010) for the governance of enterprise system, where we included the steps for complex network knowledge creation.

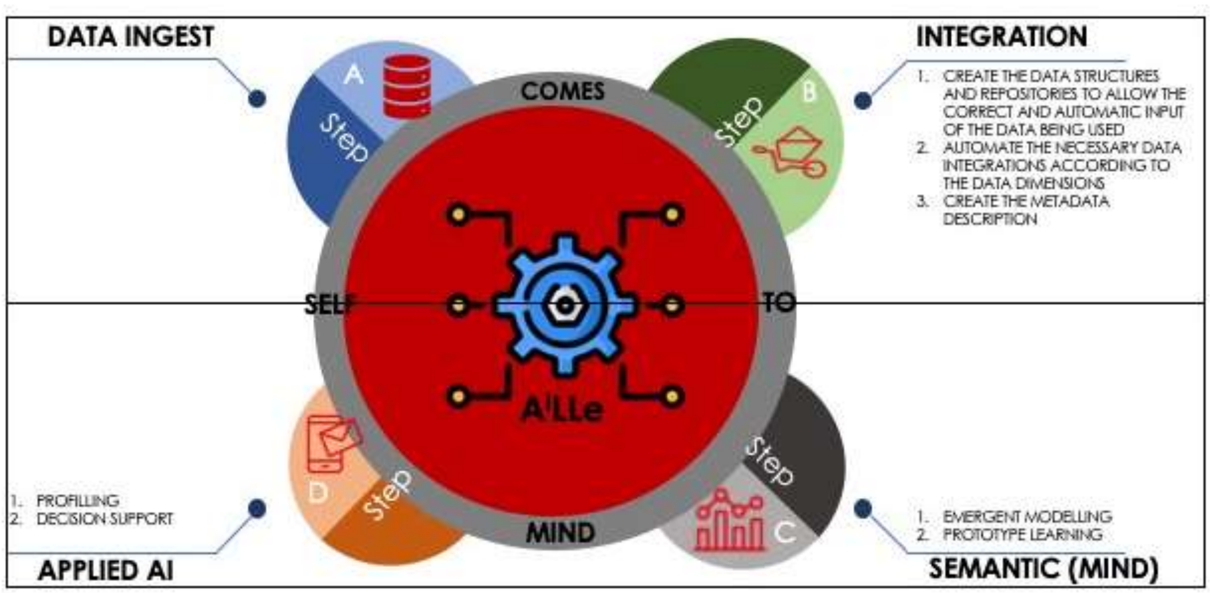

Figure 7 – The modelling framework (Source: Own).

The modelling framework can be described as a cybernetic decision-making process. In this cybernetic environment humans and machines are significantly interdependent to achieve the enterprise common goal. There are four main stages in the production of machine learning using a complex network learning process from self-data.

In the first step (A) an access and evaluation of data to be ingested is done and represents the evaluation of relevant sources of data that are used or produced by the system. Examples of relevant sources of data are the software application logs (e.g., access, Create-Read-Update-Delete (CRUD) operations) and fields of the system database (e.g., timestamps, users characteristics). However, it is also possible to consider other sources to produce IoT-based big data (Luo et al., 2019) such as sensors and software agents. This stage produces an edge list with a qualitative description of the raw data by using a mathematical function to describe each feature (combination of classification values and variable name). The main result is a compressed description of the data which can then be stored in the "AiLLe" cybernetic structure. This is done in a way that allows the data compression stage to be moved to the source of the data allowing its deployment in standard data repositories. This overcomes the traditional security problems with moving data from one system to another.

Then, (B) it is necessary to prepare data for representation in a complex network, for example, using mathematical formulas introduced earlier in the chapter or other recent techniques such as information entropy based on betweenness (Nikolaev, Razib, & Kucheriya, 2015; Pincus, 1991). This step produces the significance and interdependence of the knowledge network where significant nodes will be evidenced, and connectivity weight will be visible. Learning relies on the capability to understand the significance of the data and make sense from it. However, a commonality with deep learning exists, being it, the need to transform it into models of significance interdependence. On deep learning networks those models are developed in a combination of training and evaluation, resulting in a classification model incapable to describe the results significance interdependence. We adopt the notion of complexity and its two fundamental properties, emergence and self-organizing, and translate them into a network of significance interdependence through the measurements of betweenness, communities and connectivity weight. This produces semantic learning with model of the phenomena stored in the AiLLe cybernetic structure and possible to be visually inspected to infer decision-making.

Step C refers to the model development, extracting relevant knowledge about the system structure and to allow reasoning on change and to identify events of significant interdependence. In this step, machine learning aims to capture essential knowledge characteristics capable to support a decision-making inferential process. This task is fundamental as it allows the learning process to build in characteristics of decision-making. The attention development is even more important as it help in overcoming frame problem in machine learning by allowing the management of uncertainty. Reasoning is the last layer in a decision-making process that transforms the lessons learned into actions. A way is needed to allow the cybernetic structure to control actionability and awareness of system change without predetermined thresholds. Inspired by information theory, entropy can be used to measure systems changes and complexity (Pincus, 1991). The entropy when applied to the betweenness significance value in the network model results into a discrete number that can them be stored as a property of that model in the AiLLe cybernetics structure. Entropy value is used to provide AiLLe with a concept of reasoning and decision-making. The processes in this stage are encapsulated as a semantic mind in Step C.

Finally, step D reflection may be useful to support decisions about the system, for example, the introduction of new nodes (e.g. a new feature or software module) that may improve its performance. It provides a profiling structure for the applied AI where the knowledge resulted from the learning process is present to support decision-making.

The AiLLe artifact is the main outcome of our design science research. Multy-cycle DSR projects allow to refine the results at each iteration "*while continuously drawing on the existing knowledge base*" (Sturm & Sunyaev, 2019). Our study reveals the potential of DSR to produce artifacts able to capture the emergent changes in enterprise systems, namely, its most relevant components, boundaries, and emergent interactions (Mingers, 1994). Design is not a mere top-down and externally imposed approach

(Zamenopoulos & Alexiou, 2005), it is necessary to understand its complex nature in modern organizations and produce new visualization tools.

As stated by John Holland, a pioneer researcher in complex adaptive systems, "*changes are usually adaptations that improve performance, rather than random variations*" (Holland, 2006). Therefore, representing the networks of actants and its interactions in the context of enterprise systems evidences its capacity to improve with the existing resources.

CONCLUSION

This chapter explored the autopoietic nature of enterprise systems and presented three cases of (1) understanding and (2) graphical visualization of the most relevant sociotechnical actants and interactions. Our study adopted the lenses of complex adaptive systems and the technique of complex network modelling. The emergent complexity of enterprise systems can be modelled with data that is iteratively used and produced by the system, affecting its structure and self-adaptation. Complex networks provide an interesting visualization and, based on log files and data operations, reveal the capacity of enterprise systems to deal with organizational change.

There are also limitations that must be stated. First, our results focus on three cases of ES adoption, namely, an ERP, a corporate web portal, and a healthcare information system for specific diseases. Other types of enterprise systems and other organizational contexts may reveal different actors and interactions. The analysis is context-specific, and the networks must be applied in particular situations, impeding generalization. Secondly, the networks require data sources and are richer as the system interactions evolve. Therefore, this approach is not useful for the first stages of enterprise systems implementation. The network visualization is helpful in the evaluation of changes within the sociotechnical system. Thirdly, complex networks involving multiple nodes are difficult to read, requiring zooming in concrete zones (for example, portal use by users of a specific department and the customers that benefit from their inputs in the portal). Simpler networks, as happens with the third case that we present, are easier to interpret and may be valuable communication tools (for example, with patients and trainees). Finally, the framework that we present in this paper seems applicable for complexity modelling of enterprise systems, requiring additional research to other forms of autopoietic systems. Therefore, recognizing the limitation of generalizability in our DSR, we highlight the importance of projectability, which "*provides a language to understand how design theories and design principles, as prescriptive constructs, imply intentionality for operation in other places or times*" (Baskerville & Pries-Heje, 2019).

Several opportunities for future work are identified. First, researchers can explore how the knowledge obtained by the complex networks can assist self-adjustments or risk warnings. As stated by Ray Paul, an information system "*is what emerges from the usage and adaptation of the IT and the formal and informal processes by all of its users*" (Paul, 2007). Complex networks are not able to capture all the IS complexity but highlight some useful aspects (actants significance and relevant interactions among them). Second, ES developers could create new models to visualize complex networks of data. Third, it was interesting to evaluate complex networks over time and identify patterns of change. Some patterns, for example, a drastic increase of interactions between specific users or, conversely, a strong decrease in the use of an ES module may reveal disturbances in the system – the ES may be self-adjusting to new conditions such as different demands from the market or problems in parts of ES that need attention.

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