Towards Real-time Static and Dynamic Profiling of Organisational Complexity

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Abstract: In this position paper, I argue that although the definition and quantifiable metric for organisational complexity may still be controversial, it is possible to capture structural aspects of complexity in both static and dynamic forms. Based on Kannampallil's theoretical framework for computing complexity, it is proposed here that complexity, in an aggregate sense, can be evaluated in terms of (i) the number of components (NoC) there are within a socio-technical organisation and (ii) the degree of interrelatedness (DoI) between these components. Given these variables, it is then possible to characterise complexity in terms of simple, complicated, relatively complex and complex profiles. These profiles serve as useful toolkits for indicating the complexity level a team, a department or the entire organisation is at for useful interventions or insights to be made. Adapting the ideas of Pentland, I also argue that with technological advances in Information Systems, organisations are now able to capture relational or social network data with relative ease, to construct useful network and complexity maps of individuals, teams and organisations in real time.

1 INTRODUCTION

Wherever coordination of tasks and resources are involved, there almost always exists an element of complexity. The degree to which this complexity varies depends on a number of factors, e.g. the intellectual cognitive load required to complete the task, the experience of the person doing it, the number of entities (e.g. machines, people) required to coordinate them, etc. In organisations, decomposition of structure, tasks and responsibility is usually required to ensure efficient and effective completion of tasks to achieve organisational goals. In projects, meticulous coordination is required for tasks, resources, scheduled and cost so that the project can be completed within quality, time and budget. Although the colloquial meaning of complexity is often accepted as being "not simple" or "more than complicated", complexity is understood in different ways, not only in different fields, but has also different connotations within the same field (Mitchell, 2009).

According to Manson (2001), research in the science of complexity may be categorised broadly as either of the three: (i) "Algorithmic complexity" – which deals with deriving complexity of a system by appraising the difficulty ascribed to describing system characteristics by using mathematical complexity theory and information theory; (ii) "Deterministic complexity" – which stipulates, using chaos theory and catastrophe theory, that the entire system may become de-stabilised or inactive due to the interaction of certain few key variables; and (iii) "Aggregate complexity" – which posits that complexity can be understood by observing how individual agents interact and work in concert with each other in the system to create complex behaviour. In this paper, I focus on aggregate complexity because I consider the organisation as a larger system that comprise smaller sub-systems such as social, technological and group-level. I contend that the former two streams of complexity study do not adequately suit organisational systems. For instance, interactions between knowledge workers and organisational entities (e.g. computer systems) are diverse, rich and experiential. Therefore, information theoretic measures, which generally identify complexity as the simplest computational algorithm that can reproduce system behaviour (e.g. Shannon's entropy measure (Shannon, 1948)), are over simplified. Deterministic complexity is also marred by several limitations,

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particularly in its applicability to social phenomena (Mitchell, 2009).

In the following sections, I discuss the definition of complexity used in this paper, a proposed framework for computing aggregate complexity and how it is possible for organistions to capture and profile it in real-time.

2 EXAMINING AGGREGATE COMPLEXITY

For the purpose of this study, I define complexity in terms of one of the most salient concepts postulated by aggregate complexity – *the interrelatedness of components of a system* (Kannampallil et al., 2011). According to Kannampallil et al. (2011), complexity of a system is relative in the sense that complexity is a function of the number of components (NoC) and the degree of interrelatedness (DoI) within the system. This definition is in congruence with others in the field (Manson, 2001; Bar-Yam, 2006; Johnson, 2007; Mitchell, 2009). In other words, as both variables increase, so does complexity of the system. It is also important to note that while increasing the number of components may make the system "complicated", it is the degree of interrelatedness, or in other words the unique relationships (both manifest and latent) that makes the system "complex". As a consequence, the interrelatedness of system components results in properties that characterise complex systems (Bar-Yam, 2006), these properties being non-decomposability (that systems cannot be understood by focusing on components in isolation), emergence (where unexpected behaviour arises as a result of component interactions), nonlinear behaviour (characterised as non-predictability and non-proportionality of behaviour) and self-organisation (where individual actors take on different structural positions so the system can be maintained). Accordingly, by combining ranges of extremes for both variables, there can be four conditions (although not postulated in a prescriptive or exhaustive manner) to characterise the range of complexity as in shown in Figure 1.

Firstly, there are simple systems with few components and low interrelatedness (1), whereby the system along with its behaviour is easily predictable, understood, managed and described. For instance, an individual accountant who runs his own practice by himself may only have few components, such as patients, notes and computer, and relations

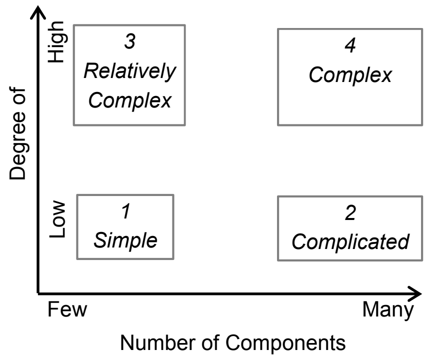

Figure 1: Range of Complexity (Kannampallil et al., 2011).

(interaction with computer, customer and stationery). The accountant is considered to be in a very simple system. Secondly, systems with many components and low interrelatedness (2) are also in many cases, quite predictable to a certain extent because of the low interrelatedness. For instance, a receptionist in a firm who handles many phone requests and relies only on the computer booking system. Thirdly, relatively complex systems have few components but a high degree of interrelatedness (3). Such systems can be studied as a "whole" because of its few components but high level of interrelatedness – e.g. section of an emergency hospital department where members are few but the interactions are quite diverse. Finally, complex systems are systems exhibiting high degree of interrelatedness and many components (4), e.g. multiple employees from varying organisational units attending to multiple victims in a disaster-struck area.

In light of the framework proposed, one cannot deny the importance of context. According to Herbert Simon (1996), "one cannot study the complexity of a system without specifying the content of complexity". Therefore, while context is important, Simon also argues that a complex system may be decomposed wherever possible, into smaller functional components, characterized by the interrelatedness between them. Thus, while the number of components is easily computable, the question remains as to what constitutes "interrelatedness" precisely.

Drawing on closing remarks from Kannampallil et al. (2011), "…complex systems can typically be considered in terms of functionally smaller components and the relations between them, based on theoretical, rational, and practical considerations….There often is a structure in the relationships that exist between care providers, artifacts, and patients….As such, it is possible to characterize it as a network of actors, where (at a high level of decomposition) the nodes are actors (or artifacts) and the edges are their relationships." Although no single operational definition of the construct, interrelatedness, is offered, I argue that there are two salient measures in network science, in social networks analysis particularly, that might help develop an operational definition of the construct.

Firstly, interrelatedness connotes a meaning of cohesiveness and integration. That is, given a system which can be represented in the form of a network, what is the current number of connections, as opposed to the maximum possible. In social network parlance, this is specifically referred to as the *density* of a given network (i.e. ratio of existing ties to the theoretical maximum) (Wasserman et al., 1994). The second important measure that taps into aspects of interrelatedness is *inclusiveness,* which refers to the number connected actors within the network. In other words, it is the total number of entities or actors or nodes minus the number of isolated ones (Scott, 2000). So if we consider a social network of 10 actors, with 5 isolated actors, inclusiveness would be 5. However, in order to allow for standardization and comparison across several networks (similar to the density measure), it is useful to express inclusiveness as a proportion of the total number of actors within the network. Therefore, using the example above, inclusiveness expressed as a proportion of the entire network would be 0.5, with the range being 0 to 1. Therefore, while inclusiveness represents the connectedness of individual actors within a network, density captures the extent to which the connections are current as compared to the latent. So while inclusiveness is a measure based at the actor level, density is about the extent to which the actors are connected and is situated at the tie level. The notion of inclusiveness is a useful indicator of social network membership as well group dynamics (Mitchell et al., 1980; Pfeil et al., 2009) and can thus be used in conjunction with the density measure as a proxy for interrelatedness. The following section describes how complexity profiles can be constructed by using these measures.

3 COMPLEXITY PROFILES – SO WHAT?

Consider a knowledge-intensive organisation such as a hospital emergency department. It comprises doctors, specialists, nurses, managers, and other hospital staff members. In effect, this can be considered as a social system. The hospital also cannot function without its technology such as computers, specialist equipment, beds and so on. We term these artefacts as being part of the the technological system. Therefore, this healthcare socio-technical system (which can be represented as a'network'), the doctors, patients, specialists and nurses are treated as 'components' of the network. Artifacts, such as beds, healthcare technologies, used by the patient or by the medical professionals within the patient's network, are also deemed as components of the network.

If we use the mean value of the 'number of components' and the mean value of the 'degree of interrelatedness' as points of segregation on the x and y axis of the framework respectively, the range of complexity can thus be categorized into 'simple', 'complicated', 'relatively complex' or 'complex' clusters or profiles. These profiles can then be associated with a myriad of dependent constructs or variables such as the coordination of care of the hospital, patient waiting times, length of patient queues, which are in a sense aspects of operational performance and indirectly, organizational performance. When sufficient historical data is then collected, one may use the data to fit to whatever model one is interested in observing or testing.

With the notion of this conceptual modelling crystallised, applying the same type of modelling to other domains and disciplines become only a matter of what phenomena one is interested in studying. For instance, one may be interested to understand the aggregate complexity level one's project team is at. In the context of Information Technology (IT) development projects, although there are a myriad of well-structured project management processes and frameworks such as Extreme Programming, PRINCE II methodologies and so on, complexity at an aggregate level is hardly captured or examined. At the minuscule level, task complexity may be measurable; for instance, COCOMO II and Lines of Code techniques allow for one to establish just how complex a software program is. Another example would be the number of dependencies a task has to and from other tasks within a project plan. In Critical Chain Project Management, resource dependencies are also accounted for along with the normal constraints of quality, time and cost. While current tools and methodologies are fairly efficient in capturing such complexity, it does not account for it holistically. Therefore, a model that accounts for human-level, organisational-level, group-level and technological-level factors is needed. The following example shows how aggregate complexity can be captured at both a micro (e.g. individual level) and macro (e.g. organisational) level.

Micro Level: At the individual-level, one can construct complexity profiles of social-professional networks of knowledge-intensive workers, that can be used to associate with individual performance or decision making (Chung et al., 2013). Taking the example of a general practitioner as a knowledge-intensive worker, one can ask him or her to list a finite (e.g. up to 15) number of contacts who are important to her in the provision of care. One can also ask her to elicit the relationship amongst the contacts she provided, thus completing the entire socio-professional network (see Figure 2). Once this is done, mean values of the distribution of number of contacts (i.e. components of the network) and the mean values of the distribution of density and/or inclusiveness of connections (i.e. degree of interrelatedness) can be derived to define cut-points for the complexity profiles. These profiles can then be associated with social and professional outcomes such as performance, coordination and decision-making. That is, patterns of performance or decision-making for various profiles can be compared (e.g. simple vs. complex) for further insights, useful for intervention mechanisms.

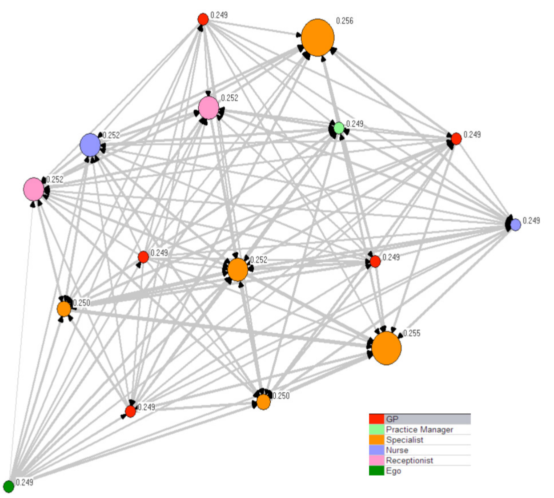

Figure 2: Example network map of knowledge intensive worker (ego's network indicated in bottom left green colour).

Macro Level: If one wants to understand aggregate complexity at an organisational level, it is also possible to account for interdependencies beyond the individual by accounting for interdependencies between individuals, departmental units and organisational units and so on, at specific points in time. Reverting back to the example where one wants to understand how such macro-level complexity may be used to indicate or even provide a sense of prediction about its impact of overall organisational or operational performance, I consider a hospital emergency department (ED), to illustrate. Here, patients, doctors, human resources and even artifacts, such as beds, healthcare technologies, used by the patient or by the medical professionals, within the boundaries of the ED, can be deemed as components of the network. Therefore, in this case, each tie would depict a form of connection, be it an interaction between the computer and the nurse, or a communication that took place between the doctor and the patient, or the utilization of the bed by the patient. In general, one may treat these relations as simply "interdependencies". One can then start obtaining a distribution of NoC and DoI variables at various points in time. Once this is obtained, complexity profile cut-points can then be obtained from the distribution and complexity profiles can be obtained and individual cases can be plotted against these profiles (Figure 3).

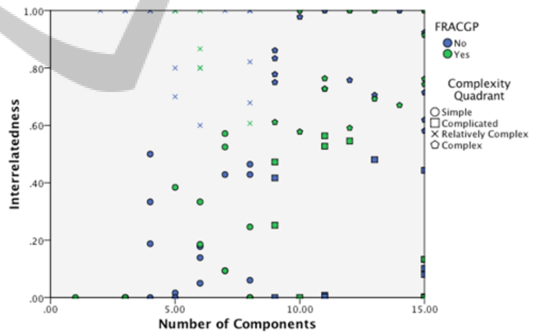

Figure 3: Example Plots in Complexity Profiles.

4 DYNAMIC COMPLEXITY

Much of the description of how aggregate complexity can be captured detailed above pertains to static states. In other words, it is analogous to taking snapshot of the number of components and interdependencies amongst them within a social or organisational system at any point in time. Similar to how movies are essentially multiple frames of snapshots put together, I argue here that dynamic complexity is simply capturing various snapshots of the interactions occurring within the system at various points in time.

Professor Alex Pentland's (2012) from MIT

Media Labs pioneered the use of wireless tags that captures relational information as well as body language, including tone, volume and pitch, from the communicator. The tags, whose size is similar to those of name cards can be worn like any ordinary ID card, are unobtrusive in nature. It ubiquitously captures the 'when', 'who', 'whom' and 'how' of the communication but not the 'what'. In other words, it does not capture content. Therefore, at any point in time, it is possible for the communication pattern of individuals to be captured. Furthermore, with the use of Radio Frequency ID tags also available these days, it is possible for these tags to be used to capture relational data, particularly when individuals deal with non human resources such as computers, machines, and so on. Pentland used the patterns of communication captured to associate with individual and team success. In reality, the association can be made with other social phenomenon such as creativity, coordination, etc.

In a similar manner, reverting back to the example of the hospital ED, it becomes possible for us to understand how organisational complexity associates with operational performance such as patient queues and waiting times. Here, one would capture the organisational complexity of the ED as a whole, having these tags in place in both human and non-human resources. This enables us to capture all relations and interdependencies at various points in time. It is also important that at these points in time, data relating to the dependent variables - patient queues and waiting times, for instance, should also be recorded. To illustrate, the relational snapshots can be taken at every 3 hours in a 24 period, yielding 8 data points. If one does this for a week, there would be 56 data points and for two weeks, 112 data points. A distribution of the NoC and DoI can then be computed, and the mean values for each of these variables can serve as the relative cutpoints for the complexity profiles to be obtained. In this manner, one can compare which organisational complexity states perform better (e.g. when at the 'simple' profile or at the 'complicated' profile) in terms of operational performance.

5 CONCLUSIONS

Complexity is still a controversial topic, one that is multi-faceted in epistemological stance, in definition and in oeprationalisation. In general, literature in complexity studies can be categorised in to deterministic, algorithmic and aggregate complexity. In this position paper, I focus particularly on aggregate complexity and argue that it is possible to capture structural aspects of complexity in both static and dynamic forms. Based on Kannampallil's theoretical framework for computing complexity, it is proposed here that complexity, in an aggregate sense, can be evaluated in terms of (i) the number of components (NoC) there are within a socio-technical organisation and (ii) the degree of interrelatedness (DoI) between these components.

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REFERENCES

Bar-Yam, Y. (2006). Improving the Effectiveness of Health Care and Public Health: A Multiscale Complex Systems Analysis. *American Journal of Public Health, 96*, 459-466.

Chung, K. S. K., Young, J., & White, K. (2013, 25 - 28 August). *Towards a Network-enabled Complexity Profile for Examining Responsibility for Decision-making by Healthcare Professionals.* Paper presented at the International Symposium on Network Enabled Health Informatics, Biomedicine and Bioinformatics, Niagara Falls, Canada.

Johnson, N. (2007). *Simply Complexity*. Oxford: Oneworld Publications.

Kannampallil, T. G., Schauer, G. F., Cohen, T., & Patel, V. L. (2011). Considering Complexity in Healthcare Systems. *Journal of Biomedical Informatics, 44*(6), 943-947.

Manson, S. M. (2001). Simplifying Complexity: A Review of Complexity Theory. *Geoforum, 32*(3), 405-414.

Mitchell, M. (2009). *Complexity: A Guided Tour*. New York: Oxford University Press.

Mitchell, R. E., & Trickett, E. J. (1980). Task Force Report: Social Networks as Mediators of Social Support. An Analysis of the Effects and Determinants of Social Networks. *Community Mental Health Journal, 16*(1), 27-44.

Pentland, A. S. (2012). The New Science of Building Great Teams. *Harvard Business Review, 90*(4), 60-70.

Pfeil, U., & Zaphiris, P. (2009). Investigating Social Network Patterns within an Empathic Online

Community for Older People. *Computers in Human Behavior, 25*(5), 1139-1155.
Scott, J. (2000). *Social Network Analysis: A Handbook*. London: SAGE Publications.
Shannon, C. (1948). A Mathematical Theory of Communication. *The Bell System Technical Journal, 27*, 379-423.
Simon, H. A. (1996). *The Sciences of the Artificial*. Cambridge (MA): MIT Press.
Wasserman, S., & Faust, K. (1994). *Social Network Analysis: Methods and Applications*. New York: Cambridge University Press.