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Beyond Macrocognition: The Transaction Level

Jan Maarten SCHRAAGEN[a],
[a]TNO/University of Twente, Soesterberg/Enschede, The Netherlands

ABSTRACT
The purpose of this paper is to respond to a number of developments in the past 15 years in the areas of NDM and macrocognition. In my view, these developments necessitate the definition of a new systems level, extending and modifying Newell's (1990) "bands of cognition". I will argue that what has been called 'microcognition' may best be viewed as a field compatible with the 'cognitive band', whereas 'macrocognition' is compatible with Newell's 'rational band'. Recent developments in various fields necessitate the introduction of a next systems level, the 'transaction level'. I will discuss the interconnection amongst the various levels. Several studies using social network analysis are discussed that illustrate the utility of adding this new level to our current repertoire of methods.

KEYWORDS
Theory and modelling; Macrocognition; Cognitive systems engineering; resilience; general.

INTRODUCTION: STATE OF THE ART

As a movement, NDM consists of applied researchers who are interested in how professionals make decisions in real-world situations, with the goal of supporting these professionals through decision aiding and training. Although NDM has broadened its scope under the flag of macrocognition to include other processes than 'decision making', its focus is still 'cognitive'. From the beginning, the focus of the movement has been on experts rather than novices, and on real-world situations rather than the controlled world of the laboratory. Although this has led to numerous insights, such as the Recognition-Primed Decision Model (Klein, 1993), theoretical progress seems to have halted over the past years. The reason for this state of affairs, it seems to me, can be traced back to a single a priori assumption that governs the practice of NDM, namely that expertise is a cognitive and knowledge-rich phenomenon. This assumption is shared by many others in the cognitive science and AI community as well, and goes back at least to the early 1970s where psychological studies of expertise demonstrated the importance of knowledge over general cognitive processes (e.g., Simon & Chase, 1973) and the early 1980s which saw the rise of the « Knowledge-is-Power » hypothesis in AI (Lenat & Feigenbaum, 1991). It is in line with Simon's (1981; 1991) views on the adaptability of artificial systems, which states that systems that are completely adapted to their environments (and experts are a prime example of those systems) will not show any of their architectural constraints. It is not possible here to flesh out the complete history of this view nor all of its theoretical ramifications or supporting empirical evidence. This view, however, leads to a subtle problem, already noted by Simon (1980), in that adaptive or artificial systems will change as their environment changes. Therefore, it is difficult to discover and verify empirical invariants in these systems, as any laws that govern their behavior must contain reference to their relativity to environmental features. As noted by Simon (1980, p.36) : « It is common experience in experimental psychology, for example, to discover that we are studying sociology—the effects of the past histories of our subjects—when we think we are studying physiology—the effects of properties of the human nervous system ». In other words, when NDM studies expert behavior, it will mostly describe the environments the experts adapt to, rather than any invariants in expert behavior itself. This may easily lead to a rather anecdotal, domain-specific, and atheoretical state of affairs within NDM, where the primary breakthroughs come from the study of a novel domain that has not been studied so far.

Simon goes on to state, however, that we should not despair of finding invariants. Rather than looking for absolute invariants, as the physicists do, cognitive science should search for relative invariants that hold over considerable stretches of time and ranges of systems : « What is invariant in adaptive systems will depend on the time intervals during which we observe them » (Simon, 1980, p. 36). Simon then mentions three time scales on which adaptation takes place : the shortest time scale in which heuristic search takes place ; a longer time scale in which learning (storing and retrieving knowledge) takes place ; and the longest time scale during which social and biological evolution takes place, in the form of discovery of new knowledge and strategies and the transmission of one system to another.

Newell (1982, 1990) has later expanded on this view by taking the time scales Simon (1980) described as his starting point. Newell (1990) distinguished a biological, cognitive, rational, and social 'stratum', each defined by a particular time band during which processes take place. For instance, the typical cognitive processes take place between 100 msec and 10 sec and the typical rational processes between minutes and a few hours. However, Newell (1982) went one step beyond Simon and equated these time scales with system levels that occur in nature

(in his 1982 article, Newell confined these system levels to computer system levels, but it became apparent in his 1990 book that he meant these system levels to apply to all biological and artificial systems).
In the next paragraph, I will expand upon the notion of 'system levels', as I believe that the introduction of a new system level could bring significant advances to the study of artificial systems, going beyond macrocognition and current views of NDM.

SYSTEM LEVELS

There are many definitions on what a 'system level' is. According to Newell (1982), a true system level is a reflection of the nature of the physical world, not simply a level of abstraction. It should be a specialization of the class of systems capable of being described at the next (higher) level. Aggregation occurs within each level and does not take us to the next level on its own; meaning should be added and some things therefore become invisible at the next level (this is another way of saying that phenomena at higher levels have emergent properties). Therefore, although the levels are ontologically irreducible to each other, each level may still be implemented at the next lower level.

Note that this view of system levels is quite different from what we normally take to be 'units of analysis'. For instance, the distinction between micro, meso and macro levels (individual, group, organization) is not a true system level description, in Newell's definition. For instance, Karsh, Waterson, and Holden (2014) proposed 'mesoergonomics' as a way to specify macro- and microergonomic integration. Their aim was to reveal cross-level interactions and to describe relationships between and among levels rather than describing phenomena that emerge from their components but that cannot be explained by them (Hackman, 2003). For instance, Carley and Newell (1984) described what a Model Social Agent would look like, in an attempt to make an individual agent behave like a social agent. They concluded that a Model Social Agent could be obtained by minimal requirements on information processing capabilities but with major extensions in the types and amount of knowledge required. Note this is a matter of aggregation and does not take us to a next system level on its own. We obtain social behavior by basically adding more knowledge to an existing system level (which Newell called the 'knowledge level' and later the 'rational band'). Newell (1990) even doubted whether a separate social band existed, due to the lack of invariants found up until then. In the paragraph below, I will note some general developments that justify the introduction of a new level, situated right above the knowledge level.

DEVELOPMENTS

In the past 15 years, some notable developments have taken place in the fields related to Cognitive Systems Engineering (CSE) and Naturalistic Decision Making (NDM), as well as in some other, unrelated, fields. Without being exhaustive, the following developments may be noted:

- The extension of NDM to macrocognition. Some particular models developed under the guise of macrocognition are the Data-Frame model of Sensemaking (Klein, Phillips, Rall, & Peluso, 2007) and the Flexecution model of Replanning (Klein, 2007a,b). These models depart from the linear Input-Output models and stress the dynamics of (re)framing, elaboration and preservation in cycles of macrocognitive activity.
- The extension of the situation awareness concept from being strictly 'in the head' to being a distributed, emergent process, arising from the dynamic interplay of humans and technological artefacts (e.g., Stanton, Salmon, Walker, & Jenkins, 2010).
- The Interactive Team Cognition approach (Cooke et al., 2013) provides a theoretical alternative to existing approaches that exclusively focus on individual team members' cognitive processes. Interactive Team Cognition views team cognition as context-dependent team interaction rather than a monolithic entity that a team can either have or not have. Rather than viewing team cognition as something that is shared among team members and then aggregated, it is viewed as an interdependent network that should be studied at the team level. Team cognition arises as an emergent property as team members communicate with each other (Walker et al., 2006).
- The move from a dyadic semiotic model of 'meaning' that views the mind as a symbol-processing system to a triadic semiotic model that suggests that a sign's meaning is grounded in the functional dynamics of the problem domain. This particular development can be traced back to ecological psychology (Gibson, 1979), and from this lineage to Rasmussen, Pejtersen, & Goodstein (1994) and Flach (2015). The implication of this philosophical view is that the focus of applied work has shifted from human-computer interaction to interactions between humans and work domains, mediated by interfaces and automation (Flach, 2015). The same shift may be noted when comparing (cognitive) task analysis with work analysis (Vicente, 1999).
- The shift from CSE to Resilience Engineering may be viewed as a shift from the engineering of cognitive systems to engineering with a particular purpose in mind, i.e. achieving sustained adaptability (Woods, 2015). The aim is still to 'outmaneuver complexity' by 'graceful extensibility', but the focus has shifted from cognitive systems to 'tangled layered networks'. There is evidence that the particular network structure that has evolved determines the long-term success of organizations to deal with disturbances (Rivkin & Siggelkow, 2007; Stanton, Walker, Sorensen, 2012). In a variety of domains, scale-free network structures

have been shown to be resilient architectures, in the sense of being robust to the (random) removal of nodes (Schraagen, 2015). Specifically, in such resilient architectures the degree distribution of nodes follows a power law.
- The introduction of the network and relational perspective in management science (Hollenbeck & Jamieson, 2015) and the social sciences in general (Borgatti, Mehra, Brass, & Labianca, 2009) and the concomitant rise of social network analysis as a methodology (Wasserman & Faust, 1994).

Summarizing these developments, we may note that there is a move away from viewing cognitive agents as independent units to viewing them as part of larger networks of interconnected units of adaptive behaviour. These networks are constrained by factors external to them, including time, physical constraints, task, technology, social structure, and culture. The networks are cross-cutting, embedded in each other, and heavily intertwined. As units of adaptive behaviour interact over time, regularities in behavior emerge. These regularities may be visible in the form of 'patterned interactions' and may be studied by methods such as social network analysis. The implications of these developments for NDM have not yet been discerned. In the next paragraph, I will connect the micro-macro cognition distinction to Newell's system level constructs and then build up to the new "Transaction level".

MACROCOGNITION AND MICROCOGNITION AS SYSTEM LEVEL CONSTRUCTS

Macrocognition as a field has defined itself as an extension to the Naturalistic Decision Making field, in the sense that its focus is on a broader set of macrocognitive functions than merely decision making. For instance, it also distinguishes sensemaking, planning, adaptation, problem detection and coordination as important macrocognitive functions. Macrocognitive functions need to be performed by individuals, by teams, by organizations, and by joint cognitive systems that coordinate people with technology. It is the study of cognitive adaptations to complexity (Schraagen, Klein, & Hoffman, 2008).

Macrocognition is distinguished from microcognition primarily by its time scale of analysis. Whereas microcognition focuses on cognitive processes in the time band of 100 msec up to 10 sec., macrocognition focuses on cognitive processes from minutes to hours. The preferred means by which these processes are studied then also varies, with microcognition frequently opting for constrained tasks in confined environments with high experimental control, while macrocognition opting for real-life tasks under actual working conditions with less experimental control (Cacciabue & Hollnagel, 1995; see Hoffman & McNeese, 2009 for a historical overview).
Interestingly, although macrocognition in principle extends to the organizational level, in practice there are very few studies that adopt the methods employed by organizational scientists, nor are the time scales adopted in macrocognitive studies weeks or months or years, but rather hours at the upper level. Methodologically, then, an important shortcoming in current macrocognitive studies is the lack of longitudinal data collection, which prohibits the discovery of emergent behaviors at longer time scales.

If microcognition is equated with Newell's cognitive band and macrocognition with Newell's rational band, then it follows that macrocognition is a 'knowledge level' construct (Newell, 1982). At the 'knowledge level', the principle of rationality applies: if an agent (e.g., an expert) has a goal and knows that knowledge A will bring him or her closer to that goal, then the agent will choose knowledge A. From the outside, the behavior of the expert is highly predictable, once we know the expert's goals and the knowledge that is required to attain those goals. For the NDM community, the principle of rationality should look familiar: it is functionally, if not logically, equivalent to the RPD model. The expert has a representation that can be accessed without any computational costs, or, in Newell's (1982) 'slogan equation': Representation = Knowledge + Access. The representation consists of a system for providing access to a body of knowledge. Access is a computational process, hence has associated costs. Thus, a representation imposes a profile of computational costs on delivering different parts of the total knowledge encoded in the representation (Newell, 1982). But if we look closer, we notice that this equation generalizes beyond the RPD model. In fact, the RPD model is a special case that applies when computational costs are low, i.e., the knowledge can be accessed highly efficiently to make selections of actions in the service of goals. In other (unfamiliar, non-routine) cases, knowledge may not be accessed as efficiently, and it is here that the macrocognitive 'deliberative search' processes are put to work to access the knowledge.

A NEW LEVEL

I now propose that there does exist yet another system level, which I will call the *transaction level*. It is a true systems level in Newell's sense, that is, it is a reflection of the nature of the physical (and social!) world and not just a point of view that exists solely in the eye of the beholder. It is not a level of analysis that can be applied to any unit of analysis, as, for instance, a network perspective that can be applied to both brains and societies. It is not an aggregation of knowledge, so its behavior cannot be obtained by expanding agents at the knowledge level with simply more knowledge. Rather, no amount of knowledge added will yield the transaction level properties that are characteristic of this level.

A quick overview of the transaction level, in terms of the system under consideration, its components, its laws of composition, its behavior laws and its medium, are in order before entering into details.

The system at the transaction level, the entity to be described, is the *network*. The system's primitive elements, its components, are *nodes* and *links*. Thus, a network is composed of a set of agents and a set of links. The components are assembled into systems by laws of composition that yield *strength* and *reciprocity*. The medium at the transaction level is the *transaction* (as might be suspected). Thus, the network generates transactions by connecting nodes through links. The transactional content may differ widely, from affect and influence to goods and services, and information. Finally, the behavior law, how the system depends upon its components and composition, is the *principle of relationality* : links are selected to attain transactions. As links are characterized by strength and reciprocity, the generation of transactions is dependent upon link strength and reciprocity.

In contrast to the knowledge level, the concept of 'goal' does not play a role at the transaction level. However, just as with the knowledge level, the transaction level is a radical approximation : entire ranges of behavior may not be describable at the transaction level, but only in terms of systems at a lower level. For instance, the transaction level is poor for predicting how team members that have never met before will interact. It is also poor for predicting the effectiveness of the introduction of a new technology on a person's behavior. However, it is good for predicting the impact of losing someone central to an organization's informal network. It is also good for predicting that a well-established team will exchange relevant information in a timely fashion.

The physical structure of a transaction is filled indirectly and approximately by knowledge systems at the next lower level. This is depicted in figure 1 :

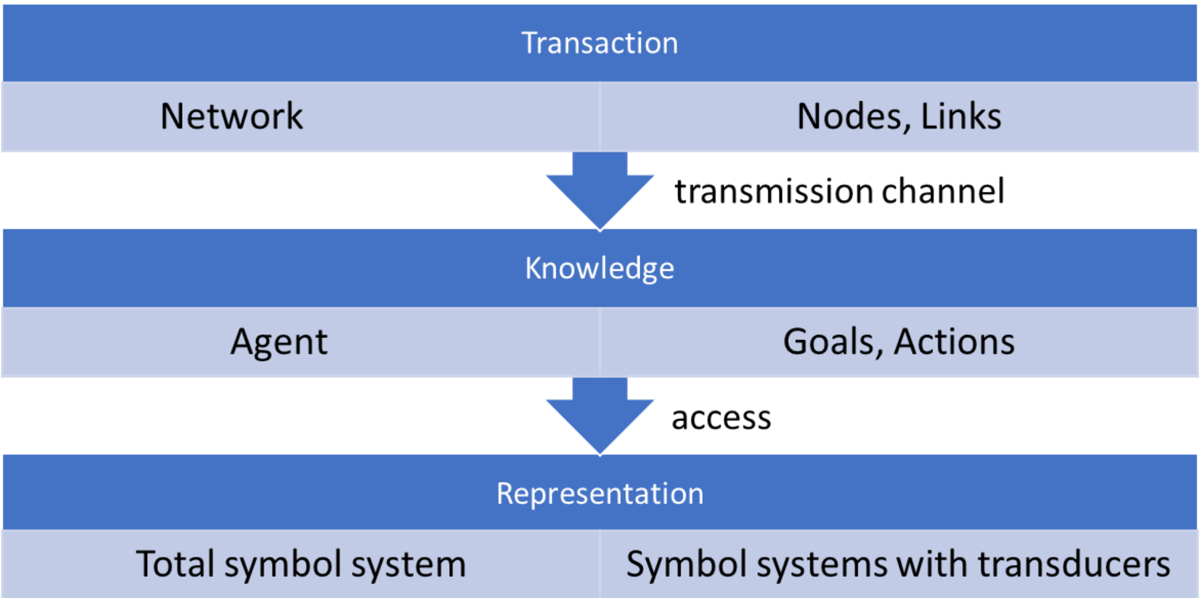

Figure 1. Reduction of the transaction level to the knowledge level and the symbol level.

The slogan equation for connecting the transaction level to the knowledge level is: Knowledge = Transaction + Transmission channel. What this means in psychological terms is that humans are social beings that have knowledge of all kinds of possible transactions, but only to a certain extent, due to limitations on communication bandwidth. This knowledge is a person's *social capital*, or the interpersonal relationships they have with others that enable successful functioning (Hollenbeck & Jamieson, 2015). Social capatial is conceptually distinct from the individual-level constructs and it has the potential to enhance prediction of individual and team performance incrementally over those constructs. Social capital information can be quantified using social network analysis. In the next paragraph, I will provide a few examples of recent research carried out at the transaction level.

SOCIAL NETWORK ANALYSIS APPLIED TO MILITARY, MEDICAL, AND SPORTS TEAMS

Social network analysis (SNA) (Wasserman & Faust, 1994) is a promising approach for studying real-time team interaction at the transaction level. It is not dependent on the availability of trained raters, as it only needs to take into account a network consisting of a set of units (or actors) and the relations that exist among them (Alba, 1982). I have applied SNA in two case studies: a medical team performing paediatric cardiac surgical procedures (Barth, Schraagen, & Schmettow, 2015), and two naval teams (Schraagen & Post, 2014).

In the medical teamwork study, degree centralisation, density, closeness centralisation, betweenness centralisation and reciprocity were chosen as the metrics of centralisation, in order to capture context-dependency of communicative behaviour within a medical team. Compared to classical behavioural rating schemes, these metrics of centralisation are not influenced by hindsight bias as they are based on real-time communication and not established immediately after the surgical procedure. Fourty surgical procedures were observed by trained human factors researchers, and communication processes amongst team members were recorded. Focusing on who talked to whom, team communication structures, in response to changing task demands, were characterised by various network measures. Results showed that in complex procedures, the communication patterns were more decentralised and flatter. Also, in critical transition phases of the procedure, such as going on or off cardio-pulmonary bypass, communication was characterised by higher information sharing and participation.

In particular, we found that in any given phase, there were always two team members linked to many others, thus scoring high on total degree centrality. Not surprisingly, the primary surgeon was always one of these, with the anaesthetist and perfusionist being the second actor, depending on the surgical phase. We also looked at complex versus non-complex procedures and found that during complex procedures the role of the assisting surgeon increased relative to the role of the primary anaesthetist, especially when going on or off cardio-pulmonary bypass. Although the primary surgeon still scored highest in total degree centrality in virtually all cases, the assisting surgeon filled in the role of communicator to the rest of the team whenever the workload of the primary surgeon prevented him from speaking to the rest of the team. This form of ‘heedful interrelating’ (Schraagen, 2011) shows that this team is at least adaptive, if not resilient.

The goal of the naval study was to apply SNA techniques to the study of naval teamwork, to be able to characterize naval team readiness. As part of a larger study to develop methods for socio-technical systems analysis applied to Oceangoing Patrol Vessels (OPV), we conducted ethnographic observations on board of two OPVs (see Post et al., 2013, for details). The ethnographic observations entailed making video recordings of two ‘internal battle’ exercises. To be able to distinguish between different levels of naval team readiness, we studied an ‘unpractised’ team and a ‘team in training’ (in more conventional terms, the first could be referred to as ‘beginners’, whereas the second team could be referred to as ‘intermediate’; however, we prefer to use our more neutral terms, as they do not imply any rank ordering on a non-existing scale). The descriptive, non-inferential, results showed that, at the transaction level, the more experienced team displayed higher levels of information sharing and team member participation compared to the less experienced team. At the actor level, the team coordinator played a much more central role in the more experienced team, whereas in the less experienced team this role was taken up by various other team members.

For both the medical and the more experienced military teams, the results clearly showed that the total degree centrality displayed a power-law distribution, indicating that the teams adopted a scale-free network structure (Schraagen, 2015). This means that one actor was highly connected to a few other actors, while the remaining actors were less well connected. We hypothesize that this particular structure is able to deal with disturbances that are not well modelled, unexpected events that an OR team or a naval team such as we have studied needs to deal with as the occasion arises. We believe therefore that, in fact, these are network architectures that can sustain the ability to adapt to future surprises as conditions evolve (Woods, 2015).

Finally, as an example of recent study in the domain of sports, Dalal, Nolan, and Gannon (2016) studied whether professional ice hockey players’ Olympic Tournament team performance could be predicted from their pre-assembly shared work experiences, that is, the extent to which pairs of teammates were familiar with each other’s work patterns, for instance because they had played together in the same division, league or position. In the Olympic hockey tournament case, team members first interacted as a team about two days before the tournament started. This question could be answered from a shared mental models perspective, which would be a knowledge level perspective. However, Dalal et al. (2016) used social network analysis measures to answer this question, taking a transaction level perspective. This perspective should be good at predicting how team members’ prior familiarity with each other’s work patterns will impact team performance. The results showed that as teams became more centralized around single members, performance decreased, basically confirming our results obtained with medical teams (Barth et al., 2015). However, a lot of variance was unaccounted for, confirming the notion that the transaction level is radically incomplete, and that the knowledge level (e.g., team mental models, team satisfaction) needs to be taken into account as well.

CONSEQUENCES

One may well wonder whether the introduction of a new system level, above the knowledge level, has any added value, in terms of surprising features, and will significantly advance the field of NDM. One surprising feature is that we may study human-machine teaming or ‘joint activity’ (Klein et al., 2004) not merely from the perspective of ‘shared goals’ and ‘joint actions’, which would be a knowledge level analysis, but also from the perspective of patterned interactions between ensembles of humans and machines. This brings with it the necessity of collecting longitudinal data of human-machine interaction. Another surprising feature is that, whereas the knowledge level has a complete absence of structure, the transaction level is characterized by high degrees of structure. Particular network structures are more robust to disturbances than other network structures (Schraagen, 2015). A third surprise is that the transaction level provides the context for when macrocognitive functions come into play, namely whenever the principle of relationality does not apply, i.e. when transactions do not occur even when nodes are connected through links. Put differently, the function of macrocognition is to transmit knowledge fluently throughout the network.

Whether the introduction of the transaction level will significantly advance the field of NDM remains to be seen, of course. The increasing use of social network analysis is merely one step in the right direction. Perhaps more significant will be the broadening of perspective that will result from embracing the transaction level. This level makes us aware that instead of focusing on single agents (commanders, officers, captains, pilots, etc.), we need to also take the broader network into account in which these agents are embedded, a network that increasingly also consists of intelligent machines. If anything, a conscious deliberation of where to draw the network boundaries would be extremely helpful in enriching our stories.

CONCLUSION

Finding relative invariants in adaptive systems takes place across different time scales. So far, the focus of NDM and macrocognition has been on the shorter to medium time scales, to the neglect of longer time scales. If nothing else, this paper is a call for more studies at the longer time scales. By introducing another systems level, the transaction level, I have attempted to describe the concepts that are required to carry out such studies. Although these concepts are closey related to social network analysis, they should not be equated with this particular method of analysis. Rather, taking a broader network-level perspective may enrich NDM and help find relative invariants across broader time scales.

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The role of expertise and organisational information in managing patient flow in hospitals

Matthew WOODWARD[a], Julie GORE[b], Christos VASILAKIS[a]
[a]*Centre for Healthcare Innovation & Improvement (CHI[2]), School of Management, University of Bath*
[b]*School of Management, University of Bath*

ABSTRACT

This research concerns naturalistic decision making by clinicians and operational managers regarding patient flow in hospitals. Naturalistic decision making in the healthcare domain has typically focussed upon clinical decisions by doctors and nurses, however patient care is enabled by a system in which many other roles manage dynamic situations. This research focuses on operational managers and clinical coordinators who strive to interpret system state to make decisions to effectively, efficiently and safely move patients through care. Of particular interest is how the availability and representation of organisational information influences decision making processes.

KEYWORDS

Planning and prediction; health care; patient flow; simulation models; mental models

INTRODUCTION

The field of naturalistic decision making (NDM) has long held an interest in the domain of healthcare as a source of research. As Bogner (1997) notes, in healthcare the locus of time stress is usually outside of the decision maker and decisions are reactive to patient needs, resulting in a demanding environment. Secondary and tertiary hospital services in particular are dynamic, complex systems with multiple people and functions interacting in a time-pressured environment. This makes them fertile ground for the field of naturalistic decision making which has a track record of studying systems in which complexity and uncertainty are inherent (Gore, Flin, Stanton, & Wong, 2015) The local situation can change rapidly, information is often incomplete or ambiguous, expertise is important and social structures and team working are integral to the hospital's function. For example, in tertiary care settings both the state of the organisation and the state of the patient are dynamic. Emergency Departments (ED) can change from calm to busy within minutes, patients can deteriorate from relatively stable to critically ill over a period of hours. Some patients may be referred with a full medical history, others may present in an emergency situation with nothing but basic demographic information.

Given such potential the NDM approach has been applied in several studies of a number of healthcare domains. For example Crandall (1993) studied the cues used by neonatal nurses Phipps and Parker (2014) have used the NDM approach to examine anaesthetists rule-related behaviour, and Xiao et al (1997) studied the mental preparatory work utilised by anaesthetists.

However the literature has primarily focussed upon clinical decisions made by clinicians; those intervening with the patient at the point of care. Yet over the last few decades the increasing complexity and specialisation of medical care has resulted in healthcare that requires intervention from different teams involving many specialised professionals (Gawande, 2010). These professionals are formed into organisations which include not only clinicians but managers, technicians, coordinators and administrators who directly and indirectly impact the quality of care delivered. The development of frameworks such as the Systems Engineering Approach to Patient Safety (SEIPS) (Holden et al., 2008) recognises that healthcare is a sociotechnical system which as a whole has significant bearing upon the safety and quality of care delivered.

Thus this research takes a broader perspective of organisational participants by seeking to understand the decision processes of hospital operational managers and clinical coordinators in facilitating the flow of patients through a care service. That is those staff who seek to understand the current situation and plan ahead regarding the state of the system in terms of available beds, patient condition, patient location, staffing and more. Nemeth et al (2006) has taken a step in this direction by using a NDM approach to research how anaesthesia co-ordinators make decisions with an emphasis on understanding the artefacts used by such roles.

One approach to assist with planning is that of operational research (O.R.) , which closely relates to management science and business analytics (Liberatore & Luo, 2010). This discipline typically seeks to abstract elements of a service (healthcare or otherwise) into a representation/model and uses quantitative data to describe system behaviour. Some models have the scope to compute the most probable process outcomes and thus can be used to analyse and optimise system configurations at a tactical level. The use of computer simulation models in healthcare particularly at strategic and tactical levels is reasonably well established; academics and consultants have developed models to help senior managers make structural decisions about service design. For example a recent study developed a discrete event simulation to model the implementation of stroke thrombolysis. Having established a validated baseline model, different interventions (such as increasing drug treatment time windows) could be modelled and treatment rates predicted (Monks, Pearson, Pitt, Stein, & James, 2015).

However recent position papers and systematic reviews regarding the application of computer simulation modelling to healthcare (Pitt, Monks, Crowe, & Vasilakis, 2015; Sobolev, Sanchez, & Vasilakis, 2011) have raised the issue of an implementation gap between the outputs provided by modellers and the engagement with and implementation of results by healthcare staff. Other recent papers in operational research have identified the importance of the behavioural aspects of OR and have identified opportunities for research in this area (Hämäläinen, Luoma, & Saarinen, 2013). They argue that given O.R. is used to facilitate thinking and problem solving, an understanding of the human-model interaction is important for making the best use of such tools.

Thus this research seeks to develop a richer understanding of the context within which such decision support models are developed and utilised. As Gore et al (2006) note in their illustrations of organisational decision making (ODM) in healthcare, "Consideration of the incentives and penalties surrounding the decision space sits well with the remit of ODM, particularly insofar as the decision space may be highly ambiguous, involving multiple parties each with different degrees and levels of accountability." Similarly NDM and the field of human factors in general seeks to use empirical data about the interactions between humans and organisational information to develop "ecologically sensitive" solutions (Gore et al, 2006). There is opportunity therefore to use NDM methods to elicit the *mental* models ("mental representations of specific situations" (Lipshitz & Shaul, 1997)) held by those making decisions about patient flow. These could then be usefully applied to the development of explicit (rather than tacit) models/representations that have the potential for learning about and anticipating patient flow dynamics. The engagement of organisational actors in this way and the provision of feedback loops for organisational learning could help forge links across the reported implementation gap.

RESEARCH QUESTION

This research thus seeks to bring together these two approaches to the analysis of work systems: naturalistic decision making and systems modelling. The research question asks: How are decision-making processes influenced by the availability and representation of system state? The concept of distributed cognition (Hutchins, 1995) will be used to frame an investigation into how knowledge regarding system state is held and shared between human and technology actors. NDM methods (Crandall, Klein, & Hoffman, 2006) will be used to elicit the perceptual cues, organisational information and mental models used by those influencing patient flow. Then an explicit representation of system state, for example a computer simulation model using resource/demand data, will be developed and used to explore how these decision processes are influenced.

The work domain will be tertiary care hospitals and the decision makers studied will be those who manage the movement of patients through hospital services and facilities, namely doctors, nurses, clinical coordinators and operational managers. Decisions may include:

- *when* to transfer a patient from one hospital department to another, e.g. emergency department (ED) to medical assessment unit (MAU)
- *which patient* to prioritise for transfer (particularly from ED)
- *which physical location/bed* to transfer a patient to
- *when* to escalate a situation (i.e. when the service is starting to fail in delivering it's function)
- *how* to manage patients close to breach (i.e. of organisational/government targets).

More specific questions will be pursued depending upon how enquiry develops, for example:

- How does the availability, representation and reliability of information/models impact the timeliness of decisions (e.g. proactive versus reactive)?
- How does the availability, representation and reliability of information/models impact upon human-model interactions (e.g. frequency, data updates, communications)?
- Do information/model artefacts change team communication?
- How do decision-makers interpret trust in information/models?
- How do decision-makers interpret confidence in decisions made by themselves and others?

APPROACH

This research is at an early stage of development (first year doctoral study) and an agreement of the methods to be used is in the process of being finalised at the time of submission. The intention is to conduct a pilot study prior to the PhD transfer point (March 2018) to improve researcher skills with the methods and to gain a sense of the data content and structure.

The intention is to take an interpretative/neo-empirical stance as defined by Johnson et al (Johnson, Buehring, Cassell, & Symon, 2006). In this approach the qualitative and subjective views of the organisational actors are of primary interest yet the intention is to report these interpretations whilst striving to minimise the biases of the researcher. The methodological approach is mixed-methods as quantitative data is integral to the work system under scrutiny and thus quantitative methods will also be used to develop a model for the intervention phase.

The approach is particularly focussed upon understanding the role of expertise and experience and how this relates to the use of organisational information. Some NDM models (e.g. the recognition-primed decision making model Klein, 1998) emphasise the importance of recognising environmental cues to support situation pattern-matching. The representation/visualisation of the current state of a hospital service (e.g. Emergency department through to emergency general surgery) could be designed to help pick-up on these cues.

PROJECT DESIGN

Three phases will be undertaken to: 1) study and interpret current decision-making processes, 2) develop a representation of system state for example, with a simulation or analytical model and, 3) evaluate how the use of such a representation influences decision making. Stages 1) and 3) will collect empirical data in the field, in this case within a large tertiary care hospital in the UK.

Phase 1 will analyse current practice by engaging with stakeholders and describing the baseline work system using task and process analyses. An emphasis will be placed on establishing decision points important to patient flow. The criteria for “important” decisions will be those that influence process effectiveness, patient safety or elicit rich decision-making processes. An ethnographic approach will be taken to collect this data through periods observing and interacting with staff in the hospital. The rationale for such an approach is to capture the wide range of artefacts that are anticipated to contribute to distributed cognition and also to build working relationships with the staff under study. Participatory methods will be used to develop the work system description and gain support for the project.

Established qualitative NDM knowledge elicitation techniques will be used with individuals to further study the decision points of interest. For example the Critical Decision Method will be employed to elicit the important cues and criteria that trigger the recognition of certain situations (for example preparation to escalate operational situation). This method is planned to be used with a wide range of actors to capture both different levels of expertise and also different social perspectives (for example clinical, operational, safety). It is likely that the Recognition-Primed Decision making model (RPD, Klein 1998) will be used as a framework to structure interview questions.

An understanding of current process/organisational information sources will be developed through an audit of business intelligence data that is available or utilised (e.g. workplace dashboards, routine audits, operational data). The alignment of these sources with the decision requirements elicited earlier in Phase 1 will be evaluated with the involvement of healthcare staff. This phase will also concern data gathering for potential simulation model population, for example staffing level rotas, service demand profiles and task/process durations and distributions. Where possible this data would be collected retrospectively from existing NHS data records. Some data (for example specific task durations) may need to be collected prospectively through observation or updates to existing recording systems.

In the second phase the intention is to develop an artefact that will provide decisions makers with a representation of system state. The preferred option is to develop a computer simulation model that may be used to anticipate future service state given a set of input variables. These variables could mirror the current system state or could be pre-set to represent different scenarios (for example low staffing or bed closures). Tests of model validity and sensitivity will be conducted. It is expected that there will be iteration between data gathering and model development as a better understanding of the system is gained. If the pragmatic demand for simplicity prevails the artefact may instead provide a near real time representation (tabular or graphical) of organisational information, for example service bed state, patients in ED etc.

The third phase will make the artefact available for the participants to interact with, and for data on user interactions and interpretation to be collected. There are two options under consideration for the intervention. In the first the artefact is made available to the participants in situ with a view to supporting their operational decisions on a daily basis (for example at a bed managers planning meeting). An alternative option is to provide the intervention as training sessions away from the operational environment in which participants are able to explore the impact of different scenarios using the model as a way of gaining a sense of system behaviour.

During this period methods including observation, verbal protocol analysis and the critical decision method will be used to evaluate model use and understanding. In particular the evaluation will look to understand if the participants interpret the hospital service in a different way and whether this effects their decision-making processes. The questions outlined in the section above will be explored. Quantitative data derived partly from the model (e.g. time to decide following a new piece of information) *may* be used as a metric to help determine decision quality.

RISKS

A barrier to this research may be the time made available by busy clinicians and managers in the hospital to engage to allow qualitative methods to be employed with sufficient rigour. Obtaining reliable quantitative process data could also be a challenge due to issues with organisational data coding and availability. Both of these risks may be mitigated by making clear the potential benefit of the research to the health service early in the project, engaging those teams who are motivated to be involved and choosing services with reasonable existing data recording.

QUESTIONS ON METHODS

The doctoral consortium will provide a timely opportunity to discuss and gain feedback upon potential methodological approaches. The following methods are under consideration and are listed with some questions for discussion.

Ethnography

- How could one best capture decisions and information use in a timely manner when they are distributed across multiple physical and social spaces?
- Is it legitimate to enrol staff as data gatherers (for example keeping a record of where they look for information)?
- With the ethnographic method to what extent can questions be posed directly (for example about choice of information source, which may then alter the observed behaviour) as opposed to passive observation?

Interviews - Critical Decision Method (CDM)

- Are there different techniques for eliciting information about proactive versus reactive decisions? Is it helpful to make a distinction, for example a decision taken in response to an event (e.g. the arrival of patient to a minor injuries unit) may be interpreted as planning ahead (arguably a proactive decision)?
- In the use of CDM how does one account for hindsight (i.e. creating a narrative to construe the decision processes in light of the outcome)?
- How many different participants should be interviewed to gain a credible and dependable account of decision-making in this context?

Artefact/model interaction

- Is it valid/credible to use quantitative data (e.g. timings) to establish the quality of a decision?
- If study of model interaction is taken out of the working environment (into a training or experimental session) can it still be classed as naturalistic decision making?

CONCLUSION

This paper outlines the direction for first year management and psychology doctoral research. The intention is to bring together the approaches of naturalistic decision making and simulation modelling to understand how organisational information can be effectively represented to help manage hospital patient flow. At this early stage of research there are many questions to be addressed regarding approach and methodology. This paper seeks to elicit discussion and guidance from those attending the NDM doctoral consortium 2017.

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HISTORY OF NDM CONFERENCES

1989	Dayton	**NDM1** set the stage for expanding the study of problem solving and decision making, linking it to expertise studies, making it more pertinent to the needs of the applied community, and giving greater focus on national needs. This Conference served as a "call."	Klein, G., Orasanu, J., Calderwood R., & Zsambok, C. E. (Eds.), (1993*). Decision making in action: Models and methods.* New York: Ablex Publishing.
1994	Dayton	**NDM2** was more specific, dealing with a host of application areas and some tentative results from NDM work. Ideas for future directions were charted since NDM was still largely a promissory note.	Zsambok, C. E., & Klein, G. (Eds.), (1997). *Naturalistic Decision Making. NJ: Lawrence Erlbaum.*
1996	Aberdeen, Scotland	**NDM3** highlighted the interest in NDM on the part of European researchers, and served to integrate the ideas of NDM with the existing paradigms in the European community, such as Work Analysis.	Flin, R., & Salas, E. (Eds.). (1998). *Decision making under stress: Emerging themes and applications.* London: Ashgate
1998	Washington DC	**NDM4** represented some of the pay-off from the initial promissory notes. A host of research studies was presented on diverse topics. There was a healthy debate on the relation of NDM to other paradigms, including those of human factors and "cognition in the wild."	Salas, E., & Klein, G. (2001). *Linking expertise and naturalistic decision making.* Mahwah, NJ: Lawrence Erlbaum Associates.
2000	Stockholm, Sweden	**NDM5** was organized around a matrix combining methodology (Cognitive Task Analysis, Observational Methods, Microworld Techniques) and application areas (Distributed Decision Making, Decision Errors, Learning From Experience, Motivation and Emotion, and Situation Awareness and Training).	B. Brehmer, R. Lipshitz, & H. Montgomery (Eds.). *(2004). How professionals make decisions.* Mahwah, NJ: Lawrence Erlbaum Associates.
2003	Pensacola Beach, FL	**NDM6** addressed the issues that experts face in situations that fall outside 'the routine'. Other discussions included NDM and cognitive task analysis methodology, NDM and traditional lab-based DM, and microcognition to macrocognition.	Hoffman, R. R. (Ed.) (2006). *Expertise out of context: Proceedings of the Sixth International Conference on Naturalistic Decision Making.* Mahwah, NJ: Erlbaum.
2005	Amsterdam, The Netherlands	**NDM7** emphasized five themes: adaptive decision support, cognitive ethnography, crime and decision making, crisis management, and medical decision making. In sessions, the NDM framework was applied to new and diverse domains, such as landmine detection, judgments in crime situations, and space exploration.	Schraagen, J.M., Militello, L., Ormerod, T. & R. Lipshitz (Eds.). *(2008). Naturalistic Decision Making and Macrocognition.* London: Ashgate.
2007	Monterey, California	**NDM8** represented the diversity of research within NDM including: knowledge management, applications to organisations and teams and military security operations. Debate centred upon the appropratemenss of the macro-cognition construct and the methodological challenges that continue to face the field.	Mosier, K. L. & Fischer, U. M. (Eds.) (2010). *Informed by Knowledge: Expert Performance in Complex Situations.* Sussex, UK: Taylor & Francis.
2009	London, UK	**NDM9** addressed the effect of modern computing technology on decision making that occurs in naturalistic settings such as medical diagnosis and treatment, command and control, financial markets, information analysis, team decision making and coordination.	Wong, B. L. W. and Stanton, N. A. (Eds.) *(2009) Naturalistic Decision Making and Computers: Proceedings of the 9th Bi-annual International Conference on Naturalistic Decision Making*, British Computer Society, London Stanton, N.A., Wong, W., Gore, J., Sevdalis, N. & Strub, M. (2011) Critical Thinking. *Theoretical issues in Egonomics Science.* 12 (3): 204-209
2011	Orlando, Florida	**NDM10** brought together researchers and practitioners from diverse domains who seek to understand and improve how people actually perform cognitively complex functions in demanding situations.	Fiore, S. M. & Harper-Sciarini, M. (2011*). Proceedings of the 10th Bi-Annual International Conference on Naturalistic Decision Making.* University of Central Florida. ISBN 978-1-4507-7872-5 *Harper, M. & Sciarini, L. (2011)* Selected Papers from the 10th Bi-Annual International Conferenne on Naturalistic Decision Making. *The International Journal Cognitive Technology 16: 2, 1-63*
2013	Marseilles, France	**NDM11** focussed on sensemaking, trust and uncertainty management and expertise interacting with technical systems across a wide range of operational domains.	*Chaudet, H., Pellegrin, L., Bonnardel (2015)* Special issue on the 11th conference on Naturalistic Decision Making, *Cognition, Technology & Work Volume 17: 3, 315–318*
2015	Washington DC	**NDM12** extended NDM thinking reaching across domains, disciplines and applications. Since the first 1989 NDM conference the NDM community of practice has grown worldwide extending well beyond the early fire ground commander studies hence an integration of multidisciplinary efforts to improve work in complex domains	*Mosier, K. & Militello, L. (2016)* Extending Naturalistic Decision Making: Reaching across domains, disciplines, and applications. *Journal of Cognitive Engineering and Decision. 10, (3), 227-228* *Adapted from Robert Hoffman, NDM 6 Organizer

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