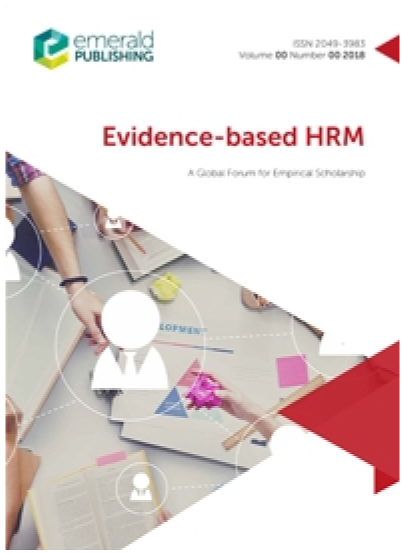

Organisational Plasticity: Can we really model Human-Agent behaviours?

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The ability for an organisation to adapt and respond to external pressures is a beneficial activity towards optimising efficiency and increasing the likelihood of achieving set goals. It can also be suggested that this very ability to adapt to one's surroundings is one of the key factors of resilience. The nature of dynamically responding to sudden change and then to return to a state that is efficient may be termed as possessing the characteristic of plasticity. Uses of agent-based systems in assisting in organisational processes may have a hand in facilitating an organisations's plasticity, and computational modelling has often been used to try and predict both agent and human behaviour. Such models also promise the ability to examine the dynamics of organisational plasticity through the direct manipulation of key factors. This paper discusses the use of such models in application to organisational plasticity and in particular the relevance to human behaviour and perception of agent-based modelling. The uses of analogies for explaining organisational plasticity is also discussed, with particular discussion around the use of modelling. When we consider the means by which we can adopt theories to explain this type of behaviour, models tend to focus on aspects of predictability. This in turn loses a degree of realism when we consider the complex nature of human behaviour, and more so that of human-agent behaviour.

Keywords: Organisational plasticity, agent-based modelling, human behaviour, human-agent partnership

Background

An organisation may be defined by the nature of its components, and invariably this will be perceived as either simple or complex entities, and is very much dependent on the nature of the business and the environment within which it operates (Mintzberg, 1989). We instinctively know that in order to be successful a businesses must possess the characteristic of being 'agile' and have the ability to respond to a complex dynamic marketplace. Measuring how a workforce is performing within a dynamic and adapting organisation also poses a number of difficulties, with many approaches viewed as being somewhat trial and error (Secchi, 2011).

In the current global market the sort of language used to describe agile businesses will resonate with some degree of truth, whereby technology is rapidly shaping how we conduct business to the extent where technology is slowly becoming more and more ubiquitous - assisting the human workers in their everyday work (Friedwald & Raabe, 2011). In order to keep up with technology and decision-support systems within modern organisations we are often confronted with the use of narrative and analogies that are designed to break the barrier of needing to understand such a phenomenon (such as artificial intelligence, or agent-based systems). Gavetti, Levinthal & Rivkin (2005) examined the use of analogy in agent-based models (ABM), in order to manipulate changes in management and structural changes, and found that adhering too closely to an orthodox analogy could sometimes be thought of as dysfunctional. However, the power of analogy was determined to be a powerful tool (as long as it was applied appropriately). We must therefore air on the side of caution, even though as humans we are intuitively guided towards narrative analogies we should carefully choose the language we use for explaining concepts within an analogy relating to our relationship with complex systems (Cameron & Larsen-Freeman, 2005).

Clearly an adaptive organisation is viewed as beneficial - but the organisation is itself but a reflection of its component parts. Richards (2017) discusses how organisations are integrating more advanced technologies and predicts a growing socio-technical trend that finds humans and intelligent systems working together in teams. The benefit of using such intelligent systems, or agents, provides the human component with a greater degree of capability across different aspects of achieving whatever goal has been set. Technology is therefore seen as a significant force within the marketplace in terms of how an organisation can dynamically respond and position itself - either through developmental or disruptive change (Lam, 2007). We seem to have arrived at a position in human history whereby we place value upon an organisation that is allowed to adapt to a changing environment and set of conditions, whilst at the same time striving to maintain a degree of stability that will allow the human element within the organisation a sense of assurance. Thus an optimised state would provide a degree of flexibility in how the human-agent teaming arrangement is set, or at least understanding the properties of organisational plasticity (and a sense of human control).

The use of analogy and metaphor

If presented with a new situation it is only natural for us to compare it to previous experience. In everyday life we use this mechanism to compare and contrast objects, things or systems against another. The act of creating this analogy (or analogical reasoning) is closely coupled to rational thought and human reasoning (Chalmers et al, 1992). Many industries have embraced the use of analogy and metaphor as a vehicle to convey meaning in a more coherent manner that facilitates better understanding or simply emphasises (or frames) a message that is trying to be delivered (Gavetti et al, 2005; Furnari, 2011). Hargadon & Sutton (1997) suggest that the role of analogy is closely tied to technological development, whereby the inventor utilises analogy and metaphor to convey meaning and develop complex ideas.

Confronted with advancing technologies we are undoubtedly going to experience confusion and uncertainty, more so when the technology may have already been adopted by others and labelled as the harbinger of new business practice. Let us consider the fourth Industrial Revolution - that of artificial intelligence (AI) striving to the forefront of innovation and business practice. With the advent of advanced AI technologies we can begin to not only perceive where such intelligent systems may be applied, but the focus shift this has in terms of implementation and operations. We are currently staring at a future that is full of advanced agent-based systems. Indeed, in many instances they may be accused of attempting to mimic our very own thought process and mentation (Asensio et al., 2014). Understanding complex organisational changes is not new and has often been used to explain and convey the nature of strategic changes that an organisation is confronted with (Douglas, 1986; Etzion & Ferraro, 2010). The use of analogy within the discourse around factors affecting organisational change can be comparative to another organisation (Fiss & Zajac, 2006) or to something completely different, but sharing similar characteristics - a metaphor (Tsoukas, 1993). While cognitive scientists have defined metaphors as statements of similarity between attributes between two specific domains (Gentner et al., 2001), we must also identify a strong linguistic nature within the use metaphors and analogies. Fillmore (1975) stressed that when we are confronted by such comparisons, they are likely to be deep-rooted within cultural and social experiences. It is not surprising therefore that we tend to use metaphors to bridge our understanding between two different domains in an attempt to convey figurative meaning (Cornelissen, 2005).

If we are providing an agent-based system to an organisation, such as assisting with the dynamic reallocation of workers, then the embryonic agent structure would need to be fostered within the system. This would allow it to understand the rules that surround it and govern behaviours, and in some instances may even possess a high degree of autonomy with which to develop its own rules within a defined framework. The agents may create other agents to support specific behaviours, or achieve other tasks or goals, but there would need to be a hierarchy of control that directs the need for creating such a system. At this stage we may begin to think about how best to understand this behaviour, and maybe predict what could happen if we were to model such a distributed multi-agent system (MAS). Indeed Macal & North (2009) propose that the use of modelling such agent systems is becoming more prevalent due to increasing computer processing power and the availability of toolkits and methods. However, modelling agent behaviour can sometime offer more questions surrounding the use of models, rather than how well they can offer predictive outcomes (Gintis, 2004; Boero & Squazzoni, 2005). The use however of analogy could perhaps present a meaningful way in which to understand this iteration of multi-agent system within an organisation, and potentially provide a narrative within which change can be forecast. Let us consider the example again, whereby agents are integrated into an organisation and are seen to adapt, replicate and respond to a changing environment. If we are reaching for an analogy, then this is similar to how neurons are developed within the brain. Cells are created for the nervous system and can become generic neurons that assist in neuronal activity and function, or become specialised neurons (referred to as progenitor cells). The plasticity of the brain (and its development) has been used as a metaphor for explaining flexible organisations and the processes used within such organisations on a daily basis (Beer, 1972; Morgan, 1986). The use of the brain as a metaphor is thought to attract interest and similarity to complex technologies due to the manner in which the brain rapidly processes and assimilates information and oversees the control of component sub-systems in order to regulate function (Arbib, 1989).

We may recognise this analogy in organisations by simply observing the narrative being used within the company; overhearing phrases that equate management to a brain and having to talk to the various organs in order to function and survive. It is therefore worth exploring this analogy a little deeper and dissect this process of neurogenesis within the brain, but also how it serves to reinforce the importance of plasticity; see Figure 1.

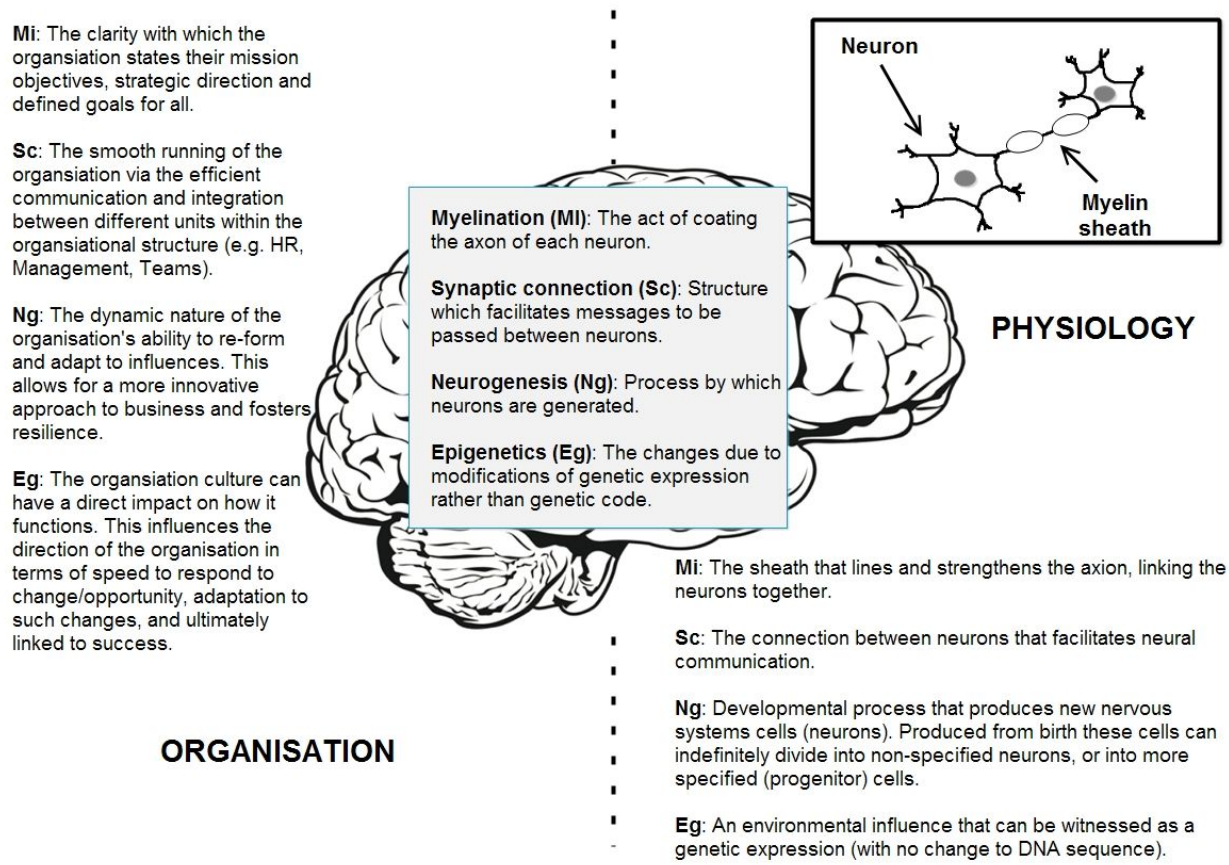

Figure 1 - The human brain analogy for organisational plasticity

By perceiving the different sides of the analogy; one side being physiological and the other organisational, we can see the similarities that are often used in comparing the plasticity of the human brain to the plasticity of organisations. By using four key components of brain physiology, we can apply an analogy across to organisational properties and characteristics for: (1) Myellination (Mi), (2) Synaptic connections (Sc), (3) Neurogenesis (Ng), and (4) Epigenetics (Eg). As outlined in Figure 1, we can see that the pairing in similarities between the functioning of the brain to an organisation appears to match relatively well. More so, in that the brain is often referred to as possessing plasticity in terms of learning and adapting to new situations and challenges through such processes as migration, maturation, synaptogenesis, and so on (Kolb & Gibb, 2011). The plasticity within this analogy is key to adopting the comparison to an organisation - and more so an organisation that may be considered to be populated by agents that possess intelligence and rationality. So, utilising this analogy this should take us a step closer to providing a basis for creating an ABM that can be used to predict organisational processes, outcomes and human behaviour? Perhaps, but exploring the nature plasticity in itself presents complexity in relation to what we exactly mean by plasticity (and its context).

Organisational Plasticity and Behavioural Operational Research

Fultot (2013) proposes that when we consider the nature of plasticity it is important to consider a number of different dimensions, rather than assuming this is a singular characteristic that may affect change. Indeed, Fultot believes that plasticity should be thought of in terms of the dimensions outlined in Table 1.

Dimension	Characteristics	Plasticity effect
Cognitive Plasticity	The ability for an agent to demonstrate outputs as defined by specified inputs. Thus an agent may be programmed to respond in a certain way, but may change these outputs based on the nature of the stimuli being presented. Also related to this is the agent's ability to learn and adapt based on experience of these inter-changing values over time and experience.	An agent's behaviour is directly affected by the external environment, but influenced via its internal mechanism that processes information. Therefore, a direct external force would cause an adaptation to the agent's cognitive architecture.
Physical (or Bodily) plasticity	This draws upon the ethos of embodied cognition and re-coupling cognition with the physical state and environment. Akin to muscles and tendons that are bound to solid bone, this level of plasticity affords the passive compliance of force within the boundaries of an agent's rules. However, just as muscles have been found to possess a degree of memory following a repeated force or action, this level of plasticity can be thought to show an effect of adaptive muscle learning.	The agent possesses a number of defined rules which are bound by set values and circumstances. This affords a degree of learning, but only within the sense of the scope as defined in the associated list of rules for that particular agent.
Developmental Plasticity	This is markedly different to cognitive plasticity, in so much that this process is set on a path that is determined in order to allow the agent to learn. And as such is not reversible like cognitive plasticity. The fundamental architecture that determines the cognitive aspects of plasticity is laid-down within the infrastructure within which the development of agent rules are formed. This may be compared to the genetic program we inherit and dictates our predetermined state of how we are formed as an organism.	In essence this is the foundation upon which the lifecycle of the agent is formed and determined. It is somewhat set in stone and pre-determined, due to the nature of how the infrastructure is designed and implemented. It will therefore offer both robust predictability in terms of how an agent will learn and behave, and also provides us with the known limitations of the system.
Environmental Plasticity	The direct effect of external forces influencing agent behaviour. This may be the introduction of new agents to assist in the task, or manipulating the environment within which the task must take place. The infrastructure of the environment is also a key factor here, as it is this that allows the behaviour to be shaped and expressed in a certain manner. Direct manipulation of this will inevitably shape the behaviour and response of the agents.	This relates to both the external landscape within which agents act and operate within, but also the infrastructure upon which agents utilise communication amongst each other and third parties. So anything that is introduced (or taken away) may directly influence the behaviour of the agent through direct effect (e.g. ability to communicate with other agents) or indirect influence (e.g. a limitation that affects achieving a goal - such as reduced time to perform tasks).

Table 1 - Dimensions to consider for organisational plasticity (taken from Fultot and expanded by author)

Fultot (2013) discusses how incorporating all of the dimensions as noted in Table 1 within an agent environment and the complexities that this must address to ensure all interactions are addressed. Indeed, Fultot believes that plasticity alone does not equate to adaptiveness, and we are inevitably unable to create a model that is truly representative of real life. Thus we are now at a stage where we have before us some key characteristics that would go towards defining factors for a model of organisational plasticity, that will help explain and predict organisational behaviour.

The dynamics of organisational behaviour is not a new area of research and has been borne from earlier endeavours within the social sciences. The discipline of Behavioural Operations Research (BOR) has its roots in both Cognitive and Social Psychology, whilst resting within the context of understanding the dynamics of human nature within an organisation. The foundation of the BOR approach is based in the nature of human decision making and the manner in which individuals differ in terms of how decisions are made (Kahneman & Tversky, 1973) and further to this how different factors can affect how individuals arrive at different decisions. By identifying and weighting identified factors some have tried to adopt a computational modelling approach to predict how you can predict human behaviour.

The creation of any model that possesses a semblance to BOR must therefore consider a number of key factors that relate to the human, social and technological aspects of what it is to be modelled. As previously noted, these factors however do not exist on their own and posses far more complex dynamics than merely considering them as isolated factors. This presents us with a problem of embodiment, whereby there is a clear disjoint between theoretical assumptions and real operations. If you add the nature of self-bias and interpretation of some of these factors, then we are left with a rather subjective list of factors with differing degrees of weighting attached to them. this presents a less than ideal case for presenting a robust model to *put your hat on*. The level of uncertainty that these sorts of models exhibit pose an issue in terms of predicting an outcome, more so when these uncertain factors are associated with probability, and the multiple options that may exist in a given scenario. Different options and when it is taken presents another degree of uncertainty into a model that is used to predict the outcome of human behaviour and the likelihood of achieving a goal. This is sometimes referred to as the optimal stopping theory (Chow, Robbins, & Siegmund, 1971).

Clearly, when we try to piece together aspects of BOR and attempts to model them within an ABM we are likely to come up against resistance in relation to embodiment, and claims that the model is too simplistic and fails to take into account multiple factors (which may or may not be unknown).

The problem with applying models and the return of the analogy

Due to the complexity of studying an organisational structure and associated dynamics, the use of computer modelling and simulation techniques has been put forward as a line of methodological enquiry (Edmonds & Meyer, 2017). For advanced simulation, or organisations that possess intelligent systems, we can consider the use of ABM in relation to how we try to predict how humans behave when confronted with complex decisions. We have discussed how analogies have been adopted in order to explain behaviour and interactions; such as that of an organism or brain. A true example of a multi-complex system that interacts within its own physicality, and responds to external stimuli. Although this narrative is easy to comprehend it can sometimes be somewhat misguided in over-simplifying what is in essence an overly-complex system of systems that requires far more understanding than we are often able to comprehend. For example, if we take a typical organisational structure and what we would perceive as comprising the main elements. Slowly we can start to identify components that draw on tangible representations of an organisation such as 'Human Resources', or a 'CEO'. But after we map the physical structure of the business we are left to ponder the intricate means of communication that is the backbone of the organisation, without even considering factors that we will not possibly know such as the culture of the workplace, personalities of individuals, etc. The main components could indeed lend themselves to factors that can be coded and placed into a computational model, with constraints and rules that allow us to exert forces into the system to predict what could potentially happen. Indeed, this would be a useful tool that could be utilised to assist in making a business robust and resilient, responding to changes in the marketplace or supply chain, sensitive to customer demands, and so on. But attempting to model this phenomenon as a simplistic system that will respond to external influences is somewhat misguided, due to the complexity of potential factors internal and external of the individual organisation. The very complexity and abstraction of factors associated with adaptive organisations is immediately challenged as soon as an environment is considered that is composed of multiple complex characteristics (Boisot & Child, 1999). So, perhaps the key to using models that explain plasticity within organisations is a mixture of intelligent decision-making agents, but with a human component monitoring and supervising the process?

We can propose that developing a model of efficient organisational plasticity lies within its foundation. Through an established set of rules and recognised behaviours an ABM may evolve and develop to a level of potential that is marshalled and supervised by a human component. Indeed, in some instances this marshalling may be significant in terms of negating agent decisions (such as a behaviour taking place within a given context/state) or less so (with a behaviour being accepted, but with slight adjustments such as ensuring information is conveyed to the human or other agents).

However, this is not as clear cut as it may appear. The human-agent partnership may very well not be a single point of interaction. Richards (2017) discussed the different composition of human-agent interaction whereby the supervisory role may be shared or switched between the human or agent. This would suggest not only a hierarchical framework, but also the ability for such delegation to dynamically pass between agents (human or non-human). The critical issue is to exploit the benefits of an agent system, which also means embracing the nature of its adaptive and flexible approach within a dynamic situation, but ensuring the human remains within a position of supervisory control - and all that entails in terms of maintaining good situation awareness and building trust. Chen et al (2014) stress the importance of aligning human situation awareness with agent situation awareness - which they term as Situation Awareness-based Agent Transparency (SAT). This approach not only takes into account the information required by both human and agent components in order to carry out tasks, but also on the interaction required between the two parties in order to effectively achieve a goal.

Discussion

There have been many arguments put forward as to whether the creation of behavioural models are the best manner with which to understand a tangible or philosophical phenomenon; in that components of a model tend to be composed of nouns, objects, verbs and processes (Franco & Rouwette, 2014). Indeed, Robinson (2014) poses a dilemma that stresses the importance of defining the use of models as relating to research that *models behaviour* or research that possesses *behaviour with models*. The two approaches are markedly different, but equally imply the benefit of adopting models to explain behaviour.

Franco & Hamalainen (2014) suggests the adoption of a logical-positivism to utilising models to be used in BOR. This approach would require the formulation of hypotheses, followed by empirical testing before arriving at a theory that explains the nature of interaction between the factors within the model. This is in contrast to approaches that have a theory in mind prior to building models to be used to explain behaviour, and using theory-specific language to explain the observations that the model offers (Abend, 2008). This latter approach may present the researcher with more structured and formal methods for conducting model-based research, but is more likely to miss interactions that do not fit within the adopted formal theory that sits at the heart of the model. For example, if we consider an agent-based model of a factory assembly line, a formal model can be used to define agent-based interactions with defined human counterparts. these would be clearly outlined in terms of communication pathways, limitations and rules. During the analysis of a given scenario, such as the effectiveness of the human-agent team in successfully producing a number of products on the assembly line, this would be measured and defined using the set rules within such a model. We may also be able to manipulate factors within the model and change the team composition, set limitations or even increase goal requirements. However, we would fall somewhat short of presenting a wider interpretation that takes other factors into consideration, such as human fatigue, personality differences in the human team, attitude of the human to the agent counterpart, and so on. If we are dealing with known entities that are highly predictable and unlikely to deviate from their known behaviours then predicting using such models becomes far easier. However, when introducing the human element into the model the level of uncertainty is bound to increase; and thus compromises the integrity of the model. Pasquini et al (2002) highlight the lack of tools in Cognitive Science approaches that allow the researcher to quantify reliability in any form of analysis, but also highlights the difficulty in measuring cognitive aspects of human behaviour in the first instance. Making generalisations from observed behaviour is one thing, as that allows us to adopt a trend analysis, but general observations based on human behaviour can differ between individuals for many reasons.

This concern has been addressed in some studies, with Kennedy (2018) proposing a model that takes into account the nature of cognitive (and affective) factors when creating models. By providing a level of cognitive abstraction to agent-based models, Kennedy suggests that this meta-cognition is a step towards creating a means by which models can use cognitive aspects of 'deliberate action' and provide the agent 'ways to think' when making decisions. This does raise the issue of requiring different types of architecture that a model must embrace when creating a structure to test and observe predicted trends and the uncertainty that human behaviour brings to the equation.

Conclusion

This paper has explored the use of analogy in describing how agents could be integrated within an organisation in order to effect change. Traditionally we would expect the use of ABM to facilitate our understanding and predict future disruptions to the organisation.

While we can view this dynamic change in agent-based systems as being primarily a positive step towards effectiveness, we must also consider how the nature of plasticity can affect the human monitoring the system, or even the human co-agents within the system. The nature of an agent framework, and more so one that is constructed of intelligent agents, proposes a degree of delegated authority when it comes to achieving a set goal. However, if the agent-based system is perceived to be allowed to adapt and change in order to achieve a level of optimisation, or a different set of behaviours or tasks, to achieve a goal, then it is fundamental that the human component of that system understands (and trusts) the different decisions that are made.

If a model is to be used then it is essential that one considers as many aspects as possible before arriving at a prediction or summing a conclusion. Modelling human behaviour is certainly a beneficial means of assessing an hypothesis, but it is wise to attempt an architecture that fits aspects of human cognition when using agent systems (Trafton et al, 2013; Holland et al, 2013). It is clear that agent-based systems can be useful for modelling some behaviours, but care is needed when stepping beyond the real limitations that they possess. To validate an ABM against real human behaviour is still out of reach, and most likely will remain so until we develop an advanced AI that possesses both narrow and general intelligence (Goertzel, 2014). It is essential that any ABM that purports to replicate human behaviour should discuss human cognition to some level. Advances in producing complex cognitive architectures (CA) could offer potential cross-over with ABM and attempt to address in essence embodied cognition (Lieto et al., 2018). A predictive model that encompassed ABM, CA and AI would present a powerful tool - but its complexity is evident.

Fundamentally, what we are striving for is a method by which we can understand and predict how organisations can be affected by internal and external agents. Whether the approach taken is one that embraces one methodology over another, there is an underlying narrative that resonates across all disciplines - the human. Only through continued multidisciplinary efforts can we take further steps towards this goal.

References

Abend,G.(2008).The meaning of theory. *Sociological Theory, 26*(2),173–199.

Arbib, M. A. (1989) The metaphorical brain 2: Neural Networks and beyond. New York: Wiley.

Asensio, J. M. L., Peralta, J., Arrabales, R., Bedia, M. G., Cortez, P., & Peña, A. L. (2014). Artificial intelligence approaches for the generation and assessment of believable human-like behaviour in virtual characters. *Expert Systems with Applications*, *41*(16), 7281-7290.

Beer, S. (1972) Brain of the firm: A development in cybernetics. New York: Herder & Herder.

Boero, R., & Squazzoni, F. (2005) Does empirical embeddedness matter? Methodological issues on agent-based models for analytical social science. Journal of Artificial Societies and Social Simulation, 8(4), 6.

Boisot, M. & Child, J. (1999) Organisations as adaptive systems in complex environments: The case of China. Organization Science, 10(3), 237-252.

Cameron, L. & Larsen-Freeman, D. (2007). Complex systems and applied linguistics. *International Journal of Applied Linguistics*, 17(2) pp. 226–239.

Catriona M. Kennedy Computational Modelling of Metacognition in Emotion Regulation. 8th Workshop on Emotion and Computing at KI2018, Berlin, Germany, September 2018.

Chalmers,D.J., French, R.M., & Hofstadter, D.R. (1992) High level perception representation and analogy: A critique of artificial intelligence methodology. Journal of Experimental Theory in Artificial Intelligence, 4(3), 185-211.

Chen, J. Y. C., Procci, K., Boyce, M., Wright, J., Garcia, A., Barnes, M. (2014). Situation awareness–based agent transparency (No. ARL-TR-6905). Aberdeen Proving Ground, MD: U.S. Army Research Laboratory.

Chow, Y.S., Robbins, H.A., & Siegmund, D. (1971) Great Expectations: The theory of optimal stopping. Houghton Miffin Company; Boston, USA.

Cornelissen, J.P. (2005) Beyond compare: Metaphor in organization theory. *Academy of Management Review, 30*, 751–764.

Douglas M (1986) *How institutions think*. Syracuse, NY: Syracuse University Press.

Edmonds, B. & Meyer, R. (Eds.). (2017) Simulating Social Complexity. A Handbook (second ed.). Heidelberg: Springer

Etzion, D. & Ferraro, F. (2010) The role of analogy in the institutionalization of sustainability reporting. *Organization Science*, *21*, 1092–1107.

Fillmore, C.J. (1975) An alternative to checklist theories of meaning. *Berkeley Linguistics Society, 1*, 123–131.

Fiss, P.C., & Zajac, E.J. (2006) The symbolic management of strategic change: Sense giving via framing and decoupling. *Academy of Management Journal, 49*, 1173–1193.

Friedewald, M., & Raabe, O. (2011). Ubiquitous computing: An overview of technology impacts. *Telematics and Informatics*, *28*(2), 55-65.

Franco,L.A. &Hämäläinen,R.P. (2014) Call for papers: Special Issue on Behavioural OR. http://bor.aalto.fi/ejor.html

Franco,L.A. & Rouwette,E.A. (2014)A typology of behavioural OR studies. In Paper presented at the conference of the International Federation of Operational Research Societies.

Furnari, S. (2011) Exaptation and innovation in architecture: The case of Chicago's Millennium Park. In

Gintis, H. (2004). Modeling cooperation among self-interested agents: a critique. *The journal of socio-economics*, *33*(6), 695-714.

Goertzel, T. (2014) The path to more general artificial intelligence. Journal of Experimental & Theoretical Artificial Intelligence, 26(3), 343-354.

Grandori, A., Gaillard, L. (Eds) Organizing Entrepreneurship, Routledge, New York, New York.

Fultot, M.F. (2013) Plasticity and Robots. Proceedings of the 1st Artificial Intelligence and Cognition Workshop (AIC 2013). 118-123.

Gavetti,G., Levinthal, D.A., & Rivkin, J.W. (2005) Strategy making in novel and complex worlds: The power of analogy. Strategic Management Journal, 26(8), 691-712.

Gentner, D., Bowdle, B., Wolff, P. & Boronat, C. (2001) Metaphor is like analogy. In: Gentner D, Holyoak KJ, & Kokinov BN (Eds.), *The analogical mind: Perspectives from cognitive science* (pp. 199–253). Cambridge, MA:MIT Press.

Hargadon, A. & Sutton, R. (1997) Technology brokering and innovation in a product development firm. Administrative Science Quarterly, 42(6), 716-749.

Holland, O., Diamond, A., Marques, H.G., Mitra, B. and Devereux, D. (2013) Real and apparent biological inspiration in cognitive architectures, *Biologically Inspired Cognitive Architectures*, pp. 105-116, available at: www.researchgate.net/publication/257744670_Real_and_apparent_biological_inspiration_in_cognitive_architectures.

Kahneman, D., & Tversky, A. (1973). On the psychology of prediction. *Psychological Review, 80*(4), 237-251.

Kolb, B. & Gibb, R. (2011) Brain plasticity and behaviour in the developing brain. Journal of the Canadian Academy of Child Adolescence Psychiatry, 20(4), 265-276.

Lam, A. (2007) Knowledge Networks and Careers: Academic Scientists in Industry-University Links, *Journal of Management Studies,* 44, 993-1016.

Lieto, A., Bhatt, M., Oltramari, A., & Vernon, D. (2018). The role of cognitive architectures in general artificial intelligence.

Macal, C. M., & North, M. J. (2009, December). Agent-based modeling and simulation. In *Proceedings of the 2009 Winter Simulation Conference (WSC)* (pp. 86-98). IEEE.

Mintzberg, H. (1989) Mintzberg on Management: Inside Our Strange World of Organizations. Free Press, New York.

Morgan, G. (1986) Images of organization. Beverly Hills, CA: Sage.

Richards, D. (2017) Escape from the factory of the robot monsters: Agents of change. Team Performance Management, 23, 96-108.

Robinson,S.(2014).Have I been doing behavioural OR for the last 20 years?. In *Paper presented at the conference of the International Federation of Operational Research Societies*.

Pasquini, A., Pistolesi, G., Risuleo, S., Rizzo, A. & Veneziano, V. (2002) Reliability analysis of systems based on software and human resources. IEEE Transactions on Reliability, 50(4), 337-345.

Secchi, D. (2011) Extendable rationality. Understanding decision making in organizations. New York: Springer.

Siebers, P-O., Herath, D.B., Bardone, E., Farahbakhsh, S., Knudsen, P.G., Madsen, J.K., Mufti, M., Neumann, M., Richards, D., Seri, R., & Secchi, D. (In print) Organisational Plasticity: A community modelling experience. Evidence-Based HRM.

Trafton, G., Hiatt, L.M., Harrison, A.M., Tanborello, F., & Schulz, A.C. (2013) ACT-R/E: An embodied cognitive architecture for human-robot interaction. Journal of Human-Robot Interaction, 2(1), 30-55.

Tsoukas, H. (1993) Analogical reasoning and knowledge generation in organization theory. *Organization Studies, 14*, 323–346.