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Ergonomists as Designers: Computational Modelling and Simulation of Complex Socio-Technical Systems

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Ergonomists as Designers: Computational Modelling and Simulation of Complex Socio-Technical Systems

Contemporary ergonomics problems are increasing in scale, ambition, and complexity. Understanding and creating solutions for these multi-faceted, dynamic, and systemic problems challenges traditional methods. Computational modelling approaches can help address this methodological shortfall. We illustrate this potential by describing applications of computational modelling to: (1) teamworking within a multi-team engineering environment; (2) crowd behaviour in different transport terminals; and (3) performance of engineering supply chains.

Our examples highlight benefits and challenges for multi-disciplinary approaches to computational modelling, demonstrating the need for socio-technical design principles. Our experience highlights opportunities for ergonomists as designers and users of computational models, and the instrumental role that ergonomics can play in developing and enhancing complex socio-technical systems. Recognising the challenges inherent in designing computational models, we reflect on practical issues and lessons learned, so that computational modelling and simulation can become a standard and valuable technique in the ergonomists' toolkit.

Keywords: modelling and simulation, agent-based modelling, socio-technical systems, complex systems

Practitioner Summary: This paper argues that computational modelling and simulation is currently underutilised in ergonomics research and practice. Through example applications illustrating the benefits, limitations, and opportunities of such approaches, this paper is a point of reference for researchers and practitioners using computational modelling to explore complex socio-technical systems.

Word count: 6916

Introduction

Ergonomists are facing contemporary design challenges of increasing scale, ambition, and complexity. Application domains range from sustainability, advanced automation and artificial intelligence, new employment patterns and Industry 4.0, to cyber security and terrorism, ageing populations, and healthcare innovation (Davis et al. 2014, Thatcher and Yeow 2016, Thatcher et al. 2018, Salmon, Bedinger, and Stanton 2017, Hancock 2014, Haslam and Waterson 2013). To explore, understand, and solve these dynamic and systemic problems is challenging for ergonomists' traditional research methods, in particular integrating multiple types of data, over time, across levels and with emergent properties (Hettinger et al. 2015, Hughes et al. 2012, Salmon et al. 2017, Waterson et al. 2015). All research techniques and methods present strengths, opportunities and limitations, making them more or less applicable to different problems (Hughes et al., 2017). In this paper, we explore how computational modelling approaches may aid ergonomists in addressing complex design problems and consider barriers to application.

We illustrate key features of computational modelling by reflecting on our own use of different approaches, presenting three models of socio-technical problems in different domains: (1) simulating teamworking within a multi-team engineering environment using Agent-Based Modelling and Simulation (ABMS); (2) simulating crowd behaviour in transport terminals using ABMS; and (3) simulating engineering supply chains in models that integrate ABMS with system dynamics models.

Our examples highlight approaches, benefits, and challenges in working across ergonomics, psychology, engineering, and computer science disciplines – reflecting multi-disciplinary, multi-stakeholder practices envisaged by socio-technical theory (e.g., Cherns 1976, Clegg 2000, Clegg et al. 2017). We demonstrate the potential for computational modelling to build theory (through observing emergent behaviours) and test theory (Smaldino 2017, Salmon et al. 2017), and to explore methodologically challenging meso-ergonomics phenomena (Karsh, Waterson, and Holden 2014, Salmon and Read 2018), in multi-team systems and across scales within engineering supply chain processes. We illustrate how modelling approaches can be used to explore phenomena in silico that may be difficult or unacceptable to study in the real-world (Hughes et al. 2012), such as crowd disasters or team membership changes, or where the costs of cross-organisation change are high, such as in supply chains, or where the socio-technical system is itself being designed.

We do not describe how to programme computational models, nor do we review all of the conceptual and technical steps required to build them, as these issues have been detailed within the computer science, social science, and psychological literatures (see: Hughes et al. 2012, Gilbert and Terna 2000, Smith and Conrey 2007). Instead, we reflect upon our own multi-disciplinary experiences of the practical challenges and lessons from modelling human behaviour and complex systems, then discuss how ergonomists may engage more with computational modelling techniques. In so doing, we hope to stimulate discussion and reflection regarding the role of ergonomists as designers in contributing to well-constructed, valid, and practically useful models.

We begin by describing key computational modelling approaches, in particular ABMS, and outlining how they differ from traditional methods that ergonomists employ. As noted by other scholars, the human mind has difficulty in conceptualising complex systems (e.g., Resnick 1994) and computer simulation models can capture and represent these without verbal models to explain the interactions, behaviours, and relationships within and between subsystems. Simulation models enable examination of phenomena across differing levels of abstraction, and exploration of the implications of aggregating individual and group behaviours at scale and in context (Salmon et al. 2017). In addition, such models help overcome the issue of studying complex systems in an overly reductionist manner (Hettinger et al. 2015), and enable the study of social behaviours within a context (Smaldino, Calanchini, and Pickett 2015, Norling, Edmonds, and Meyer 2017). The value of such approaches to ergonomics is increasingly being demonstrated. For example, within physical ergonomics ABMS have been used to simulate building occupants' behaviour and social interactions (Chapman, Siebers, & Robinson, 2018) and co-simulation to predict buildings' energy use (Li, Wei, Zhao, & Zeiler, 2017). Computational models have been developed to aid safety, particularly regarding evacuations (e.g., Shi et al., 2012), fire safety management (Wang, Wang, Wang & Shih, 2015), along with workers' safety attitudes and behaviours (Shin, Lee, Park. Moon, & Han, 2014). ABMS have been employed to examine complex cognitive tasks, for example, relating to multi-agency operations in rescue operations (Baber, Stanton, Atkinson, McMaster, and Houghton, 2013) and discrete event simulations to explore fatigue, productivity, and wellbeing (Dode, Greig, Zolfaghari, and Neumann, 2016). These applications illustrate the breadth and utility of computational methods.

There are many different forms of computer model - illustrated by the range of crowd evacuation simulations developed. Zheng et al. (2009) describe seven approaches for computer evacuation models: (1) cellular automata, (2) lattice gas, (3) social force, (4) fluid dynamics, (5) agent-based, (6) game theory, and (7) animal experiments. They differ in many of their key features. For example, approaches, such as cellular automata and lattice gas models, model space and time discretely, whereas others, such as fluid dynamics models, and social force models, model space and time continuously. Fluid dynamics and social force models are complex models requiring high computational power - due to relatively complex individual behaviours and interactions between agents in the model. Conversely, cellular automata and lattice gas models are simple models with less behavioural complexity and have high computational efficiency. Crowds can be modelled as homogenous or heterogeneous groups. Most cellular automata, fluid dynamics, game theoretic, and lattice gas models model crowds homogenously, while ABMS and social force models tend to model heterogeneous crowds. This reflects macroscopic and microscopic perspectives on crowds. In microscopic models (e.g., cellular automata, lattice gas, social force, ABMS), pedestrians are modelled as particles. However, in macroscopic models (e.g. fluid dynamic models), a crowd of pedestrians is modelled as a fluid where particles represent individual pedestrians. Different phenomena can be analyzed dependent upon the model, e.g., exit selection, panic propagation, herding, decision making, competitive and collaborative behaviours. The purpose and focus of the simulation therefore influences the choice of which computational approach is most appropriate to apply.

Considering ABMS specifically, *agents* have individual behavioural rules, which can be called *local* or *microscopic* knowledge (Epstein 2006, Wilensky and Rand 2015). Through agent interactions, a stable global or macroscopic social phenomenon can *emerge*, enabling scientists to study the micro-to-macro mapping – a phenomenon described by Epstein (2006) as *"generative social science"*. In this way, ABMS can provide *candid* explanations of complex social phenomenon, such as evacuation dynamics or team performance (Epstein 1999, 2006, Hughes et al. 2017, van der Wal et al. 2017). ABMS has helped to overcome dichotomous analytical differentiation. Coleman's (1990) formula – known as Coleman's boat – explains the relationships for the shifts in social structure (macro) and reciprocal behaviour (micro). He poses that social structure (macro) regulates reciprocal behaviour (micro) and vice versa, the micro behaviour (methodological collectivism) regulates the macro behaviour (methodological individualism). With ABMS, we can analyse both levels simultaneously, i.e., both local microscopic individual agent rules and macroscopic level emergent group behaviour.

Examples of Modelling in Practice

To demonstrate the value of modelling to ergonomics, we now present three examples of computational modelling of complex socio-technical systems. Each case illustrates the challenges that can be productively addressed, and discusses the application of the methods and key benefits realised.

Application 1: Teamworking in Engineering

Teamworking is a norm for most contemporary organisations. Accordingly, the literature on teamwork is vast, often existing in disciplinary silos, such as psychology, social science, and ergonomics, (see, Crowder et al. 2012), with models of varying sophistication, complexity, and focus (Guzzo and Dickson 1996, Ilgen et al. 2005, Mathieu et al. 2017, Salas, Sims, and Burke 2005). Variables influencing teamwork are especially complex, because teams can be considered a microcosm of an organisation. Almost any variable that applies at an organisational level can also be considered at a team level (Crowder et al. 2012, Mathieu et al. 2017). This has led to some scholars focussing on intra-individual variables that influence team dynamics and performance (e.g., personality characteristics, attitudes), while others have considered the interpersonal (inter-individual) aspects of team members (e.g., communication, trust), or the impact of organisational contexts and wider socio-technical issues (e.g., structure, process, goals).

Today, scholars recognise teamwork as a multilevel phenomenon, often drawing on synthesised frameworks and models (e.g., Mathieu and Chen 2011, Walker et al.

2006). Nevertheless, the range and number of potential variables creates almost unlimited complexity for researchers looking to understand team mechanisms (Hughes et al. 2012), posing a range of methodological challenges (Epstein, 1999). For instance, teamworking practices are known to be dynamic and cyclic (Salas, Cooke, and Rosen 2008), yet conceptual models typically represent teamworking as a linear, sequential process, which can be understood through Structural Equation Modelling (SEM), and other relatively static models. Studies of phenomena such as conformity show us how team cognitions and behaviours can be skewed by individual members and single interactions (Reagans and Zuckerman 2001).

The key characteristics of ABMS are well suited to the study of teams, because they mirror those of employees working in large organisations (Crowder et al., 2012). ABMS presumes (a) that agents have incomplete data or capabilities to enable them to problem solve, (b) that no individual agent has global control, (c) that data is decentralised, and (d) that the computation is asynchronous (Crowder et al., 2012; Jennings, 2000; Sycara, 1998). Through application of rules to agents and heterogeneity, ABMS permits understanding of dynamic processes in ways that statistical analyses such as regression do not.

Between 2006 and 2009 we participated in a project simulating engineering team behaviours within the manufacturing sector (see Crowder et al., 2012). The research involved psychology, engineering, and computer science colleagues in collaboration with engineers employed by two large multi-national manufacturing organisations. Engineering teams in contemporary manufacturing environments typically work on complex tasks where no single individual has all the information required (Elliot and Deasley 2007). Information needs to be shared at the right times with the right people, and team members need to recognise how and when to do this (Cross and Baird 2000, McKay et al. 2018). They also need sufficiently high competence to understand task requirements and to communicate effectively; and they need to trust the competence of their fellow team members to develop shared mental models of the problem domain. Equally, team performance can be understood in different ways, such as the speed and cost of the work, and the quality of outputs (Crowder et al. 2012). These outcomes might be inversely related, e.g., where a high-quality solution might cost more or take longer. This process is inevitably dynamic and complex, with such teams typically comprising different job roles, working on multiple goals through defined processes, and often comprising teams-of-teams (multi-team systems – see: Marks et al. 2005).

To develop our ABMS of engineering teams we conducted research within the participating organisation, so that we could identify and measure variables underpinning the teamwork. This involved literature reviews, interviews with engineering experts, and surveying the design team engineers about their teamworking behaviours. The variables selected for inclusion in the simulation models were diverse (see Figure 1). This enabled us to represent aspects from structural and contextual factors (e.g., project workflows, engineer availability, communication response rate), to interpersonal variables (e.g., shared understanding, trust) and individual characteristics (e.g., competence, motivation, learning time).

Using these models, we were able to conduct a range of experiments to simulate teamworking and team performance (working time, and task quality), in different situations. For instance, we tested the impact on performance where the team's composition (competency and motivation) was held constant, but the sequence of tasks was varied. We also ran experiments changing team composition characteristics to examine performance sensitivities (see: Crowder et al., 2012). These experiments provided useful insights for the organisations, with the process of developing the model often as illuminating as the experiments' results: for example, forcing us to question and test assumptions about communication paths and workflows. The data also provided information to aid the organisations in their decision making and design processes.

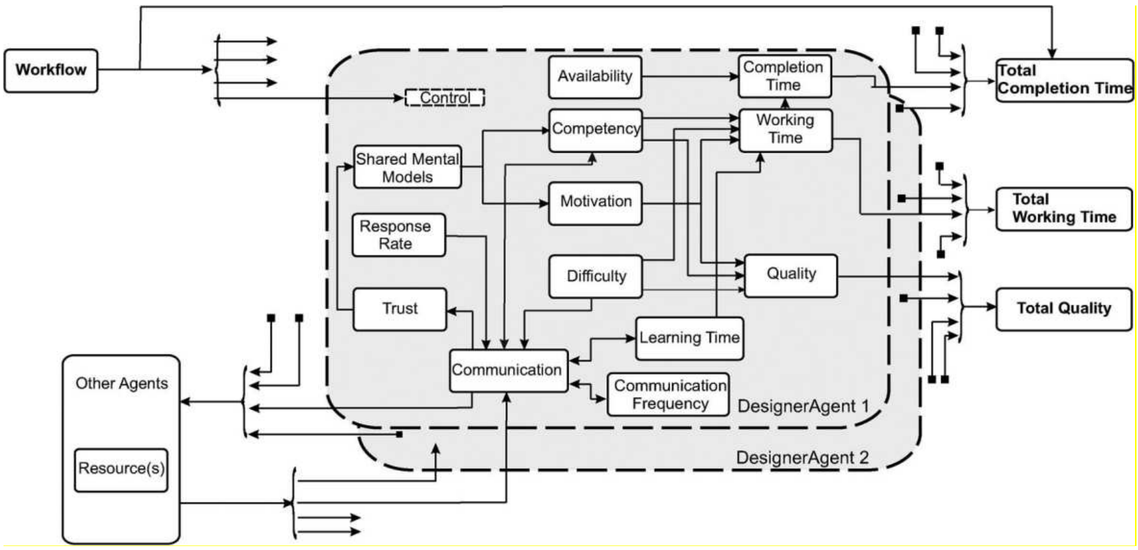

Figure 1: *Structure of an agent-based model of engineering teamwork (from Crowder et al., 2012, p. 1429)*

ABMS incorporates features ideal for exploring teamwork and other socio-technical systems with subsystems and multiple inter-relationships. Crucially, an ABMS is built from the bottom-up rather than from the top-down, starting with a landscape (model context) and team members of different number and type. Team member *agents* can have heterogeneous attributes (e.g., personalities, competencies) and, for instance, some might only allocate 20% of their time to the task while another may allocate 100%. Some team agents with low competence need time to learn, unlike others with high competence. ABMS enables team members to be treated heterogeneously, such as assigning different levels of trust to individual team members rather than the average level of trust to all.

The coding of ABMS through rules, which require hypotheses in an 'if X, then Y' format, enables variables to be modelled in relation to other variables. For instance, in our model of teamwork (Crowder et al., 2012) one might specify how competence level and task difficulty would operate in practice. So, for instance, if an agent's competence is lower than the task's difficulty it might need time to seek or learn information, which can be modelled as delays in responses, whereas agents with higher competence might be able to complete the same task more quickly. Other variables (e.g., trust, or attitude knowledge sharing) can be similarly incorporated. This can enable researchers to examine tipping points, dependencies and bottlenecks.

Furthermore, ABMS enables the incorporation of organisational context into the model. For example, teams-of-teams can be represented by building a team landscape and variables from the wider socio-technical system, such as people with different goals, can be captured by translating them into *rules* for the agents. Delays in processes can also be created. For example, in our model, if a team member had lower competence they would seek information, creating a delay, but that information would then increase their competence. This helps elucidate the impact of different rules on system parameters and outcomes (e.g., team goal success, speed, cost, and quality of work) and the process forces modellers to think through the consequences of assumptions (i.e., by creating "If… then…" rules), which may not always be correct, but enable the testing, adjustment and calibration of parameters.

We collected real-world data from the teams to populate our models with behavioural data, e.g., in relation to the time that engineers spend undertaking particular activities (e.g., solo work, social work, seeking information – see, Robinson 2012).

Models may also draw on existing theoretical frameworks (see Walker et al. 2006). After running simulation models, it can be possible to refine and validate simulation models against real-world performance data to inform further revisions of the model. Of course, this does not guarantee that your rules are *correct* so it is better to consider them as *explanatory* rather than predictive (Epstein 2006).

As the sophistication of such models develops, there will be advantages for organisations to combine these models with other approaches. For example, developing a small number of business scenarios using an approach like the System Scenario Tool (Hughes et al. 2017) and simulating these against specified system goals/metrics.

Application 2: Crowd Management within Transport Terminals

Our second exemplar application also involves ABMS and concerns a safety critical and practically challenging issue to research directly. Between 2015 and 2017, we participated in an EU Horizon 2020 funded research project during which we developed an agent-based model to simulate crowd behaviour and management in transport terminals (see, van der Wal et al. 2017). This interdisciplinary project involved academics from organisational psychology, computer science, human factors and engineering, together with transport operators from rail, marine, and aviation sectors.

While several excellent crowd simulation models exist, their foundations in the physical sciences typically view crowd members as molecules in a fluid, whose passage from A to B is governed by rationality and efficiency (Challenger, Clegg, and Robinson 2010). While oversimplified, these assumptions work reasonably well for routine situations. However, human behaviour is considerably more complex and less predictable than fluid dynamics, particularly in emergencies, and it is therefore essential that more realistic assumptions are incorporated into computational models (Templeton, Drury, and Philippides 2015).

In emergencies, rapid evacuation time is critical for survival (McConnell et al. 2010). Consequently, providing adequate emergency exits to enable this is essential so civil engineers and architects consider this carefully when designing buildings (Wang et al. 2015). For instance, a large building may have a capacity of 1000 people and four large exits, enabling 250 people to evacuate from each within a two minute requirement. However, psychological research indicates that most people will use familiar exits in emergencies, often via the way they entered, irrespective of whether they are nearest (Grosshandler et al. 2005). So, in reality, 750 people may use just one exit, far exceeding its design capacity, and leading to congestion and potentially fatal crushing as well as delayed evacuation times. Similarly, while psychological research indicates that people evacuate relatively quickly once they are moving, their initial response to the alarm is often substantially delayed (Proulx 1995) which is rarely accounted for in existing models of crowd behaviour. So, to address these limitations, our model incorporated both of these more realistic behavioural assumptions. We now describe our simulation model and some sample results.

When developing the model, we first used a simplified version of reality, incorporating just one single large room from which our computer agents evacuated (see, van der Wal et al. 2017, for full details of the model). This was important initially, to isolate the effects that we wished to examine in controlled experiments. Furthermore, it is very easy to over-complicate computational models by including too many variables, making outputs difficult to interpret (Hughes et al. 2012). Just a few variables can create tremendous complexity when interacting dynamically over time as they do in agent-based models (Gilbert 2008, North and Macal 2007, Epstein 2006). Once initial effects have been established and verified, it is then possible to increase the complexity of the model, which we then did by integrating architectural plans of actual transport terminals and including more variables.

The evacuation model we developed (see, Figure 2) simulated passengers evacuating a transport terminal and included the following psychological and behavioural variables: falling, helping behaviours, social influence, compliance, environmental familiarity, travelling in groups, age, and gender. Through workshops and discussions with stakeholders from the transportation industry, we selected variables that were most relevant to them and the project's goals. During development, we iterated the model among the project's computer scientists, psychologists, ergonomists, and other consortium members to fine-tune the behavioural complexity represented and ground it in the research literature. Using a series of structured simulations, we then systematically manipulated the input variables to determine their unique and interactive effects on two outcomes: (1) evacuation time, and (2) number of falls.

The key results related to emergent system-level behaviours including doors creating bottlenecks, social contagion speeding up evacuation time, falls not affecting evacuation time significantly, and travelling in groups enabling faster evacuation. These findings are emergent effects because they could not be predicted from the rules governing the behaviours of individual agents. Rather, these outcomes emerged from the dynamic interactions between the agents. Next, we performed a sensitivity analysis to determine the contribution of each variable, with evacuation time reduced by up to 30% when travelling in groups, for instance. These results demonstrated the need for evacuation simulations used in the design of public spaces such as transport terminals to include behavioural and psychological variables to create more realistic simulations.

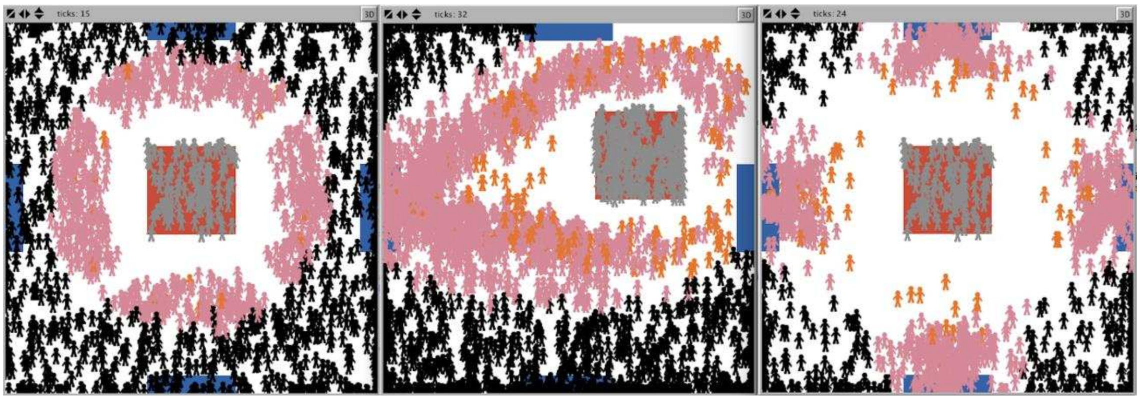

Figure 2. *Screenshots from evacuation simulations. Left: start of simulation. Middle: majority of agents choose familiar exit. Right: majority of agents take nearest exit. Pink agent = decided to evacuate, black agent = routine non-incident behaviour, walking randomly, orange agent = fallen, grey agent = injured, red area = location incident, blue area = exit.*

In this domain, a key advantage of ABMS is that they operate in an artificial environment and can therefore examine scenarios that are extremely rare or that would be dangerous to research in real life. Furthermore, multiple iterations of the same scenario can be run with slightly different parameters to identify critical tipping points or effective preventative and/or reactive solutions (Hughes et al. 2012). For instance, in our example, the number and placement of emergency exits can be changed quickly between experimental conditions, or even another floor added, which would be essentially impossible in real life research. This capability is invaluable for decision making in crowd management, such as by the emergency services or the planners of music festivals or sporting tournaments (Stoate 2015). Finally, ABMS is particularly suitable for studying crowd behaviour such as evacuations because the movement of each agent directly affects the movement of neighbouring agents in an emergent, dynamic, and non-linear way (e.g., collisions) that is difficult to study with traditional methods.

Application 3: Engineering Supply Chain Processes

Our final exemplar application, focussing on engineering supply chain processes, allows us to contrast system dynamic modelling, discrete event simulation and ABMS. In the examples provided, we report integrations of system dynamic modelling with ABMS and then a separate application of discrete event simulation to build understanding of the behaviours and risks in the operation of these complex systems. We chose this domain as engineering has utilised computational modelling for many years, their systems are socio-technical, and the extant literature indicates how and when different forms of modelling may be applicable (Shappiro, 2016; Oliviera et al. 2016).

Typically, the modelling and simulation of engineering supply chains focusses on improving the efficiency and effectiveness of supply chain operations and logistics (Lin and Naim 2019). Within the broader engineering sphere, three process simulation methods are commonly used to model human and organisational behaviours. System dynamics uses causal loops to model the behaviour of the overall network, such as in supply network management (Aldemir, Beldek, and Celebi 2018), engineering design processes (Al-Kadeem et al. 2017, Kasperek et al. 2015, Kasperek et al. 2016), and the design of business models for innovation (von Peinen et al. 2018). In contrast to systems dynamics, ABMS enables the visualisation and analysis of collective behaviours of autonomous agents and discrete event simulation enables the simulation of processes that can be characterised by series of events that occur over time.

ABMS has been frequently applied to improve the design of engineering products and systems, such as diffusion of design innovations (Dilaver 2015, Lee et al. 2019) and pricing strategies (Wang et al. 2018). Here, the agents represent market players. To help understand engineering product development systems, other researchers have developed ABMS where the agents represent players in the development process. For example, Fioravanti, Novembri, and Rossini (2017) simulate actors in construction projects, Yin and McKay (2018) simulate vicious circles in product development systems, and Utami, Holt and McKay (2018) simulate the design of supply networks.

In contrast, as its name suggests, discrete event simulation models processes with a focus on events that occur within them. It has been widely used to simulate production systems to support the visualisation of bottlenecks, queues, and inventory levels when implementing lean methods (Omogbai and Salonitis 2016). Some applications focus on human interaction, such as Dode et al. (2016) who simulated the effects of (human) fatigue in production systems. Similarly, McKay et al. (2018) applied discrete event simulation methods to design-and-make supply networks in the aerospace sector.

Applying any of these approaches effectively demands “systems thinking”. This involves a hierarchical structure comprising a *system of sub-systems*, where each sub-system is a part of the wider system, and *a system of systems*, where each system is itself a sub-system interacting with other sub-systems. As each sub-system can have different governing principles, this necessitates the development of hybrid simulation approaches. For instance, Morgan, Howick, and Belton (2017) propose a framework for combining discrete event simulation and system dynamics approaches, and Nomaguchi and Fujita (2017) provide a wider framework for modelling systems of systems.

Choong and McKay (2014) and Sitepu, McKay, and Holt (2016) report applications of mixed methods (system dynamics and ABMS) to simulate sustainable supply chains, where some dimensions are governed by human behaviour and others by causal loops. In both cases, design research methodology (Blessing and Chakrabarti,

2009) was used in the formulation and validation of the simulation models. After an initial literature review, a descriptive study related to the supply chain under consideration (Malaysian palm oil and Indonesian rubber) was completed. This built understanding of the problem to be addressed, established working relationships with industry stakeholders, and was key to establishing the needs of the industry whom the simulation model was to support. Subsequently, simulation models were built, integrated, and evaluated with industry stakeholders to ensure that they were driven by data that was readily available and yielded realistic results. In both cases, the research resulted in simulation tools that are suitable for use in policy making decisions.

A key issue to be addressed when integrating simulation methods lies in defining and implementing interfaces between models. Sitepu, McKay and Holt (2016) used the composite indicators method in their rubber industry case to translate data between system dynamics and ABMS to derive optimal tree replanting scenarios. We have not yet integrated discrete event simulation with other methods but can see opportunities to use ABMS to inform the probability distributions that represent the process randomness that is key to discrete event simulation models.

For the design of product development systems, there is substantial literature on design processes (Wynn, Clarkson, and Eckert 2019, Wynn and Eckert 2017); the key challenge is understanding how this knowledge might inform models that practitioners can use to understand the systems they manage and operate within. Product innovations delivered through new or improved designs are critical for business success by creating value for customers. However, realising this value depends on the performance of product development systems and processes, and product-related services. Given this, there is an increasing interest in the design of such systems and processes, often across extended enterprises such as engineering supply networks, because this is the environment within which such systems typically operate.

Central to any design process is the ability to evaluate design alternatives by simulating their behaviours. For physical products, such simulations build on the laws of physics where, for example, it is possible to simulate the stresses and vibrations under given operational conditions. In contrast, product development and service systems are governed by human and organisational behaviours. For this reason, a prerequisite for the design and development of such systems lies in establishing ways of evaluating design alternatives by simulating human and organisational behaviours. Practical applications of this include the development of risk profiles with which human users can visualise supply chain risks given defined system architectures and make/buy scenarios (McKay et al. 2018).

Reflections and Lessons Learned

Our application examples have highlighted the potential value of computational modelling in exploring and understanding human behaviour within complex socio-technical systems. Next, we outline key practical challenges and reflect on broader lessons to propose an approach to applying computational modelling within ergonomics.

Practical Challenges

Undertaking computational modelling poses specific practical challenges that have the potential to impede or limit progress in the application of these methods. In particular, we have found that it can be difficult to engage with potential clients when resultant models are relatively simplistic. These approaches require long-term investment for maximum benefit, which can be difficult to market to commercial partners. The computational hardware and software required to develop the simulations can be expensive. Additionally, training staff in the development or interpretation of computer models and working with clients to specify or validate models, can increase the time from client brief development, to generation of value-adding insights and solutions. These kinds of long-term investment can be at odds with clients' requirements for a speedy solution (one that may be readily delivered and implemented using other ergonomics approaches). Furthermore, clients can be seduced and impressed by more visually realistic simulations and video-like virtual environments, often with little appreciation of, or interest in, the underlying science or resources needed to build such models. It is therefore challenging to educate clients about the value of computational modelling.

Related to clients' perceptions of realism, bounding and simplifying the system can lead to scepticism regarding face validity and generalisability (c.f., Chung and Williamson 2018). As simulation rules interact, even simplistic models can generate highly complex outputs very quickly (Hughes et al. 2012), making it difficult to identify cause and effect, and untangle data. Although this can be addressed through simulation testing and calibration against real-world datasets, this can be a time-consuming process. The resulting trade-off between the comprehensiveness (and realism) of a model and what can be readily understood and interpreted mirrors more general dilemmas in model abstraction that are typically addressed by clarifying the purpose of the model. For example, Thorngate (1976) has compellingly argued that no single model – simulated or otherwise – can be general, simple, and accurate simultaneously, and this argument also applies to ergonomics methods more generally (Waterson, Clegg, & Robinson, 2014). Rather, different levels of exploration (macro, meso, micro) offer different perspectives and understanding of particular problems (see also North and Macal 2007).

Within any model, 'garbage in' will lead to 'garbage out', so face validity is important but insufficient. This can be addressed in part by feeding-in real-world data, and feeding-off simulation data to test questions that the emergent dataset yields. The frequent paucity of real-world data to inform, train, or test models against can be a limitation, but also spurs ingenuity in seeking out suitable proxies. For example, while constructing the crowd evacuation model we realised that there was no available data on different demographics within transport terminals at different times of day and under different social and goal conditions (e.g., solo vs. family, commute vs. leisure), so we had to conduct primary field observations to collect suitable data.

Integrating findings from different modelling techniques and traditional methods can be challenging and presents additional complexity to those experienced with only applying a single technique. In particular, attempting to reflect true socio-technical systems, with a mixture of technical processes, causal loops, emergent behaviours, and shifting environmental properties poses questions regarding levels of abstraction and relative specificity of different components and subsystems. However, the flexibility of modelling techniques can integrate very diverse types of data (e.g., footfall, financial performance, spatial location, relational measures) with temporal dynamism in a single model. As we have discussed, undertaking computational modelling of complex problems often requires contributions from colleagues with different skillsets and knowledge. However, when collaborating across disciplines, it can be difficult to find modellers who are also competent in the subject domain and vice versa. Some of the meaning can disappear between rule articulation and computational implementation, or it can require substantial time to develop shared understanding of key concepts between researchers.

Lessons Learned

Computational modelling is a form of socio-technical design

While the potential application of computational modelling approaches to help understand complex socio-technical systems has been well articulated (e.g., Salmon et al. 2017), recognising the process of constructing a computational model as essentially socio-technical itself (e.g., Hettinger et al. 2015) is less widely acknowledged. Our experience has reinforced to us that the nature and complexity of the research process itself is a quintessential socio-technical design problem and so involves familiar ergonomics principles and practices (see, Mumford 1983, Clegg 2000, Cherns 1976). Research does not happen in isolation, but is influenced by the individuals, groups, and organisations constituting the research team itself (who bring varying skillsets, expectations, roles, technical expertise, computational hardware or software). It is also influenced by the funders, clients, end-users, partners or institutions, who often have differing objectives and priorities, imposing conflicting timeframes and resource constraints. These constrain, inhibit and promote outcomes and interactions across the organisational system assembled to conduct the research.

Hettinger et al (2015) note the value that the key socio-technical principles of stakeholder engagement and participation can yield within system dynamics modelling in maximising face validity (e.g., with users and organisations) and ensuring utility in practice (i.e., solving practical problems). We suggest that forming the design team and brief should also be approached with a socio-technical mind-set. As with any design team, it will require different specialisms and expertise such as an understanding of both computing and mathematical knowledge to construct the model, and behavioural, social, and technical knowledge to understand the problem and the steps from conceptual model, to simulation model, to exploration of results. This requires careful management to prevent misunderstandings, incompatible outputs and work practices, and general frustration along the way (c.f., Davis, Leach, and Clegg 2011).

Furthermore, adopting a socio-technical approach forces us to define at the outset what the project objectives and desired outcomes are, and to question how best to realise these (Davis, 2019). This reflects Clegg's (2000) contention that there are always multiple design solutions to any given problem and that design should reflect the needs of the stakeholders rather than designers' preferences or convenience. In this context, this means avoiding conceptual models being designed around what is technically expedient or problems being overly simplified to allow the application of computational modelling approaches a priori and ahead of considering alternative approaches. Modelling techniques should complement existing ergonomic toolsets and methods, not replace them, and their use should be driven by carefully judging their incremental value.

Improving model building in ergonomics theorisation

Much has been written regarding the value of techniques such as ABMS in studying processes over time or comparing competing models or sets of rules and parameters (e.g., Hughes et al. 2012, Ibrahim Shire, Jun, and Robinson 2018, Smaldino, Calanchini, and Pickett 2015). These enable the study of dynamic processes, non-linear relationships, and phenomena at different levels of abstraction (e.g., Hughes et al. 2012, Walker et al. 2017). As noted earlier, they also permit the observation of emergent behaviours and factors underlying complex behavioural patterns. However, our experience has also taught us that one does not need to actually programme a model to realise the greater conceptual clarity which may aid ergonomic theorisation. We discussed previously the benefits of having to define and specify a formal simulation model, in terms of rules, parameters, and temporal ordering. Smaldino, Calanchini, and Pickett (2015) describe this process as going beyond mere verbal models (which explain verbally how systems behave or humans interact, often using vague or broad descriptions), to one which explicitly details when and how behaviours or changes occur. Although difficult, this process can identify differences in mental models, understandings, and operationalisations between colleagues, from even the same discipline, which can be both enlightening and instructive.

For ergonomists, adopting the rigour and discipline required in formal model definition is beneficial regardless of whether the intent is to construct such a model. It forces a move beyond descriptive conceptual models or abstract boxes-and-arrows diagrams to explain in detail, thereby addressing criticisms of ergonomics as atheoretical (Salmon et al. 2017). This precision, explanation, and lack of ambiguity are antecedents to strong theorization and clear predictions (c.f., Popper 1963).

To be more amenable for ergonomics and socio-technical systems analysis, the ABMS modelling community could define verification and validation procedures more clearly. This is still work in progress and requires collaboration on both sides.

What is an Ergonomist's Role?

As academics, it is easy for us to call for the use of more sophisticated methods and to lament the slow uptake of computational modelling within ergonomics in comparison with other social and behavioural sciences (see, Gómez-Cruz, Loaiza Saa, and Ortega Hurtado 2017, Walker et al. 2017, for indications as to relative uptake of computational modelling). However, we must also consider openly the barriers to adopting computational modelling, and ask more broadly how researchers and practitioners can best utilise these approaches.

A key explanation for the slow adoption of modelling techniques in practice is undoubtedly limited awareness of how and when to use such methods, as most ergonomists will not have been taught computational modelling as part of their formal ergonomics education, and because of the low readership of academic journals by practitioners (Chung and Williamson 2018). This is reflective of a broader issue within the discipline, whereby professional ergonomists have been found to favour a small number of familiar techniques, regardless of the specifics of the problem at hand (see, Stanton, 2004; Stanton & Young, 1998). We cannot just assume that because a method's merits and limitations are discussed in contemporary academic literature that it will gain traction in practice. Moreover, we suggest that it is not essential for ergonomics researchers or practitioners to become experts in modelling techniques themselves, to leverage their potential usefully.

Instead, we should view computational modelling as we do statistics. As educators, we teach the fundamentals of research design so that students (and, later, practitioners or researchers) can appreciate what classes of statistical techniques may be necessary to answer particular questions. We teach students the basics from which they can specialise and develop more advanced knowledge. Just as we are unable to teach all students advanced SEM, developing advanced programming and coding expertise is most likely beyond the scope of undergraduate or postgraduate ergonomics courses. However, appreciating how computational modelling sits alongside traditional methodological approaches, where the techniques may be best applied, their limitations and constraints, is perfectly achievable. There are risks to such an approach. For example, even if awareness and engagement with computational modelling increases, it may remain a niche pursuit within the ergonomics profession. This could make ergonomists too passive in the model development process and naïve to the limitations of specific programmes, or unable to communicate their impact to others.

There is a further risk if ergonomists do not develop advanced knowledge regarding the philosophy of computational modelling in general, and the specific technical functioning of different modelling paradigms and software implementations. Programmes such as NetLogo[1] and AnyLogic[2] make it relatively easy for most novice programmers to build ABMS, system dynamics, or discrete events simulations (in the same way as the graphical interface of AMOS[3] makes it easy to construct a SEM without necessarily understanding the conceptual requirements and methodological parameters). However, a lack of understanding regarding how programmes work or what happens within the black box when you hit "run" can lead to inappropriate interpretations or misplaced trust in the reliability, validity, and/or utility of the model. These considerations highlight the barrier that a lack of specialist modelling expertise presents for ergonomists who are not embedded within a wider team possessing such capabilities. This may limit opportunities to utilise such approaches or lead to ergonomists working beyond their competencies. We must ensure that we work within our professional expertise and, similarly, that we do not advocate or aid the development of models for commercial use that users do not understand, or that are

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[1] https://ccl.northwestern.edu/netlogo/

[2] https://www.anylogic.com/

[3] https://www.ibm.com/uk-en/marketplace/structural-equation-modeling-sem

used because they provide a level of visual realism that more trusted and validated tools do not.

Ergonomists as designers and enablers

We suggest that ergonomics is ideally positioned as a hub discipline, which can build upon the rich tradition of integrating relevant theoretical insights from across disciplines (e.g., cognitive, social, and organisational psychology, engineering, health sciences and so forth) in order to draw links between differing conceptual paradigms, thereby addressing complex problems in a truly interdisciplinary way. It is unnecessary for ergonomists to cast themselves as expert modellers, but rather as enablers and influencers in the design and application of complex models, thus playing to recognised strengths and utilising socio-technical design principles to manage multi-disciplinary teams. We envisage this role would vary depending upon the composition of the design team and the nature of the problem, but it is likely to include: (1) defining and operationalising the conceptual model; (2) identifying the most relevant or important system factors to model; (3) defining rules, parameters, and relationships; (4) constructing competing conceptual explanations to test; (5) inferring and interpreting results; (6) identifying measurable proxies for behavioural and psychological elements in the model; and (7) feeding data in or developing scenarios and evaluating against real-world data. Such activities fall within the purview of existing techniques and professional competencies, allowing ergonomists to draw upon methods such as Cognitive Work Analysis or Hierarchical Task Analysis (e.g., Hettinger et al. 2015, Read et al. 2015) to inform model design. Stakeholder engagement could be used to elicit validation data with experts and users (e.g., Hughes et al. 2017) or to make predictions (e.g., Clegg et al. 2017). Furthermore, abstract lessons and rules developed by models could be extended into generalised principles, tool kits, risk assessments, and design guidelines.

Conclusion

The potential application of computational modelling to ergonomics problems is genuinely exciting. It enables researchers and practitioners to explore and test things that are just not feasible in the real-world and to examine a wide variety of design solutions or experiments in silico at minimal cost. The approach integrates different forms of data, across multiple levels and subsystems, with heterogeneous individuals or groups that behave in non-linear ways. It allows us to explore complex socio-technical systems deeply and holistically, and to undertake the type of predictive and dynamic observations that we have long theorised about, but could not directly observe. It frees us from the shackles of what is available and tangible, to explore that which is specifiable.

Ergonomists have a chance to position themselves as designers and enablers of all manner of models of socio-technical systems and problems, permitting them to employ these to support valuable practical activities with clients such as prediction, planning, risk analysis, and organisational change. To capitalise on the opportunities that computational modelling, and in particular ABMS present, ergonomists need to be energetic in demonstrating benefits both to colleagues and to clients. To drive uptake, those engaged in the area have a responsibility to develop practical guides regarding how traditional methods or data sets can be augmented by computational modelling and to challenge the modelling community to demystify technical steps in the process. Above all, we should engage in the kind of practical and conceptual problem solving that inspires others to want to move beyond their favoured methods and to experiment with computational modelling.

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