

## **Abstract**

This article explores the potential of complex adaptive systems theory to inform behaviour change research. A complex adaptive system describes a collection of heterogeneous agents interacting within a particular context, adapting to each other's actions. In practical terms, this implies that behaviour change is 1) socially and culturally situated; 2) highly sensitive to small baseline differences in individuals, groups, and intervention components; and 3) determined by multiple components interacting "chaotically". Two approaches to studying complex adaptive systems are briefly reviewed. Agent-based modelling is a computer simulation technique that allows researchers to investigate "what if" questions in a virtual environment. Applied qualitative research techniques, on the other hand, offer a way to examine what happens when an intervention is pursued in real-time, and to identify the sorts of rules and assumptions governing social action. Although these represent very different approaches to complexity, there may be scope for mixing these methods – for example, by grounding models in insights derived from qualitative fieldwork. Finally, I will argue that the concept of complex adaptive systems offers one opportunity to gain a deepened understanding of health-related practices, and to examine the social psychological processes that produce health-promoting or damaging actions.

*Keywords: Agent-based modelling; Behaviour change; Complex adaptive systems; Health Behaviour; Qualitative research; Social networks*

One of the key debates in health psychology concerns the level of complexity in health behaviour theories (Adler, 2003; Prilleltensky & Prilleltensky, 2003). Should we aim for parsimony and simplicity, as many writers have advocated? Or are health behaviours so complex, so situated in time and place, that one can only really understand them through idiographic approaches such as phenomenology and culturally informed health psychologies? A closely related question is whether health psychologists should restrict themselves to isolating psychological determinants of health behaviours or whether we should venture into the wider domains of politics, economics, and social theory to explain health-related practices – as advocated in several recent textbooks and writings (Horrocks & Johnson, 2012, 2014; Marks, Murray, Evans, & Vida Estacio, 2011; 2011; Murray, 2015, see Murray, 2014, for a review).

The differing perspectives on these questions among health psychologists are, to a certain extent, normative. Early writers offered up behavioural medicine to governments as a solution with which to curb health care expenditure (Holtzman, Evans, Kennedy, & Iscoe, 1987; Matarrazzo, 1980, 1982). Grounded in the tenets of classical experimental social psychology and cognitivism, these theorists suggested that the determinants of health behaviour were assumed to be found predominantly “within the head”, as people calculated the costs and benefits of a particular behaviour. By contrast, researchers using culturally informed approaches (e.g., Campbell & Murray, 2004; Marks, 1996; Murray, 2014; Horrocks & Johnson, 2014; Yali, & Revenson, 2004), social constructionist theory (Cornish, 2004; Hodgetts & Chamberlain, 2006; Mielewczyk & Willig, 2007), and social epidemiology (e.g., Marmot et al., 1991; Smith, Dorling, Mitchell, & Shaw, 2002; Wilkinson, 1997; Wilkinson & Pickett, 2009) have highlighted a range of contextual and social influences on health outcomes. Critical histories of health psychology (Crawford, 2006; Murray, 2014)

have argued that health psychologists need to take a role in addressing those social injustices that produce ill-health. Despite this, behaviour change interventions targeting social context have become rarer in the last decade (Holman, Lynch, & Reeves, 2017). Cognitivism, it seems, continues to hold significant appeal among practitioners and policy-makers.

In this article, I would like to suggest a new way to think about complexity in health behaviour theory. Complex adaptive systems (CAS, Eidelson, 1997; Holland, 1992; Miller & Page, 2009; Stacey, 2011) will be examined as a potential resource for unravelling the paradoxical interweaving of “individual” health behaviours and wider social processes. From such a perspective, health behaviours are viewed as 1) socially and culturally situated; 2) highly sensitive to baseline differences among individuals and groups; and 3) determined by multiple components interacting in a nonlinear and “chaotic” way. Although this viewpoint has recently been explored in a number of helpful public health articles (Luke & Stamatakis, 2012; Leischow & Milstein, 2006; Li, Lawley, Siscovick, Zhang & Pagan, 2016), CAS theory is little known among health psychologists. As I will go on to show in this article, however, the approach could be a rich resource for understanding how and why behaviour change interventions do or do not work in different contexts.

The remainder of this article runs as follows: First, I will examine the mechanistic perspective which I suggest has dominated behaviour change theory, using the reasoned action approach (Ajzen, 1991; Fishbein & Ajzen, 1975, 2011) as an example. I will then describe a conceptual basis for developing a CAS-informed health psychology. The basic tenets of agent-based modelling and applied qualitative health research are briefly reviewed as ways to examine complexity, and the tensions and points of contact between these

perspectives on complexity are examined. Finally, I will argue that CAS theory could help health psychologists to design better interventions and gain deepened understandings of the psychological and social processes involved in behaviour change.

### **Social cognition and reasoned action: the mechanics of health behaviour**

In their foundational text on social behaviour, Fishbein and Ajzen (1975) developed a social cognitive model – Theory of Reasoned Action (TRA) – setting the tone for much subsequent work in health psychology. In the TRA, beliefs, attitudes, intentions and behaviour were linked in a causal chain. It was proposed that intentions were the immediate antecedents to behaviour. Intentions, in turn, were a function of beliefs (which were assumed to be formed on the basis of available information from the environment) and subjective norms (the “perceived social pressure to perform or not to perform the behaviour”, Ajzen, 1991, p. 188). To these constructs, Ajzen (1991) would later add perceived behavioural control, creating the Theory of Planned Behaviour (TPB). Introducing their approach, Fishbein and Ajzen explain their understanding of social cognition. As they write:

“Generally speaking, we view humans as rational animals who *systematically utilize or process* the information available to them. The theoretical structure or conceptual framework we have adopted *assumes a causal chain* linking beliefs, formed on the basis of available information, to the person’s attitudes, beliefs, and attitudes to intentions, and intentions to behaviour” (Fishbein & Ajzen, 1975p. vi, my italics).

The italicised sections of the text above draw our attention to two key theoretical assumptions of the reasoned action approach: first, that humans are systematic processors of information; second, that this information processing sets in motion a chain of causality, terminating in a particular behaviour. While the model has since been subject to further attempts at refinement (most notably the addition of implementation intentions, e.g.,

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Gollwitzer, 1999; Gollwitzer & Sheeran, 2006; Orbell, Hodgkins, & Sheeran, 1997), and debates about the utility of the model continue (Ajzen, 2015; Armitage, 2015; Cooke, Dahdah, Norman & French, 2015; Ogden, 2003, 2015; Sniehotta, Pesseau & Araújo-Soares, 2014), the underpinning idea – that a satisfactory understanding of health behaviour can be explained with reference to a limited set of relatively simple psychological constructs – remains the same. The constructs of interest are linked in a “causal chain” of determinate relations: Beliefs, which form the starting point of the model, develop from the “stimulus situation”, and/ or “residues of the person’s past experiences” (1975, p. 133). In turn, as we develop beliefs about an object, we “automatically and simultaneously acquire an attitude toward that object” (p. 216). The causal processes underlying each factor of interest can be expressed in linear algebra, so, for instance, attitudes develop as follows:

$$A = \sum_{i=1}^n b_i e_i,$$

(1975, p. 223)

Where  $A$  is the attitude,  $b$  represents the beliefs about the object’s attributes, and  $e$  is the evaluation of the attributes or consequences of a behaviour. A process was proposed in which each evaluation of an object’s attribute was multiplied by the perceived probability the object had that attribute, and the products were summed for the total set of beliefs. The person enacting a behaviour is assumed to possess the solution to the equation. Practically, behaviour change therefore consists in correcting a faulty internal algebra: perhaps in finding new ways to resist perceived social norms, to improve perceived behavioural control, or to challenge unconscious biases and flawed beliefs.

The model of the person here, then, is one for whom decision-making is a question of maximising utility by calculating the outcome expectancies of a behaviour. They are a kind of naïve economist or, *pace* classical cognitive theory, an information processor. However, since the 1990s, this perspective in cognitive science has been challenged by theorists who view cognition as situated (Smith & Semin, 2007; Suchman, 1993; see Robbins & Aydede, 2009, for a helpful introduction), and a number of ingenious experiments have been performed to explore the ways in which thought is embedded in its social, economic, and political context (e.g., Kraus, Piff, Denton, Rheinschmidt, & Keltner, 2012; Mani, Mullainathan, & Zhao, 2013). Many critical health psychologists have made similar complaints about the decontextualized understandings of thought and behaviour that have predominated in health psychology – they have suggested turning our attention to power relations, cultural meanings, and social processes (Campbell & Murray, 2004; Crawford, 2006; Hodgetts & Chamberlain, 2006; Horrocks & Johnson, 2014; Marks, Murray, Evans, & Estacio, 2011; Mielewczyk & Willig, 2007; Murray, 2014; Murray & Poland, 2006).

There is another intriguing conceptual issue to consider here, and it concerns the temporality of behaviour change models. In traditional models of health behaviour, it is implied that one can follow a line proceeding through time *from* thought *to* behaviour. The constructs included in the model are assumed to act as mechanisms that determine behaviour in a linear, and reasonably predictable way. When one is interested in behaviour change, however, one is necessarily dealing with a diverse set of social actors, who may react to change in unpredictable ways in real-time. If empirical studies of technologically-driven attempts to change behaviour are anything to go by (Cresswell, Worth, & Sheikh, 2010; Greenhalgh, Wong, Potts, Bark, & Swinglehurst, 2009; Greenhalgh, Stones, & Swinglehurst, 2014; Mol, 2000; 2008; Mortenson, Sixsmith, & Beringer, 2016), the most

important impacts of an intervention are often the least anticipated. For example, Greenhalgh and colleagues (2014) showed how the real-world effects of implementing the “Choose and Book” referral system in the NHS differed sharply from the expectations of system designers, policy makers, and managers. Rather than shifting aspects of clinical decision-making to patients, as had been hoped, these researchers’ fieldwork showed how the technology was resisted at multiple levels of practice. For example, they cite examples in which patients were “confused” by being offered a choice of different treatment centres. GPs who did offer a choice to patients did so in a tokenistic way – invoking “the government” or “the computer” to mitigate patients’ confusion (p. 216), and recorded the offer of choice on the system to improve the performance of their practice in terms of the audit metrics used by “upstream” actors in the system – particularly Primary Care Trusts and the Care Quality Commission.

### **Complex adaptive systems**

For researchers who are interested in understanding those unexpected, real-time impacts of behaviour change interventions, I would like to suggest that the concept of complex adaptive systems (CAS) could provide useful analytical leverage. A CAS is a system which is made up of heterogeneous actors (hence, it is complex), and the behaviour of each is responsive to the actions of others within the system (hence, it is adaptive). Examples of CAS include financial markets (Mandelbrot, 1999), the immune system (Holland, 1992), insect colonies (Wilson, 1971), and social systems such as businesses (Dooley, 1997; Schneider & Somers, 2006), healthcare organisations (Plsek & Greenhalgh, 2001), and schools (Keshavarz, Nutbeam, Rowling, & Khavarpour 2010). Additionally, Keshavarz et al.,

(2010) distinguish three types of CAS: artificial, computerised simulations; natural complex adaptive systems, and social complex adaptive systems.

Adopting a CAS perspective on behaviour change could mark a significant departure from cognitive and linear models of behaviour. However, although certain types of CAS research have some overlap with critical health psychologists' focus on power relations, social contexts, and situated action (Campbell & Murray, 2004; Marks, 1996; Murray, 2014; Horrocks & Johnson, 2014; Yali & Revenson, 2004), the approach adds a distinctive theorisation of the features of social systems. Specifically:

1. *A CAS is made up of diverse agents.* A CAS describes a collection of agents that have relative freedom to direct their behaviour. In the context of behaviour change interventions, different agents come into the system with different agendas, knowledge, power, and politics. The agents within a CAS are interconnected, so that every action from one individual affects the context for the other agents – with knock-on implications for all subsequent behaviours (Plsek & Greenhalgh, 2001).
2. *Distributed (network) control.* Because a CAS is made up of diverse agents, and each CAS is interacting with other systems, control of behaviour is distributed, rather than hierarchical (Axelrod & Cohen, 2000). It is the responsiveness to change among agents acting locally within the CAS that gives such systems their dynamic, responsive, and productive nature. Consequently, not only are attempts at top-down control difficult and costly, they tend to hamper the agents' ability to adapt creatively (Zimmerman, Lindberg, & Plsek, 1998), and frequently produce unintended outcomes that run counter to the objectives of intervention planners (Greenhalgh et al., 2014).



3. *Emergence*. The aggregate behaviour of the system displays properties that cannot be seen at the level of individual behaviour. This tendency for a higher-level *gestalt* to develop from agents interacting in a local context is what complexity theorists call emergence. However, although the emergent *gestalt* is always more than the sum of its parts, aggregate and local patterns tend to enter into feedback loops. One example of this process is the spike in deaths in Scotland related to suicide, violence, and drug and alcohol use among young adult men in the 1990s and 2000s (McCartney, Collins, Walsh & Batty, 2012; Minton, Shaw, Vanderbloemen, Popham & McCartney, 2017). This aggregate pattern would be difficult to explain with reference to individual decisions. Instead, social epidemiologists have looked to upstream, contextual factors – particularly this cohort’s coming of age in a context of the neoliberal “reforms” of the labour market in the UK, which had a particularly adverse impact in Scotland. While this shows high-level political decisions feeding into individual-level action, this lower level, in turn, feeds back upstream – the adverse health consequences of health inequalities place further pressures on health care systems, creating further, emergent difficulties in supporting those at the sharp end of such inequalities.
4. *Adaptation*. Because of the dynamic, changing nature of social contexts, agents within a complex system are constantly adapting to change at a local level. Since social behaviour is evolving in this way, a CAS does not reach stasis – instead, it expresses a double-movement between stability and instability; regularity and irregularity (Stacey, 2011). This does not imply that one cannot make any predictions about a CAS. Rather, a CAS exists at what Miller and Page (2009) call the “edge of chaos”. At times, fluctuations in the system are minimal, but at different times it

displays explosive instability and far-reaching change. Qualitative and quantitative approaches to exploring this stable instability are described further below.

5. *Nonlinearity*. Because a CAS involves multiple levels of interaction between heterogeneous agents, not all intervention components are created equal. It may be that what researchers predict to be the key features of the intervention end up having little impact on behaviour. Conversely, small, apparently inconsequential changes in inputs can lead to profound changes in outputs (Resnicow & Vaughan, 2006; Resnicow & Page, 2008). In fact, some of the coming examples show how apparently identical behaviour change interventions may have diametrically opposed outcome depending on the “starting point” – that is, the context in which the intervention is implemented.

These characteristics of complex adaptive systems create a number of challenges in studying health changes. Because health practices emerge from local, unplanned, and socially situated interactions happening in real-time (see, e.g., Gomersall et al., 2017; Greenhalgh et al., 2014; Mowles, 2014; Stacey, 2011), it can be difficult to predict and identify the most important processes of change, and researchers must constantly be aware of unintended consequences arising. To say this is not to deny that certain important processes of change can be identified and studied systematically. It does, however, mean that researchers need tools that are up to the job of such study. Thankfully, a range of approaches have developed in the social sciences over recent years to examine complex systems. In the remainder of this article, I will examine two possible ways to study behaviour change from a CAS perspective. Although these approaches to CAS research are quite different, I will go on to suggest that dialogue between them could offer some interesting ways forward.

## **Agent-based modelling**

Agent-based modelling (ABM) offers one way of studying CAS. ABM has attracted a good deal of attention in computer science over recent years, and is beginning to be taken up in the social sciences and health-related disciplines (Hammond, 2009; Maroulis et al., 2010; Miller & Page, 2009; Resnicow & Page, 2008). In contrast to “traditional” computer models, which start from assumptions about the general properties of a system, ABM takes a “bottom-up” approach, starting from the individuals that make up the system.

Computational models of social CAS are designed to mimic the behaviour of “interacting, thoughtful (but perhaps not brilliant) agents” (Miller & Page, 2009, p.93). A number of software platforms are now available for ABM – though health researchers would need a basic grasp of coding language before getting started on building models. Although a full account of the various ABM platforms and their functionalities is beyond the scope of the present article, interested readers should consult the recent review from Abar, Theodoropoulos, Lemarinier & O’Hare (2017) for an overview.

In practical terms, ABM simulates the behaviour of a collection of decision-makers and institutions, interacting under sets of prescribed rules (Farmer & Foley, 2009). These agents are capable of learning in the context of a dynamic environment, and can respond to changes in other agents to pursue their own objectives within the context of the CAS. For example, an intervention to increase healthy eating among people with diabetes might include health psychologists, specialist clinicians, GPs, patients, their work colleagues, and their friends and families. While the chief aim of clinicians and health researchers might be to achieve improved illness control, people with diabetes and their families might be pursuing other objectives, such as meeting social obligations or maintaining a sense of

“normality” (Gomersall, Madill, & Summers, 2012). Not only that – complexity in such an intervention is increased by the wider social contexts involved in a healthcare ecosystem: from the local clinical resources, to the wider political-economic context, and even to broad ideological currents, such as what Mol (2008) identified as the “logic of choice”. Figure 1 illustrates such a system. Note the multiple interactions and feedback loops between levels of the system, which are discussed in more detail in the accompanying notes. Although ABM can offer some interesting predictions based on the interactions of agents in the model, the political contexts and feedback loops between different levels of the model can be a stumbling block for ABM – but, as we will see later, one can address these features of a CAS using other methods.

ABM has been applied to make interesting, and sometimes counter-intuitive predictions about the impact of different intervention approaches to increase daily walking (Yang & Diez-Roux, 2013; Yang, Diez-Roux, Auchincloss, Rodriguez, & Brown, 2011) and to reduce inequalities in healthy food consumption (Blok, de Vlas, Bakker, & Lenthe, 2015). Perhaps most interesting for health psychologists designing behaviour change intervention are some recent agent-based models of smoking. In one study, Chao, Hashimoto and Kondo (2015) developed a model to examine the impact of changes in between- and within-gender inequality in Japan. Their model comprised a network of 1000 agents, making decisions to smoke or not smoke at time  $t$ . Each agent in the model observes the behaviour of adjacent agents in order to calculate the expected benefits of smoking or not smoking/ quitting during an iteration of the model. The agents’ smoking decisions were jointly determined by  $S(t_s)$  – the utility of smoking at time  $t$ , and  $R(t)$  – the social influence of adjacent agents weighted by socioeconomic status. Chao et al. (2015) examined the impact of five counterfactual scenarios on smoking prevalence among the agents (increased within-gender

inequality, decreased within-gender inequality, increased between-gender inequality, decreased between-gender inequality, equal susceptibility to social influence among men and women) by manipulating these variables at the start of each simulation run. The model output – defined as the percentage change in smoking prevalence between the start and end of the simulation – suggested that reduced socioeconomic inequality had little overall impact on smoking reduction. By contrast, increased socioeconomic inequality appeared to impede smoking reduction among women, while reducing smoking prevalence among men.

Another simulation of smoking prevalence was developed by Adams and Schaefer (2016). Drawing on recent research on peer influences and empirical data on smoking in schools from a nationwide longitudinal study, these researchers developed a model to examine the impact of three factors on smoking prevalence change: Strength of peer influence, smoker popularity, and baseline smoking prevalence. By varying the baseline levels of peer influence, smoker popularity, and baseline smoking prevalence, this model generated an interesting, complex range of outcomes: While most scenarios showed decreases in smoking prevalence over time, exceptions were seen in conditions where smoker popularity, peer influence, and baseline prevalence were all high. Figure 2 shows two of the scenarios from Adams and Schaefer – in real-world contexts where baseline smoking prevalence, peer influence, and smoker popularity are high, interventions to reduce peer influence are likely to have a beneficial effect in reducing smoking rates in schools. By contrast, in scenarios where baseline smoking prevalence and smoker popularity are low, reducing peer influence may diminish reductions in smoking over time.

Simulating different intervention approaches in an agent-based model before going ahead with a particular approach could enable health psychologists to make more informed

decisions about which intervention components to activate. For example, if the assumptions from the Adams and Schaefer model hold, interventions to reduce peer influence could have an unintended consequence of limiting reductions in smoking prevalence. However, as we will see in the next section of this article, ABM alone cannot solve the knotty problem of unintended consequences. Since the boundaries between different systems are porous and fuzzy, and since people often act in more complex, unpredictable ways than ABM can write into code, any health intervention has consequences beyond the immediate variables of interest (Mooney, 2017).

### **Simple or complex complexity?**

Agent-based modelling, then, offers some tantalising possibilities for designing health interventions. However, the computational approach to analysing social complex adaptive systems is not without its critics. Mowles (2014), Stacey (2011), Byrne (2005), Byrne and Callaghan (2013), and Keshavarz et al., (2010) all, in their own ways, draw attention to the difficulties in studying social complex systems using mathematical models. People, unlike bit strings of computer code, are embedded in cultural contexts and power relations, are subject to more complex informational feedback, and may break or subvert rules. In fact, in ABMs, one key assumption is that agents are homogeneous at different levels of abstraction – in the smoking studies discussed above, for example, the smoking behaviours of the agents were governed by identical decision rules. Furthermore, and as Chao et al. (2015) acknowledge, the agents in their model were following a broadly rational approach to decision-making. Hence there is a risk in agent-based modelling of returning to the very cognitivism critiqued earlier in this article – albeit a cognitivism that allows researchers to observe some interesting hypothetical emergent patterns.

In short, complexity is seldom as simple as the coding language of agent-based models might imply. For health psychologists to really understand the complex causal pathways leading to health-related actions, we will need some way to grapple with what Byrne (2005) and Byrne and Callaghan (2013) call “complex complexity”. For this purpose, many have advocated the use of applied qualitative approaches such as narrative interviews, ethnographic observation, and documentary analysis (Byrne, 2005; Byrne & Callaghan, 2013; Mowles, 2014; Keshavarz et al., 2010; Plsek & Greenhalgh, 2001; Stacey, 2011). When considering health behaviours that make little sense from a rationalistic, individualistic perspective – such as smoking – one has to consider the cultural and discursive context through which such behaviours *do* “make sense”. This is why a number of theorists have dropped the term “behaviour” altogether, with all the mechanistic baggage it carries. Instead they have turned the discussion to *practices* – that is, culturally embedded phenomena whose meaning shifts across time and place (Blue, Shove, Carmona & Kelly, 2016; Cockerham, 2005; Mielewczyk & Willig, 2007). As Cohn (2014) argues, in a similar vein to the critique of social cognition examined earlier in this article, health practices are not “outcomes of mental processes but emerge out of the actions and interactions of individuals in a specific context” (p. 160). This being the case, the singular features of a specific time and place are not simply statistical white noise to be parsed out from a tightly defined psychological model of behaviour: Such features are the true phenomenon of interest. However, while sociologically informed approaches typically examine the interplay of individual-level agency and sociocultural context broadly conceived, CAS provides a number of helpful metaphors and concepts – emergence, nonlinearity, network control, adaptation – that give purchase on causality in a systematic, complex way.

These metaphors have yielded some valuable insights. Keshavarz and colleagues (2010) studied the implementation of a system-wide behaviour change intervention in Australia – health promoting schools. Taking a CAS-informed approach, they undertook qualitative interviews, observations, and documentary evidence to examine how and why the intervention did, or did not work in different school settings. Several concepts from a complex adaptive systems perspective proved invaluable in understanding the problem. Each school had a particular “nested structure” made up of teachers, principals, and management. The schools were diverse in terms of the socioeconomic and ethnic makeup of the student bodies. Rules and expectations varied from site to site, and the schools interacted with other systems in different ways. Consequently, health promoting schools did not function as a single intervention that produced common outcomes. Rather, the effectiveness of the intervention in each school was dependent on the interactions between multiple levels of the school system: between students and staff; between different schools; between schools and the policy context. Additionally, Keshavarz and colleagues noted some important feedback loops between different levels of the school system: Teachers would notice changes in engagement with health practices among the students, and reorganise their own practice in response.

In the context of health technology research, a lively debate has developed concerning evaluation methods for the new generation of computer-assisted assistive technologies, such as telemedical systems and ambient assisted living devices, which are designed to support illness self-management in the home. Several authors have suggested that the randomised trial approach to evaluation is not fit for purpose to study the impact of these technologies (Gomersall et al., 2017; Greenhalgh, Procter, Wherton, Sugarhood, Hinder, & Rouncefield, 2015; Greenhalgh & Stones, 2010; Mortenson et al., 2015). Rather



than treating technology as a simple bounded “intervention” whose effects can be neatly separated out from context and measured, these researchers have argued that health technologies are profoundly context-bound. For instance, Gomersall et al., (2017) describe how their participants’ technology use was largely determined by the social networks surrounding them. In a similar way, Greenhalgh and colleagues (2013) describe how the use and non-use of telecare was often dependent on the social systems in which the “users” were embedded: One participant never used his monitoring system because the couple he lived with were unable to assist him in sending his readings at the allotted time. A CAS perspective on health technology impact, rather than searching for some uniform effect, could examine how technologies enter and reshape the systems in which people live.

### **Mixing methods in CAS research?**

The two approaches to CAS research reviewed above view complexity are – to say the least – rather different. Agent-based models seek to understand general patterns at the aggregate level of a system. Complexity is viewed as an emergent property arising from simple rules. Questions of subjectivity are largely absent, and in many models, agents are treated as utility-maximising individuals (e.g., Miller & Page, 2009). Byrne (2005) is particularly scathing of this reductionism in ABMs. He sees such models as a rehash of technocratic elitism in the social sciences, noting their attractiveness “to the worst sort of evolutionary psychology and ideologues of market models. Write a few rules – the selfish gene, the territorial imperative, profit maximisation, rational choice [...] and away we go” (p. 103). Conversely, applied qualitative approaches to complexity focus on the emergence of health behaviours in real-world social contexts, focusing on power relations, cultural meanings, and the emergent nature of change (Gomersall et al., 2017; Greenhalgh et al., 2014, 2015;

Mowles, 2014). The focus is on provisional, context-bound knowledge, and – this is crucial – on the potential for research knowledge to contribute to empowerment and social change. In this way, CAS theory, while offering new conceptual tools for understanding health-related practices, speaks to much older debates in psychology about interpretive and quantitative research.

This is not the place to reiterate the debates on mixed methods in psychology, but it is worth noting that the two perspectives on CAS seldom seem to speak to one another. The recent turn to complexity in public health (e.g., Leischow & Milstein, 2006; Li et al. 2016; Lich, Ginexi, Osgood, & Mabry, 2013; Luke & Stamatakis, 2012; Mabry, Marcus, Clark, Leischow, & Méndez, 2010; Maglio, Sepulveda, & Mabry 2014; Walton, 2014) tends to focus on applying complex models to the population level to predict outcomes. At most, there have been some suggestions to include qualitative research techniques alongside more “traditional” evaluation models to provide context (Lich et al. 2013). However, perhaps there is room here for dialogue between these approaches, and health psychologists could take some initiative to explore some interesting possibilities. For example, if Agar (2001, p. 364) is right to say that the most insightful complex models “express qualities learned through anthropological research, using functions instead of words”, then it is important to ask whether it is possible for agent-based models to integrate thick description (Geertz, 2003) using the insights developed in local qualitative fieldwork. Applied qualitative researchers, for their part, could draw on agent-based models to compare the predictions of ABMs with the unfolding of behaviour in real-world settings. Perhaps most importantly, applied qualitative work could remind modellers of the need for health psychologists to remain engaged in efforts towards health-promoting social change.

These possibilities are yet to be seriously explored, but they could provide a fruitful area of health psychology research over the coming years. I am only aware of one attempt to inform ABMs of health behaviour with rich, qualitative findings – namely, the ethnography of a local heroin market in Denver, Colorado (Hoffer, 2006) and the subsequent agent-based models developed by Hoffer, Bobashev, and Morris (2009, 2012), and Heard, Bobashev, and Morris (2014). By using Hoffer’s detailed understanding of the actors in the heroin market, and the types of relationships that existed between them, these researchers were able to construct a simplified, yet informative picture of the system. Their model involved six types of agents: customers, “junkie brokers”, street dealers, private dealers, police, and homeless people. The rules followed by each agent in the model was based on knowledge obtained in the ethnography, and Hoffer and colleagues were able to simulate the likely impact of increasing or reducing the numbers of brokers in the market, and increasing police raids. The results of the model showed some intriguing possible effects of such interventions – for instance, while police busts resulted in an initial, dramatic drop in street dealing, this effect was mitigated by an increase in the activity of private dealers, who were able to supply customers through junkie brokers (for more details see, especially, Hoffer et al., 2009). In fact, in the broader world of health research, there are promising precedents to draw on. The influential framework for evaluating complex interventions developed by the Medical Research Council, for example, acknowledges that clinical trial methods require input from qualitative research to understand processes of change in any intervention with interacting social components (Craig, Dieppe, Macintyre, Michie, Nazareth & Petticrew, 2008). Similarly, realist evaluation theory (Pawson, 2006, 2013; Pawson, Greenhalgh, Harvey & Walshe, 2005) takes the perspective that one can only really understand outcomes by paying close attention to the social context in which interventions

take place, and, again, by understanding the processes of change that are activated within the context.

## **Conclusion**

This article has examined how CAS theory could contribute to health psychology research, and has offered empirical examples to illustrate some possible applications of the approach. In contrast to early health psychology writings (e.g., Matarazzo, 1980, 1982), which promised to solve hitherto intractable health problems with some forward planning and application of psychological understandings of behaviour, a CAS perspective acknowledges that health outcomes cannot be controlled by savvy health psychologists. However, we may be able to introduce components into the system that reduce inequalities, and guide health-related actions in the right direction (Durie & Wyatt, 2007). Even then, because change is intimately tied to context, CAS-informed interventions are likely to produce unforeseen effects in health behaviour (Greenhalgh & Stones, 2010; Greenhalgh et al. 2014, 2015; Keshavarz et al. 2010). Consequently, if health psychologists are to make the most of CAS theory, we should focus our efforts particularly on studies of processes in local situations – unpicking the components that interact to produce wanted and unwanted changes, and comparing these with other local contexts.

CAS ideas are, in my view, ideally suited to health psychology. Any behaviour change intervention includes a diverse range of actors with differing goals, views, and knowledge. Consequently, behaviour change within a system often takes on a life of its own, developing in unforeseen directions. Using agent-based modelling and applied qualitative research techniques could help uncover some of the more arcane features of behaviour change, informing future theory and intervention design. However, in contrast to other applied

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disciplines such as ecology, economics, and organisational and management research, CAS theory as applied to health psychology is currently in its infancy. Hence, although I have referred the reader to key texts on CAS, and illustrated applications of the approach to health psychology, this article should be read as a preliminary attempt to draw out the possibilities of CAS research within the discipline. As computer-based modelling techniques continue to advance, and qualitative research makes ever more important contributions to evidence-based practice, it is my hope that CAS could become a fruitful area of research and practice within the discipline.

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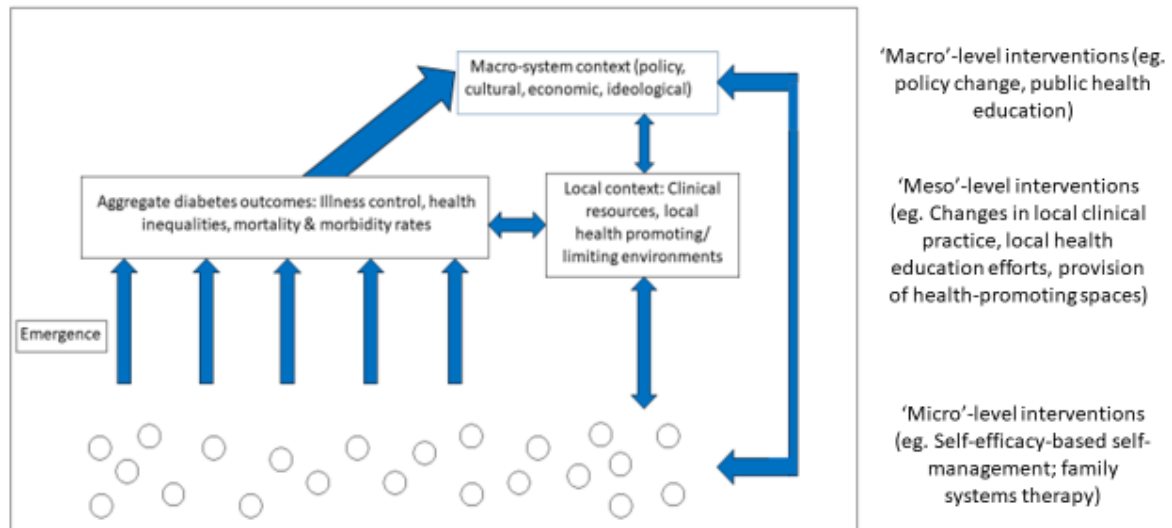
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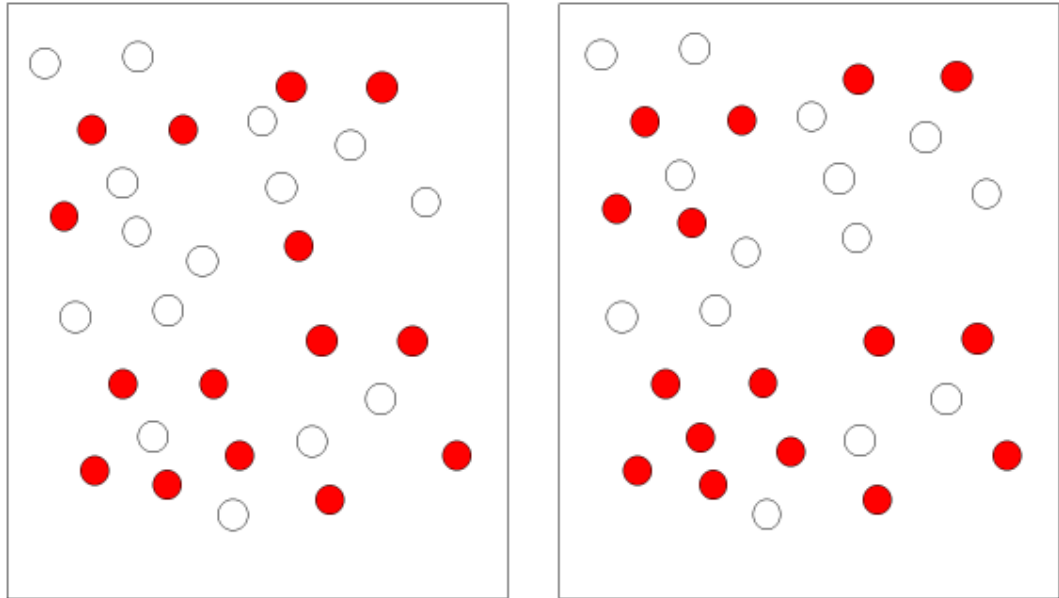
Figure 1. An example of a complex adaptive system focused on patterns of diabetes management.



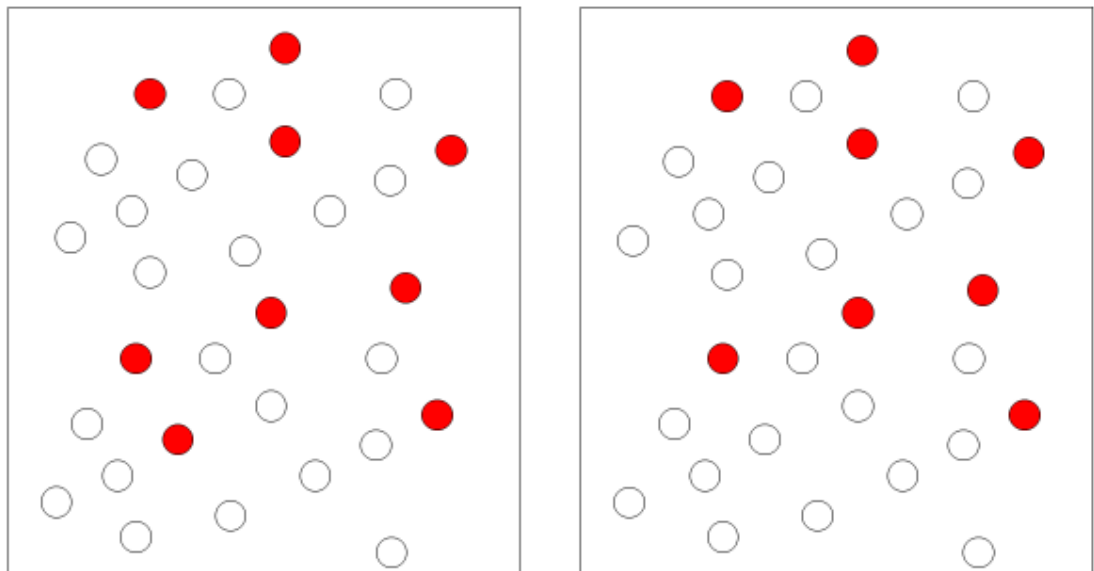
A representation of a CAS centred around diabetes illness management. The circles at the bottom of the diagram represent the various 'agents' involved in the system locally – people with diabetes, their social networks, and clinicians – all of whom are following their particular objectives, and who influence the behaviour of adjacent agents in the system. The aggregate illness management outcomes arise through the interactions of agents acting locally within the system, but are also influenced by both the local health care system and wider health care context. Note the multiple feedback loops between different levels of the system: The actions of individual agents can affect the local and wider health care context, and in turn, these wider systems can feed back into individual actions.

Figure 2. Smoking prevalence change examples based on Adams and Schaefer (2016)

Panel A



Panel B



An illustration of projected changes in smoking change among agents based on the estimates in Adams and Schaefer (2016). Shaded dots indicate smoking agents, and white dots represent non-smokers. In Panel A, baseline smoking prevalence is 50%, and peer influence and smoker popularity are high. Agents in this scenario are more likely to take up smoking based on the behaviour of their neighbours (an increase of ~13%).

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By contrast in Panel B, baseline smoking prevalence is 30%, smoker popularity is low, while peer influence is high (a projected reduction of ~10%). In real-world settings resembling the first scenario, reducing peer influence may help reduce smoking prevalence over time. In scenario 2, reducing peer influence is likely to inhibit reductions in smoking.