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Systems science and oral health: Implications for Dental Public Health?

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Systems science methods offer an alternative way to approach problems within Dental Public Health by encouraging the consideration of the wider systems and structures in which oral health problems exist. Through such an approach, and consideration of interacting systems over multiple hierarchical levels, it may be possible to better understand the complexity associated with oral health related outcomes, and to improve theoretical understanding of these relationships. Simulation methods associated with systems science can also be used to help model and capture these real-world problems, and to help test the interactions associated with different elements of a system. The aim of this review is to summarise the concepts behind systems science approaches, and what they can offer the field of Dental Public Health. This will include an overview of the way systems science can approach problems associated with complexity, and the benefits these approaches can have. The main methods associated with the field will then be reviewed, along with examples of their application. This paper will then outline some of the main implications, both conceptual and methodological, that adopting systems science methods may have for Dental Public Health. Finally, the challenges associated with systems science will also be presented. It is hoped that this review will highlight the benefits of systems thinking, and how it can add to our conceptual knowledge of the contexts in which complex health problems are embedded.

Keywords: *Systems science; dental public health; oral health; complexity*

Introduction

Systems science approaches and methods are increasing in prominence in public health research, although there is still a relative lack of such research within the field of Dental Public Health (DPH). This review will present an overview of systems science methods and thinking, and the potential benefits it can offer. The first part of this review will outline what systems science is and how these approaches differ from more traditional statistical methodologies. This is followed by a summary of the different types of system science methods, and previous applications of these to public health related scenarios. Finally, this review will outline the main implications of adopting systems science, including examples from Dental Public Health, and areas that could benefit from these approaches.

What is systems science?

Systems science is essentially a way to study a complex system, which can be defined as 'one whose properties are not fully explained by an understanding of its component parts' (Gallagher and Appenzeller, 1999). Luke and Stamatakis (2012) have stated that complex systems must have large numbers of heterogeneous entities, interaction between elements, emergent phenomena from interactions that differs from effects of individual entities, and effects that persist and adapt over time. Thus, systems science acts as a 'collective of analytical approaches that share in common the capacity to examine the big picture, that is, a problem and the context in which it is embedded' (Mabry and Kaplan, 2013 - p.9). Mabry and colleagues (2008) in their excellent overview of systems science, state that such systems can be viewed as a coherent whole which also recognises the relationships between each of the interrelated components of the system, the interactions of which give rise to system level emergent properties. They further state that systems science approaches therefore offer a more comprehensive insight into the public health problem being studied; more so than would be possible through the study of the individual components that make up the system.

The models used for such analysis are designed to study complexity dynamically through their incorporation of interactions, feedback loops (where a change either balances or reinforces further changes – Rutter *et al.,* 2017), and lag effects over time in what are often non-linear relationships (Mabry and Kaplan, 2013). These approaches are usually simplified versions of real-world problems, whilst also retaining the most important aspects of the system being studied (Mabry *et al.,* 2010). This is in line with Axelrod's (1997) 'KISS' principle ('Keep it simple, stupid!') regarding simulation modelling. Such an approach allows for a better understanding of the complex structures emerging from the interactions of entities and their environments in relation to real-world problems (Mabry *et al.,* 2010). The increased interest in such approaches in a public health context is partly due to the acknowledgement that traditional regression-based methods, which often offer narrow definitions of problems along with linear

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representations, are not adequate to address the complex issues surrounding public health scenarios on their own (Auchincloss and Diez Roux, 2008). This is not to say that more traditional regression-based methods have not been useful, as they have been, and will continue to be helpful in gaining knowledge on relationships, associations and sub-components of systems (Baker and Gibson, 2014). This can include the use of statistics to find relevant variables to include in studies, as well as helping to parameterise models. However, the use of systems science methods 'can add to this arsenal of analytical tools' (Mabry *et al.,* 2010 – p.1161) and, thereby, extend the conceptual and analytic scope of (dental) public health research.

Systems science research does not represent one discipline or methodology; rather, it links disciplines and makes use of a wide variety of methods depending on the nature of the problem at hand. Mabry and colleagues (2008) have stated that most common health problems of a serious nature cannot be addressed or solved by one discipline, despite the expert knowledge of the individuals in these fields. Sometimes a more comprehensive approach, involving viewpoints and knowledge from other disciplines, is the way forward (Metcalf *et al.*, 2013) is a good example of this approach). The concept of systems science began in research fields such as physics, engineering and computer sciences, and is now becoming more common within the social sciences and health related research (Trochim *et al.*, 2006). This is recognised through the formation of formal institutions such as the Office of Behavioural and Social Sciences Research, which, among other aims, strives to integrate approaches from biomedical, individual behaviour, and population level systems (National Institutes of Health, 2017). The use of systems science models has increased for several reasons. First, as stated above, there has been a growing recognition of the ability of this approach to address complex and rampant public health problems in general (Rutter *et al.,* 2017), but also in specific domains such as neighbourhood effects in relation to obesity (Mabry *et al.,* 2010). Secondly, from a practical point of view, computer processing power, the availability of appropriate software packages and the more widespread use of personal computers have increased their use (Maglio and Mabry, 2011).

Overview of system science methods

Computer simulations have been cited as a key method for studying complex systems (Diez Roux, 2011), and there are multiple methods for this approach that can be used to undertake analysis associated with systems science. Luke and Stamatakis (2012) provide an overview of three prominent methods associated with this field: system dynamics, agent-based models, and network analysis. These are discussed below.

System dynamics simulations are 'top-down' approaches to modelling systems, meaning that they view the system and its dynamic complexity at an aggregate level (Luke and Stamatakis, 2012). Further, they model systems based on the idea that non-linear behaviours emerge as a result of stocks and flows, feedback loops and time-delays, with the models often taking the form of differential equations. An oral health related example can be found in the work of Spleith and Flessa (2008), who evaluated the economic consequences of using fluorides to reduce caries in a German population. Their system dynamics model confirmed the benefits of fluoride use in reducing caries, while revealing that combinations of fluoridated salt, fluoride gels and fluoride toothpaste were the most cost-effective approach when applied in 6-18 year olds. System dynamics models also tend to have a broader range of explanatory variables and are more adaptable at including variables where strong empirical data may be lacking. Homer and Hirsch (2006) cite studies that have included clinicians or community representatives who are involved in the scenarios being modelled as good examples, as they provide their own data, knowledge on influential variables, policy concerns, and experience-based estimates in lieu of other data sources.

Agent-based models take a 'bottom-up' approach to simulating complex systems, starting at the level of microentities which interact with other entities to produce macrosystems (Auchincloss and Diez Roux, 2008), or emergent properties of a system. This is usually through individual characteristics and rules about agent behaviour, creating dynamic histories that lead to system level properties and behaviours. The work of Sadeghipour and colleagues (2017) provides an oral health related example, through the use of agent-based modelling to investigate the influence of friendship networks on toothbrushing habits among schoolchildren in Iran. A notable difference to system dynamics models is the lack of central globalised system behaviour, with agents, complete with their own properties, free to move about their environment, interacting with it and other agents. Macal and North (2010) found the focus of the method on the modelling of heterogeneous agents across populations, and 'the emergence of self-organization' (p.151) to be two distinguishing features that result in agent-based models comparing favourably to other simulation methods. Whilst championing systems science approaches in general, Maglio and Mabry (2011) specifically highlighted the value of agent-based models in improving public health. Indeed, agent-based models have proven particularly successful in the study of infectious diseases, through modelling phenomena such as contagion, flows, behaviours and diffusion (Luke and Stamatakis, 2012).

Network analysis focuses on relationships between sets of actors, which can take the form of any type of entity that has a connection to another (Luke and Stamatakis, 2008). Visualisation, description and statistical modelling of networks constitute the three main analytical purposes of the method, with visualisation an advantage for gauging extra insight into the size and extent of networks. Additional advantages include the ability to focus on individual actors within networks as well as local connections and sub-groups, being able to analyse multiple networks and the relationships and ties between these, as well as analysing network change over time. An example from the DPH field includes the work of Maupome and colleagues (2016a), who analysed associations between dental health, social networks and psychological and behavioural acculturation in an adult population in the American Midwest. This work highlighted the importance of acculturation and social networks, as both behavioural and psychological acculturation influenced dental insurance coverage, while behavioural acculturation was a predictor for frequent dental care. Perhaps due to its longer history and ability to analyse real-world data quickly, network analysis has seen more wide-ranging applications and approaches than system dynamics or agent-based models within a public health context (Luke and Harris, 2007; Luke and Stamatakis, 2008).

Mabry and colleagues (2013) have also suggested several other methods of systems science research. *Markov modelling* is a stochastic method that assumes entities to be in one finite state at a given time (or Markov states), with 'all events of interest modelled as transitions from one state to another' (Sonnenberg and Beck, 1993 – p.323). Every state has a utility, which contributes towards the classification in the next state via probabilities, depending on the length of time spent in the current state. This is not dissimilar to the idea of decision trees, with the analysis divided into equal time increments of meaningful length (or Markov cycles), during which entities may or may not transition from one state to another. These models have previously been applied in medical decision making (Sonnenberg and Beck, 1993), as well as economic evaluations (Briggs and Sculpher, 1998).

Soft-systems analysis is better described as a set of methodologies (Wilson, 2001), where methodologies are represented by concepts, which are set out in a way that is appropriate given the situation being studied. This approach can be used when there are differing views on the definition of the problem by using a 'system' to encourage debate between involved parties. The approach dismisses assumptions that the world contains systems of every necessary kind, and that such systems 'could be characterized by naming their objectives' (Checkland, 2000 – p.13). This flexibility allows the tailoring of methodologies through understanding a users' specific situation, the associated problems, the required information, as well as the style of the analyst using it. This can act as a powerful problem-solving tool. Finally, *discrete-event modelling* has two distinct properties: that state space is discrete rather than continuous, and that state transition mechanisms are event driven, rather than by time (Cassandras and Lafortune, 2008), while state evolution 'depends entirely on the occurrence of asynchronous discrete events over time' (p.30). the setup of the models could be thought of in a similar way to flowcharts, with entities passing through blocks of the flowchart, where they can be delayed, put in queues, processed, or acquire resources before moving to the next block (Borshchev and Filippov, 2004).

In addition to the methods mentioned above, several texts give extra information on the principles, and practicalities of the systems science approach. This includes overviews by El-Sayed and Galea (2017), which detail background concepts, methods and systems thinking in a public health context, as well as the work of Northridge and Metcalf (2016) which reviews the application of best principles associated with systems science. Online tutorials are also available, such as those detailing the building and running of agent-based models and network analysis (Berryman and Angus, 2010).

Implications for Dental Public Health, and what has been done so far

There are five key implications of adopting systems science approaches for Dental Public Health: (i) the inclusion of interactions and feedback mechanisms at individual and system levels; (ii) the inclusion of traditional statistical methods, and approaches from other disciplines; (iii) policy relevant analysis; (iv) testing theoretical frameworks and pathways and (v) methodological advances over current approaches in the field. These implications are discussed below, with relevant examples related to tooth decay (among a number of examples) included, in order to better situate them within the field of Dental Public Health.

Interactions and feedback mechanisms

Firstly, systems science methods allow for studies to contain a dynamic element within their analysis through the inclusion of interactions and feedback. These two features are key components in understanding complex social systems and are particularly important for a field like DPH where interactions associated with behaviours, and the feedback that occurs as a result will be key to oral health. The inclusion of these interactions over multiple hierarchical levels is important too, as Mabry and colleagues (2008) recognise that 'because of its unique ability to consider simultaneously both the whole system and its individual parts, systems science is capable of producing solutions that take into account a broad range of factors pertinent to the problem under consideration' (p.219). For example, in relation to tooth decay, the ability to model interactions and feedback based on biological (cortisol secretion, effects of fluoride), behavioural (toothbrushing, sugar intake, dental attendance), socio-economic (income, education) and neighbourhood variables (service locations, shops) would allow for a more thorough understanding of the mechanisms causing decay, and is an approach that is beyond traditional statistical modelling (Auchincloss and Diez Roux, 2008). The work of Sadeghipour and colleagues (2016) included interactivity and feedback mechanisms within Dental Public Health. Their agent-based model on demand for dental visits featured individuals whose dental visiting patterns were influenced by their 'state of attention' to dental health and whether they had attended recently, before agents potentially undergo treatment when visiting the dentist. Agents could transition in their 'state of attention' variable in a positive way through experiencing disease, treatment, or through social interactions and word of mouth, but this 'attention' to dental health could also deteriorate through 'forgetfulness' as the model progressed. Through these interactions emergent properties and collective actions emerge, demonstrating that oscillatory patterns of visits are highly affected by social network structures, and the number of connections within these.

Inclusion of traditional statistical methods, and approaches from other disciplines

Secondly, Mabry and colleagues (2010) suggested that systems science approaches supplement the tools available to study complex health related scenarios, and advocate their use alongside existing approaches (i.e. regression modelling). Systems science methods are capable of dynamically simulating real-world problems (e.g. levels and fluctuations in tooth decay in a population), while more traditional statistical approaches can be used to analyse the trends of the output of these dynamic methods, and assess whether statistically significant patterns exist in the data. As previously mentioned, statistical methods can also be used to help parameterise models, as well as to elucidate relationships between variables, and potentially the pathways associated with them. This allows existing knowledge within the field (both conceptually and methodologically) to be combined with approaches that offer an alternative, and more interactive way of analysing population dynamics. The work of Saman and colleagues (2010) represents an example of this. In their research investigating the condition of the dental workforce in the US state of Kentucky, the authors combined existing knowledge of dental providers with system dynamics modelling. Using data from the Kentucky Dental Workforce Provider Analysis, the number of practising dentists was calculated for the period 2007-2016 using system dynamics, before the simulation results were compared to Census estimates to calculate dentist-to-population ratios. These demonstrated that incoming dentists would not match the rate of retiring dentists, leading to a declining dentist-to-population ratio in the state.

The adaptable nature of systems science methods is further demonstrated by the work of Metcalf and colleagues (2013), representing a novel approach within the DPH literature. This research combined an agent-based model with a system dynamics simulation to investigate the importance of the spread of word of mouth for screening programme usage among an elderly population in New York City. Using this combination the authors were able to implement a diffusion process (through the agents' social networks), with agents classified as either 'without care', 'seeking care', or 'receiving care'. The system dynamics model was also equipped to account for the resource capacity and availability of the screening programme being studied. This work demonstrated how increased diffusion of word of mouth led to increases in care seeking and preventive screening. Recent work has also discussed the integration of data from a spatial microsimulation model, a geographical tool for small area population analysis, into an agent-based model for research on neighbourhood effects on tooth decay (Broomhead, 2017). The addition of this microdata to the agent-based models allowed for the inclusion of a representative synthetic population complete with data on socio-demographics, behaviours, attitudes, and clinical data related to tooth decay scores. This research aimed to dismantle the false division between more traditional regression approaches and systems paradigms (Mabry *et al.,* 2010), by demonstrating how different simulation methods can be used in combination to answer key questions related to oral health.

Finally, the flexible design of methods for studying complexity allows for the inclusion of data and methods from other fields to which DPH in inextricably linked (e.g. social sciences, epidemiology). The inclusion of these data and perspectives while focusing on the interdisciplinary nature of problems is vital in obtaining a full understanding of the problem at hand (Maglio and Mabry, 2011). It is also important to consider the inclusion of public health figures and advocates from outside academia, as health research and strategies are not confined to this sphere. The generally positive responses to the idea of systems thinking across multiple fields (Wutzke *et al.,* 2016) suggests such partnerships have exciting future potential.

Policy relevant analysis

As well as aiding in the understanding of the multi-factorial nature of population oral health, a third implication of systems science approaches is the potential for policy related analysis (Rutter *et al.,* 2017). For example, such approaches allow for policies (interventions) to be artificially 'created' and tested on a population before they are enacted in the real-world to explore different intervention strategies or the potential outcomes of varying intervention 'types' (Maglio and Mabry, 2011). One topical example could be the introduction of the sugar tax in the UK in 2018 and its subsequent potential impact on tooth decay (HM Revenue and Customs, 2016). Diez Roux (2011) has pointed to the ability of systems approaches to 'identify previously unidentified leverage points or yield clues as to why certain interventions or policies may not have yielded the expected results' (p.1631). A systems approach is vital when considering interventions, as 'simple interpretations of complex phenomena have led to ineffective, or even harmful, interventions' (Fink and Keyes, 2017 – p.2), as well as unforeseen actions following the completion of trials (i.e. smokers trialling low nicotine cigarettes smoking high numbers to compensate – Kozlowski and Pillitteri, 1996).

Several DPH related studies have tested interventions. Hirsch and colleagues (2012), used system dynamics models to investigate the effects of a number of health interventions to reduce caries in children from Colorado, USA. The authors conceptualised and modelled the stages of disease progression from 'no caries' to 'symptomatic caries', before testing numerous interventions to see if these could change the progression of disease at any point along the caries continuum. They found that fluoride varnish for children, treating mothers with xylitol, and motivational interviewing lead to significant reductions in dental caries, more so when combined. Similarly, Koh and colleagues (2015) used Markov modelling in evaluating the cost effectiveness of interventions on dental caries in children aged 6 months to 6 years. Home-visit interventions by oral health therapists were tested against telephone-based and 'no intervention' scenarios. This demonstrated that for every 100 children, \$167,032 and \$144,709 was saved through the home and telephone-based interventions respectively over a 5-year period compared to usual treatment.

Discrete event modelling has seen few applications within DPH. However, several studies have assessed the effects of policies and interventions. Scherrer and colleagues (2007) used the method to assess school-based sealant programmes in Wisconsin children, in an attempt to determine the most efficient use of resources for these programmes. The discrete event simulation demonstrated that the state could save the most money by placing fewer restrictions on the types of personnel who could administer the sealants, while savings could be used to improve access to sealant services. Similarly, Kiley and colleagues (2008) used the method to create an evidence-based policy tool to guide oral health program managers in developing and deploying services. The analysis also demonstrated the need for differentiation when considering the service needs of populations. Children for example benefited more from increases in prevention strategies, while adults derived more benefit from higher staffing levels.

Testing theoretical frameworks and pathways

Fourthly, the testing of theoretical pathways on dynamic entities is another area in which systems science methods can continue to aid DPH. Understanding the underlying conceptual processes (the *why? questions, i.e. why do children in the East of Sheffield have higher numbers of decayed teeth than those in the West?)* is a key first step in informing the development of intervention strategies (Baker and Gibson, 2014). Systems science approaches allow for a more flexible testing of such theory. Diez Roux (2011) has illustrated how studying whole systems can reveal multiple causal pathways to the same outcome, as well as how some variables lead to different outcomes depending on the conditions of the system (e.g. parental socio-economic status influencing offspring health, education, or peer characteristics). Indeed, Fink and Keyes (2017) have stated that through modelling systems in this way, 'we are forced to confront the interactions among causes across levels that may be ignored when we reduce our vision to specific risk factors and causal effects that comprise the larger system' (p. 8). A systems approach also means that mental models need to be made explicit, with feedback and dependencies as essential features when they are formulated (Diez Roux, 2011). These approaches can add to the theoretical grounding of studies.

Within oral health, previous research has incorporated a custom conceptual framework concerned with how social factors affect attendance at oral health screenings, by mapping links between the formation of social capital and the impact this may have in the context of health promotion (Wang *et al.,* 2016). Using system dynamics and agent-based modelling to test this framework showed that as social influence took effect through social 'leaders', agents chose to go directly to oral healthcare services that were widely trusted, rather than waiting for referrals, demonstrating the influence of social networks on the visiting patterns for screening. This in turn led to better oral health outcomes. Further to this, recent research explored the theoretical pathways by which neighbourhoods may influence tooth decay, based around the themes of physical features of local environments; healthy home, work and play environments; public and private services that aid people in everyday life; socio-cultural features of neighbourhoods; and the reputation of different areas (Macintyre *et al.,* 2002). This research allowed for the 'teasing out' of the social determinants of tooth decay between those 'upstream' factors (e.g. presence of shops selling sweets in an area) and more individual (e.g. psychological stress) or behavioural (e.g. diet) determinants, by creating pathways through which these effects take place (Broomhead, 2017). This addresses a much needed 'upstream' social determinants research agenda much advocated for within DPH (Watt and Sheiham, 2012).

Methodological advances over current approaches in the field

A fifth and final implication considers advantages in study design that systems science methods offer, specifically over 'gold standard' approaches such as randomised controlled trials (RCTs). Luke and Stamatakis (2008) comment that such designs are more concerned with internal validation and the precise measurement of the effects of interventions, at the cost of external validity and measuring and understanding ecological and contextual effects. They further state that RCTs also use randomisation for group assignment and sample selection to gain precision, which leads to participants not being selected from regular social or organisational systems. Thus, the behavioural effects of these systems are excluded, while participants are not given the chance to interact as would typically happen. Case-control studies are also designed primarily to find the size of the effects of relationships, if they exist, rather than the mechanisms behind the effect (the 'black box' problem – Baker and Gibson, 2014). While measurement precision may be sacrificed to a certain degree by systems science approaches, external validity is gained along with the ability to analyse the effects of contexts on behaviour (Luke and Stamatakis, 2008).

Additionally, Rutter and colleagues (2017) commented that it is often near impossible to randomise population level interventions (citing examples such as the sugar tax, or factors supporting cycling), and the infrastructure, planning and implementation that surrounds these. Approaches looking to study single factors in a system, or that lose the context of a system by using randomisation and control, will usually be limited in their ability to influence these complex systems to improve population health (Rutter *et al.*, 2017). Such approaches can be detrimental to studies of oral health, as, for example, the randomisation of groups and sample selection processes do not reflect the way social groups work. The importance of the structure of these social groups has been demonstrated through the work of Sadeghipour and colleagues (2017), who used agent-based modelling to demonstrate the importance of friendship groups and the closeness of connections within these for oral health. The authors conducted initial qualitative research among schoolchildren in Iran, before using statistical analysis to inform parameters for their model of the dynamics of toothbrushing behaviours, and the diffusion of associated behaviours through friendship networks. The analysis revealed that behaviours diffused through developed friendship networks, with closer agents more likely to adopt similar habits. More popular agents were shown to have better brushing habits and were more likely to influence these habits in others. Such behaviours are key for maintaining oral health, and avoiding tooth decay (Kumar *et al.,* 2016).

The importance of including social interactions has been further demonstrated using social network analysis to explore the effects and importance of social interactions in groups. Maupome and colleagues (2016a) used social network analysis to demonstrate the importance of these networks for both behavioural and psychological acculturation of dental habits, including dental insurance coverage in a Mexican population. Additionally, Maupome and colleagues (2016b) used the method to study collectivist orientation in Latino groups in the USA with regard to oral discussion networks. Analysis of the individual social networks of adult Mexican-American immigrants showed that close kin tended to be relied upon if they were perceived to know more about dental related problems, although this was lower amongst those with greater behavioural acculturation. Such structures cannot be accurately replicated using RCT designs. Maupome and McCranie (2015) offer an excellent overview of network science and oral health research.

It is also worth acknowledging that quasi-experimental methods allow for the investigation of the impacts of interventions under 'real-life' conditions and enable causal inference in the absence of RCTs. For example, the 'difference in differences' approach tests for differentiation by using comparison groups that are experiencing the same general trends as the 'control group' (i.e. availability of free dental check-ups), but that are not exposed to a given policy intervention (Dimick and Ryan, 2014). Ikenwilo (2013) used this approach to demonstrate a 3-4% increase in dental service usage upon the implementation of free NHS dental check-ups in Scotland, compared to the rest of the UK. Similarly, the 'instrumental variables' approach is used for controlling unmeasured confounding in data that is not randomised (Rassen *et al.,* 2009), removing bias in the data through the use of structural equations (Koladjo *et al.,* 2018). The work of Matsuyama and colleagues (2018) on school reform, education and tooth loss is an example of this. Measures such as the 'regression-discontinuity-design' make use of thresholds, based on knowledge of rules that lead to differences in the treatment status of different patients (Listl *et al*., 2016), and has been used to investigate the effects of patient cost sharing on denture use and subjective chewing ability (Ando and Takaku, 2016). Listl and colleagues (2016) offer an excellent overview of these approaches in DPH.

Challenges in adopting systems science approaches

Previous research has shown that cross institutional collaboration in a systems science paradigm has been viewed positively by most institutions that were surveyed (Wutzke *et al.,* 2016). Despite this, the article also highlighted numerous challenges, including confusing language associated with the field, as well as practical concerns related to translating systems science approaches into achievable actions that are different to those currently in place. In addition, and related to these concerns, there are also challenges associated with data sharing across institutions and academic boundaries, particularly where such arrangements are not already in place. Leischow and Milstein (2006) have commented that 'new and more complex ways of linking data and exploring hidden relationships carry profound ethical, legal, financial, and social implications that must be understood and described' (p.404). Despite the advantages of systems science thinking, it is worth remembering that the inclusion of such approaches should not 'obscure the continuing need for specialized studies, on which all good systems theory depends' (p.403). These add to the evidence base from which relationships can be established.

More practical concerns regarding the running of systems science methods include the balancing of model accuracy, versus model simplification for practical reasons. Models that are too complex may take too long to run or may be harder to extract results from due to the number of interactions and parameters involved. Such challenges extend to issues such as defining the boundaries of a system, setting relevant time horizons, and considering which variables are exogenous and endogenous (Diez Roux, 2011). Additionally, the analysis of intervention effects dictates the need for sophisticated modelling which requires support by abundant data sources (Diez Roux, 2011), further adding to the challenge (although simplified models can be useful for proof of concept designs, and raising additional research questions). While simplified models (or various sub-models linked together) offer a solution to this, there is a danger that by simplifying, or reducing the number of dynamics present in a model, the analysis may miss key parts of a system. There is no easy answer regarding this trade-off, which will also depend on the aims of a given study. In addition, the parameterisation of variables related to behaviours and reactions can be difficult to define.

Concluding thoughts

This review has demonstrated the nature of systems science thinking, as well as the benefit that these approaches can have for the field of DPH. Systems science offers an alternative dimension to the field, in the form of feedback mechanisms and emergent properties, as well as the advantages it holds over traditional research methods. Additionally, the flexible nature of systems science approaches has also been demonstrated through the incorporation of current knowledge from the field into a dynamic approach for studying population oral health. While this approach has been applied within DPH, it is still an area lacking in depth, particularly when considering the advantages it offers.

Systems science approaches could also be used to build on previous related research to study highly complex policy relevant topics within the field. One such example in the UK would be the potential oral health effects of the recently introduced sugar tax applied to soft and sweetened beverages (HM Revenue and Customs, 2016). Other examples could be changes in nationwide dental contracts, the effects of interventions to address the persisting inequalities in a variety of oral health outcomes, as well as better understanding the impacts of the introduction of fluoridated water to different geographical areas. All of these examples are multifaceted problems, with relevant entities on multiple interlinked levels. A systems science approach could help to map out, and unpick, the most important mechanisms that are part of these processes, and the effects these may have. An increase in the use of systems science within DPH would be beneficial in terms of better understanding the complexity associated with the systems we study, and to advance our conceptual knowledge of the important mechanisms and emergent properties which are key to understanding and promoting good oral health for all.

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