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Neighbourhoods and oral health: Agent-based modelling of tooth decay

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ABSTRACT

This research used proof of concept agent-based models to test various theoretical mechanisms by which neighbourhoods may influence tooth decay in adults. Theoretical pathways were constructed using existing literature and tested in two study areas in Sheffield, UK. The models found a pathway between shops and sugar consumption had the most influence on adult tooth decay scores, revealing that similar mechanisms influence this outcome in different populations. This highlighted the importance of the interactions between neighbourhood features and individual level variables in influencing outcomes in tooth decay. Further work is required to improve the accuracy and reliability of the models.

1. Introduction

Tooth decay (dental caries) remains one of the most common non-communicable diseases, being the 10th most prevalent condition in deciduous (milk) teeth, affecting 9% of the world's population, while also affecting 35% of adults with permanent teeth, making it the most prevalent disease worldwide for that group (Peres et al., 2019). Despite overall reductions in tooth decay, inequalities in the disease persist (Schwendicke et al., 2015), particularly in the most deprived areas of England (Public Health England 2015).

Despite this, there has been a lack of geographical studies analysing pathways that lead to these inequalities. Many geographical studies within dental public health have used aggregate statistics or single deprivation indicators, limiting their ability to study patterns within smaller geographical areas (Broomhead et al., 2019). More advanced simulation modelling, such as agent-based models (ABMs), offer advantages over traditional statistics methods, through inclusion of dynamic interactions and independent feedback mechanisms occurring between individuals, groups and their environments over time (Auchincloss and Diez Roux 2008). ABMs have been becoming increasingly powerful with the inclusion of geocomputational capabilities (Dragićević, 2008), and have previously been used to investigate numerous health related themes, including mortality (Wu and Birkin 2012), healthy eating (Auchincloss et al., 2011) and walking patterns (Yang et al., 2011). The use of ABMs in dental public health remains rare however, and while several studies have used this method in combination with GIS and other systems science methods (Metcalf et al., 2013; Wang et al., 2016; Jin et al., 2018; Zhang et al., 2018), this research has focused more on social networks than the effects of neighbourhood environments.

The research presented in this paper builds on this work and presents proof of concept ABMs for the socio-spatial analysis of oral health. The key objective was to test a series of hypothesised theoretical pathways by which neighbourhoods may influence adult tooth decay (derived from existing literature), to examine which had the greatest influence on tooth decay scores, and whether this differed between areas of higher and lower socio-economic status within the city of Sheffield, UK.

1.1. The determinants of tooth decay: key theoretical and research challenges

Numerous social determinants of health (Wilkinson and Marmot 2003) have been linked to inequalities in tooth decay. Income has shown strong associations with tooth decay (Costa et al., 2012; Schwendicke et al., 2015) through both area based (Celeste et al., 2009) and average income measures (Aida et al., 2008), with higher decay scores being found in lower income brackets (Geyer et al., 2010). Income can also influence access to amenities such as dental services, fluoridated water, and dental information (Costa et al., 2012), and can influence decay in early life through material circumstances (Nicolau et al., 2005). Education has also been shown to be important for decay in childhood (Muirhead and Marcenes 2004) as well as adulthood (Brennan et al., 2007; Geyer et al., 2010; Mamai-Homata et al., 2012), and can act as a mediating pathway between socio-economic position and decay

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(Schwendicke et al., 2015). Negative associations between employment standing and decay have also been found (Costa et al., 2012), with parental occupation being linked to levels of decay in children (Vanobberge et al., 2001; Gokhale and Nuvvula. 2016). Associations between unemployment and increased decay (Tellez et al., 2006; Roberts-Thomson and Stewart 2008) have also been found, while unemployment is also associated with less favourable oral health related behaviours (Guiney et al., 2011; Al-Sudani et al., 2016). Related concepts including socio-economic position have also shown social gradients in decay in children (Watt and Sheiham 1999) and adults (Hobdell et al., 2003; Schwendicke et al., 2015).

Psychological stress has shown links to detrimental oral health, including self-reported oral health (Sanders and Spencer 2005; Finlayson et al., 2010) and periodontal disease (Warren et al., 2014). Stress has been associated with increased decay through biological factors such as cortisol secretion (Boyce et al., 2010), although not all studies have found such associations (Armfield et al., 2013). Coping mechanisms for stress, specifically smoking, can have detrimental effects on decay (Hudson et al., 2007; Bernabe et al., 2014), although this literature is inconsistent (Reibel 2003; Vellappally et al., 2007). Diet is vitally important to oral health, with undernourishment (known to be higher in lower income groups - National Diet and Nutrition Survey 2014) leading to decay (Moynihan and Petersen 2004; Sheiham 2006). Increased sugar consumption has been conclusively linked to increasing numbers of decayed teeth (Sheiham 2001), particularly through soft drink consumption (Burt et al., 2006; Warren et al., 2009). Oral health-related behaviours such as the use of fluoridated oral dentifrice have also been shown to be important for decay (Zero 2006). Attitudes towards oral health (Chu et al., 1999) and brushing frequency are also associated with levels of decay, with socio-economic (Sabbah et al., 2009) and educational gradients (Singh et al., 2013) in oral health behaviours also being demonstrated, as well as in dental education and knowledge (Williams et al., 2002). However, while there is evidence that attendance follows a social gradient, dental self-care does not always (Sanders et al., 2006). Despite evidence to the contrary, the majority of the literature demonstrates the importance of social gradients in influencing disease and oral health behaviours.

Longitudinal research has demonstrated the benefit of dental attendance for decay (Thomson et al., 2004), and positive associations with preventive oral health habits (Hill et al., 2013). Attendance has been shown to vary by socio-economic group (Lang et al., 2008), and irregular attenders can experience significant differences in decay compared to regular attenders (Tickle et al., 1999). Negative relationships have also been found between decay scores and dental service use (Tickle et al., 2000), with children from deprived areas being more likely to attend only due to experiencing symptoms (Eckersley and Blinkhorn 2001). Certain 'favourable' socio-economic and demographic characteristics have been associated with attendance (Guiney et al., 2011; Muirhead et al., 2009), with low income groups facing more barriers to services (Wallace and Macentee 2012). Importantly, socio-economic gradients in the number of sound teeth in adulthood can be partly explained by attendance, determined by the effects of socio-economic status on barriers to services (Donaldson et al., 2008).

Neighbourhood level variables have also been shown to be important for oral health, including social capital, which can be beneficial through shared knowledge and resources, and psychological processes (Lida and Rozier 2013), as well as through influencing behaviours and practices (Turrell et al., 2007). The presence of community centres has shown significant associations with decay scores (Aida et al., 2008), with improvements in oral health also linked with institutions such as churches (Tellez et al., 2006). Neighbourhood level empowerment has also shown negative associations with decay experience (Santiago et al., 2014), although not all studies have found links between oral health and social capital (Mathur et al., 2016). The location of dental surgeries may also influence oral health due to some areas being underserved (Lang et al., 2008). This has been demonstrated historically in the UK (Cook and Walker 1967; Jones 2001), although contemporary evidence for this is lacking (Macintyre et al., 2008). The importance of shops has also been hypothesised (Mobley et al., 2009; Fonseca 2012), with links found between decay scores and grocery stores (Tellez et al., 2006; Aida et al., 2008), despite some findings to the contrary (Borenstein et al., 2013). The presence of fluoridated water in different locations has also been shown to reduce social gradients in decay (Slade et al., 1996; McGrady et al., 2012). Despite these examples, less attention has been paid to neighbourhood level determinants within the tooth decay literature.

The literature demonstrates the complex dynamics of tooth decay (Broomhead and Baker 2019). Research is needed to clearly delineate and test the pathways associated with these factors and their interactions (Diez Roux, 2011) and at the same time take into consideration the complex dynamics of tooth decay, including socio-spatial factors and the importance of place to oral health (Broomhead et al., 2019). It is also important to take a comprehensive theoretical approach to hypothesising potentially important pathways that account for neighbourhood level features, and their impacts on individual characteristics and health outcomes (Macintyre et al., 2002). These pathways can be quantified and tested using ABMs (Speybroeck et al., 2013). ABMs are computational representations of systems which include multiple discrete entities, the interactions of which give rise to system level patterns and behaviours (Auchincloss and Diez Roux 2008). ABMs take a 'bottom-up' approach to simulating behaviours at the individual level, and are more suited to analyses involving individual interactions in small area geographies. Crucially, ABMs have the ability to test theoretical hypotheses (Johnson and Groff 2014; Cerda et al., 2014), track agent characteristics (Gorman 2006), and analyse 'what-if' scenarios (Paolillo and Jager, 2019).

2. Model framework – theoretical pathways

Hypothesised pathways were derived using a health-related place based theoretical framework (Macintyre et al., 2002), which includes (1) physical (naturally occurring) features; (2) availability of healthy environments at home, work and play; (3) public and private services to aid in daily life; (4) socio-cultural features of neighbourhoods; and (5) the reputation of an area. Use of existing dental public health and health inequalities literature led to the creation of the pathways for tooth decay within each domain (Table 1). Pathways were operationalised through the 2009 Adult Dental Health Survey (ADHS – Office for National Statistics 2012), a representative decennial population-based survey of 11, 380 individuals from England, Wales, and Northern Ireland. Dental examinations were conducted on 6469 individuals as part of the survey. Pathways for water fluoridation were not created, as neither study area was naturally nor artificially fluoridated, while 'the reputation of an area' could not be operationalised due to a lack of literature on this topic. The ABMs are described using a standardised protocol for presenting ABM features and details (ODD - Grimm et al., 2006).

The ABMs were designed to replicate behaviours within the conceptual model for the research (Fig. 1), as derived from the literature, which demonstrates three hierarchical levels (neighbourhood, collective features, individuals) at which different concepts sit. Concepts can be situated between two hierarchical levels, or have features of both, and this is reflected in the positioning of the boxes for these concepts (dotted lines are in place to avoid obscuring the links in the framework). This demonstrates the complexity of this system, and the need to break this structure down into individual pathways to aid the modelling process.

3. Model description

3.1. Purpose

The purpose of the proof of concept models was to understand how (if at all) features of neighbourhood environments influence spatial inequalities in tooth decay, through an exploratory approach. The aim was

Table 1
Hypothesised place based theoretical pathways for the tooth decay ABMs.

Pathway	Domain	Pathway components
1	Availability of healthy environments at home, work and play	Material circumstances - > financial constraints - > stress - > smoking - > decay
2	Availability of healthy environments at home, work and play	Material circumstances - > financial constraints - > diet/sugar intake - > decay
3	Availability of healthy environments at home, work and play	Material circumstances - > financial constraints -> (dental) knowledge - > health habits - > tooth decay
4	Public/private services to aid in daily life	Employment - > social gradient position - > decay
5	Public/private services to aid in daily life	Education - > social gradient position - > decay
6	Public/private services to aid in daily life	Education - > dental knowledge - > damaging behaviours - > decay
7	Public/private services to aid in daily life	Shop - > diet/sugar intake - > damaging behaviours - > tooth decay
8	Public/private services to aid in daily life	Dental service usage - > associated benefits/knowledge - > decay
9	socio-cultural features of neighbourhoods	Health behaviours - > diet- > sugar/ nutrition - > decay
10	socio-cultural features of neighbourhoods	Health behaviours - > oral health habits - > decay
11	socio-cultural features of neighbourhoods	Health behaviours - > attendance - > knowledge - > decay
12	socio-cultural features of neighbourhoods	Social capital - > acquired dental knowledge - > decay
13	socio-cultural features of neighbourhoods	Social capital - > Healthy behavioural norms - > decay
14	socio-cultural features of neighbourhoods	Social capital - > stress - > smoking - > decay

to test a series of theoretical pathways by which neighbourhoods may influence tooth decay in adults, using ABMs in order to find which of these had the largest influence within two neighbourhoods in Sheffield, UK.

3.2. State variables and scale

Three hierarchical levels were present: individuals, collective features of individuals, and neighbourhood environments. Individual state variables were derived from a spatial microsimulation model combining data from the ADHS, and the 2011 UK Census (Office for National Statistics 2011) at Lower Super Output Area (LSOA – Office for National Statistics, 2014) level. Individual agents had the following state variables (Table 2): age, education, and national statistics socio-economic classification (NS-SEC – Office for National Statistics, 2010) status. In addition, individuals were characterised by self-reported variables associated with oral health behaviours, these being: whether cost led to delays in dental treatment; dental hygiene product use; whether cost affected dental treatment type; psychological discomfort; whether individuals received smoking cessation advice; sugar intake; dental attendance frequency; fluoride intake; sweet consumption frequency; cake consumption frequency; brushing frequency; reason for dental visits; and whether individuals received advice on dental attendance habits. Agents were also assigned tooth decay scores (the outcome variable) through the 'numdu98' variable from the ADHS, which represents the number 'of decayed or unsound teeth', not including those with fillings or those that have been extracted. This process assigned agents characteristics relevant to the theoretical pathways, which could be referenced and updated in the simulations whenever a pathway affected an agent. Individuals did not form families or social groups within the models.

While previous ABMs have predicted certain scenarios (Potter et al., 2012; Merler et al., 2013) or used historical data to parameterise models (O'Neil and Sattenspiel, 2010), this research was exploratory in nature. Given the difficulties in parameterising proof of concept models, the trends of the results, rather than absolute values, were the focus of the research. This was seen as appropriate given that results of ABMs should be interpreted conservatively as they are not empirical tests, but rather explorations of the plausibility of a theory (Johnson and Groff, 2014).

In order to include real world locations (dentists, shops, education facilities), local road networks were included to allow agents to navigate between points. These were also included in order to test the role of

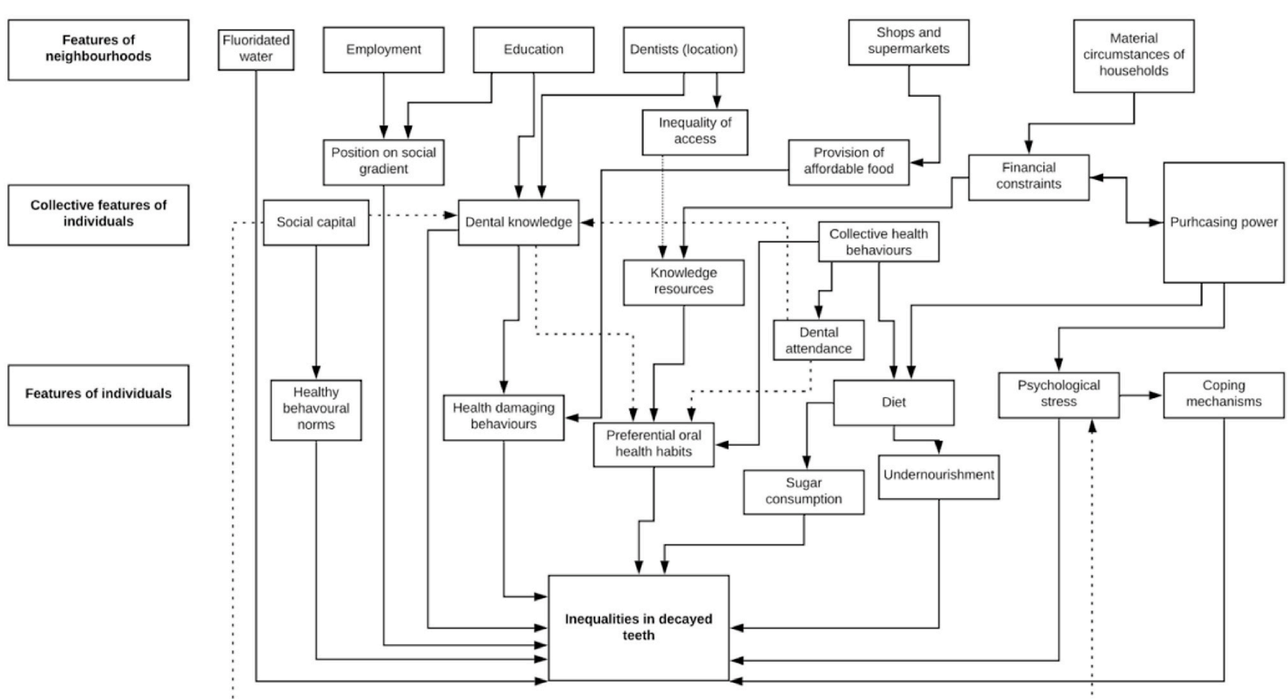

Fig. 1. Conceptual model of tooth decay and neighbourhoods.

Table 2
Overview of individual agent characteristics (state variables).

Variable	Meaning	Parameter value range	Source
Education level	Whether individuals were educated to degree level, or below	Degree or higher; below degree level	ADHS/ Census 2011
NS-SEC classification	The National Statistics Socio-economic Classification of each individual	Large employer/higher managerial; higher professional occupation; lower managerial/ professional occupation; intermediate occupation; small employers/own account workers; lower supervisory/technical occupation; semi-routine; routine occupations; never worked and long term unemployed	ADHS/ Census 2011
CostDly	Whether an individual had to delay treatment due to cost	Yes; no	ADHS
TPaste	Whether individuals used other dental hygiene products	Yes; no; I don't have a toothbrush and/or toothpaste	ADHS
CostTyp	Whether cost affected the type of treatment or care an individual received	Yes; no	ADHS
PsycDisc	Whether an individual felt psychological discomfort in the form of feeling tense	Never; hardly ever; occasionally; fairly often; very often	ADHS
EvrAdSm	Whether individuals had ever been given advice about giving up smoking	Yes; no; I have never smoked	ADHS
HighSug	Whether an individual had a high sugar intake	Yes; no	ADHS
Regular	General dental attendance	Regular check-up; occasional check-up; only when having trouble; never been to the dentist	ADHS
Fluoride	Fluoride level (intake in parts per million)	1350–1500 ppm; 1000–1300 ppm; 550 ppm or less; no fluoride	ADHS
Sweets	How often an individual ate sweets	6 or more times a week; 3–5 times a week; 1–2 times a week; less than once a week; rarely or never	ADHS
NCakes	How often an individual ate cakes	6 or more times a week; 3–5 times a week; 1–2 times a week; less than once a week; rarely or never	ADHS
ClnTthG3	How many times an individual brushed their teeth per day	Twice a day or more; once a day; never, less than once a day	ADHS
FreqDen	How often an individual went to the dentist	At least every 6 months; at least once every year; at least once every two years; less frequently than every two years; only when having trouble	ADHS
EvrFrqy	Whether an individual had ever been given advice about frequency of visits to the dentist	Yes; no	ADHS

neighbourhood layouts and locations in the development (or lack thereof) of tooth decay. It was deemed important to test how the locations of hypothetically important facilities such as shops and dentists may impact disease (if at all). Adding this spatial dimension to the models allowed for the contexts and constraints of the environments to be incorporated into the analysis. As agents moved between these points they would be affected by the interactions of the pathways associated with each location shown in Table 1. Environments were created in NetLogo (Wilensky 1999) using the GIS extension to import administrative shapefiles[1] from the UK Borders Boundary Data Selector (UK Data Service, 2011), to create two study areas in Sheffield. LSOAs with the 30 highest and lowest mean decay scores (based on data from the spatial microsimulation model) were selected from the 345 LSOAs in Sheffield. Where LSOAs shared common boundaries, these clusters were taken and used as a study areas. This led to the creation of two study areas, one in an area with a higher socio-economic profile (based on education level and NS-SEC status), and another with a lower socio-economic profile. The 'Sheffield East' study area consisted of LSOAs with the 1st, 2nd, 5th, 7th, 10th, 14th and 21st highest mean decay scores, while 'Sheffield West' comprised LSOAs with the 1st, 4th, 11th, 12th, 14th, 20th and 26th lowest tooth decay scores. The 'edges' of the environments acted as boundaries, and agents could move through each LSOA in their study area. Buffers were added to avoid cutting off roads where possible (Fig. 2).

Agents navigated road networks through the use of a previous GIS based NetLogo model (Zhou 2016). Geocoded shop, dentist and further education (FE) facility locations were added, allowing agents to distinguish between, and navigate to different locations. Types of services available (e.g. private versus NHS dentists, corner shop versus supermarket) was not differentiated.

Where locations occupied the same 'patch' (i.e. locations on opposite sides of a road), one was adjusted, and placed as near to its real-world position as possible, as two locations could not be present in the same patch. Variables not representing physical locations were stored as 'background data' in the shapefiles (Table 3). Social capital was represented by data on violence, burglary, theft and criminal damage per LSOA (Ministry of Housing, Communities and Local Government 2015), as crime variables (homicide rate) have been used as a measure of social capital in previous oral health research (Pattussi et al., 2001). The material circumstances of an area were represented through house price data (Office for National Statistics 2015), due to its importance as a material indicator (Nkosi et al., 2011; Tunstall et al., 2013). Collective health behaviours were represented by the years of lost life per LSOA. This measure of premature death, taken from the health domain of the Indices of Multiple Deprivation (Ministry of Housing, Communities and Local Government 2015), is calculated by comparing age at death with life expectancy at a given age (Public Health England, 2018), as the idea of co-morbidities posits that poor oral health may occur alongside other conditions (Bailey et al., 2004; Chroinin et al., 2016). Finally, employment was represented through model-based income estimates (Office for National Statistics 2009), due to the effects of employment on income.

The timespan of the models was two years, based on expert dental advice as to the morphology of tooth decay from a professor and honorary consultant in dental public health: a 2-year timespan is the estimated average timeframe for an individual, under a given set of circumstances, to transition from having non-decayed teeth, to having visible decay. This was considered an appropriate timeframe in which decay could develop in those with previously healthy teeth, and increase in those with already decayed teeth. Each 'tick' in the model represented one day, with simulations running for 730 ticks.

3.3. Process overview and scheduling

For each 'tick' of the models, three processes took place in the following order: agent movement, agent interaction with their environment, updating agent characteristics. A separate process, time lag events, took place independently to the first three processes.

Agent movement involved interaction with the road network in order to move around the study areas. Road networks were constructed through a series of nodes, with agents able to transfer across multiple nodes per tick in order to move in the direction of their intended location

[1] https://doc.arcgis.com/en/arcgis-online/reference/shapefiles.htm.

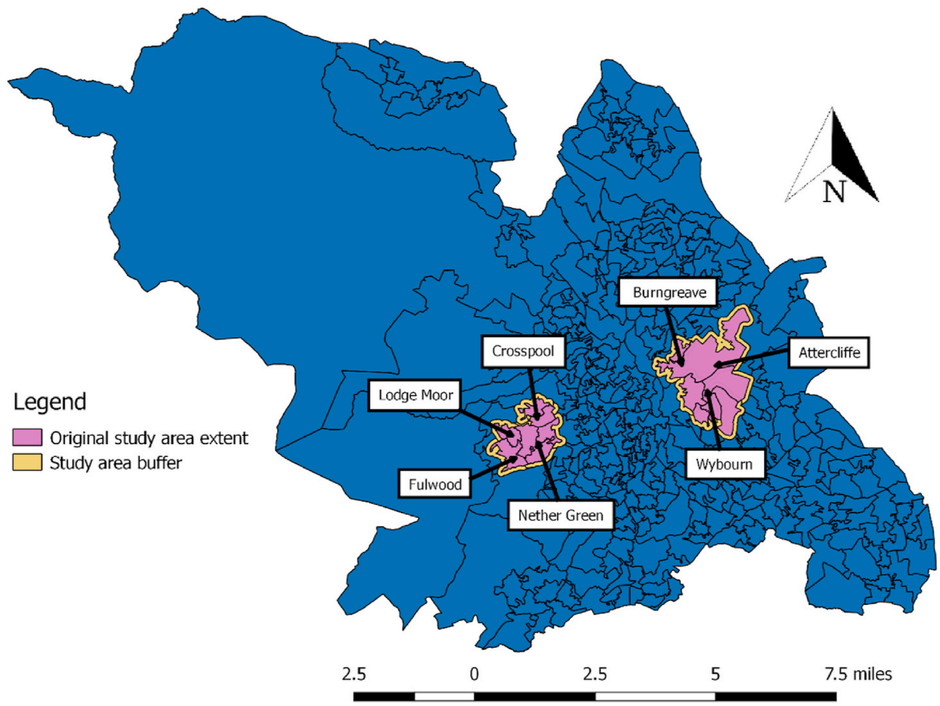

Fig. 2. The two study areas for the ABMs.

Table 3
– Background variables used in the simulations.

Variable	Meaning	Parameter value range	Source
Material circumstances	Median house price statistics for small areas (MSOA)	£63,000 - £256,500 (continuous scale)	Office for National Statistics (2015) - Neighbourhood Statistics
Employment	Model based income estimates - per week (MSOA)	£449.62 - £1321.69 (continuous scale)	Office for National Statistics (2009) – Neighbourhood Statistics
Health behaviours	Years of potential life lost – age and sex standardised measure of premature death (i.e. before 75 - LSOA)	49.192–79.736 (continuous scale)	Indices of Multiple Deprivation (2015) – Health domain
Social capital	Crime score - combined data on violence, burglary, theft and criminal damage per 1000 individuals (LSOA)	−1.302–0.637 (continuous scale)	Indices of Multiple Deprivation (2015) – Crime domain

(i.e. shop, dentist). The second type of interaction was between agents and their environments (i.e. when reaching their intended locations). Interactions varied depending on the agent and the location they arrived at (see pathways 6–8, Table 1, Section 2), and the timing of these interactions was dependent on when an agent arrived at a given location. The third and final process was the updating of agent characteristics, based on their recent interactions. Each theoretical pathway, and the interactions associated with these, influenced the characteristics of a given agent. For example, if an agent was more likely to exhibit health damaging behaviours, this would result in a change to that agent's 'sugar consumption' variable, increasing the chances of consuming sugary products. Updated characteristics could then influence future interactions (in this case those involving diet and behaviours). A fourth process (time lag events affecting agents) acted separately, and could also update the characteristics of agents. These represented effects on agents that occurred at differing intervals, regardless of agent positioning in their environment (e.g. the cumulative effects of health damaging behaviours, or stress), and were not associated with location. The occurrence of time lag events differed depending on the process, being implemented at either 7 or 14 ticks, to represent the immediate conditions in which agents lived which may affect them more regularly (7 ticks), and those which were likely to have longer term effects, or occur less frequently (14 ticks). The sequence of processes are visually depicted, with scheduling, in Fig. 3 (thicker lines represent the main processes of the models, and dashed lines the effects on agents). More detailed information on the four processes is provided in Section 3.6.

Tooth decay is affected by the characteristics of a given agent (e.g. sugar consumption). These characteristics are themselves influenced by the processes within the models. Over the course of the models these processes will influence agent characteristics that have a direct effect on their tooth decay score (e.g. sugar/fluoride consumption), through the interactions introduced through the theoretical pathways.

3.4. Design concepts

Emergence: Aggregate decay scores emerged from the decay scores of individuals, which were influenced by behaviours and interactions with environments (defined by the theoretical pathways).

Adaptation: Agent characteristics adapted as the models progressed, with variables changing based on existing variable scores, and interactions within the models. This meant variables could move over/under given thresholds, which may change how processes affected agents at later points.

Interaction: Agents interacted with their environment through three processes: interactions with the road network, interactions with point-based locations, and changes to agent variables through the previous two interactions. Time lag processes also interacted with agent characteristics as the simulations progressed. These interactions were modelled explicitly. Agents did not interact with each other within the simulations.

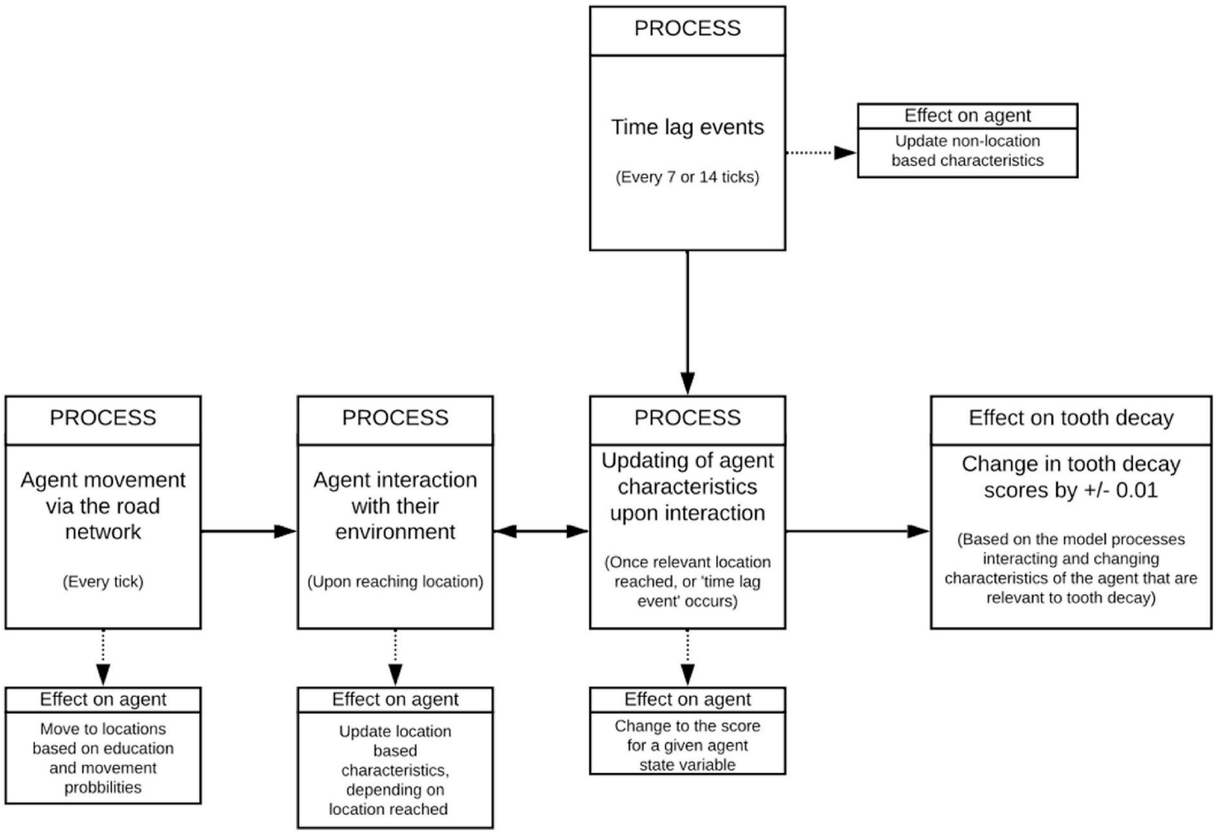

Fig. 3. Diagram representing the scheduling of events in the ABMs.

Stochasticity: Visiting patterns to point-based locations were based on probabilities, with visiting probabilities differentiated by educational attainment. This allowed for an element of randomness, and the assumption that expected behaviours may not occur on every occasion (see Section 3.6.1).

Observation: For model testing, the effects of each pathway and agent movement were observed process by process in simplified environments. Analysis of the final models involved observation of one population level variable (aggregated decay scores), which was the final outcome variable. Scores were compared across models to assess the effects of different pathway combinations.

3.5. Initialisation

The Sheffield East study area initialised with 8524 agents, while Sheffield West had 8644. Each model run started at the beginning of the study time period, equating to 2011 (based on using Census data). Initialisation was influenced by the experiment that was undertaken. This involved sequentially adding an additional pathway to each new iteration of the models. The effect on the models was assessed after each run, in order to identify pathways which influenced the outcome score. This allowed for comparisons of the effects between the study areas. Similar approaches have been used for geographical ABMs, such as iteratively increasing the percentage of preference for living with similar types of individuals in models of residential segregation (Crooks 2008). All point-based destinations were consistent in their initialisation location, while the starting location of each agent differed, not always corresponding to their ‘home’ LSOA (in which they resided at the 2011 Census). This feature was included to account for the probabilistic nature of the models, and the assumption that it is was plausible for agents to start the simulation at a location in their ‘neighbourhood’ other than their home.

3.6. Submodels

3.6.1. Agent movement within the models

Movement between road network nodes was considered important in representing movement across real world geographical spaces (see

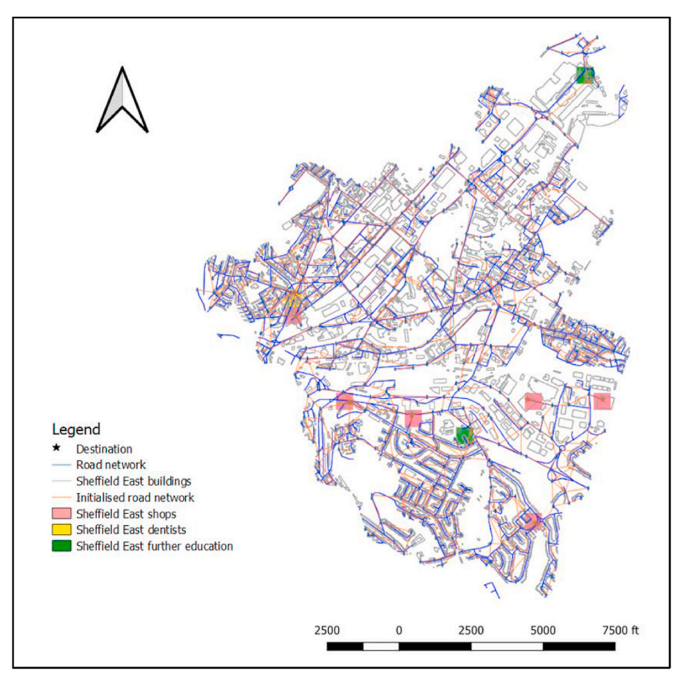

Fig. 4. Example of the road network, and slight mismatch between roads (blue) and the nodes/links (orange) in the Sheffield East study area.

Fig. 4). The aim of the models was to test the effects of neighbourhood environments on oral health, and therefore it was deemed imperative to include the real world locations in attempting to model human movement between different locations in specific geographical contexts, and to have realistic distances between locations. This allowed for spatial contexts of different areas, and constraints involved in navigating these, to be included. Movement was based on a previous NetLogo model of student movement at George Mason University (Zhou 2016). Agents would select one of the three potential destinations at the start of the simulation (based on probabilities and a random number generator, detailed below), calculate the shortest path to this destination, then navigate the nodes and links to reach it. The model uses the A-star path finding algorithm (Hart et al., 1968), which searches all possible paths leading to the desired destination in the shortest distance. Due to agents attempting to find the shortest paths (assuming agents would attempt to navigate in the most efficient manner), geographical proximity of agents played a key role in the locations that were visited. Therefore the spatial nature of the model affected the routes agents took to their desired locations. Agents stayed at their destination for one tick, before moving onto the next destination. Customisation meant agents could tell destination types apart, and aim for a destination different to the one they were at previously.

Probabilities for visiting shops, dentists or FE facilities were assigned, and differed depending on agent characteristics. If agents possessed higher levels of dental knowledge (represented through the fluoride consumption variable), they would be more likely to seek out further dental care in future. If agents were aged 16–24 and had lower education they would be more likely to seek out FE facilities. The determination to visit different locations was influenced by each individual's traits, which in turn determined the degree to which locations were prioritised. Visiting probabilities differed by education, as this has been linked to oral health behaviours (Williams et al., 2002; Singh et al., 2013). Positive associations between education and dental attendance have also been found (Riley et al., 2006), so it was assumed to be a suitable proxy for influencing visiting probabilities. Those with higher levels of education were likely to visit shops less often, and prioritise dentist locations more than those with lower levels of education. In a normal simulated day (or tick), each agent would visit one destination per day. Fig. 5 demonstrates the daily process of agent movement in the model, while the probabilities for Sheffield East are presented in Table 4.

While probabilities have driven ABM dynamics before (Tracy et al., 2014; Olivella-Rosell et al., 2015) quantifying these is difficult. None of the previous oral health focused ABMs (Metcalf et al., 2013; Wang et al.,

Table 4
Probability of movement to destinations, based on educational attainment (Sheffield East).

Agent characteristic	Action	Probability of action
Has degree	Movement to dentist	20%
Has degree	Movement to shop	60%
Has degree	Movement to FE	20%
No degree	Movement to dentist	10%
No degree	Movement to shop	80%
No degree	Movement to FE	10%

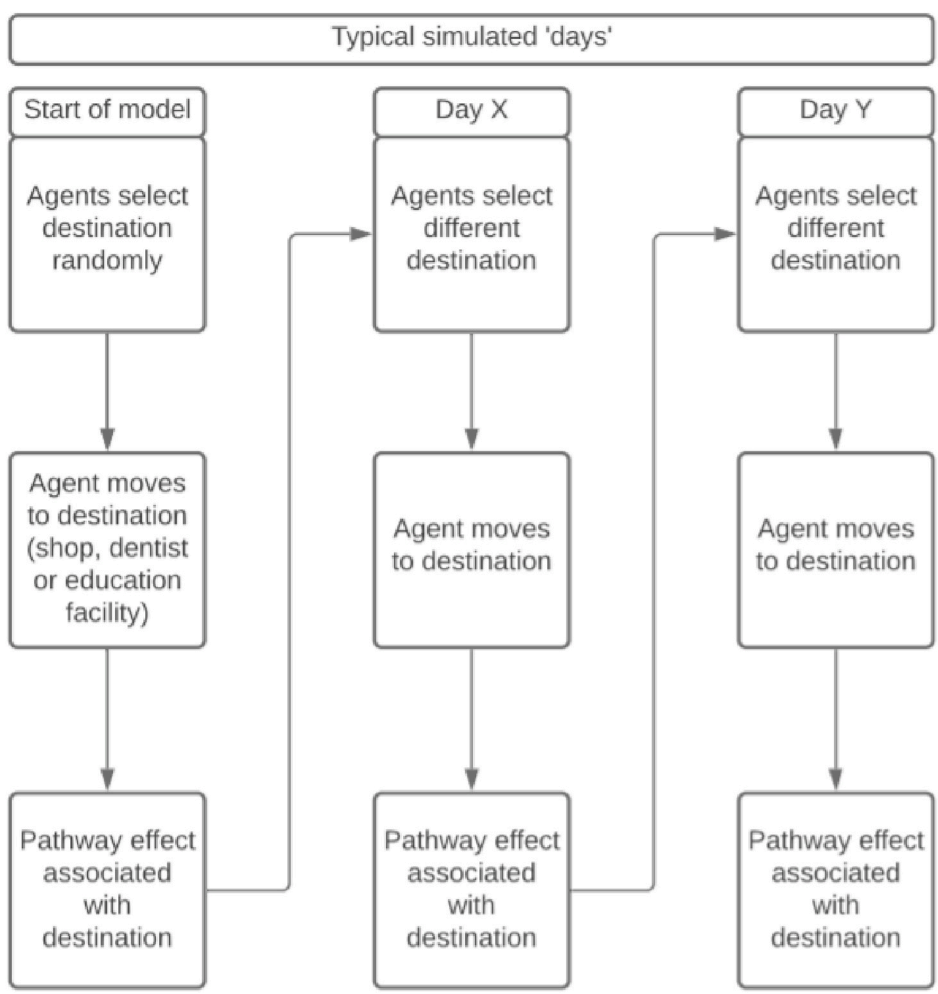

Fig. 5. Flowchart representing agent movement on a typical day.

2016; Jin et al., 2018; Zhang et al., 2018) used probabilities for dental visits in relation to other neighbourhood based features, and while literature shows attendance patterns vary by deprivation and education, it is hard to quantify this effect. Official data sources such as The United Kingdom Time Use Survey (Gershuny and Sullivan 2017) does not contain data on visiting patterns to dentists. The probabilities in Tables 4 and 5 therefore attempt to quantify these patterns as logically as possible. Shops were given a higher probability as shopping likely occurs more often than visits to dentists and FE facilities. Dentists and FE locations were given equal weighting as they were presumed to be less frequently attended. Based on the literature however, those with higher levels of education were given higher probabilities of attending dentists and FE locations.

Probabilities were implemented using random number generators. For agents with a degree living in Sheffield East, if the random number fell between 0 and 0.2 the agent would go to the nearest dentist. If the number was over 0.2 and equal to or below 0.8 they would go to the nearest shop, and if the number was over 0.8 they would go to the nearest FE facility. Their next location would be one of the two other destinations, as it was deemed unlikely individuals would visit the same facility twice in a row. Probabilities were edited for Sheffield West as only shops and dentists were present (Table 5).

Each simulation was run 10 times to account for the probabilistic nature of the models, and average scores were taken. Although 50 runs are more commonly used (Malleson et al., 2010), 10 runs have also been used in previous geographical (Crooks 2008) and labour market based ABMs (Meyer and Vasey, 2018). However due to computing resources this was not possible.

3.6.2. Agent interactions with their environment

Behaviours, or effects on agents, differed depending on whether variable scores were above or below predefined thresholds. This approach can be advantageous when behaviours are well known and documented (Heppenstall et al., 2016), and has been used in previous ABMs (Matthews et al., 2007). Destinations were differentiated by patch colour (pink = shops, green = education, yellow = dentists), so when agents landed on a patch the appropriate theoretical interactions could be triggered (i.e. landing on a pink patch affected sugar consumption).

Some interactions were differentiated using the NS-SEC classification, a proxy for social gradient position. The NS-SEC classification is non-hierarchical in nature, making it inappropriate to create arbitrary thresholds between groups in the middle of the data scale. Agents were therefore split between those in group 8 (‘long term unemployed and never worked’), and those in NS-SEC groups 1–7 (working). While a slightly crude assumption, it avoided violating the conceptual structure of the data, and matched the dichotomous way employment had been used in previous oral health research (Roberts-Thomson and Stewart 2008; Costa et al., 2012). For pathways where NS-SEC was a differentiating variable, the two groups would experience the opposite effects from the theoretical pathways. For example, if groups 1–7 saw their decay score decrease, ‘group 8’ saw theirs increase. Despite some evidence refuting that those in less favourable socio-economic positions care less for their teeth, the majority of the literature (Section 1.1) suggests that social gradients exist for oral health, which influence disease outcomes and habits and behaviours. Given the weight of this theory in the literature, it was deemed appropriate to implement this structure within the models.

A list of the model interaction types are listed below, outlining different entities within the models that agents could interact with. It is worth remembering that not all interactions and examples mentioned here represent full theoretical pathways, and in some cases only detail subsections of these. These examples form part of a pathway that impacts on decay, and are included to demonstrate the nature of these interactions - full pathways can be seen in Fig. 1, or Table 6 (Section 3.6.3).

- Agent-dentist interactions: When reaching a dentist, agents either derived benefit or experienced negative effects on their health based on their characteristics. For example, agents attending the dentists every six months saw their dental knowledge increase, while attending less regularly saw agents’ dental knowledge decrease. The rationale was that those attending less often would be less likely to accrue dental knowledge, and this pathway acted as a way to reflect this.
- Agent-shop interactions: When reaching a shop, if an agent’s NS-SEC score was equal to 8 their sugar intake increased, while this decreased for those with a score of 1–7. This pathway reflects dietary habits, so that agents who were more likely to consume sweets and sugar, or those with ‘unhealthier’ behaviours, would see increases in their sugar consumption score when visiting a shop. The pathway to increase this score reflected this overall intake, and acted as a cumulative indicator of sugar consumption that may be used in other model interactions.
- Agent-FE interactions: Educational facilities were included that provided apprenticeships, or further training and education for adults. Agents without a degree aged 16–24 headed to these facilities, which were only present in Sheffield East. Attendance increased individual’s dental knowledge (as a proxy for wider education).
- Agent-material circumstances interactions: Mean values for house price data (proxy for material circumstances) for the two areas were used as thresholds. If house prices for an area were above the threshold agents in that area saw their psychological stress variable reduce, and vice versa.
- Agent-employment interactions: Agents in areas with average income (proxy for employment) above the mean threshold saw their decay score decrease, and vice versa. This interaction represents the one direct pathway between a predictor variable and decay scores, designed to mimic the importance of social gradients on oral health outcomes.
- Agent-health behaviour interactions: Agents in areas with years of lost life (proxy for health behaviours) scores over the mean threshold saw their fluoride intake decrease, and vice versa.
- Agent-social capital interactions: Agents from areas with crime scores (proxy for social capital) above the mean score saw their psychological stress scores increase, and vice versa.
- Agent-road interactions: Agents interacted with road networks to navigate the study areas, through turning the network into a series of links and nodes.

3.6.3. Updating agent characteristics

Through model interactions, individual characteristics and decay scores increased or decreased by 0.01, allowing for scores to cross at least one threshold during the model runtime. This approach attempted to keep decay scores more balanced, so they did not increase too much. This also allowed a buildup of conditions over time that influenced changes in decay, mimicking the accumulation model of the life course approach (Sisson 2007), and accounting for longitudinal effects on oral health (Poulton et al., 2002; Thomson et al., 2004). This also allowed agent characteristics to be continually referenced and updated in a dynamic way. The 14 pathways (Table 1) were coded into the models, with some variables combined in the same section of code when closely linked conceptually - for example, material circumstances (‘h_price’)

Table 5
Probability of movement to destinations, based on educational attainment (Sheffield West).

Agent characteristic	Action	Probability of action
Has degree	Movement to dentist	25%
Has degree	Movement to shops	75%
No degree	Movement to dentist	15%
No degree	Movement to shops	85%

Table 6
Theoretical pathways, concepts, indicators and parameters.

#	Concept	Variable	Parameter in model	Effect on agent
2.1	Material circumstances	House price data (MSOA)	East: ≤ 88,654 West: ≤ 251,636	Stress variable increased
	Financial constraints	Whether delayed dental treatment due to cost	1	
	Stress	Psychological discomfort	>3	Smoking variable increased
	Smoking	Ever been given advice on giving up smoking	<2	Tooth decay variable increased
2.2	Material circumstances	House price data (MSOAs)	East: ≤ 88,654 West: ≤ 251,636	Purchasing power variable decreased
	Financial constraints	Whether delayed dental treatment due to cost	1	
	Purchasing power	Whether cost affected type of dental care/ treatment	<2	Diet variable increased
	Diet	Number of cakes eaten per week	<3	Sugar variable increased
	Sugar intake	High sugar intake	<2	Tooth decay variable increased
2.3	Material circumstances	House price data (MSOAs)	East: ≤ 88,654 West: ≤ 251,636	Purchasing power variable decreased
	Financial constraints	Whether delayed dental treatment due to cost	1	
	Dental knowledge	Fluoride level	>2	Healthy habits variable decreased
	Healthy habits	General dental attendance	1	Tooth decay increased
3.1	Employment	Model based income estimates (MSOAs)	East: ≤ 491.8 West: ≤ 1056.1	Tooth decay variable increased
	Social gradient position	NS-SEC classification	8 vs < 8	
3.2	Education	Highest qualification above or below degree level	Above vs below degree level	Tooth decay variable increased
3.3	Education	Location of further education providers in Sheffield	N/A	Dental knowledge variable decreased
	Dental knowledge	Fluoride level	<2	Health damaging behaviours variable increased
	Health damaging behaviours	Consumption of sweets	<3	Tooth decay variable increased
3.4	Shop	Location of shops and supermarkets within Sheffield	N/A	Sugar intake variable increased
	Diet/sugar intake	High sugar intake	<2	Health damaging behaviours variable increased
	Health damaging behaviours	Consumption of sweets	<3	Tooth decay variable increased
3.5	Dental attendance	How often individuals go to the dentist	1	Dental knowledge variable decreased
	Dental knowledge	Fluoride level	<2	Tooth decay variable increased
4.1	Health behaviours	IMD health domain - Years of potential lost life (LSOAs)	East: > 75.09 West:> 52.94	Diet variable increased
	Diet	Number of cakes eaten per week	<3	Sugar intake variable increased
	Sugar/nutrition	High sugar intake	<2	Tooth decay variable increased
4.2	Health behaviours	IMD health domain - Years of potential lost life (LSOAs)	East: > 75.09 West: > 52.94	Oral health habits variable decreased
	Oral health habits	Tooth brushing habits	>1	Tooth decay variable increased
4.3	Health behaviours	IMD health domain - Years of potential lost life (LSOAs)	East: > 75.09 West: > 52.94	Dental attendance variable decreased
	Dental attendance	How often individuals go to the dentist	1	Dental knowledge variable decreased
	Dental knowledge	Fluoride level	<2	Oral health habits variable decreased
	Oral health habits	Tooth brushing habits	>1	Tooth decay variable increased
4.4	Social capital	IMD (2015) crime domain (LSOAs)	East: > 0.24 West: > −1	Dental knowledge variable decreased
	Dental knowledge	Fluoride level	<2	Tooth decay variable increased
4.5	Social capital	IMD (2015) crime domain (LSOAs)	East: > 0.24 West: > −1	Healthy behavioural norms variable decreased
	Healthy behavioural norms	General dental attendance	<2	Tooth decay variable increased
4.6	Social capital	IMD (2015) crime domain (LSOAs)	East: > 0.24 West: > −1	Stress variable increased
	Stress	Psychological discomfort	>2	Smoking variable increased
	Smoking	Ever been given advice on giving up smoking	<2	Tooth decay variable increased

```
to d2p3
  if ticks mod 50 = 0[
    ifelse h_price < 88564 and costdly = 1
     [set fluoride fluoride + 0.01]
     [set fluoride fluoride - 0.01]
  ]
  d2p3-effect
end
```

Fig. 6. Example of two variables being combined in the theory code.

and financial constraints ('costdly') in Fig. 6. Used in previous ABMs (Grimm et al., 2006), this also reduces the amount of code to debug.

Table 6 outlines each pathway, how theoretical concepts were represented, and parameter values for each variable. Individual level parameters applied equally across study areas, while neighbourhood level parameters differed, and are stated separately, due to the divide between east and west Sheffield (Thomas et al., 2009). Averages were taken in each area to represent local contexts. Parameter scores were standardised to represent the direction that leads to negative effects, with the final variable in each pathway influencing decay scores. Where the 'effect on agent' column (highlighting how an agent characteristic has been affected by the process in that line of the table) has been extended to cover multiple factors, this demonstrates where multiple variables were used at the same time (similar to Fig. 6). The pathways made use of 'ifelse' statements to implement thresholds, applying an effect to an agent if they matched certain criterion, and different effects to those that did not, thus updating agent characteristics using rules from the pathways.

3.6.4. Time lag events affecting agents

Table 7 shows the intervals at which the pathways were implemented. Some were implemented more often, reflecting differences between immediate conditions people live in, and those which have longer term effects at less regular intervals. Previous research has highlighted the longer-term health effects of unemployment (Mitchell et al., 2002), as well as growing inequalities in society (Adler and Newman 2002). Zero time lags between exposure and outcomes are also highly implausible (Macintyre et al., 2002). Due to difficulty in quantifying these intervals, the values in Table 7 were chosen based on the 2-year time frame, as increases/decreases of 0.01, with interactions occurring every 7/14 ticks, meant that thresholds could be crossed within the model run time (e.g. going from 2 decayed teeth to 3). Indicators such as socio-economic position (NS-SEC), income, education, and long-term health issues ('years of lost life') were assumed to have longer term effects on health, whereas housing conditions, inability to pay for treatment or other material items, fluoride and sugar intake, and the threat of crime were assumed to have more immediate effects.

3.7. Verification

Verification, or checking models behave as expected (Brown, 2005), involved debugging code, identifying incorrect theoretical model implementation, and verifying calculations. Pathways were verified separately, so that processes within them could be assessed individually. Code influencing agent movement between locations was tested in a simplified Sheffield East model (with no pathway code). The model ran for 100 ticks with 100 agents, and the number and type of agents arriving at destinations was monitored, to see whether different agents were visiting locations in proportion to expected probabilities (Table 8).

Table 7
Pathways and ticks between implementation.

Pathway	Main variables associated with pathway	Ticks/days	Time period
2.1	House price and cost delaying treatment	7	Weekly
2.2	House price and cost delaying treatment	7	Weekly
2.3	House price and cost delaying treatment	7	Weekly
3.1	NS-SEC and income estimates	14	Bi-weekly
3.2	Education	14	Bi-weekly
3.3	Fluoride intake and sweet consumption	7	Weekly
3.4	Sweet and sugar consumption	7	Weekly
3.5	Fluoride intake	7	Weekly
4.1	Years of lost life	14	Bi-weekly
4.2	Years of lost life	14	Bi-weekly
4.3	Years of lost life	14	Bi-weekly
4.4	Crime scores	7	Weekly
4.5	Crime scores	7	Weekly
4.6	Crime scores	7	Weekly

Table 8
Expected versus actual visits to destinations, by educational attainment.

Variable	Expected visits (%)	Visits in verification test (%)
Dentist visit – degree	20	20.4
Dentist visit – other qual	10	8.8
Shop visit – degree	60	57.4
Shop visit – other qual	80	81.1
Education visit - degree	20	22.2
Education visit – other qual	10	10.1

As can be seen, the percentage of visits was close (allowing for the probabilistic nature of the models) to what would be expected, and deemed fit for use in the research.

Code for the pathways was tested one at a time, in a non-spatial ABM. Patches were randomly set to different colours when destinations were relevant to a pathway, and set to have no effect when testing pathways where destinations were not relevant. Agents were given simple movement instructions, as directions were not important in this context. This process was similar to tracing, involving following entities within models and interactions, to ensure correct model logic (Xiang et al., 2005). Effects of pathways were applied every 50 ticks (the code for which was also tested). One issue was identified, this being an extra 'ask' command in pathway 3.3, causing models to implement effects of that pathway more frequently than required.

3.8. Calibration

Parameter values were manually adjusted to fit appropriate ADHS values, in order to ensure these accurately matched theoretical concepts in the models (Table 9). Calibration of the parameters involved three processes. Firstly, ensuring that parameters values were logical

Table 9
Re-parameterising of the theoretical Pathways.

Pathway	Variable	Original parameter	New parameter	Reason for new parameter
2.1	Smoking	>1	<2	Incorrect data scale direction
2.2	Sugar intake	>2	<2	Incorrect data scale direction
3.1	NS-SEC	<4	8	Violates structure of the data
3.3	Education	Increase fluoride score if education = 1	Decrease fluoride score if education = 1	Incorrect data scale direction
3.3	Fluoride	>2	<2	Incorrect data scale direction
3.4	NS-SEC	<4	8	Violates structure of the data
3.5	Freqden	Increase fluoride if freqden = 1	Decrease fluoride if freqden = 1	Incorrect data scale direction
3.5	Fluoride	>5	<2	Incorrect data scale direction
4.1	Cake consumption	High cake consumption increased sugar score	High cake consumption decreased sugar score	Incorrect data scale direction
4.1	Sugar intake	>2	<2	Incorrect data scale direction
4.3	Freqden	>3	>2	Adjusted to include appropriate data points above threshold
4.4	Fluoride	Decay increased if fluoride <2	Decay increased if fluoride >2	Incorrect data scale direction

compared with ADHS data, and that model parameters were moving in the correct direction, relative to this data. For example, in the ADHS a dental attendance value of 1 relates to attendance every 6 months, with each value above 1 indicating less frequent attendance. It was important that parameters matched this format, and this represented the most common change during the calibration. The second process involved shifting model thresholds, to accommodate theoretical important responses. For example, a dental attendance score of '>3' was changed to '>2' in order to include 'at least once every two years' alongside 'less frequently than two years' and 'only when having trouble', when creating thresholds for favourable/unfavourable attendance patterns (the above responses represent the unfavourable side). The third process related to the NS-SEC variable, with parameter values altered so only those in category 8 would be affected by a particular interaction (with the opposite effect for groups 1–7). Future models may benefit from automated calibration and optimization methods, such as genetic algorithms (GA), which undertake parallel searches through numerous parameters (Ngo and See, 2012). However, it was not guaranteed that the set of parameters produced by GAs would match ADHS values, or theoretical concepts being tested, which risked invalidating the models' theoretical basis. Manual calibration was therefore considered appropriate on this occasion.

3.9. Validation

Model validation was complicated by a lack of available data on decay in adults for small area geographies, highlighting a limitation of exploratory ABMs in areas with few data sources. Despite this, methods could be used to partially validate the models, albeit in a limited capacity. Both models were verified and calibrated using a 'tracing' process, involving following model behaviour to determine if model logic is correct (Xiang et al., 2005). Additionally, model to model validation was conducted through comparison of the models' output. Parameter variability tests were also performed, through the use of different (and sequential) combinations of pathways when running the models. Model outputs were also compared statistically to test for significant differences, and testing at which stage of the simulation these occurred.

Expert opinion was also used as a validation method, which has previously been described as crucial for ABMs (Bonabeau, 2002). It is important to remember though that this is one of a suite of methods that can be used to validate ABMs and does not constitute a full validation. The lack of real-world data against which to validate the model is still a concern and should be borne in mind for future research. A panel ($n = 11$) of experts (with expertise in dental public health, oral health inequalities, determinants of health, network analysis and other systems methods) were asked to rate their confidence in each of the 14 pathways on a 7 point Likert scale (1 = strongly disagree, 7 = strongly agree) with higher scores indicating a higher level of confidence, as well as whether they agreed with the overall model and its findings. The results of this process (average score and range of scores) are presented in Table 10.

Table 10
Results of the expert panel validation ($n = 10$) validation.

Pathway	Average score from expert panel	Range of scores from expert panel
2.1	4.6	2–7
2.2	6	4–7
2.3	4.5	2–7
3.1	5.9	2–7
3.2	5.9	3–7
3.3	4.5	1–6
3.4	4.8	1–7
3.5	4.3	1–7
4.1	5.4	3–7
4.2	5	2–7
4.3	4	1–6
4.4	5	2–7
4.5	5	1–7
4.6	4.6	1–7
Overall model and findings	N/A	Agree = 8; Neither agree nor disagree = 3

The results in Table 10 indicate a reasonable level of agreement with the pathways, although with a wide range of responses from the expert panel. Eight out of the 11 experts 'agreed' with the overall model and its findings, while 3 responded 'neither agree nor disagree'. The expert panel were also given the option to comment on the individual pathways. These comments generally related to issues of conceptualisation and operationalisation of some pathways. For example, the link between smoking and caries, which was meant to be representative of wider coping mechanisms, and the link between dental knowledge, fluoride intake and sugar intake were questioned, and relate to issues of data availability and not having 'ideal' variables available for each step of these respective pathways. The wording and definitions of some variables was also questioned, such as 'dental knowledge' and what this represented, as well as whether this construct was needed on a pathway between attendance and behaviours for example. Other comments included increases and decreases in the model not always being well matched to theoretical associations (for example, the link between dental costs and high calorie food intake) and whether a chain of causation could always be inferred between sections of pathways. Again, it is worth mentioning that these pathways and associations were meant to be representative of more general associations, and were constructed using the data available (and proxies), however this process does highlight areas of the model that could be improved in future.

4. Experiments and results

Descriptive statistics for both models as well as the overall results and model change statistics are presented in Table 11. In Table 11 'no pathways' refers to baseline model scores, where no pathways were included, and only contains the mean total number of decayed teeth in each study area's population over 10 model runs. The score for each subsequent row represents scores for models where pathways have been added sequentially (e.g. the data in row 3 includes pathway 2.1, row 4 contains pathways 2.1 and 2.2, etc.), and the new mean score for each model after 10 runs. It is worth remembering that these are initial results of an exploratory ABM with numerous limitations (see Section 5), and any results should be interpreted with caution. It should also be remembered that the trends associated with the results, rather than actual figures, were the focus of the research.

The results were non-normally distributed, however there is debate over the use of non-normally distributed data in repeated measures tests, where 'evidence suggests that when group sizes are equal the F-statistic can be quite robust to violations of normality' (Field et al., 2012 - p.413). Given this, and the extensive post-hoc analysis options available for analysis of variance (ANOVA) tests, this method was used instead. The ANOVA test for Sheffield East showed a statistically significant difference between the original scores and the post simulation scores ($F(1.000, 13.000) = 1410.471$, $P < 0.05$), indicating that scores had increased as pathways were added.

Bonferroni post-hoc analysis demonstrated a significant interaction between time and model run ($p < 0.05$). Pairwise comparisons showed the models including pathways 2.1–3.3 were not statistically significantly different from each other ($p = 1.000$), whereas these model runs were statistically significantly different to the models including pathways 3.4–4.6 ($p < 0.05$). The models including pathways 3.4–4.6 were not statistically significantly different to each other, demonstrating that pathway 3.4 (interaction with shops, which influences sugar consumption) had the most significant impact on decay scores in this area.

The ANOVA for Sheffield West again demonstrated a statistically significant difference between the two time points ($F(1.000, 13.000) = 91988.461$, $P < 0.05$). Post-hoc tests showed a significant interaction between time and model run ($p < 0.05$). The models including pathways

Table 11
Mean decay scores, and change in scores for each simulation run.

	Sheffield East				Sheffield West			
Pathway added to model	Mean	Std. Deviation	Change (n)	Change (%)	Mean	Std. Deviation	Change (n)	Change (%)
No pathways	46686.6	.000			24379	.000		
2.1	42828.86	.000	−3857.74	−8.26	19521.68	.000	−4857.32	−19.92
2.2	46491.5	.000	−195.1	−0.42	24706.26	.000	327.26	1.34
2.3	53855.84	.000	7169.24	15.36	33068.94	.000	8689.94	35.65
3.1	49338.12	.000	2651.52	5.68	28487.62	.000	4108.62	16.85
3.2	49330.7	.000	2644.1	5.66	24733.1	.000	354.1	1.45
3.3	54459.4	1.671	7772.8	16.65	32063.6	.000	7684.6	31.52
3.4	23056017.53	1230455.505	23009330.93	49284.66	50482041.9	432210.453	50457662.9	206971.83
3.5	23604131.47	2853969.941	23557444.87	50458.69	50523178.77	246795.721	50498799.77	207140.57
4.1	23823930.36	1733739.780	23777243.76	50929.48	50289110.81	534639.868	50264731.81	206180.45
4.2	22488133.03	2694973.098	22441446.43	48068.28	50411316.67	580296.236	50386937.67	206681.72
4.3	20773675.92	1272643.452	20726989.32	44396.01	50692145.71	346456.806	50667766.71	207833.65
4.4	17740303.38	13844567.463	17693616.78	37898.70	50627428.37	313984.183	50603049.37	207568.19
4.5	22541373.66	1078614.480	22494687.06	48182.32	51803747.65	4067459.632	51779368.65	212393.32
4.6	23892514.47	3024731.118	23845827.87	51076.39	50582640.46	467343.027	50558261.46	207384.48

2.1–3.3 showed no statistically significant differences to each other ($p = 1.000$). However, the models including pathways 2.1–3.3 were statistically significantly different to the model including pathway 3.4 ($p < 0.05$), and those that followed (pathways 3.5–4.6). Models including pathways 3.4–4.6 again showed no statistically significant differences to each other, again highlighting pathway 3.4 as having the largest impact.

5. Discussion

The aim of this study was to test theoretically derived, neighbourhood based pathways using proof of concept ABMs in two areas of Sheffield. This analysis represents the first ever attempt to develop and use ABMs to test the effects of neighbourhoods in this way. Strengths of the research include use of a relevant conceptual framework and literature to guide the modelling and data selection, and the use of spatial microsimulation to give ABMs accurate, representative populations with relevant variables. Results from the proof of concept models suggested pathways where agents visit shops, which affected sugar consumption, had the most influence on the decay scores in both study areas.

Before discussing the results, it is important to consider limitations. First, the outcomes of the ABMs cannot be considered equal to empirical data and should be considered initial exploratory analysis. This is primarily because ABMs can be greatly influenced by the way models are conceptualised, built, and initialised. In addition, the operationalisation of variables, and the occasional binary nature of these, may have affected the results. There were, at times, issues with data availability from the ADHS and while all constructs were suitably operationalised, more appropriate proxies may have been present in other surveys. Additionally, the conceptual model for the research may have been limited by use of literature from the dentistry and oral health field. The addition of an extra pathway to each model iteration may also have affected the outcome. The computational intensity of the models also meant fewer iterations could be run, and important demographic features (social networks, family structures, ageing and deaths) could not be included. More analysis of *how* geographical space and the features of the study areas may affect patterns of tooth decay, and the precise mechanisms behind these, would also provide additional knowledge on the importance of neighbourhood environments. This was unfortunately beyond the scope of the current research but is an area that should be improved in future iterations of the model. Use of administrative boundary data to define study areas also meant that relational concepts could not be modelled. A panel of experts from dental public health were asked to rate the pathways, which were generally favourable, although a number of other issues related to the model were also raised (including some of the limitations listed in this paragraph), and point to areas that the model could be improved in later iterations. Despite the use of this expert panel as a form of validation, the model cannot be considered validated without additional measures and analysis.

Furthermore, approaches such as parameter sweeps may have helped provide more of an empirical base for attendance probabilities. In addition, it should be noted that probabilities of agents visiting particular locations were set arbitrarily, with one destination type (shops) being the main destination (visiting probability of 60–85%, depending on the social group). The perceived significance of shops and sugar intake, and effect of reduced dentist attendance might therefore simply be caused by differences in destination choice probability. Agents having between a 10% and 25% chance of attending the dentist may also be too high, but was designed to represent differences in preventive healthcare behaviours between different social groups more generally. An additional limitation is the incorporation of one pathway at the time, as the different pathways considered have not been tested in isolation. This means our analysis does not take into account possible interactions and/or co-dependencies that might affect model output when different pathways are included together. Moreover, another limitation is that agents navigate road networks at the same speed, with no consideration of events or obstacles which may slow down agent movement. The inclusion of pathfinding did allow for spatial positioning to play a role within the models though, as real-world locations of shops, dentists and FE facilities determined the routes taken by agents (via real world road networks). This allowed agents to navigate realistic distances and routes, while accounting for the spatial contexts of their neighbourhoods. More research is needed to assess the precise and nuanced influences of spatial positioning of agents and their environments, due to the simplified way neighbourhoods were conceptualised here.

Despite the above limitations and caveats, the models can provide very useful and exploratory insights into the socio-spatial determinants of oral health. Model outputs can be used to consider possible explanations of different pathways and behaviours that can be detrimental to oral health. For instance, one possible explanation for the significance of the pathway between shops and sugar consumption could be that individual behaviours that influence oral health can be mediated by features of built environments such as shops, indicating that neighbourhood and individual level variables play important roles in tooth decay. This would be in line with previous studies that found evidence for neighbourhood effects on health, despite individual level data explaining more of the variance (Curtis and Rees-Jones 1998; Pickett and Pearl 2001; Riva et al., 2007). Most studies tend to conclude that where you live matters for health, but not as much as who you are (Macintyre et al., 2002). The second and third sections of pathway 7 were concerned with high sugar intake, and consumption of sweets, which is in line with previous findings on the negative effects of sugar on decay (Sheiham 2001; Warren et al., 2009). Sugar consumption is particularly important to consider given the recent introduction of the UK sugar tax (HM Revenue and Customs 2016).

Most of the (few) studies investigating the importance of shops for oral health have found links between the two, including how residential location influences purchasing of healthy food, leading to difficulties for low income and minority ethnic groups, particularly in rural and poorer urban areas (Mobley et al., 2009). Low-income groups also experience difficulties due to double burdens of price, and distance of shops from their homes (Fonseca, 2012). Other studies found associations between carious lesions and grocery stores per neighbourhood (Tellez et al., 2006), and grocery stores per resident and dmft scores (decayed, missing and filled teeth) (Aida et al., 2008). Conversely, Borenstein et al. (2013) found no associations between supermarkets and self-rated oral health, dental visits, or dental insurance. The findings of this research are therefore in line with the majority of the literature, and provide useful insights into the effects of neighborhoods on oral health. This is due to the research being a rare example that assesses the effects of multiple theoretically informed pathways together, involving a variety of behaviours, social norms, and features of neighbourhood environments. This type of comparative approach, combined with simulation modelling, is not seen often in the oral health literature.

Counter to previous literature (Donaldson et al., 2008; Listl 2012) the locations of dentists, and dental attendance, did not have significant influences on decay. Numerous social determinants of health including income, material circumstances, socio-economic positon, unemployment and education also had little influence. These findings may be due to the operationalisation of these variables, as differentiating between service types (NHS vs private) and featuring dentists for the whole city may have had more of an impact. Results may also have been affected by the binary use of NS-SEC data, which may not accurately reflect social gradients. The binary use of education data may have caused similar issues, while using crime data to represent social capital may not embody this concept's nuanced nature (Celeste et al., 2009). Additionally, factors such as stress may act through biological pathways (Boyce et al., 2010), which are not captured in the ADHS data. It may be that certain combinations of dietary variables have more influence than others, given only one pathway containing sugar had significant influence. Finally, oral health habits including brushing and fluoride intake did not have significant impacts, contrary to previous literature (McGrady et al., 2012; Kumar et al., 2016).

6. Conclusions

This was the first study to use a place based theoretical framework to create pathways by which neighbourhoods may influence tooth decay in adults. Using proof of concept ABMs, it was found that the interaction between shops and sugar consumption had the largest influence, leading to increases in decay in areas with both higher and lower socio-economic profiles. Despite the study's strengths, results should be interpreted with caution, and considered in the context of the limitations of the research, and the nature of data produced by ABMs. Additionally, as findings relate to two areas in Sheffield, wider generalisability to other geographical contexts should be interpreted with caution.

Despite these limitations, the work presented here offers theoretical insights pertaining to neighbourhood effects in relation to oral health, and demonstrates the potential for testing theoretical scenarios using dynamic simulations. There is great potential to build on this to better understand interactions within the models, and to build in features that help to better replicate real world scenarios. These features can include tests of pathways in isolation in order to identify the separate effects, carrying out parameter sweeps for setting visiting probabilities for agents, and adding additional pathfinding capacity by considering possible obstacles and/or events that may affect or stop agent movement. In future, we hope to include additional complexity, and further calibration and validation, in order to improve the accuracy and reliability of these proof of concept models.

Disclosure of potential conflicts of interest

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