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# Probing causation: socialising in later life and perception of neighbourhood

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## Abstract
We use an agent-based model to probe the relationship between older people's perceptions of area and frequency of socialising. Maintaining a social life is a key determinant of healthy ageing and frequency of socialising is associated with perception of area. However, the direction of causality is unclear. Are those who are socially active more likely as a result to view their area more favourably? Or do the most positively evaluated areas facilitate greater frequency of social interactions? Traditional regression models are ill equipped to probe the direction of causality. Alternative techniques, such as agent-based models, are used infrequently and, in response, we develop a simple agent-based model to explore the drivers of the association between area perception and socialising. We consider various scenarios and use data from the English Longitudinal Study of Ageing to benchmark our findings. Our agent-based models suggest that both causal processes are plausible but a synergy of both is the most likely. We detail an agent-based model as a future foundation for more interactive work on neighbourhood health effects.

## 1. Introduction
Research shows that participation in social activities is a key component of healthy ageing in many countries (Sirven & Debrand 2008; Chiao et al. 2011) . Whilst such effects have been found outside the oldest ages, it is proposed that they are particularly strong for the older population who have more time to take part in social activities due to retirement or lower familial commitments (Sirven & Debrand 2008).

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Older people's perceptions of their neighbourhood are associated with frequency of socialising (Bowling & Stafford 2007). Older people who view their area positively tend to spend more time socialising and have more social contacts than those who have less favourable views of their immediate environment. However, as is often the case in studies of area-based effects, the direction of causality underlying the association is unclear (Auchincloss & Diez Roux 2008). It is plausible that those who socialise more frequently might view their neighbourhood more positively as a result, perhaps because in using local facilities and services and enjoying themselves within their neighbourhood they form a more balanced and positive view of their local area than those who socialise less frequently. Alternatively, if older people have a poorer perception of their area this might act as a barrier to socialising particularly, for example, if an older person feels unsafe within their neighbourhood. Clearly the operation of causality in both directions is possible and each process might act in synergy.

In this paper we use agent-based models to examine the plausibility of different scenarios relating to the direction and strengths of causality that drives the association between retired older people's perception of their area and the extent to which they socialise.

The agent-based models that we fit simulate the time that older people spend socialising, resting (including sleeping) or dealing with other responsibilities such as caring or chores. We apply agent-based models to test a series of 'what if' scenarios that place differing importance on the two directions of causality that might underpin the association between area perception and time spent socialising. We validate our scenarios by tracking the agents in high and low perception areas and considering the plausibility of the results obtained. Under different assumptions, we compare the associations between area perception and socialising to those observed within the English Longitudinal Study of Ageing.

Traditionally, research on area health effects has used multilevel regression models to isolate an 'area effect' that influences a health outcome independently of the characteristics or composition of the resident population (Diez Roux & Mair 2010). One limitation of multilevel models in such settings is there are usually interrelations or feedback mechanisms linking both area and individual explanatory variables. Although other methodologies have been developed to address this shortcoming, these are, in general, poorly equipped to deal with complex situations where there are many dynamic interrelations among individuals and between individuals and their environment (Auchincloss & Diez Roux 2008).

One response to this issue is a randomised controlled trial where samples of similar populations are placed in different neighbourhood environments. The subsequent social outcomes for each group are then tracked to assess whether differences develop. However, the ethical dimensions and cost of such schemes are usually prohibitive. A more feasible alternative is to use agent-based modelling, a relatively modern technique that is intended to mimic complex systems. A computer model is used to simulate the behaviour of a population of 'agents' (in this paper older people) based on a set of inputs, assumptions and rules. Agents are assigned an initial condition which then changes over discrete time steps. Agents can flexibly interact with one another and with their environment with potential for feedback between individual and environmental attributes. Stochasticity is usually introduced to incorporate variability to agents' initial conditions and their interactions. Agent-based models have been used in a wide variety of setting such as crime (Malleson et al. 2010), residential segregation (Schelling 1966), alcohol consumption (Giabbanelli and Crutzen 2013), marriage and divorce (Hills and Todd 2008) and access to public services (Harland & Heppenstall 2012). However, they are, as yet, an emerging technique in the modelling of health and health-related behaviour (Auchincloss & Diez Roux 2008), with a recent paper examining the inequalities in walking behaviour within a city and the impact of possible intervention (Yang et al. 2013). One of the key uses of agent-based models is to extend theory and to test hypotheses about particular processes; agent-based models enable a range of scenarios to be considered to identify the most salient areas of uncertainty, robustness and the identification of important thresholds (Epstein 2008). For example, a recent paper in the Journal of Artificial Societies and Social Simulation (JASSS) used an agent-based model to predict binge drinking based on a range of hypotheses around social influences and interactions (Giabbanelli and Crutzen 2013). Similarly Hills and Todd (2008) use an agent-based model to test the plausibility of hypotheses around the influence of rising population heterogeneity and individualisation on age at first marriage and divorce. Here we use an agent-based model to test hypotheses around the direction (and strength) of causation underlying an established correlation between socialising and neighbourhood perception (Bowling & Stafford 2007), with a specific focus on the older population. Our implementation of agent-based models is guided by Robert Axelrod's 'kiss' (keep it simple stupid) principle which holds that the most revealing results are derived from agent-based models that make simple assumptions at the macro-level (Axelrod 1997). A secondary aim of this paper is to develop an agent based model to serve as a foundation for other researchers interested in untangling neighbourhood effects on health and health-related behaviour. As noted by Galea et al. (2009), complex systems computational approaches have been adopted in only a small number of studies within population health research. The Matlab programming code required to run this model is available to download with this paper.

After this introduction this paper is divided into three parts. First, we define the agent-based models we fitted, the assumptions made and introduce the data sources used to benchmark our results. Second, we describe the results derived from the models fitted. Third, we state the key conclusions of the paper and their implications for academic and policy debate.

## 2. Models

Agent-based models rely on an 'architecture' which provides the philosophical framework under which agents replicate human behaviour and on which the quantitative assumptions are based. We base our model on the 'PECS' architecture (Urban & Schmidt 2001), which models human behaviour as a product of physical conditions, emotional states, cognitive capabilities and social status. A key aspect of the PECS architecture is the strength of competing ‘motives’ which might, for example, include eating, studying, sleeping or socialising. The strongest motive determines the action of an agent at a particular time. Motive strength varies according to factors such as the time of day, time since last participating in a particular activity and other factors such as the particular attributes of an agent which might include, for example, their financial resources. The PECS architecture has been successfully used to model use of hospital services (Brailsford & Schmidt 2003) and educational planning (Harland & Heppenstall 2012). We base our agent-based model on that developed in a recent study which uses the PECS architecture to model spatial patterns of burglary (Malleson et al. 2010)

The focus of the agent-based model developed in this paper is to simulate the daily behaviour patterns of retired people. These patterns will vary from one agent to another and may also change over time. To keep the model as simple as possible, we classify each agent's behaviour into just three broad types: (i) resting; (ii) fulfilling responsibilities; (iii) socialising. Resting includes sleeping, as well any sedentary activities within the home, such as watching television or reading. Responsibilities may include caring for a relative or friend, household chores or grocery shopping. Socialising is any leisure activity outside the home that involves meeting other people in a social setting. The model is non-spatial, meaning that the physical locations of the agents are not explicitly included.

*2.1 State variables, motives and actions*

In the PECS architecture, each agent has a motive for each of the three behaviour types. At any given time, the strongest of the three motives is the one that drives that agent's actions. In general, these actions may take the form of working towards sub-goals required to achieve a longer-term goal to satisfy the relevant motive. For example, an agent whose strongest motive is to socialise may have to complete particular tasks, such as making arrangements to meet a friend and travelling to an arranged location, in order to achieve the goal of socialising. For simplicity, we do not include such sub-goals in our model and the agent's behaviour is directly determined by its strongest motive.

The motive, $m_i$, for behaviour type i (i = 1, 2, 3) consists of three components: the agent's state variable, $s_i$, associated with that behaviour type; the agent's preference, $p_i$, for that behaviour type; the time of day, t.

$$m_i = p_i f_i(t) / s_i$$

The state variable $s_i$ is an internal variable roughly measuring the length of time since the agent last engaged in behaviour type i. For instance, the state variable for the resting behaviour type corresponds to the agent's energy level: a low energy level would result in a high motive to rest. An agent's state variables are continually changing depending on their current behaviour: the state variable $s_i$ receives a boost for every unit of time the agent spends engaged in behaviour type i and gradually declines for every unit of time engaged in other behaviour types. As we divide by the state variable a high state value, $s_{i,}$, results in a lower motive to participate in behaviour type i. Thus, as an agent rests, their state variable associated with resting increases and the motive to rest declines.

The preference $p_i$ reflects the agent's preference for behaviour type i relative to other behaviours. Different agents will have different preferences for different behaviours. For example, an agent who  is a full-time carer for a sick relative will have a high “preference” for fulfilling responsibilities. This allows us to model a heterogeneous population of agents. These preferences can also depend on other agent-level variables. In the current model, we assume that each agent's preference for resting and preference for fulfilling responsibilities are fixed. The preference for resting is the same for all agents, but the preference for fulfilling responsibilities is different for different agents. We allow the preference for socialising to depend on an agent's perception of the area in which it lives. Perception is different for different agents and may also change over time.

The function $f_i(t)$ models the dependence of motive on time of day. The motive for resting is highest during the night and lower during the day. The motive for fulfilling responsibilities peaks in the middle of day and is lower in the evening and night. The motive for socialising peaks during the afternoon/evening and is zero during the night. The functions modelling this daily variation are shown in Figure 1.

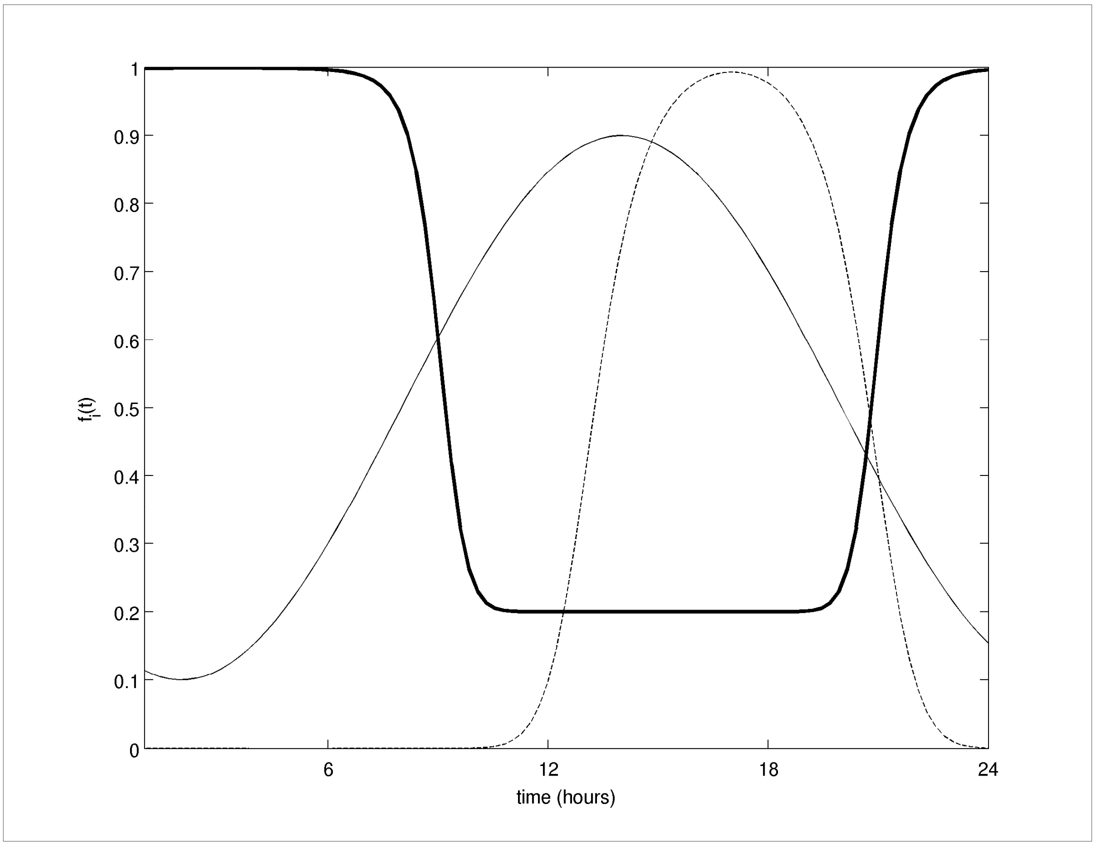



**Figure 1:** Functions modelling daily variation in the motives for the three behaviour types we model: resting (thick solid line), fulfilling responsibilities (thin solid line) and socialising (dashed thin line).

The other important agent-level variable in the model is the amount of money each agent has. Because the focus of this study is on the link between socialising and perception of the area rather than differences in income, we assign all agents the same weekly disposable income (i.e. income after deduction of mandatory expenditure, such as housing and food costs). Agents accrue money that is available for discretional spending at a constant rate and must save up to a specified level before they are able to socialise. Socialising is assumed to deplete money at a fixed rate. If an agent's strongest motive is to socialise but they do not currently have sufficient money, their behaviour is instead determined by their second strongest motive. Only when they have accrued a minimum amount of money are they able to engage in socialising. An alternative approach would be for the agent to engage in some other behaviour to generate income. However, this is less appropriate as our model represents a retired population and we do not consider it here.

The model was run with n = 100 agents and a time step of 1 hour.

*2.2 Feedbacks between perception and socialising*

We use the model to investigate two different mechanisms that create feedbacks between an agent's perception of its area and the time it spends socialising. The first mechanism is that perception directly influences the preference for socialising. We denote the strength of this effect by $a_1$. An agent with the worst possible perception of its area (perception = 0) will have a preference for socialising that is reduced by a factor of $a_1$ below baseline; an agent with the best possible perception (perception = 1) will have a preference that is a factor of $a_1$ above baseline.

The second mechanism is that time spent socialising directly influences perception. We denote the strength of this effect by $a_2$. Every unit of time spent socialising shifts an agent's perception towards maximal perception (perception = 1) by a factor of $a_2$. Every unit of time engaged in behaviours other than socialising reduces an agent's perception by a factor of $a_2$.
We study the behaviour of the model with each of these mechanisms operating at various strengths, and with both mechanisms operating simultaneously. When both mechanisms operate simultaneously, there is the potential for a positive feedback loop: better perception increases the drive to socialise; more time spent socialising improves perception.

The modelling procedure is illustrated schematically in figure 2.

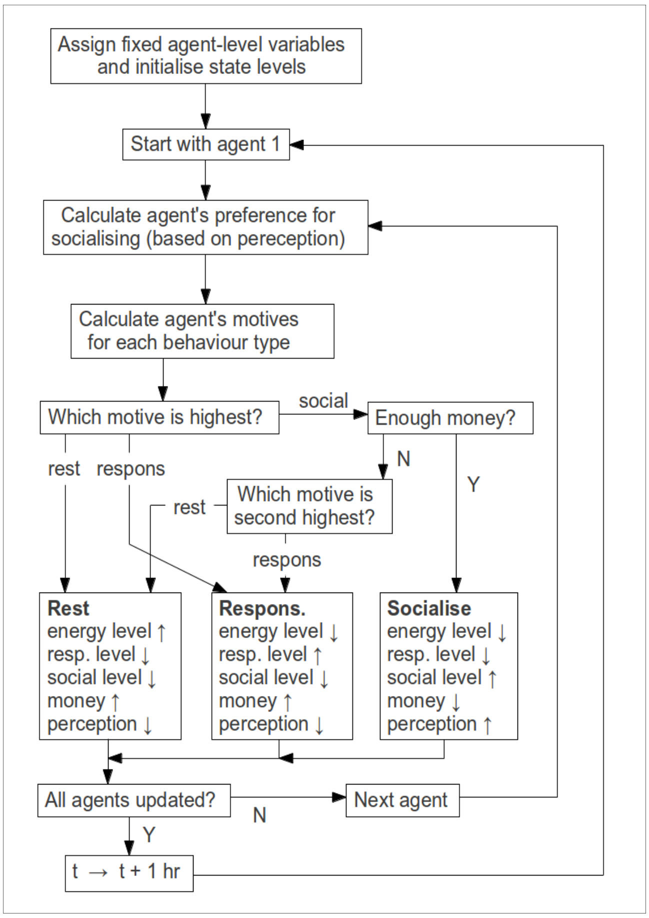



**Figure 2:** flow chart indicating the assumptions underpinning the model and the method of simulation.

*2.3 Model outputs*

The basic output from the model is a time line of each agent's hour-by-hour behaviour over the period of the simulation. Figure 3 shows the proportion of agents engaged in each of the three behaviour types over a representative five-day period of an example simulation. This shows that, during the night, all agents are typically in the resting category. During the day, the majority of agents are either fulfilling responsibilities (primarily during the morning or early afternoon) or socialising (primarily during the later afternoon or evening), although, at any given point in time, there are usually some agents in the resting category.

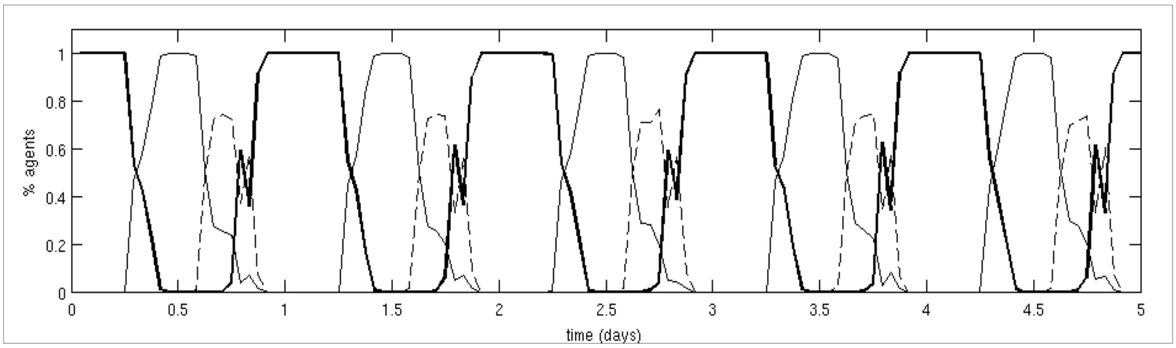


**Figure 3**. Example output from the model showing the proportion agents that are resting (thick solid), fulfilling responsibilities (thin solid) and socialising (dashed) over a five-day period.

After a 90-day simulation of the model, we record the proportion of time in the final 7 days of the simulation that each agent spent socialising. We restrict attention to the final 7 days to allow any effects of change in perception to unfold over the preceding 83 days. Examination of results over longer periods did not give results that alter the conclusions drawn. We perform a linear regression using this simulated data of the proportion of time spent socialising against perception and record the slope of the regression.

There is some random variability built in to the model (in the initial variables assigned to each agent, in the motive strengths any point in time, and in the changes in perception as a result of the different behaviour types). For each scenario (parameter set) investigated, we repeat the 90-day simulation m = 100 times to obtain the average regression slope.

*2.4 Benchmarking using the English Longitudinal Study of Ageing*

The English Longitudinal Study of Ageing (ELSA) is a representative sample of the population aged 50 and over, living in private households in England. The first wave of the survey was collected in 2002 and respondents are re-interviewed every two years with 5 waves of data currently available. The survey contains a wide range of questions on the circumstances of older people including, for example, their health (objective and subjective measures), finances, social networks and caring responsibilities. Importantly for this paper, waves 1 and 3 of ELSA include a set of questions on perceptions of area (see table 1) and we use these data to benchmark findings from our agent-based models. Our benchmarking approach has some similarities with that of Walker and Davies (2013), who fit agent-based models to predict partner selection and validate parameter values within their models through comparison with distributions observed in census statistics. We sum the area perception responses within ELSA to create a variable ranging from 0 (worst possible neighbourhood perception) to 63 (best possible neighbourhood perception). ELSA respondents were asked how often they socialised with their friends on average with options ranging from less than once a year or never to three or more times a week.

| Question | Response and score |
|---|---|
| Respondent really feels part of this area | Strongly agree (7) Agree (6) Slightly agree (5) Neither agree nor disagree (4) Slightly disagree (3) Disagree (2) Strongly disagree (1) |
| Vandalism and graffiti area a big problem in this area | Strongly agree (1) Agree (1) Slightly agree (3) Neither agree nor disagree (4) Slightly disagree (5) Disagree (6) Strongly disagree (7) |
| Respondent often feels lonely living in this area | Strongly agree (1) Agree (1) Slightly agree (3) Neither agree nor disagree (4) Slightly disagree (5) Disagree (6) Strongly disagree (7) |
| Most people in this area can be trusted | Strongly agree (7) Agree (6) Slightly agree (5) Neither agree nor disagree (4) Slightly disagree (3) Disagree (2) Strongly disagree (1) |
| People would be afraid to walk alone after dark in this area | Strongly agree (1) Agree (1) Slightly agree (3) Neither agree nor disagree (4) Slightly disagree (5) Disagree (6) Strongly disagree (7) |
| Most people in this area are friendly | Strongly agree (7) Agree (6) Slightly agree (5) Neither agree nor disagree (4) Slightly disagree (3) Disagree (2) Strongly disagree (1) |
| People in this area will take advantage of you | Strongly agree (1) Agree (1) Slightly agree (3) Neither agree nor disagree (4) Slightly disagree (5) Disagree (6) Strongly disagree (7) |
| This area is kept very clean | Strongly agree (7) Agree (6) Slightly agree (5) Neither agree nor disagree (4) Slightly disagree (3) Disagree (2) Strongly disagree (1) |
| If you were in trouble there are lots of people in this area who would help you | Strongly agree (7) Agree (6) Slightly agree (5) Neither agree nor disagree (4) Slightly disagree (3) Disagree (2) Strongly disagree (1) |

**Table 1:** Area perception questions in waves 1 and 3 of the English Longitudinal Study of Ageing
*Total sum of scores gives the overall area perception for each respondent which varies from 0 (worst perception) to 63 (best perception).

Figure 4 and table 2 give the distribution of these variables on area perception and socialising respectively. In the results section we use these ELSA data to estimate the relationship between area perception and socialising. We also look at changes in area perception and socialising between waves 1 and 3. The purpose of this analysis is to benchmark results from our simulations. We include only those respondents who classified themselves as retired giving a sample size of at wave 1 of 5,696 which falls to 3,611 in wave 3 as a result of attrition stemming from non-response and deaths of survey participants.

| Frequency of socialising | Wave 1 | | | Wave 3 | | |
|---|---|---|---|---|---|---|
| | Freq | % | Cum % | Freq | % | Cum % |
| **Less than a year or never** | 94 | 2.1 | 2.1 | 57 | 2.0 | 2.0 |
| **Once or twice a year** | 162 | 3.6 | 5.7 | 100 | 3.5 | 5.6 |
| **Every few months** | 448 | 10.0 | 15.7 | 285 | 10.1 | 15.7 |
| **Once or twice a month** | 964 | 21.5 | 37.3 | 654 | 23.2 | 38.8 |
| **Once or twice a week** | 2,026 | 45.3 | 82.5 | 1,262 | 44.7 | 83.5 |
| **Three or more times a week** | 782 | 17.5 | 100.0 | 465 | 16.5 | 100.0 |

**Table 2**: Frequency of socialising amongst retired ELSA respondents in waves 1 and 3

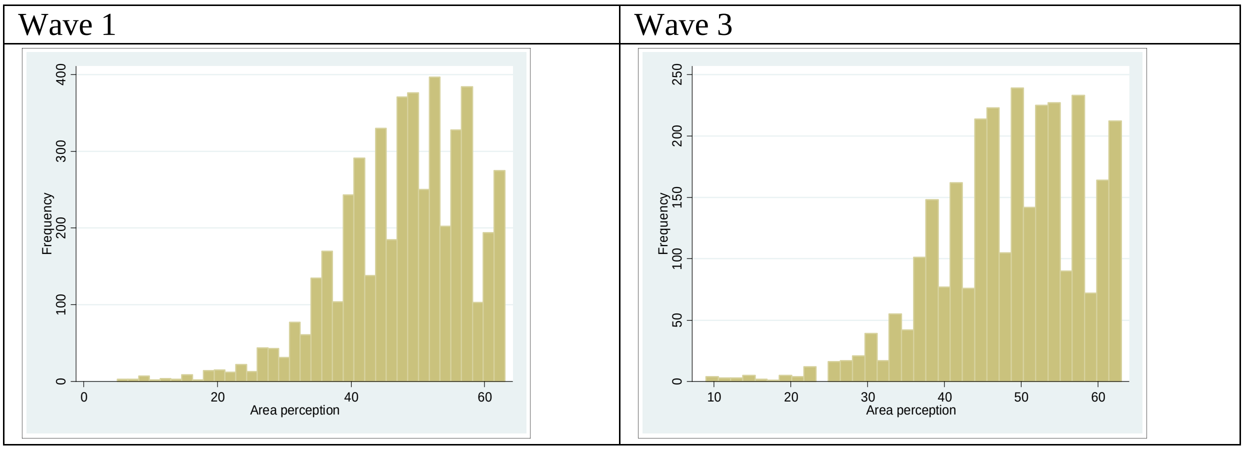



**Figure 4**: Histogram showing the distribution of the area perception variable in waves 1 and wave 3 of ELSA (0=worst possible perception of area; 63=best possible perception of area).

## 3. Results

### *3.1 Income and responsibilities as constraints on socialising*

Figure 5 shows how the average proportion of time spent socialising in the agent-based model varies with disposable income and with the preference for fulfilling responsibilities. The proportion of time spent socialising increases with disposable income before levelling off (Figure 5a). Agents with a very low disposable income spend little time socialising and money, rather than spare time, is the limiting factor for these agents. Agents with a higher income socialise more frequently. However, once disposable income reaches approximately 130 pounds per week, additional income makes no difference to the proportion of time spent socialising; for these agents, spare time is the limiting factor.

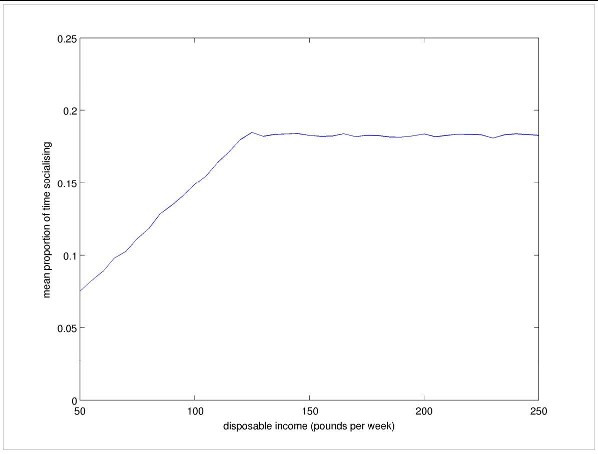
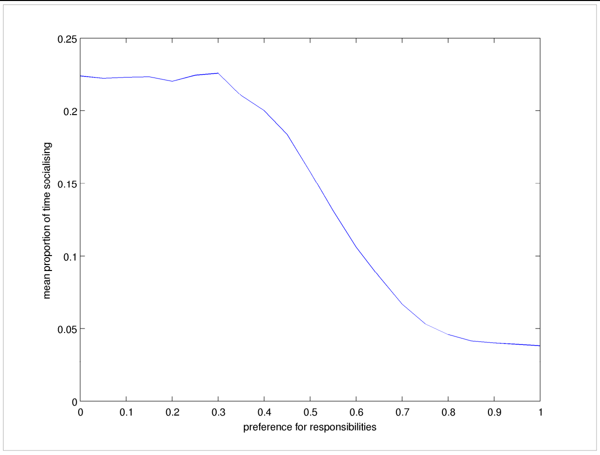
| Socialising versus disposable income | Socialising versus preference for responsibilities |
| --- | --- |
|  |  |





**Figure 5**. Mean proportion of time spent socialising in the agent-based model as a function of: (a) disposable income; (b) preference for responsibilities.

The proportion of time spent socialising decreases with the preference for fulfilling responsibilities (Figure 5b). This preference can be thought of as representing demands on an agent's time, such as caring for a relative and carrying out household chores. Agents with few demands on their time (low preference for responsibilities) have plenty of spare time and therefore spend a high proportion of time socialising. Agents with high preference for responsibilities have little spare time and therefore spend a low proportion of time socialising. Again, the curve levels off when preference for responsibilities drop below approximately 0.3. This indicates that these agents have more than enough spare time and that money is instead the limiting factor for socialising.

*3.2 Case study 1: feedbacks between area perception and socialising*

Figure 6 tracks the behaviour and perception of an individual agent over time who initially has a very poor perception of their local area; Figure 7 shows an agent that initially has a very good perception. These scenarios might represent the experiences of an agent moving house to a new neighbourhood, or a response to an event or development within the local area. In each case, we simulate the model: (i) with the feedback from perception to preference for socialising operating; (ii) with the feedback from socialising to perception operating; (iii) with both feedbacks operating; (iv) with neither feedback operating (control case).

We first consider the scenario in which the agent's perception is initially very poor (Figure 6a, b). If the feedback from perception to socialising is operating, the agent spends very little time socialising as a result. If the feedback from socialising to perception is operating, the agent's poor perception does not affect its behaviour and the agent spends a moderate amount of time socialising. This feeds back to the agent's perception, which improves over time. If both feedbacks are operating, there is a positive feedback loop: improving perception leads to more tendency to socialise, which in turn improves perception. However, this loop can operate in the opposite direction: poor perception leads to a reluctance to socialise, which prevents or slows improvement in perception. This is evident in Figure 6a, where perception does not improve as rapidly under this feedback loop as under the one-way feedback. It takes a long time (approximately 200 days in Figure 6b) for the agent's behaviour to begin to change. However, after a longer period of time, the positive feedback takes over and eventually the agent has a better perception, and spends more time socialising, than under the one-way feedback alone.

Similar trends are present in the second scenario, where the agent's perception is initially very good (Figure 7,a,b). The changes in perception and behaviour over time are slower than in the first scenario. This is largely a consequence of the way the model has been parameterised, which means that the “equilibrium” perception is relatively high (approximately 0.8). Nevertheless, as in Figure 6a, b, perception responds more slowly, and ends up at a higher level, when both feedbacks are operating than when only one feedback is operating.

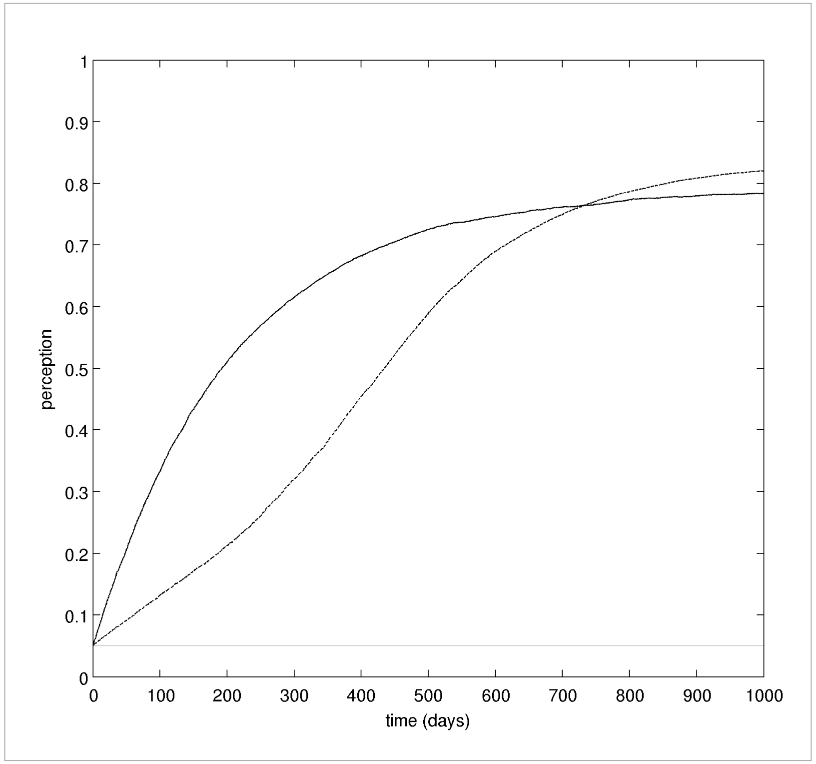
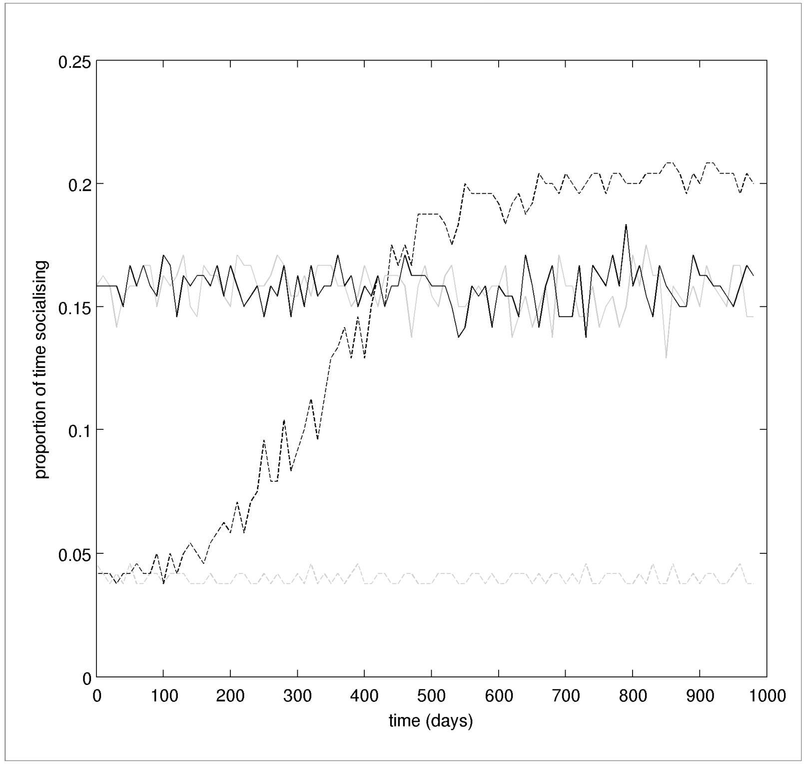
| Case study 1: An agent that initially has a poor perception of their local area | |
|---|---|
|   Figure 6a |   Figure 6b |

Figure 6. Simulations showing the change in the average proportion of time spent socialising (fig. 6a) and the perception (fig. 6b) of an individual agent over time. This scenario presents an agent that initially has a very poor perception (perception = 0.05 at t = 0). The graph show the results of a simulation with no feedbacks operating (solid grey); feedback from socialising to perception (solid black); feedback from perception to socialising (dashed grey); both feedbacks (dashed black).

Case study 2: An agent that initially has a poor perception of their local area

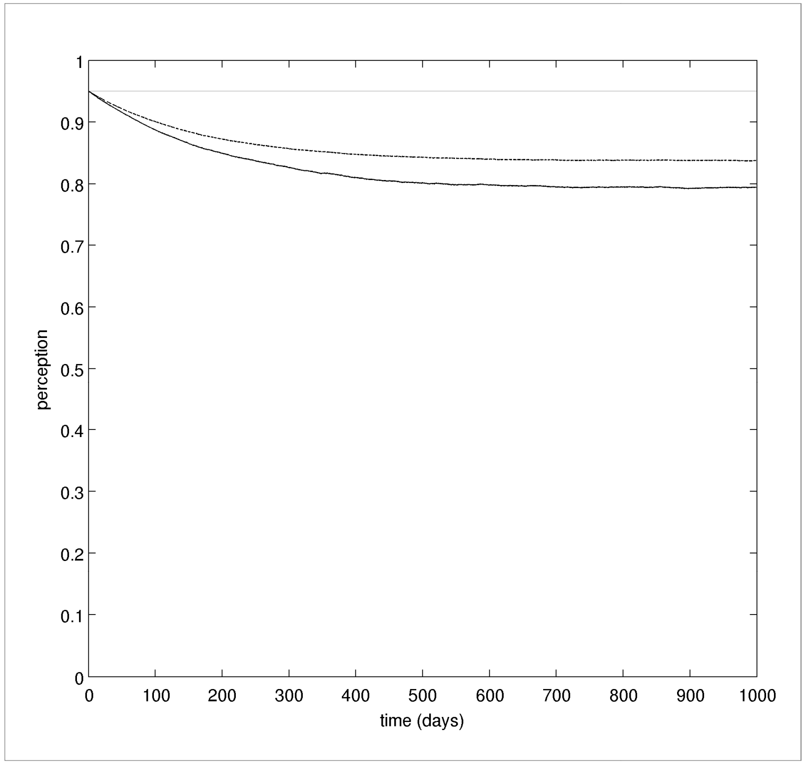



Figure 7a.

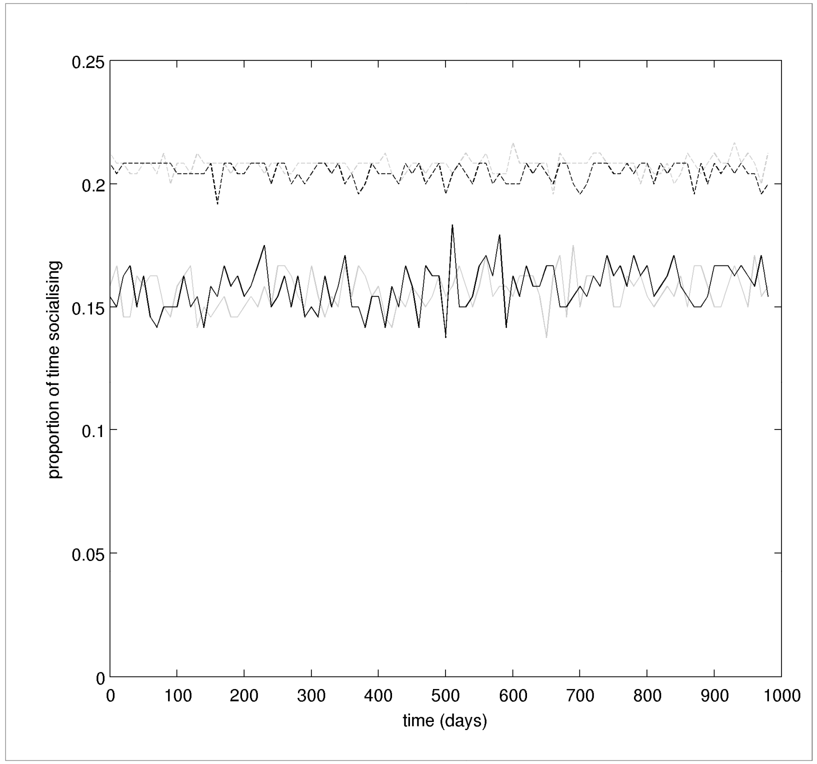



Figure 7b.

Figure 7. Simulations showing the change in the average proportion of time spent socialising (fig. 7a) and the perception (fig. 7b) of an individual agent over time. This case study shows an agent that initially has a very good perception (perception = 0.95 and t = 0). The graph show the results of a simulation with no feedbacks operating (solid grey); feedback from socialising to perception (solid black); feedback from perception to socialising (dashed grey); both feedbacks (dashed black).

*3.3 Case study 2: varying the strength of the feedback mechanism*

We varied the strengths of the two feedback mechanisms in our agent-based model and investigated the relationship between agent perception and proportion of time spent socialising. For each combination of parameter values, we ran the model and calculated the slope of the regression between proportion of time spent socialising and perception. We repeated this process m = 100 times to obtain an average slope (Figure 8). Unsurprisingly, when neither feedback operates (strength of both feedbacks = 0), there is no relationship between perception and time socialising. Introducing either feedback leads to a positive relationship, and the slope increases with the strength of the feedback. When both feedbacks operate (interior of Figure 8), the slope is greater than when a single feedback operates alone (top edge or left-hand edge of Figure 8).

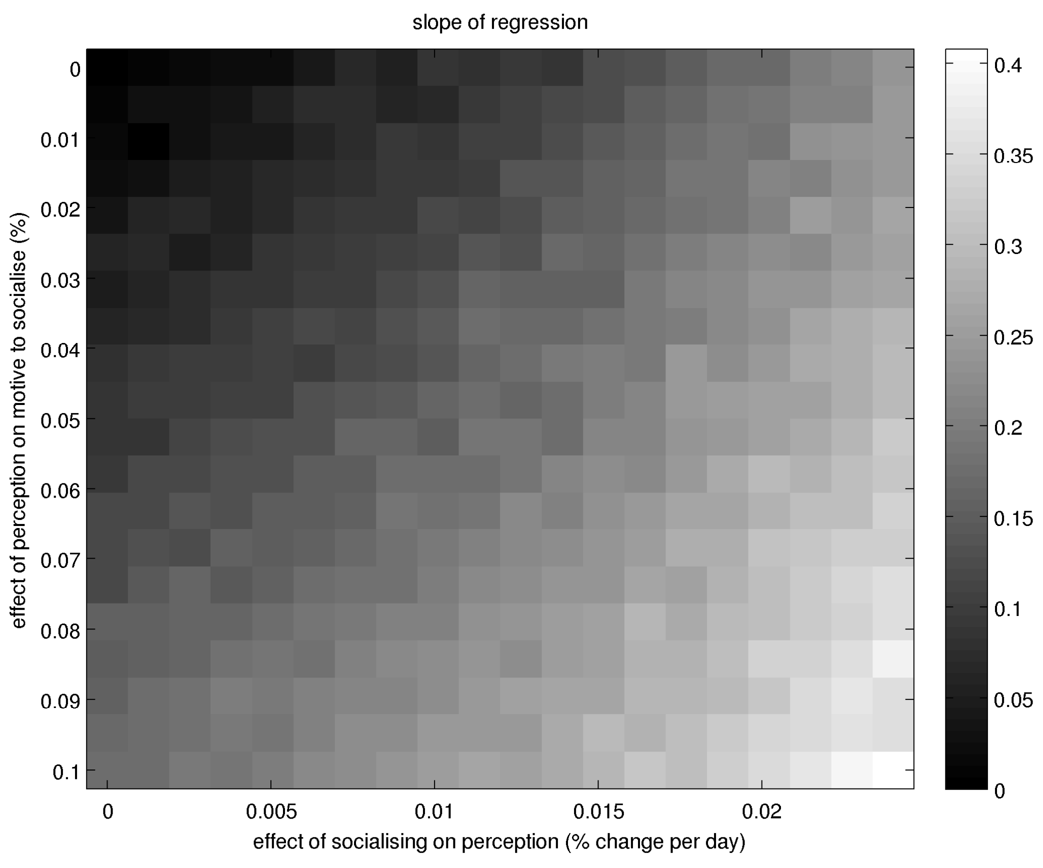



**Figure 8**. Coefficient (b) of the regression of y = a + bx, where y is the proportion of time spent socialising and x is perception. There is no relationship between these variables (b = 0, black shading) when there is no feedback of socialising on perception or vice versa (top-left corner). As the strength of the feedback of socialising on perception increases (moving right) or of perception on socialising increases (moving down), the relationship between y and x becomes stronger (lighter shading).

*3.4 Validation of findings*

We use ELSA to perform a regression of frequency of socialising against area perception, adjusting both the variables so that they have a 0-1 range for comparability with the agent-based models. This gives a regression slope of 0.1 ($p<0.0000$); a regression using data from wave 3 gives a comparable result. Introduction of other explanatory variables (age, sex, wealth, caring responsibilities) did not affect the relationship between frequency of socialising and area perception Comparison of the regression slope observed in ELSA with that in figure 8 suggest our agent-based models with varying feedback strengths are reasonable in many of the scenarios tested, particularly where both mechanisms are in operation.

Examination of data from waves 1 and wave 3 reveals little change in area perception and socialising across waves. Although this finding is at odds with our agent-based models, we argue that our results still have salience. It could be that that the time elapsed between ELSA waves that included questions on area perception (4 years) is not long enough to pick up the long-term effects within our agent-based models. It is also possible that the infrequency of data collection in the English Longitudinal Study of Ageing misses short-term changes that are captured in our simulations. Finally, it is possible that the majority of older people do not undergo substantial shifts in perception over time, but that there is an important minority that do. For example, this might include people who have recently moved house, who live with a neighbourhood experiencing rapid changes, or who have lost a partner. For these people the effects of changing perception that we model are important, but are lost in the ELSA data given its aims to be nationally representative. One of the values of agent-based modelling is that we can pick such individuals out and track their outcomes.

## 4. Conclusions

The agent-based model fitted in this paper suggests that the correlation observed between area perception and frequency of socialising among older people is driven by two feedback mechanisms; as individuals socialise more their area perception improves whilst at the same time a favourable perception of local area can drive additional socialising. We draw this conclusion for two reasons. First, the behaviour of the model is more realistic when both feedbacks are operating than when either feedback alone is operating. For example, when perception affects tendency to socialise, but not vice versa, a model agent with a poor perception of a neighbourhood will socialise infrequently. This will not change over time as the agent's perception is fixed. When socialising affects perception, but not vice versa, the same agent will socialise more frequently. This will lead to a rapid improvement in perception, but no change in behaviour over time. When the feedbacks operate in both directions, the agent's behaviour reinforces its perception. This can operate either as a positive feedback loop, with frequent socialising and good perception reinforcing one another, or as a vicious circle, with infrequent socialising and poor perception. Which of these two situations apply to a given agent depends on the other model variables, such as the level of demand on the agent's time (i.e. preference for responsibilities), the agent's initial perception, and the agent's disposable income.

The second reason for our conclusion is the comparison of the regression slope between area perception and socialising in the agent-based model and in the ELSA data. When both feedbacks are in operation, the agent-based model produces a regression slope similar to that of the ELSA data more frequently than when a single feedback is in place. This suggests that a synergy between both feedbacks is plausible. That the model replicates some of the relationships in ELSA validates the assumptions to some extent. Whilst ELSA reveals less change in socialising and area perception than in our simulations, we argue that out models pick out particular people and places whose experiences cannot be accurately monitored given the constraints of sample size and the aim that ELSA should be nationally representative.

The agent-based model we have fitted in this paper is deliberately simply and ignores many potentially important variables. However, agent based models are an emerging technique in the modelling of health and health-related behaviour (Auchincloss & Diez Roux 2008) and a simple model is appropriate under these circumstances. The advantage of this approach is that it allows us to focus on underlying mechanisms rather than solely on observed correlations between variables. This enables causal relationships to be isolated and identified while controlling for other potential sources if variation. We argue that the PECS architecture is particularly appropriate for modelling the influence of neighbourhood on health-related behaviours. The behaviour of each agent is governed by a set of motives and needs that, in this case, affect the amount of time spent socialising. The role of neighbourhood in mediating these relationships can be easily accommodated within the PECS architecture and the approach could be modified to model other behaviours that influence health (smoking, exercise, diet). In this paper, we present a simple base model as a foundation to be developed in future research to include further more complicated interactions between agents and place and to consider other aspects of health-influencing behaviour.

The model could be extended in several ways to produce more realistic patterns of behaviour to enable more general hypotheses to be tested. For example, each agent's behaviour in the model is assumed to be independent of all other agents. It would be possible to extend the model to explicitly include each agent's network of social interactions, so that an agent's motive to socialise and changes in perception depend on the attributes and behaviour of other agents in their social network. These social networks may involve non-retired people and a second category of agent could be added to the model to represent this. The model currently does not include any spatial information. This could be incorporated, for example, by linking agents' tendency to socialise with their proximity to public transport and local facilities, and with the spatial locations of other agents in their social network.

From a policy perspective we note the importance of strategies that enable older people to socialise (e.g. free public transport) as well as steps to improve the attractiveness and safety of the local area. The nature of policy implemented should take account of the circumstances of the individual including their area perception and baseline level of socialisation. We would encourage focussed research on particular areas to test the conclusions of this paper further.

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