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Improving the Effectiveness of Fire Prevention using the 'Premonition' Agent-Based Model of Domestic Fire Risk Behaviours

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Abstract

Purpose

Understanding and predicting the behaviours of households within a community is a key concern for fire services as they plan to deliver effective and efficient public services. In this paper, an agent-based modelling approach is used to deepen understandings of changing patterns of behaviour within a community.

Design/methodology/approach

This "Premonition" model draws on historical data of fire incidents and community interventions (e.g. home safety checks, fire safety campaigns etc) collated by South Yorkshire Fire & Rescue, UK, to unpack patterns of changing household behaviours within the region.

Findings

Findings from simulations carried out using the Premonition model, show that by targeting close-knit groups of connected households, the effectiveness of preventative interventions and utilization of associated resources is enhanced. Furthermore, by repeating these interventions with the same households over time, risk factors within the wider area are further reduced.

Originality/value

The study thus shows that annual repeat visits to fewer and more targeted high-risk postcodes increases the overall reduction in risk within an area, when compared with a scattered coverage approach using one-off (i.e. not repeat) household visits within a postcode.

Keywords: Co-Evolution; Connectivity; Agent-Based Model; Domestic Fire Risk Behaviour

Introduction

Understanding and predicting the behaviours of households within a community is a key concern for local authorities as they plan to deliver effective and efficient public services. This is particularly so for fire services as they seek to protect the most vulnerable in the community within increasing budgets constraints. In addition to causing physical injury, the cost of fires can account for up to 0.22% of a country's GDP (Jennings, 2013). In this research we develop an approach which deepens our understanding of changing patterns of behaviour within a community. Emergency services often have access to large amounts of data, and yet despite such potential, much remains to be done in terms of deriving real insights for policy (Mergel et al., 2016). Building on this big data, we adopt an analytical approach which searches for the underlying mechanisms driving behavioural change within communities. We put forward a view of social change as a process in which household behaviours co-evolve within connected social networks (Breslin et al., 2015; Dobson et al., 2013). This approach shifts the focus of attention from individual households to connected and co-evolving social systems. To further advance this research and in collaboration with South Yorkshire Fire & Rescue (SYFR), UK, we develop an Agent-Based Modelling approach (ABM) to simulate changing household behaviours within the Sheffield City region. This "Premonition" model draws on historical data of fire incidents and community interventions (e.g. home safety checks, fire safety campaigns etc) collated by SYFR, to unpack patterns of changing household behaviours within the region (Breslin et al., 2016). This decision-support tool aims to improve the identification of areas at risk and patterns of change within key groups, and so optimise resource allocation planning of operations, and community prevention work across the city and the South Yorkshire region. Resources can thus be better targeted to prevent domestic fire risk practices emerging in the first instance, improving the effectiveness of SYFR's presence, interventions and governance. We therefore answer Jennings' (2013) call for holistic studies of communities, using sophisticated analytic techniques to better identify those most at risk, and increase the effectiveness of interventions.

Studying Fire Risk Behaviours in Homes

Previous studies of domestic fire risk behaviours have focused attention both on socio-economic and demographic classifications of individuals, and on the historical analysis of fire incidents, as predictors of future behaviours. When considering demographic and socio-economic factors, research has pointed to a number of significant correlations. First, fire incidents are more likely to occur in households where the occupant suffers from a disability and/or illness (Bain et al., 2002; Holborn et al., 2003; Maull et al., 2010; Smith et al., 2008; Taylor et al., 2005). Moreover, poor health and disability amongst the elderly further reduce the likelihood that they can escape during a fire (Harpur et al., 2014). Second, studies have identified social deprivation as a significant factor in house fires (Bain et al., 2002; Chhetri et al., 2010; Duncanson et al., 2002; Mulvaney et al., 2008; Shai, 2006; Smith et al., 2008: Taylor et al., 2005). Third, research has shown that households with single occupants also appear more at risk of domestic fire incidents (Holborn et al., 2003; Smith et al., 2008; Taylor et al., 2005). These studies therefore point to key demographic (e.g. age) and socio-economic (e.g. social deprivation) predictors of domestic fire risk.

However, to further understand the causes of fire incidents, one must explore the specific behaviours of individuals, alongside demographic backgrounds. Reviewing research in this area reveals four key behaviours associated with fire incidents, namely; smoking, alcohol consumption, cooking practices and use of electrical appliances. These behaviours are associated with increased risks for individuals with certain demographic and socio-economic backgrounds. First several studies have identified smoking specifically as a cause of household fires (Holborn et al., 2003; Jennings, 2013; Leistikow et al., 2000; Mulvaney et al., 2008; Taylor et al., 2005), leading to higher levels of risk amongst single occupancy homes in particular. Second, studies have pointed to drinking of alcohol, and intoxication as a significant factor in domestic fire incidents (Holborn et al., 2003; Taylor et al., 2005). Moreover, the combination of smoking and alcohol drinking behaviours significantly increases these risks. There are further links between lower socioeconomic status and an increased likelihood of smoking, drinking and other risk factors (Sharma et al., 2010). Third, certain cooking practices (e.g. use of chip pans) are also linked to increased risks of household fires (Mulvaney et al., 2008). Dangerous cooking appliances, and in particular the use of chip pans is cited as a common cause of nonfatal fire incidents (Holborn et al., 2003). Cooking practices are again linked to the consumption of alcohol and the demographic characteristics of the individual concerned. In this way, a large percentage of chip pan related burns occur when victims are under the influence of alcohol (Ghosh et al., 1996; Wijayasinghe and Makey, 1997). Similarly, elderly people were shown to suffer more severe injuries and fatalities from cooking appliance and chip pan related fires (Mulvaney et al., 2008). Finally, an increasing area of concern is the use of dangerous electrical appliances. There is evidence that electrical devices such as electric blankets and space heaters are a common cause of fires (Elder et al., 1996; Holborn et al., 2003). As with cooking appliance fires, elderly people were shown to suffer more severe injuries and fatalities from electric appliance related fires (Elder et al., 1996; Mulvaney et al., 2008). Although modern appliances have built-in safety features to prevent fires, increasing usage of cheap electrical devices, such as mobile phone chargers, increase the risk of fires.

Fire Prevention through Interventions

Evidence has shown that fire incidents can be reduced through prevention activities carried out by fire services, including home safety visits (HSV) (Clare et al. 2012). These visits seek to increase the householder's awareness of fire risk, and trigger changes in behaviour. However, more research is needed to determine when and how often to target key individuals. Many services target higher risk individuals based on their socio-demographic backgrounds as noted above. However, it is seen that the effectiveness of such interventions decreases over time, with the biggest impact seen in the months immediately following their enactment (King et al. 2005). This highlights the ineffectiveness of 'one-off' home visits in sustaining longer-term change in behaviours, with repeat home visits seen to be more effective, as shown in the East Sussex Fire & Rescue (ESFRS) studies, carried out by the University of Brighton. This latter research set out to examine the impact of HSVs on fire risk behaviours and its sustainability or 'decay' over time. One hundred households within two separate regions were studied over a 2-year period, during which time, each household received an annual HSV followed by an interview. Therefore, each home received a total of two HSVs over the two years. One year after the first HSV was carried out, ESFRS found that risk-per-household [1]had fallen, when compared to pre-study levels. Examining specific comments made by respondents, whilst some households learned a lot from these visits, over a third did not produce the behaviour/attitude changes hoped for (East Sussex Fire and Rescue Service,

[1] ESFRS calculated risk-per-household by totalling up a range of risk factors identified, and then averaging across the overall sample of households.

2010). When ESFRS completed a repeat visit in year two it was seen that the risk-per-household continued to remain lower than the pre-study levels. Moreover, ninety-six percent of respondents said they recalled the previous visit, a significant improvement on the previous year. Furthermore, sixty-five percent of households said they could recall specific advice from the HSV, and a further forty-one percent said they had made some changes to their homes, behaviour or domestic routines following the advice given (East Sussex Fire and Rescue Service, 2011). This study clearly highlights the increasing effectiveness of repeat HSVs in triggering behavioural change.

Understanding Social Change as a Co-Evolving Connected System

To better understand community fire risk, a bottom-up theoretical model was developed to represent the changing behaviours and interactions of households over time. This involved three key elements. First, examining household behaviours it can be argued that individuals develop habitual behaviours over time, and that these behaviours become increasingly automatic and tacit, the more they are repeated (Dewey, 1922; Duhigg, 2013). In this manner an individual will develop habitual behaviors related to smoking, drinking, cooking and the use of electrical appliances, and their daily behaviours will be constrained by these ingrained habits.

Second, the attitudes and behaviours of individuals are shaped by the influence of others, such as family and friends (Christakis and Fowler, 2007; 2008). This connectedness of community behaviours was seen in the Framingham studies, in which a community of 12,067 individuals was studied between 1971 and 2003 (Christakis and Fowler, 2007; 2008). Christakis and Fowler found that inter-personal relationships had a significant influence on a range of factors, including smoking, obesity and even happiness. They found that a family or friend was more likely to smoke, be obese, and even be happy if the focal individual also smoked, was obese or happy (Christakis and Fowler, 2007; 2008). This influence of a friend on another decreased as the degree of separation increased (i.e. friend of a friend, or friend of a friend of a friend). They found therefore that social distance played a much stronger role on interpersonal influences than geographic distance (Christakis and Fowler, 2007). However, when examining happiness, geographic distance was seen to have a compounding effect on interpersonal influence, given its link to frequency of social contact. Therefore, when "nearby" friends (who live within 1.6 km of each other) become happy, the probability that one influences the other is increased by 25% (Christakis and Fowler, 2008). In sum, individuals can exert significant influence on the behaviour of those close to them. In this way, a bed smoker might be swayed to abandon such behaviours if family and friends continually disapprove of such actions. On the other hand, the same individual might disregard similar disapproval expressed in a national safety campaign.

Finally, and reflecting this localizing effect from the Framingham studies it can be argued that communities are local (Breslin, 2011). In other words, people are more influenced by others who are geographically close to them (Fowler and Christakis, 2008). When viewed through this socio-behavioural theoretical lens, a number of implications can be drawn for the study of changing domestic fire risk behaviours within a community. First, habitual behaviours are path dependant, in the sense that previous enactments of a behaviour make it increasingly likely that future behaviours will follow the same pattern (Dewey, 1922; Duhigg, 2013). Thus the longer these behaviours persist, the more likely they will resist any attempt to change. Therefore, changes triggered following a home safety visit for instance, might be reversed as previous ingrained habitual behaviours return. Interventions should thus be designed along

long-term time horizons, with repeated cycles of learning and unlearning in mind. Second, key individuals have more power and influence than others within the wider community. Thus, interventions can be more effective by identifying and targeting these thought leaders. Equally however, some members of the community will be socially isolated, and beyond the reach even of these local influencers. Finally, communities tend to be drawn towards local issues over time, to the detriment of wider signals from the outside world (Breslin, 2011). This can present challenges to local authorities, who may be seen as external to such local concerns. Engagement with the community is therefore key to influencing this localisation force.

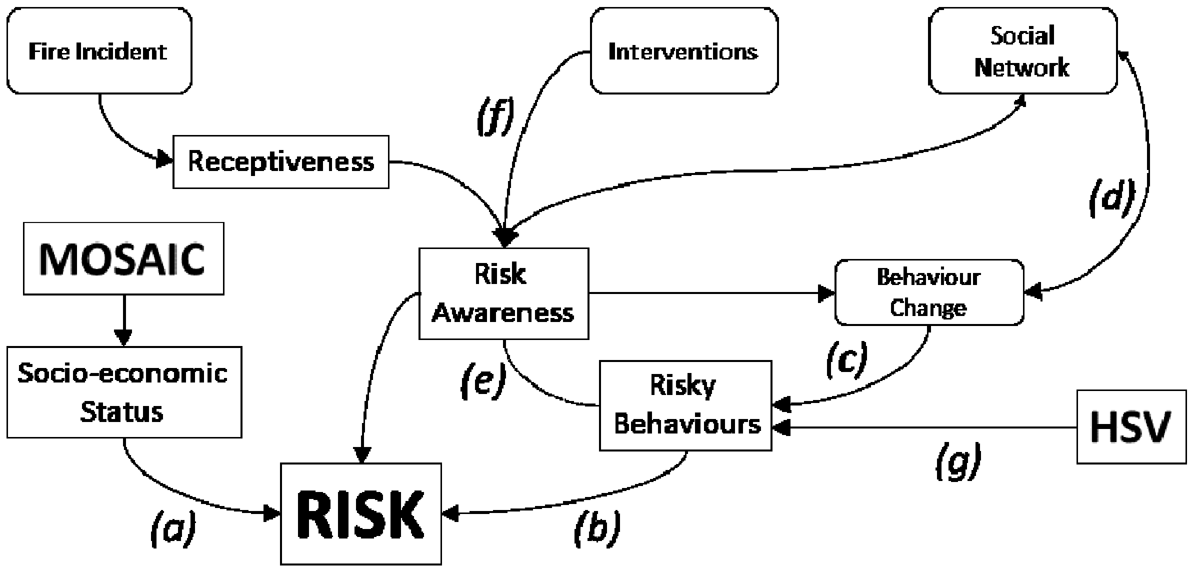
Method

Premonition: An Agent-Based Model of Community Change

To analyse the impact of these individual-level socio-behavioural ‘rules’ on wider community-level change, an agent-based modelling (ABM) approach has been used. ABM is a computer-based analytical approach which simulates patterns of change within a population through the individual actions of diverse ‘agents’ (Crooks et al., 2008; Farmer and Foley, 2009; Gilbert, 2008). Prescribed ‘rules’ define how each agent interacts with others, and how they learn and adapt over time (An, 2012; Axelrod and Cohen, 1999), with the rules being derived from theoretical representations of interactions, behaviours and processes of decision-making (Axelrod, 1997; Filatova et al., 2013). As a bottom-up approach, ABM allows researchers to connect high-level population change with micro-level behaviours and interactions of agents, and thus better understand changing patterns of urban behaviour (Axelrod and Cohen, 1999; Crooks et al., 2008; Gilbert, 2008). A key advantage of ABM is that it provides a simulated environment enabling the researcher to carry out innumerable experiments that would be impossible in “live” communities, such as for example the simulation of future scenarios, and the development of approaches that maximise intervention effectiveness (without the associated costs of such trials in real-life) (An, 2012; Breslin et al., 2015; Crooks et al., 2008; Gilbert, 2008; Seppelt et al., 2009).

Purpose. In this study, a population of agents representing the Sheffield City region has been modelled using the ABM approach. The model simulates key domestic behaviours (i.e. smoking, consumption of alcohol, use of electrical appliances and cooking practices) for each agent within this population. The purpose of the model is to investigate the impact that different intervention strategies have on household fire risk in different areas.

Figure 1 Overview of Premonition Agent-Based Risk Model



Model Overview. The ABM centres on calculating changing *risk* factors for each household as shown in figure 1. First, drawing on the review of literature (see above), a baseline risk is determined from the demographic and *socio-economic* background of the individual (i.e. MOSAIC classification at the household level) (see figure 1, relationship a). Second, and again drawing on the review of literature, specific data on *risky behaviours* within the home (e.g. smoking, drinking) gathered via SYFR home safety visits are further used to develop associated risk markers[2] (see fig 1, relationship b). These behaviours change over time, according to the socio-behavioural rules outlined above (see fig 1, relationship c). In this manner, an agent's risk factor is modified directly through *interventions* (see fig 1, relationship f, and 1, relationship g), and indirectly through the influence of other households in their respective *social networks* (see fig 1, relationship d). The latter addresses the call for more research to explore the role of social networks on agents' behaviour (An, 2012; Christakis and Fowler, 2008). Drawing on the findings of the Framingham Studies noted above (Christakis and Fowler, 2007; 2008), levels of influence are seen to be dependant both on the strength of a connection, and the degree of separation between household agents. Relationships can also be both bi-directional and unidirectional, depending on the direction of influence between agents. In the way, fire risk behaviours are continually influenced by the diversity of family and friends that the subject interacts with. Individuals will also have different levels of *risk awareness*, which in turn affects their overall level of risk (Kruth et al, 2014) (see figure 1, relationship e). As Kruth et al (2014) note, the greater the perceived risk, then the more prepared individuals become when faced with fire risk.

The fire service might change both *risky behaviours* and *risk awareness* through *interventions*. In the former, they might use *HSV*s to directly change household behaviours (see figure 1, relationship g). At the same time, they might use a combination of *HSV*s, local media safety campaigns and the distribution of leaflets to change an individual's *risk awareness* (see figure 1, relationship f). An intervention will also have an area of influence (*strength*) representing its effectiveness, and *duration*, representing how long the influence of the intervention will last. For example, a home safety visit may have a high strength of influence, but lower radius being limited to one household. Alternatively, a media campaign may have a lower level of direct influence, but larger duration and radius of influence. The

[2] This data is anonymised in the model, as no personal data has been used in its development and presentation.

reduction in risk factors as a result of interventions is seen to decay over time reflecting the influence of habitual behaviours noted above, which can impair an individual's ability to make long-term permanent change. For instance, an individual may temporarily change a cooking practice following a safety campaign intervention. However, after a period of time, a previous unsafe practice may 'creep' back in. The longer the household adopts a certain behaviour, then the more difficult it will be to change this and 'reset' the inertial clock (Breslin et al., 2015). For example, studies have shown that very few people succeed in changing habitual behaviours aimed at weight loss (Wing and Phelan, 2005). Whilst individuals may have good intentions to change habits, previous ingrained behaviours may resurface when the person is faced with the same environmental cues (Duhigg, 2013). In another study of changing exercise regimes among cardiac patients, Sniehotta et al. (2005) found that individuals regressed to previous patterns of behaviours from 2 weeks to 4 four months after the interventions.

Simulations and Scenarios

Following a sensitivity analysis of each of the factors noted above (Filatova et al., 2013; Gilbert, 2008), a series of simulations were carried out within two different Lower Layer Super Output Areas (LSOA) within the Sheffield region. In this paper, the specific identity of those areas is not given. The simulation runtime covered a 4-year period, and explored the effect of interventions carried out in years 1 and 2 of this period. These simulations examined a number of different scenarios, which included a) current approaches used by SYFR, and b) interventions based on a repeated community level approach outlined above:

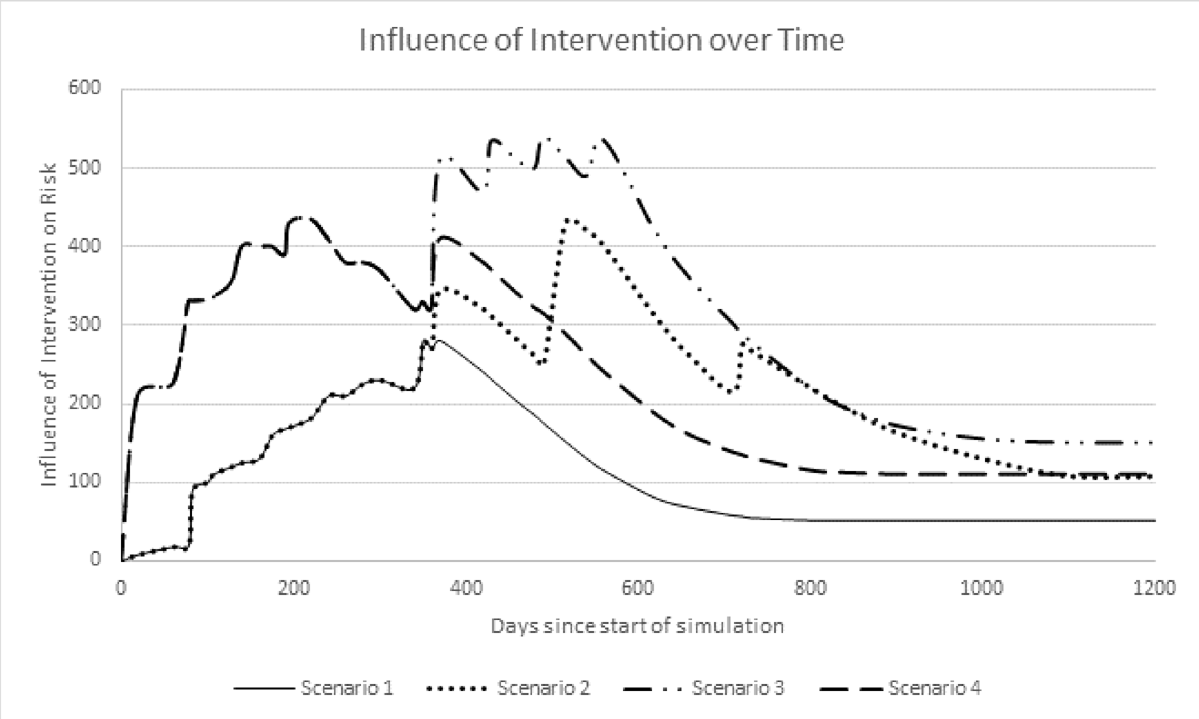
- *Scenario 1*: In this scenario a range of households were visited within the target LSOA using Home Safety Visits (HSV), over the course of the first year of the 4-year simulation period. There were no repeat visits to any homes over the 4-year period. These targeted homes included those deemed high risk, based on MOSAIC classification, and addresses referred to SYFR from third parties. This list of addresses reflects the actual approach used by SYFR within that LSOA.
- *Scenario 2*: In this scenario the approach adopted in Scenario 1 is repeated for first two years of the 4-year simulation period. The purpose here is to evaluate the additional regional impact of completing home safety visits over two years as opposed to one year only (Scenario 1). Again no addresses are visited twice during this 2-year intervention period, as reflected in the approach used by SYFR prior to the Premonition project.
- *Scenario 3*: Here, the most visited postcodes found in scenario 1 are visited in year 1 only (total of 4 postcodes). However, unlike Scenario 1, all homes within that post codes are visited. In year 2, homes in the same post codes are visited again for a second time. By visiting the same households a second time, an attempt is made to revert ingrained habitual behaviours. It should be noted that this scenario employs the same resources (i.e. crew availability and time) as Scenario 2.
- *Scenario 4*: As in Scenario 3, the most visited postcodes found in scenario 1 are visited in year 1 only (i.e. same 4 postcodes as scenario 3). This scenario employs the same resources in year 1 as Scenarios 1-3. In year 2, a leaflet drop is carried out within the wider LSOA.

Findings

Results from Simulations

The results from the simulations of the four scenarios for one of the chosen LSOA are shown in figure 2. This figure shows the changing influence of intervention strategy over the 4-year simulation time period within the LSOA. A number of observations can be made from this figure. First it is seen that each successive intervention (i.e. HSVs completed) leads to a cumulative increase in influence for each of the four scenarios. Second it is seen that once the intervention has been completed, the influence over time decreases through a decaying effect described above. Third, once this decay has stabilized there is a net permanent increase in influence for each scenario.

Figure 2 Simulation results showing the influence of different intervention scenarios on risk over time. (The units given on the y-axis represent computational values of risk generated for the purposes of the agent-based model. Whilst these values can be linked to external measures of risk, they are used here to compare outputs from different intervention scenarios)



Examining these figures together, it is seen that the approach currently adopted by SYFR, in which a range of target addresses are visited in two successive years (Scenario 2), results in a long-term reduction in risk for the wider LSOA, when compared to visits carried out in one year only (Scenario 1). This extension of visits over two years, results in a doubling of influence within the LSOA.

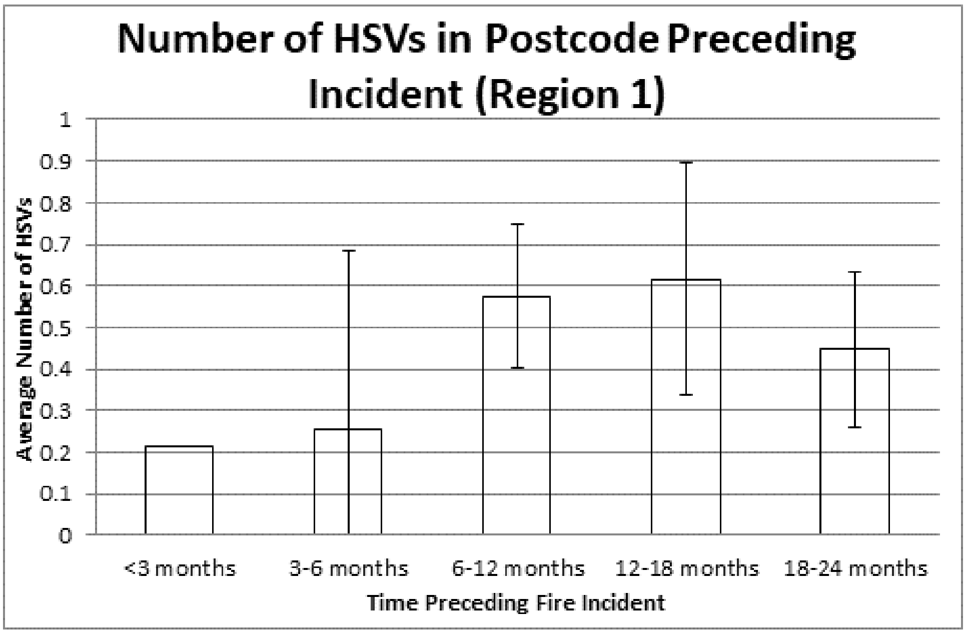
If on the other hand, HSVs were focused on the 4 most visited postcodes only within year 1, with a repeat visit to those same post codes in year 2 (Scenario 3), then there is a further increase in overall influence within the LSOA (see figure 2). Indeed, if a leaflet drop replaces the repeat visits in year 2 (Scenario 4), the effect is similar to two years of scattered HSVs within the LSOA (Scenario 2). This same effect was seen in simulations carried out within a second LSOA.

In summary, greater impact of interventions can be achieved using the same resources, by concentrating HSVs on key target high risk postcodes and repeating these visits over time. Furthermore, the same effect can be achieved with fewer resources, by targeting those most at risk postcodes and following this up with a leaflet drop. In terms of intervention strategy, these findings highlight the importance of repeated visits to connected households over time, as opposed to a more scattered coverage of unconnected households.

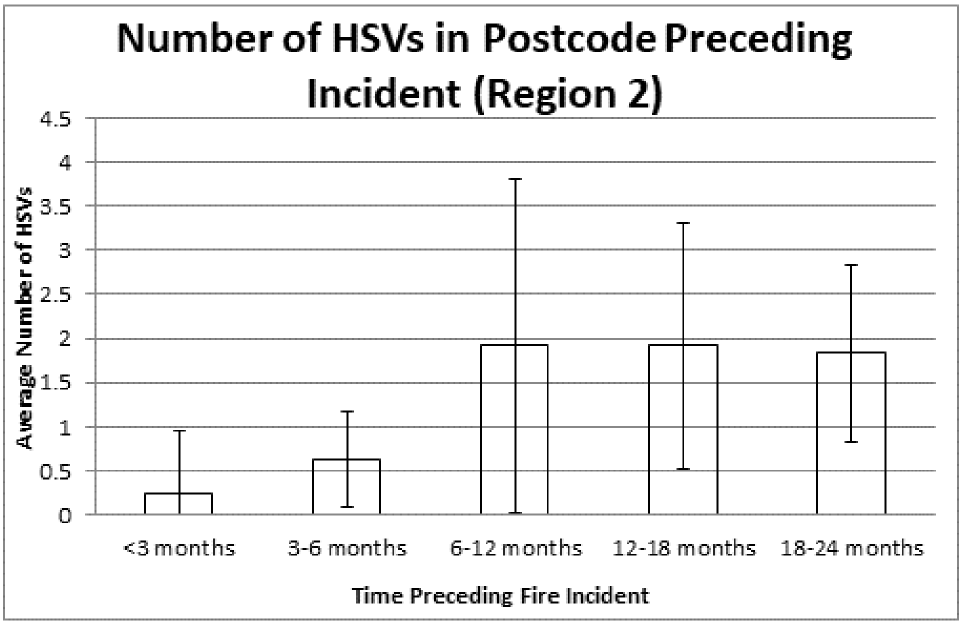
Analysis of Incident and HSV Data

To further explore this relationship between intervention and influence, historical data collected by SYFR for fire incidents and HSVs in each of the targeted LSOAs was analysed[3]. Data for accidental fires between 2014 and 2016 was compared against HSVs completed within the same postcode area in the two years preceding the incident (i.e. 2012 to 2016). When a fire incident had occurred within a post code area, the total number of HSVs completed within that same postcode in the preceding two years was examined. Interpreting this data (see figure 3) one can see that when an incident occurs, the majority of HSVs completed took place between 6-18 months earlier for both region 1 and region 2. In other words, incidents tend to occur within postcodes which have had fewer HSVs within the previous 6 months. This highlights a "decaying" effect as the immediate positive impact of the HSV fades 6 months after the visit, as seen in separate studies carried out by ESFRS and King et al. (2005).

Figure 3 Number of postcode HSVs preceding a fire incident in regions 1 and 2 between 2014-16. Error bars indicate standard errors of the mean.



[3] Between 2014-16 there were a total of 47 fire incidents for region 1, and 24 for region 2.



Taken together with the simulations, these findings indicate that the frequency of HSVs within a postcode is clearly linked to the number of fire incidents (Clare et al., 2012). In other words, the higher the number of HSVs in a postcode the lower the probability of an incident occurring. In addition, examining the change over time (see figure 3), it is seen that incidents are more likely to occur in post codes which have been visited less frequently within the previous 6 months. These findings reflect the recall effect seen in the East Sussex study, and point to an average 6-18-month time lag between HSV and fire incident (see figure 3).

Discussion

Drawing from the findings both of the simulations noted above, and the incident data analysed for SYFR, two key conclusions can be drawn. First, as noted above, fire incidents are more likely to occur in postcodes, when the most recent HSV was completed between 6-18 months beforehand (see figure 3). This suggests that one-off isolated home visits have limited longer-term impact on fire risk behaviours. Therefore, and second, repeat HSVs within those same high-risk households improves the chances that the individual will change fire risk behaviours, as seen in the results of the simulations (see figure 2). These findings suggest that annual repeat visits to fewer and more targeted high-risk postcodes increases the overall reduction in risk within an area, when compared with a more scattered coverage approach using one-off (i.e. not repeat) household visits within a postcode.

These findings add to those from the ESFRS studies (East Sussex Fire and Rescue Service, 2010; 2011) by highlighting not only the benefit of repeat visits, but the need to target interventions at communities of households (i.e. complete post codes), as opposed to isolated homes across a range of regions. By focusing on changing fire risk behaviours within a defined community, these findings clearly have implications for the wider understanding of social change. While service providers can plan and execute interventions aimed at spreading good practices, the selection and dissemination of behaviours is influenced by key individuals with high levels of connectedness (Breslin et al., 2016). This has implications for the management of intervention policies, directing communication at key disseminators and thought leaders. For example, the behaviours of many individuals are influenced by close networks of family and friends, with the Framingham Studies showing individuals having on average just over seven such connections within a network (Christakis and Fowler, 2007; 2008). In these close-knit communities, local authorities and service providers need to be closely engaged and embedded in order to affect change. Interventions should therefore be targeted at key thought leaders, and positioned in terms of local issues. On the other hand, in more sparsely connected networks, interventions would tend to be costlier given that such socially isolated households are difficult to reach both using broad safety campaigns and more targeted approaches. This presents considerable challenges for service providers seeking to serve and safeguard those most vulnerable and isolated within the community.

Future Research

Validation is key to developing the predictive power of ABM. In a sense the validation process involves comparing and then fine-tuning the model to reflect actual recorded behaviours of households (Gilbert, 2008; North and Macal, 2007). However, validation with ABM can be problematic given the richness of the data needed to test model outputs (An, 2012; Crooks et al., 2008; Filatova et al., 2013). To validate the results of the simulations reported in this paper, SYFR will carry out a pilot study in which the scenarios described above are implemented within two chosen LSOAs. First, for each target LSOA, repeat HSVs will be carried out for two target postcodes (Scenario 4). In two separate postcodes, a leaflet drop will replace the second repeat HSV visit (Scenario 3). The findings from this pilot study will then be compared against comparable 'control' LSOAs and simulation outputs from the ABM. Drawing on the insights obtained from the East Sussex study noted above, a number of output measures will be gathered. To measure the influence of these different scenarios, data will be collated from HSV questionnaires, follow up telephone surveys with visited households, and incident data were relevant. Informed consent will be sought from all participating households.

Conclusions

Decision support tools are an invaluable resource to fire and rescue services, as they continue to protect the most vulnerable in our society in the face of growing funding constraints. Approaches such as ABM can leverage both the big data available to local government services, and advances in socio-behavioural research, unpacking the complex processes underpinning community change. Using this approach, the Premonition ABM targets connected groups of households in a sustained manner over time, reflecting the path-dependant co-evolutionary nature of change in communities.

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