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Appleton, D, Jones, M, Dean, E and Taylor, MJ

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Advances in fire risk modelling

Deb Appleton (Merseyside Fire and Rescue Service Director of Strategy and Performance)

Mark Jones (Merseyside Fire and Rescue Service Fire Station Management)

Emma Dean (Liverpool John Moores University Visiting Research Fellow)

Mark Taylor (Liverpool John Moores University Department of Computer Science)

Fire risk modelling was typically previously based upon analysis of patterns of historical fire incidence. In this article we examine a community based fire risk modelling approach. Population segmentation using socio-economic characteristics data is used to provide a deeper understanding of the fire risks associated with different social groups.

Community profiles based upon population segmentation can be used to support analytical work such as annual reports on fire fatalities produced by fire and rescue services. Currently the focus of fire prevention activities is largely centred on older residents, particularly where they have health conditions or other needs that place them at higher risk of a fire, because current trends suggest that these people are at most risk. For elderly individuals, social isolation can not only increase their level of fire risk, but can also have a detrimental effect on health and wellbeing (SCIE, 2016).

Population segmentation modelling has been used by social services and health services as a way of understanding the needs of different community groups. In this article we examine population segmentation modelling as a means of understanding the needs of different community groups in terms of fire risk and fire prevention, especially the elderly. Recent research shows that personal fire-risk increases with age. Merseyside Fire and Rescue Services therefore focuses considerable effort and resource on identified vulnerable older households. The majority of fire deaths in the UK occur amongst the elderly population. Older people are most vulnerable to fire and a number of other risks.

The community based fire risk analysis approach described in this article was developed by Merseyside Fire and Rescue Service and Liverpool John Moores University in the UK. Having recognised that the population segmentation provided by the standard Mosaic model was not meeting the needs of Merseyside Fire and Rescue Service, a completely bespoke segmentation was undertaken based on local datasets to fully understand the needs and fire risks of individuals in Merseyside. Population segmentation can support collaborative working between local authorities and their partners focused on using customer insight and social media tools and techniques to improve service outcomes. These approaches offer public services bodies the opportunity to engage customers and gather insight into their preferences and needs, and thereby provide the evidence and intelligence needed to redesign services to be more targeted, effective and efficient (CALG, 2012).

Socio-economic data for the Merseyside region was gathered at the Output Area level of geography (ONS, 2016). An Output Area typically contains approximately 120 households. A statistical technique known as k-means cluster analysis was used to identify segments (or clusters) in the socio-economic variables such as average life expectancy at birth, the percentage of the population in different age groups, and the number of people in receipt of different types of benefits within the different Output Areas in the Merseyside region. A statistical technique known as a z transformation was used to standardize the variables prior to k-means cluster analysis in order to attempt to ensure that the socio-economic variables with the largest ranges of values did not unduly influence the process. Avoidance of co-linearity (that is when the variables used are highly correlated) was also used to select appropriate data for the cluster analysis process. The cluster analysis undertaken used twenty variables to represent social groups in terms of age, housing type, health indicators, and level of deprivation.

The actual k-means cluster analysis was performed using the SPSS statistical software package to create ten distinct population segments (or clusters). The number of population segments chosen (the k in the k-means technique) was based upon the fire and rescue service's operational need for a usable number of population segments to support selective targeting of fire prevention resources.

Community profiles were then developed for the ten population segments generated by using the k-means clustering technique. The profiles were developed by banding the socio-economic characteristics represented by the variables used for the k-means cluster analysis, into low, medium and high bandings. The community profiles developed for the Merseyside region were:

1. Wealthy over 50 population living in semi-rural locations
2. Older retirees
3. Middle income residents living in privately owned properties
4. Average income older residents
5. Students living in city centre locations
6. Young families
7. Young families with high benefit need
8. Residents living in social housing with high need for benefits
9. Transient population living in poor quality housing
10. Younger, urban population living in high levels of deprivation.

(Higgins et al, 2013)

An example of one of the community profiles developed was:

Wealthy over 50, population living in semi-rural locations.

Key information about this profile group:

1. Wealthy, older population, in particular larger 75+ population.
2. Privately owned, high value detached properties
3. High life expectancy.
4. Good levels of general health, with low obesity rates and low rates of emergency admissions to hospital.
5. Low levels of health inequalities.
6. Generally low benefit need, however there may be a need for disability related benefits.
7. Low crime levels within the local area.
8. Low numbers of accidental fires and related fatalities.
9. Less likely to participate in sport, however activities such as golf and bowls appeal. Improving access to facilities is likely to increase participation.
10. Generally low levels of fuel poverty and low levels of poor quality housing.

11. May be willing to volunteer within their local community.

Communication preferences:

Almost 89 per cent of residents within this group have a landline telephone. In addition, approximately 80 per cent have a mobile telephone. However, nearly 35 per cent of residents do not have internet access at home.

(CALG, 2012)

Analysis of the numbers of accidental dwelling fires and types of accidental dwelling fires highlighted clear differences in fire risk between the different population segments. For example community groups consisting mainly of elderly individuals are more at risk of fire injury and fire fatality.

The rationale underpinning community-based fire risk analysis is that different population segments represent different forms of fire risk. For example, families with young children have different fire risks compared to elderly individuals. Population segmentation via k-means cluster analysis allows the examination of communities (modelled by the population segments) within a region. This then allows fire prevention activities to be tailored to the needs of the different community groups. Community profiling can support targeted fire initiatives that address the needs of different community groups via analysis of the frequencies of different types of dwelling fires affecting different community groups, for example the elderly. One of the driving factors in the initiation of community profiling via population segmentation was the need to continue to deliver the benefits of fire prevention work (i.e. to reduce numbers of fires and associated injuries and deaths) provided by the blanket provision of Home Fire Safety Checks (HFSCs) without access to the levels of funding provided in earlier years. Home Fire Safety Checks are delivered by firefighters, with high risk ones being delivered by advocates. Although advocates do receive high risk referrals from fire crews, most of their work comes from direct referrals from partner organisations. Advocates can offer direct help from Merseyside Fire and Rescue Service and also signpost the resident onto relevant partner organisations who may be able to provide additional help and support. The move towards a more targeted delivery of prevention is becoming ever more important because of an increasing pressure on the fire and rescue service financial budgets. The majority of Home Fire Safety Checks are now targeted at people aged 65 or over.

Overall community fire risk profiling can have advantages over other forms of geodemographic classifications that might be used for fire risk modelling, since a community profiling approach can make use of locally available information and knowledge regarding fire risks (Taylor et al, 2015). Community profiling supports the development a full understanding of community risks and needs through customer segmentation by using a combination of freely available open data, partner's customer insight data and data held internally by Merseyside Fire and Rescue Service. Formalised data sharing agreements were put in place to ensure the timely sharing of data. This allows community safety teams to plan and target preventative measures such as advocacy (including promoting services offered by other authorities, in particular Adult Social Services), the Fire Support Network (who provide initiatives that can be used to improve community cohesion and build on Community Involvement) and the Home Fire Safety Check, which could be targeted towards "at risk" community groups such as the elderly (CALG, 2012).

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