

The geography of smoking in Leeds: estimating individual smoking rates and the implications for the location of stop smoking services

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Smoking is an important and topical health issue in the UK. In Leeds, the target is to reduce smoking prevalence by 9 per cent by 2010. However, a key unknown is the likely distribution of smokers across the city. This paper aims to estimate individual smoking rates using microsimulation and hence evaluate the performance of established stop smoking services, e.g. how well do they serve local areas and to what extent does attendance vary between service point locations? Location-allocation modelling is employed to test various location scenarios and provide insight into where to optimally place centres.

Key words: health geography, microsimulation, geography of smoking, location-allocation modelling, stop smoking services

Introduction

To cease smoking is the easiest thing I ever did. I ought to know because I've done it a thousand times. (Mark Twain)

Smoking is the largest cause of preventable death in Britain and is responsible for various types of cancer (notably lung cancer) and heart disease. Peto (1994) points out that 30 per cent of all deaths for people aged 35 to 69 in Britain are due to smoking and nowadays this habit is responsible for around 86 500 deaths a year (Department of Health 2006). A related health issue is that of passive smoking, where people are at greater risk of developing lung cancer and coronary heart disease when living with a person who smokes (Hackshaw *et al.* 1997; He *et al.* 1999). Children in households that have a smoker are often exposed to health risks, but a study by Blackburn *et al.* (2003) showed that only 20 per cent of parents stop

smoking in the home to protect their children. The consequences are that such children can have higher incidences of lower respiratory tract infections, greater absenteeism from school and higher use of health services (Stanton *et al.* 2005).

Smoking is an important factor driving geographical variations in mortality, but most studies focus on national or regional trends and less has been done at the small area level (Pearce *et al.* 2003). The national target in England is to reduce the number of smokers by 2010 from 26 per cent down to 21 per cent (Department of Health 2004). To help smokers quit, stop smoking services were set up in 1999, raising a crucial geographical question: 'where should these facilities be located?' The recent White Paper *Our health, our care, our say: a new direction for community services* (Department of Health 2006) highlights the increasing need to provide more services away from hospitals and clinics and into community areas (particularly hard-to-reach communities

that might contain large numbers of poor residents or ethnic minority groups). This is a particularly important policy as statistics show that smoking rates are much higher in population groups of low socio-economic status (Goddard 2006). Thus, when attempting to reduce health inequalities, it is important that efforts are concentrated in more deprived communities.

Statistics also show that smoking rates vary by age, socio-economic status and ethnicity. The smoking rate in the UK has decreased steadily over time, especially for men. In the 1970s, more than 50 per cent of the male and 40 per cent of the female population smoked, whereas by 2006 the rate has declined to 27 per cent for men and 21 per cent for women (Goddard 2006). Smoking rates vary amongst different age groups, with people aged 20–24 the most likely to smoke. A high number of young people are seduced into smoking at an early age (often through peer pressure) and Stanton *et al.* (2005) and Sargent and Dalton (2001) report that children who start smoking at an early age are more likely to smoke into adulthood (Department of Health 1998).

An important issue for understanding spatial variations in smoking within a city or region is the strong association between smoking and socio-economic class. In general the proportion of smokers in higher socio-economic classes (such as people in managerial and professional occupations) is less than in lower socio-economic classes. People in lower income groups often smoke to cope with stress (Datta *et al.* 2006) and in turn, tend to have higher stress levels (Elliott 2000). Further, Barbeau *et al.* (2005) discovered that in the US the number of tobacco advertisements in lower socio-economic communities is higher in comparison with those in higher income communities, and the focus of tobacco companies is mainly on minority communities with low incomes (Luke *et al.* 2000). Other indicators related to socio-economic status, such as unemployment, housing tenure and car availability, are also good predictors for smoking prevalence and health inequalities in general (Gordon *et al.* 1999).

Smoking prevalence also varies between and within different ethnic groups. The highest smoking rate in the UK can be found for Bangladeshi men (around 45%), whereas Indian women record rates as low as 4 per cent. The highest prevalence amongst women is found for White and Asian women, with around 33 per cent, whilst the lowest smoking rates for men come from the Indian community, with 17 per cent. Looking at all persons, the lowest rates are found for

the Indian population, with 10 per cent, and the highest rates for the White and Black African community, with 33 per cent (Goddard 2005).

Geodemographic variations in the resident population are likely to cause significant variations in small-area smoking rates. However, there are few detailed statistics that identify rates of smoking at small geographical areas, making policy implementation challenging. Estimates of small-area rates have been produced by Twigg and colleagues, who used multi-level synthetic estimations at ward level (Twigg *et al.* 2000 2004). Further research on small-area estimates of smokers can be found in Pearce *et al.* (2003) and Vaish *et al.* (2004). These authors focused on one or two variables, such as sex and age. An advantage of the microsimulation method used in this paper is that it can consider a larger number of variables.

The aim of this paper is to provide a clearer understanding of the geographical variations in smoking rates and to suggest an approach for locating more stop smoking services within areas of high need. This maps well on to increasing interest between health inequalities and social exclusion in UK cities in particular (Department of Health 2006). The study area selected is Leeds, West Yorkshire, UK which consists of approximately 750 000 people.

The rest of the paper is structured as follows: first the current policy situations both in the UK and Leeds are highlighted and future plans to reduce the smoking population in the city are outlined. Attention is also given to the issue of passive smoking. Second, the paper explores the inequalities in smoking patterns, focusing on estimates of smoking prevalence by age, socio-economic status and ethnicity. As each of these attributes shows different spatial patterns of smoking, a microsimulation approach is used to combine those attributes to produce more robust estimates of smoking rates. Third, the performance of existing stop smoking centres is evaluated in terms of market penetration (how well they serve the estimated smokers). Fourth, the methodology of location-allocation modelling is used to demonstrate different scenarios illustrating possible locations of stop smoking services in Leeds. This enables policy-makers to make comparisons between current and optimal locations and identify good locations for new centres. Finally, it is argued that such a novel combination of microsimulation and location-allocation models will offer health planners considerable power to examine 'what if' scenarios of future smoking patterns.

Smoking and smoking cessation services

Concern over the links between smoking and ill-health has developed since the pioneering work of Doll and Hill (1950), although these concerns took considerable time to be translated into policy (Edwards 2004). The first successful steps against smoking in the UK were taken in the 1960s by banning the advertising of cigarettes on television. However, in comparison with other countries such as Norway, France and Australia, the UK was weaker in developing anti-smoking policies despite the Department of Health's (1992) review on advertising smoking. In 1998, the Department of Health published a White Paper entitled *Smoking kills: a white paper on tobacco*, which argued that National Health Service (NHS) services were needed to help smokers who wanted to quit. The main groups targeted are (Department of Health 1998 2004):

- *Adults* (in general), with the aim of reducing smoking rates from 28 per cent to 26 per cent by 2005 and 21 per cent by 2010.
- *People aged below 16*, with the aim of reducing prevalence of their smoking from 13 per cent in 1998 to 11 per cent by 2005 and 9 per cent by 2010.
- *Adults in different social classes*, with the focus on the manual group as it has the highest smoking prevalence. Here the aim is to reduce the smoking rate from 31 per cent in 2002 to 26 per cent or less by 2010.
- *Women who smoke during pregnancy*, where the aim is to reduce the smoking prevalence from 23 per cent in 1998 to 18 per cent in 2005 and 15 per cent or less by 2010.

In Leeds, around 30 per cent of the adult population smokes. To meet the UK national targets, Leeds needs to reduce this to 21 per cent, which represents about 55 000 adult smokers (The Healthy Leeds Partnership 2006). This is a huge challenge, as it means that almost one in three smokers will have to quit. A recent White Paper in 2004, *Choosing health: making healthy choices easier*, consisted of plans to make public areas, such as offices and factories, smoke free (Department of Health 2004). England and Wales became smoke free in all public areas on 1 July 2007 to protect against passive smoking and to continue to reduce smoking prevalence. Fichtenberg and Glantz (2002) show that restrictions on smoking in workplaces do

encourage smokers to stop smoking or at least to reduce their cigarette consumption.

It is estimated that 70 per cent of people would like to stop smoking but perceive it to be very difficult (Department of Health 2004). The NHS has recognised this problem and has invested extensively in stop smoking services. These services are free of charge, and people can self-refer or can be referred by health professionals. Services consist of either one-to-one or group sessions with a trained advisor. In addition, free telephone help lines, an information website and nicotine replacement therapies have been introduced.

Estimating small-area smoking rates

In the Introduction it was shown that smoking rates vary depending on different geodemographic variables. Here, the variables age and socio-economic class are mapped for Output Areas (OAs) in Leeds using data from the General Household Survey (GHS) of 2006 (Goddard 2006) and the UK Census 2001 (Figures 1 and 2). Figure 1 shows the estimated small-area smoking rates based on the individual age of residents in Leeds OAs and the national smoking rates by age group available from the GHS. For instance, it is known that the national smoking rate for people aged 20–24 is 31 per cent. Thus, if there are 16 people aged 20–24 living in a Leeds OA, then we can multiply the national smoking rate (31%) by the number of people (16) to generate the number of smokers for this age group. This is then applied to all age groups (as smoking rates vary for different age groups) to obtain the total number of smokers in each of the 2439 OAs in Leeds. The same procedure was carried out to estimate small-area smoking rates by socio-economic class. This, however, produces a very different picture of smoking rates (Figure 2). We have also estimated smoking rates by ethnicity (not shown here) and, again, the spatial patterns are different.

Figures 1 and 2 demonstrate variations in smoking prevalence by age and socio-economic class. Ideally, therefore, we need to estimate smoking prevalence by sex, age, socio-economic class and ethnicity (which are the main predictors of smoking) simultaneously. To do this we employ a microsimulation technique where it is possible to combine all relevant variables with the advantage of obtaining one result of smoking estimates. Large-scale datasets based on the attributes of individuals are built and 'what if' analyses are powerful to model the impacts of

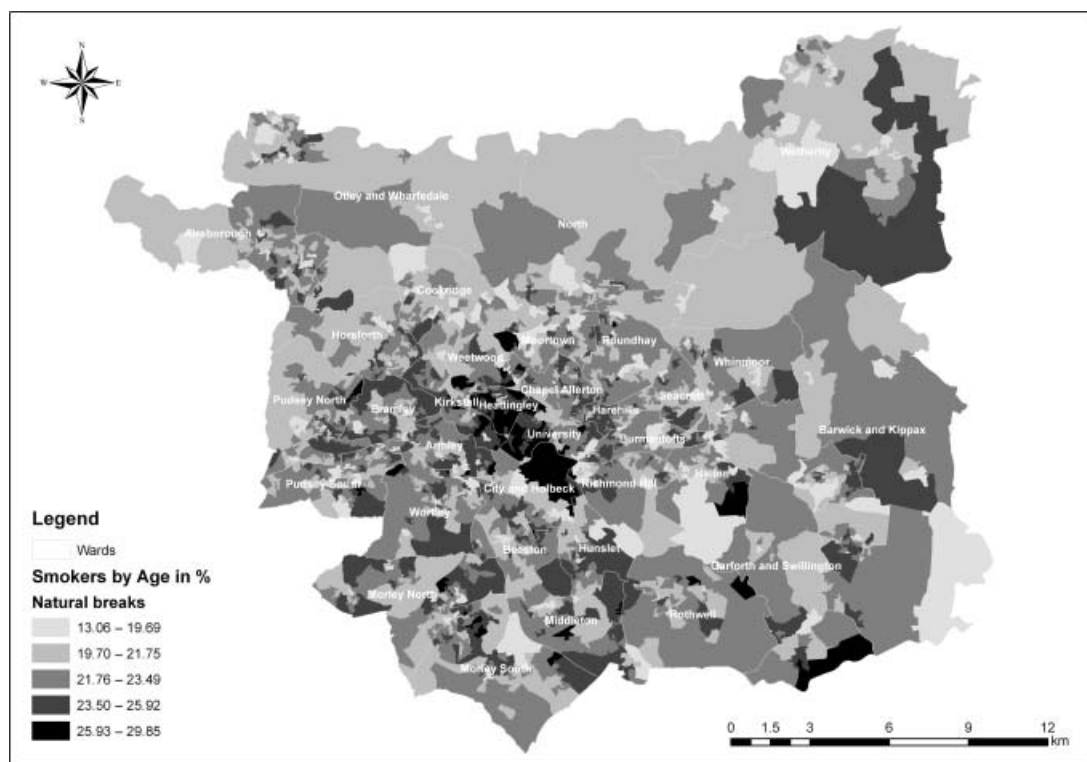


Figure 1 Smoking rates estimated using age for Leeds Output Areas (2006)

changing household demographics. Such microsimulation models cover many policy-relevant issues in welfare geography and are used to analyse policy impacts based on microunits (Birkin and Clarke 1995; Clarke 1996; Orcutt *et al.* 1986).

In this paper, the microsimulation method applies a static deterministic reweighting approach developed at the University of Leeds (Smith *et al.* in press). In the model two data sets are used: the General Household Survey (GHS) 2005 ($n = 19\,480$) and the UK Census 2001. The GHS is an annual cross-sectional survey that holds information on individuals and households at the regional level and the survey consists of more than 1000 variables including information about a person's lifestyle, such as smoking and drinking. The UK Census is conducted every ten years and the most recent data available are for 2001. The Census provides a rich dataset on demographic and socio-economic information, including age and socio-economic class, for the whole population down to OAs (where one OA consists of around 250 people), although no information about smoking is given.

The microsimulation model consists of four constraint variables (which have to be available in both data sets), namely sex, age, socio-economic class and ethnicity. These variables are grouped and entered sequentially into the model as socio-economic class (five categories), age (six categories), ethnicity (five categories) and sex (two categories). The order of constraints is important as the first variable is reproduced most accurately. The deterministic microsimulation modelling used here is a kind of 'cloning' exercise where individuals from the GHS are selected to populate each OA if they match the socio-economic conditions used as constraints. Further, marital status (two categories) is used as an unconstrained or validation variable as it is also a predictor if someone is a smoker or not (but the variables mentioned before are stronger). An error threshold is set where the simulated constraint variables are compared with the actual constraint variables where the error is less than 10 per cent for 90 per cent of the OAs. For the validation variable marital status, the threshold is set to less than 20 per cent of error in 90 per cent of the OAs

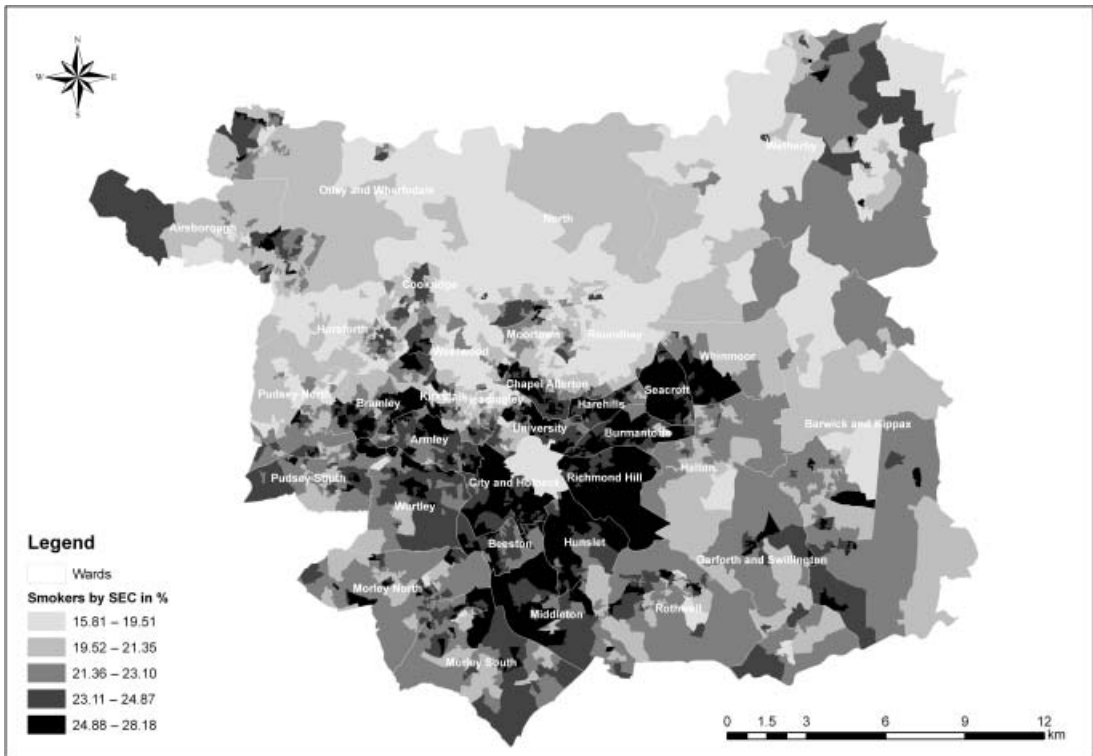


Figure 2 Smoking rates estimated using socio-economic group for Leeds Output Areas (2006)

as the validation variables are more difficult to model. The criteria were successfully met in this application. More detail of the microsimulation methodology appears elsewhere (Ballas *et al.* 2005; Clarke 1996; Smith *et al.* in press).

Figure 3 shows the estimates of smoking from the microsimulation (based on a combination of age, sex, socio-economic class and ethnicity). This map of smoking rates clearly picks out areas of Leeds where smoking is driven by age (student areas such as Headingley and University), social class (most of East and South Leeds) and ethnicity (low rates in some inner city areas driven by low smoking rates of Asian women). Although it is recognised that the smoking rates in Figure 3 are still only estimates, we argue that these are a substantial improvement on rates estimated using only one variable.

Market penetration analysis of stop smoking services

Having estimated small-area smoking prevalence rates, the next task is to evaluate the performance

of existing stop smoking centres. Data supplied by the Leeds Primary Care Trust (PCT) showed that in October 2006 there were 51 service points in Leeds, with considerable variation in days and times of opening. For example, on a typical Monday, 11 centres were available, whereas on a Saturday there were only two centres open. Most of the facilities are located close to the city centre. There are no centres in the north at all and only two locations cover the whole north-east and eastern parts of Leeds. Planning stop smoking services is a complex task because the PCT is quite flexible as to where to set up its services and hence numerous options are available (providing suitable premises can be found). It can respond to complaints by setting up services where there are a large number of new requests for help. Hence ongoing changes can be made but in a rather haphazard way. Obviously stop smoking services will have greater success when focusing on people who wish to stop. According to The Healthy Leeds Partnership (2006), there is £2.1 million available over the next three years for smoking cessation services. Further specialised services are

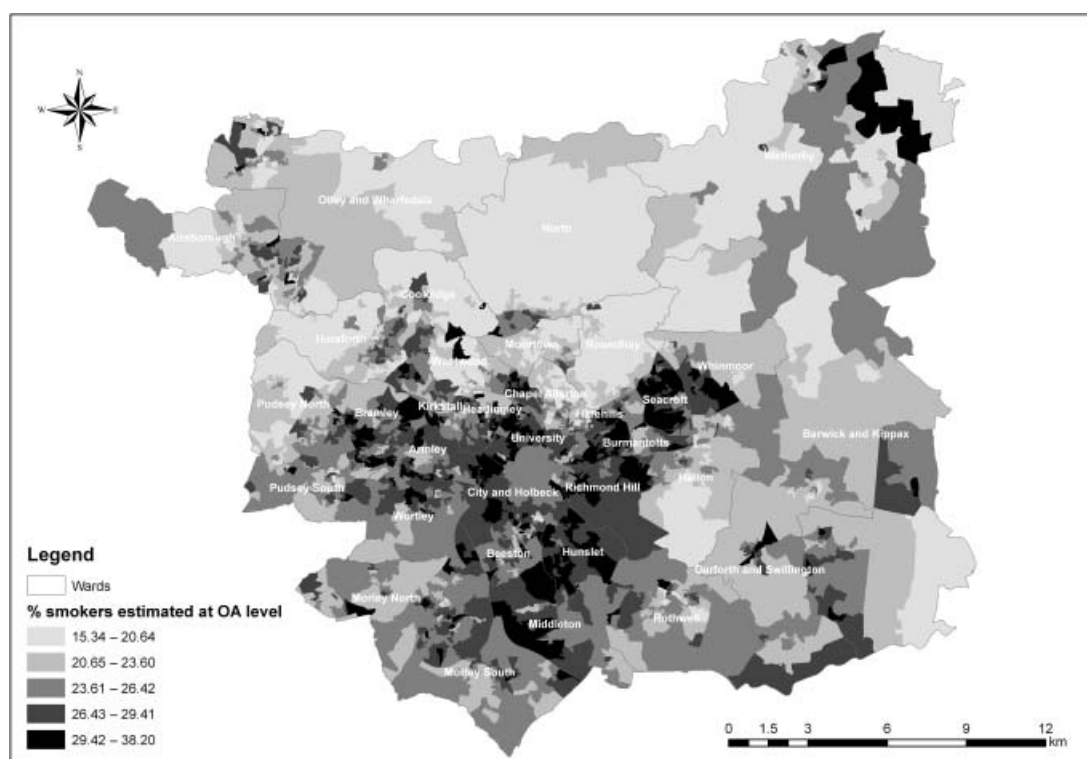


Figure 3 Estimated smoking rates for Leeds Output Areas from the spatial microsimulation

Table 1 Example of data set obtained from the Leeds PCT

1	Sex	Age	Ethnicity	Postcode	Clinic Date	Clinic Room	Time	Att?	*4 week outcome	*52 week outcome	ID No
2	2	16			29/06/2006	Stop Smoking Service 1	12 pm	No	No quit date set	No quit date set	1
3	1				29/06/2006	Stop Smoking Service 1	12 pm	No	Quit	Quit	2
4	1	42			29/06/2006	Stop Smoking Service 1	12 pm	No	No quit date set	No quit date set	3
5	2	72			29/06/2006	Stop Smoking Service 2	12 pm	No	Quit	Relapsed	4
6	1	74	White		08/03/2006	Stop Smoking Service 2	5:30 pm	Yes	Lost	Lost	5
7	1	37	White		26/04/2006	Stop Smoking Service 3	5:30 pm	Yes	Lost	Lost	6
8	2	35	White		08/03/2006	Stop Smoking Service 3	5:30 pm	Yes	Quit	Quit	7

also available, such as services for South Asian Communities ('Tambakoo') or services for pregnant women ('Fresh Air Babies') to encourage visits to stop smoking services.

Analysing areas where a high number of smokers attend any of the services is important for planning, as it is then possible to see what kind of population groups are most likely to give up and make use of a stop smoking session. Further research can then explore why people from these areas attend any particular service. For example, better media campaigns in certain areas achieve a higher attendance

at certain centres. For the analysis in this paper, data on persons who contacted one of the smoking cessation services in Leeds between October 2004 and September 2006 were obtained from the Leeds PCT at the unit postcode level. The dataset contains information on 4068 people (of whom 2394 attended a session and 1674 did not) including sex, age, ethnicity and unit postcode address. Data are available on persons actually attending a service, which centre they attended and at what time, and if they stopped smoking after 4 weeks and 52 weeks. Table 1 shows a sample of the data.

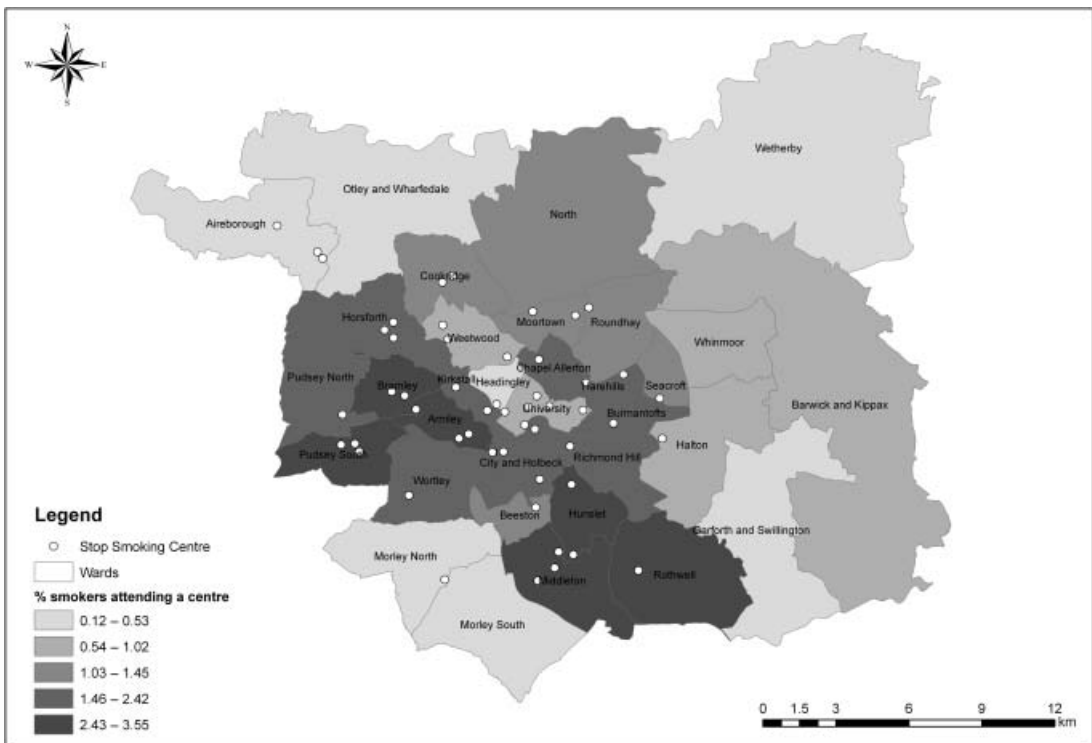


Figure 4 Market penetration of stop smoking centres in Leeds by ward

As shown above in Figure 3, our demand estimations of smokers according to sex, age, socio-economic class and ethnicity are made at Census OA level but the stop smoking centre dataset holds information at unit postcode level. Therefore it was necessary to match the data by using look up tables to see which postcode belongs to which Census OA. This information can be downloaded from UKBORDERS (http://borders.edina.ac.uk/html/lut_download/eng_pct00a.html; accessed 27 February 2007). Having information on the number of attendees for each stop smoking centre along with the OA estimations of numbers of smokers means it is possible to analyse the market share or penetration of the different centres by calculating the proportion of smokers attending a centre. As the OA level is a very fine level of spatial resolution, the data are aggregated to ward level to get a broader picture of how effective centres are. Figure 4 shows that the highest market penetration is found in the south (Rothwell, Middleton and Hunslet) and the west (Pudsey South, Bramley and Armley) and the lowest market penetration in the centre of Leeds (Headingley) and the north-east (Garforth and Swillington).

A corresponding analysis can be completed for people who contacted any of the stop smoking services but did not actually attend ($n = 1674$) (Figure 5). It can be seen that Beeston, Middleton and Hunslet in the South and Burmantofts in the centre of Leeds have the highest number of people who contacted a service but did not show up. However, three stop smoking services are located in Middleton, two in Hunslet, one in Beeston and one in Burmantofts, so people should be aware of these services nearby. The actual reason for not turning up is not known and in-depth research is needed to understand this. Reasons could include the opening hours or the day the service operates. Barriers such as language problems for immigrant populations could be another possible reason. Interestingly, in terms of future provision, it was found that most people attended sessions from 6 pm onwards, which shows the importance of timing sessions outside main working hours. Also of interest are that women were more likely to attend a stop smoking session than men and that people in the age group 30–44 were most likely to attend any of the services.

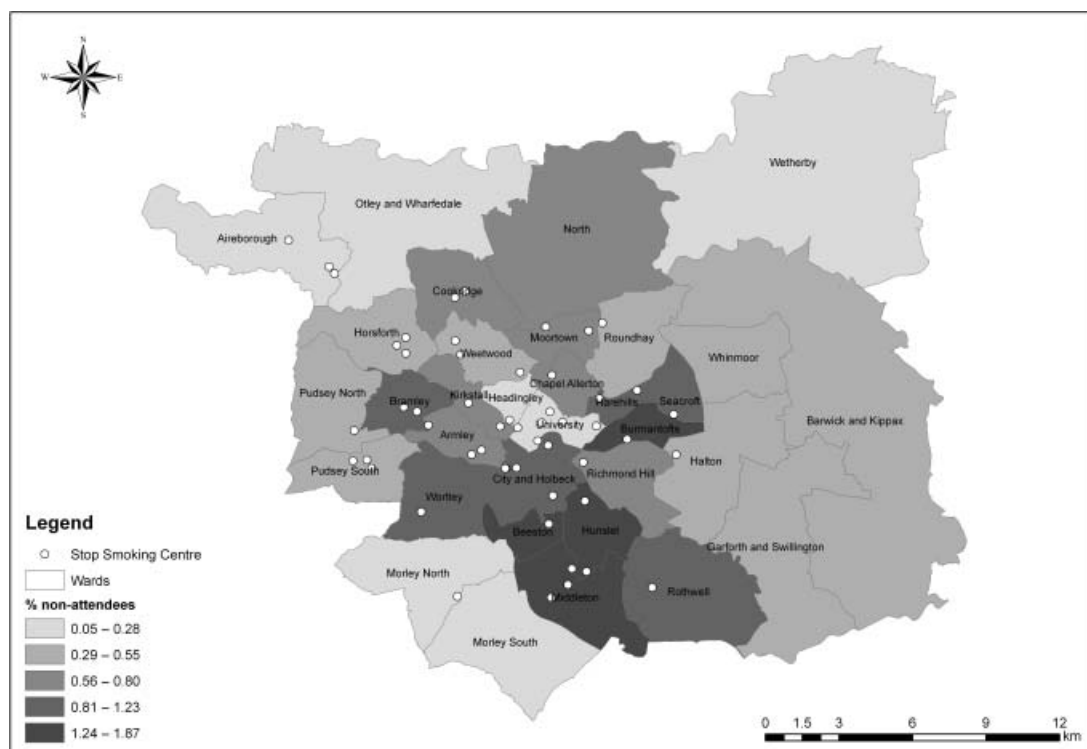


Figure 5 Proportion of estimated smokers who booked an appointment and failed to attend

Analysing individual centres gives useful information on different catchment area sizes. Figure 6 shows the results for Seacroft Hospital in East Leeds. The map shows a wide catchment area for the centre, highlighting that Seacroft Hospital is one of the centres with the highest attendance records. Figure 6 highlights high attendance in relation to smokers in Seacroft itself (where the centre is located) and in Richmond Hill and Burmantofts, which are adjacent wards. High attendance can also be seen from the north-east and eastern part of Leeds, where no centre was located at the time of the analysis. Such market analysis can help health planners target areas where current penetration of the smoking community is low.

Optimally locating stop smoking services

Location-allocation models are a tried and tested modelling technique for locating facilities in the best possible way given the location of demand. With such models it is possible to understand complex relationships between access and facility location

and variations over space and time (Nemet and Bailey 2000). Most models assume a person will be allocated to his/her nearest facility, so the objective is then to minimise total travel cost or distance for all persons. The most common location model is called the *p-median model* and was first defined by Hakimi (1964), where a set of constraints are defined and each demand site (here the number of smokers at OA level) is allocated to only one facility (stop smoking centre) so that all service needs are met. If the interest lies in locating facilities to cover a set of demand sites within a defined travel distance or time, then the *location set covering problem (LSCP)* is the most appropriate (Toregas et al. 1971). The *maximal covering problem (MCP)* uses elements of the *p-median* problem and the LSCP to locate a number of facilities within a set of supply sites (Church and ReVelle 1974). This should maximise the number of people obtaining a certain service and it is mainly used for emergency service facilities. For more information on location-allocation and healthcare planning see Hodgson (1988), Ross et al. (1994) and Møller-Jensen and Kofie (2001).

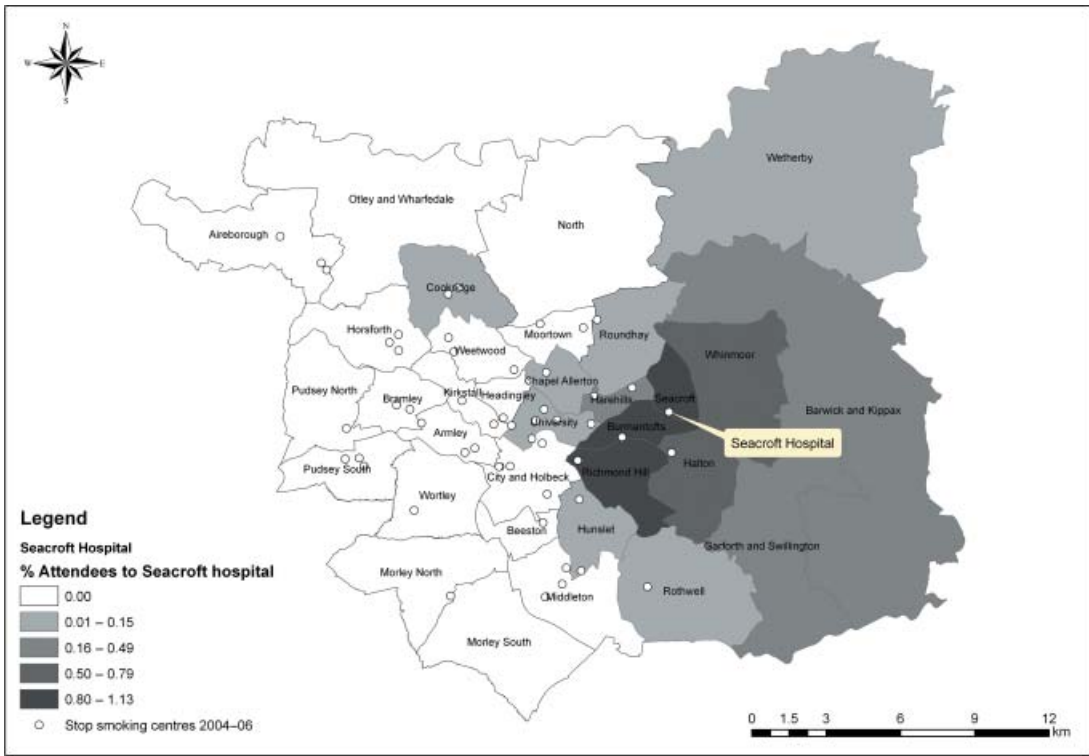


Figure 6 Catchment area for the attendees at Seacroft Hospital

The method to be adopted here is the p-median problem as the focus is to minimise total distance travelled (the further away the service, generally the lower the uptake), emphasising the importance of geography or distance-decay effects. In reality, when people cannot access certain facilities, utilisation is normally lower. Studies have highlighted that distance between home/work and medical centres influences the number of health visits and people sometimes do not go to primary healthcare centres even though they actually need to visit them (Carr-Hill *et al.* 1997; Haynes and Bentham 1982; Nemet and Bailey 2000). Demographic and socio-economic factors strongly influence the access to a health service: for instance, people with low incomes and no cars are more dependent on public transport, which is often poor away from key arterial routes. This is especially crucial for young people with low or no income or for the elderly, more immobile population. Therefore, disadvantaged groups often make less frequent visits to facility locations.

To solve the p-median problem the following data are required:

- Number of demand sites (number of estimated smokers in each OA).
- Number of possible supply sites (number of stop smoking centres).
- Distance, time or cost of travel from each demand site to each potential supply site.
- Number of new facilities to open.

The p-median problem can be written as follows (Cromley and McLafferty 2002):

Objective function:

$$\text{Minimise } Z = \sum_{i \in I} \sum_{j \in J} a_i d_{ij} x_{ij} \quad (1)$$

Subject to the constraints:

- An individual demand site must be assigned to a facility $x_{ij} \leq x_{ji}$ for all (i, j)
- Demand must be assigned to an open facility $\sum_{j \in J} X_{ij} = 1$ for all i
- Exactly p facilities must be located $\sum_{j \in J} X_{jj} = p$ for all j
- All demand from an individual demand site is assigned to only one facility $x_{ij} = (0, 1)$ for all (i, j)

Table 2 Location-allocation results for each day of a typical week (figures are rounded)

	Longest distance one has to travel to the nearest centre (km)	Average distance (km)	% of smokers who need to travel further than 5 km
<i>Monday</i>			
11 existing centres	7.8	2.4	23.6
11 'optimal' centres	1.6	3.0	3.9
<i>Tuesday</i>			
19 existing centres	11.0	2.1	13.8
19 'optimal' centres	10.0	2.6	0.4
<i>Wednesday</i>			
15 existing centres	5.5	2.3	27.8
15 'optimal' centres	2.5	2.9	2.6
<i>Thursday</i>			
15 existing centres	11.0	2.1	23.0
15 'optimal' centres	2.5	2.9	2.6
<i>Friday</i>			
9 existing centres	11.0	2.5	39.3
9 'optimal' centres	10.5	3.1	9.4
<i>Saturday</i>			
2 existing centres	10.6	2.9	76.1
2 'optimal' centres	1.9	3.4	53.0

where:

Z is the objective function (see equation 1)

I is the set of demand areas and the subscript i is an index denoting a particular demand area

J is the set of candidate facility sites and the subscript j is an index denoting a particular facility site

a_i is the number of people at demand site i

d_{ij} is the distance or time (travel cost) separating place i from candidate facility site j

x_{ij} is 1 if demand at place i is assigned to a facility opened at site j or 0 if demand at place i is not assigned to that site

p is the number of facilities to be located.

For the location-allocation model there are various ways to calculate distance. The easiest and computationally fastest is the *Euclidean distance*, which calculates the route from one point to another as a straight line, whereas road networks reflect real travel patterns more closely. Hence a road network was implemented where OS Meridian 2 data were downloaded from Digimap with the scale 1:50 000 (<http://digimap2.edina.ac.uk/downloader/Downloader?tab=0>; accessed 16 January 2007) and a road network was built within a GIS. Church and Sorensen (1996) point out that there are two basic approaches to solve the p-median model: optimal and heuristic.

Optimal techniques would take a high amount of computation time for larger datasets and hence mostly heuristic processes are used to obtain reasonable results. Heuristics are algorithms that work faster when working with large datasets by providing a result close to the 'optimal' result but do not guarantee that the best result will be found. The first heuristic for the p-median problem was developed by Teitz and Bart and other heuristics followed, such as genetic algorithms, simulated annealing, TABU search, GRASP, hybrids and GRIA (Global-Regional Interchange Approach). The two heuristics Teitz and Bart and GRIA were embedded into ESRI's network module developed for ArcInfo7.0 (for more detail see Church and Sorensen 1996) and for this work GRIA was chosen (which is the predefined command).

In October 2006, 51 stop smoking services were run between Monday and Saturday at different times of the day. The following analysis is based on such a typical week. Table 2 shows the overall results of comparing the results from the location-allocation model (optimal sites) with the actual sites chosen by the healthcare planners on each day of the week. The summary indicator chosen is the number of smokers that have to travel more than 5 km to reach a service location. The demand population in the model is the number of smokers estimated through

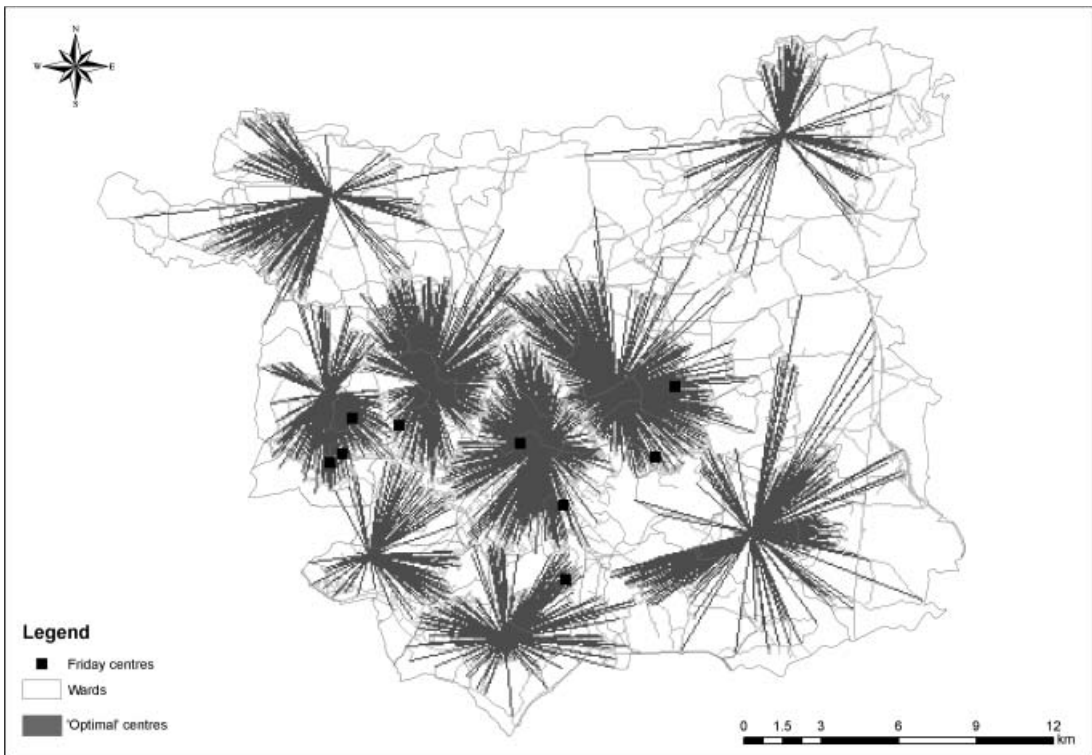


Figure 7 Nine actual centres (black squares) compared with nine 'optimal' centres (centre of spider plot) on a typical Friday

the microsimulation model for Leeds OAs. ESRI's ArcInfo Workstation is used to construct the location-allocation model. The results of scenarios for each day are shown in Table 2.

It can be seen that the 'optimal' locations reduce the travel distance for smokers on all days. The best reduction can be seen on Friday, where 30 per cent more smokers could be reached. Figure 7 shows the results of the scenario mapped for Friday using ArcInfo. The results are shown as spider maps, where the centre of the spider is the 'optimal' location for a stop smoking service and the legs of the spider show the area it covers. The black squares show the nine current stop smoking centres, whereas the centre point of the grey spiders show the 'optimal' locations and the grey lines indicate the area that is covered by a particular centre. The light grey lines beneath the spider plots show the road network and dark grey boundaries are the ward boundaries (for better orientation). It can be seen that currently the centres available every Friday are quite clustered in the western part of Leeds and no sessions are available

in the north and east at all on that day. Here the model locates one centre in each of the north-east, north-west, east and south, and two in central Leeds where there are no centres. Only three of the current centres are near optimally modelled locations. The results from the nine existing Friday centres show that 39 per cent of the smoking population would need to travel more than 5 km to access their nearest stop smoking service, whereas the outcome from the location-allocation model reduces this to 9 per cent.

Table 2 shows that the 19 centres open on a Tuesday in comparison to the weekend, when no sessions are running on a Sunday and only two on a Saturday. Therefore it would be beneficial to move some sessions to the weekend. These results should be a starting point for healthcare planners to redistribute the centres in a more efficient way, although more criteria need to be taken into account, such as varied opening times of services, and people's willingness to give up. Discussions with Leeds PCT are now on-going in relation to future service provision.

Discussion and conclusion

The results above show the importance of estimating smoking prevalence at small areas to help tackle health inequalities and to locate services more efficiently and effectively. A preliminary analysis of the smoking prevalence for different demographic and socio-economic variables was shown at the start of the paper. This analysis showed that there is a need to combine these variables (as each variable on its own showed different spatial patterns) and for this purpose microsimulation is a useful and powerful methodology.

Mapping the market penetration of stop smoking centres is useful to identify areas with relatively high rates of attendance and it helps to identify elements of performance relating to target numbers. Areas with low attendance could be the result of individuals facing problems accessing the service. More in-depth analysis about the reasons for non-attendance is suggested.

Finding the best locations for stop smoking services is crucial to meet the national targets in relation to lower smoking rates. Location-allocation models are a useful tool as numerous scenarios can be created. Here, the present versus the optimal locations on a specific day were modelled and average distance travelled was calculated and expressed as the number of smokers that have to travel further than 5 km to reach stop smoking services. Clearly, if health planners felt that in the future 5 km was too far to travel, then this could be reduced and the accessibility scores re-calculated.

One has to keep in mind that the small-area smoking rates used in this paper are only estimates and that it is not possible to construct the real smoking population without extensive data collection. Only the people aged 16–74 were modelled, which hides a certain proportion of smokers. Further, the PCT has to face certain constraints, including focusing only on particular deprived areas or they do not get any premises for their services. This makes it difficult to distribute centres more equally or probably efficiently. The location-allocation analysis here is based on people travelling from their home to their nearest centre, which means people travelling from their workplace to a centre are not captured.

Future work will involve policymakers in the development of new scenarios. For example, there is interest in targeting specific population groups such as women aged 30–44 (as the statistics show they are the group most likely to quit) or to target

different ethnic groups (such as Bangladeshi men, as they have a very high smoking prevalence). Also the time of the day could be modelled to see the potential impacts on changing opening times, and the travel patterns of those that rely on public transport could be more explicitly addressed in the network analysis part of the location-allocation models. Finally, other ‘what if’ modelling scenarios could give supporting information for policymakers and healthcare planners in the future. These might include forecasting smoking patterns based on previous trends and updating the population base through modelling births, deaths and migrations. Further interest lies in the impacts of the smoking ban in public places which came into force in July 2007. The impacts in Leeds could be modelled by using data/trends seen in other areas which have witnessed such a ban earlier than England (such as Ireland and Scotland). Additional ‘what if’ policy scenarios can include the impacts of media campaigns or tax increases on the smoking population in England.

The combination of microsimulation and location-allocation models in this paper showed the power of the analyses to support decisionmakers and it is the first time that such analyses have been applied. The findings of this research will hopefully lead to a new approach to targeting smokers in Leeds and allow centre locations to be found that should help to decrease inequalities of access for different population groups and in turn reduce health inequalities.

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