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Evaluating the potential of agent-based modelling to capture consumer grocery retail store choice behaviours

Charlotte Sturley
Leeds Institute for Data Analytics, Level 11 Worsley Building, University of Leeds, Clarendon Way, Leeds, LS2 9NL, UK.
C.E.Sturley@leeds.ac.uk, 0113 343 9680

Andy Newing*,
Centre for Spatial Analysis and Policy, School of Geography, University of Leeds, LS2 9JT, UK,
Consumer Data Research Centre, University of Leeds, LS2 9JT, UK.
a.newing@leeds.ac.uk, 0113 343 6720

Alison Heppenstall,
Centre for Spatial Analysis and Policy, School of Geography, University of Leeds, LS2 9JT, UK.
a.j.hepenstall@leeds.ac.uk, 0113 343 3361

*Corresponding author

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Abstract

Evolving consumer behaviours with regards to store and channel choice, shopping frequency, shopping mission and spending heighten the need for robust spatial modelling tools for use within retail analytics. The UK groceries retail sector has traditionally been at the forefront of applied retail modelling through sustained research and innovation, in-part via collaboration with academia. In this paper we report on collaboration with a major UK grocery retailer in order to assess the feasibility of modelling consumer store choice behaviours at the level of the individual consumer. We benefit from very rare access to our collaborating retailers' customer data which we use to develop a proof-of-concept agent-based model (ABM).

Utilising our collaborating retailers' loyalty card database, we extract key consumer behaviours in relation to shopping frequency, mission, store choice and spending. We build these observed behaviours into our ABM, based on a simplified urban environment, calibrated and validated against observed consumer data. Our ABM is able to capture key spatiotemporal drivers of consumer store-choice behaviour at the individual level. This could offer considerable enhancement to traditionally-applied spatial interaction models (SIMs) which, even after considerable disaggregation, cannot fully capture the complex and individualised spatiotemporal drivers of shopping mission and store choice.

Our findings could afford new opportunities for spatial modelling within the retail sector, enabling the complexity of consumer behaviours to be captured and simulated within a novel modelling framework. We reflect on further model development required for use in a commercial context for location-based decision making for store revenue estimation and impact assessment. We strongly assert that changing consumer behaviours, coupled with the growing availability of individual-level consumer data, creates a unique opportunity for a 'step change' in retail modelling.

Keywords: agent-based modelling; grocery retail; consumer behaviour; spatial interaction model; store choice

Introduction

The UK groceries (food, drink and household goods) sector is at the forefront of applied spatial modelling in retailing following sustained investment in model development, calibration and application, often in collaboration with academia (Davies and Rogers 1984; Wrigley 1988; Birkin, Clarke and Clarke 2010; Birkin, Clarke and Clarke 2017). The spatial interaction model (SIM) has a crucial role as a robust retail location model, enabling retailers to predict store revenues, identify retailer market shares and assess the modelled impacts of demand and supply side changes (Wilson 2010; Reynolds and Wood 2010; Birkin, Clarke and Clarke 2010). The willingness of senior decision makers to make multi-million pound strategic investments (for example new store construction) using insights derived from these models highlights a long-held business confidence in their accuracy at capturing consumer behaviours (Birkin, Clarke and Clarke 2010; Wood and Reynolds 2011). The habitual and thus predictable nature of consumer behaviours in respect of their regular weekly food shop (for which consumers traditionally exhibited considerable routine and brand loyalty) (Wood and Browne 2007) enabled model builders to calibrate these models such that they demonstrated excellent predictive accuracy - typically predicting new store revenues to within +/- 10% of subsequent observed store performance (Birkin, Clarke and Clarke 2010).

Preferences towards more frequent ‘top up’ shopping and a convenience culture have fundamentally altered consumers’ store choice behaviours (Wrigley et al. 2012; Hood, Clarke and Clarke 2015; Smithers 2015; Clarke et al. 2006; Jackson et al. 2006). These changes present challenges for retail analytics, particularly the calibration and application of SIMs. Progress has been made in disaggregating SIMs to capture more complex representations of demand and supply (for example incorporating e-commerce, discount stores and grocery convenience retailing), but the aggregate nature of SIMs may limit their ability to capture some of the increasingly complex, individualised and less habitual consumer behaviours.

Moving from simulating at the aggregate to the individual level could afford considerable potential in capturing and modelling these more complex and individualised consumer store choice behaviours. We demonstrate that individual-based modelling approaches such as agent-based models (ABMs) could enable the development of a retail modelling framework which incorporates the spatial and temporal components of individualised store choice behaviours in a robust fashion. ABMs have been used to model a range of geographical systems such as riots (Torrens and McDaniel 2013), residential location (Benenson, Omer and Hatna 2002) and crime (Malleson et al. 2013), generating new insights into the consequences of individual decisions and behaviours. Within retail, there are few published examples, primarily due to the lack of access to consumer data (Heppenstall, Evans and Birkin 2007; Heppenstall et al. 2013). However, with the recent proliferation of ‘big data’ generating novel insights on individual behaviour and preferences (for example, loyalty card data and social media data, see Mayer-Schonberger and Cukier (2013) for a range of examples), individual-based methods offer the prospect of an artificial laboratory within which we can capture and simulate the more nuanced and individualised components of consumer behaviour.

This study assesses the feasibility of refining and enhancing models of consumer interaction using an ABM framework. Specifically, we assess the potential of ABMs to capture and simulate the individual level consumer behaviours which drive store and channel choice, shopping frequency, shopping mission and spend. The research reported in this paper has been carried out in conjunction with a major UK grocery retailer, enabling us to benefit from very rare access to customer level data derived from their loyalty card scheme.

In the following sections we briefly outline the role of SIMs as a location-based decision making tool in the retail sector and explore the potential enhancements afforded by ABMs within this context. We outline the steps taken to build and test a proof-of-concept ABM to capture key aspects of consumer store choice behaviours. This includes a classification of our collaborating retailers' loyalty card consumers based on their observed behaviours. We assess the potential benefits of ABMs in modelling these behaviours and critically reflect on the model developments that are required to operationalise our proof-of-concept ABM in a commercial context.

Spatial interaction for capturing changing consumer store choice behaviours

Spatial interaction models (SIMs) estimate flows (e.g. of people, goods or money) between origins and destinations. They are an important tool for analysing, explaining and predicting aggregate level flows over space within geography, transport planning and regional science (Birkin, Clarke and Clarke 2010). Applications include modelling commuter flows (Lloyd, Shuttleworth and Catney 2007), education provision (Harland 2008), migration (Dennett 2010) and retail location-based decision making (Birkin, Clarke and Clarke 2010). When applied as a retail location model, flows are determined by the volume of demand in a given small-area origin, the attractiveness of the retail 'destination' (often using floorspace and brand as a proxy), the 'cost' of interaction (distance or travel time are commonly employed) and the level of competition (Birkin and Clarke 1991).

SIMs have proved incredibly effective at capturing consumers' grocery shopping behaviours. Consumers have traditionally exhibited considerable routine in the characteristics of their spatial and temporal store choice behaviours, often undertaking their weekly food shop at the same store, on a consistent day of the week and often at a similar time of the day on a week-by-week basis (East et al. 1994). The routine and habitualised nature of these behaviours (which were particularly evident between the 1980s and early 2000s) suited the demand and supply side representation within the SIM, predominantly modelling a single trip from a residential origin to a proximate supermarket. As noted above, changing consumer store and channel choice behaviours resulting from the growth of convenience grocery retailing (Hood, Clarke and Clarke 2015), the strongly performing discount sector (Thompson et al. 2012) and accelerating uptake of e-commerce (Clarke, Thompson and Birkin 2015) are driving more complex consumer interactions with the supply side. There is evidence of a tendency for consumers to shop more frequently and at a broader range of stores. Many consumers are not planning ahead beyond the next few meals, thus shopping little and often, exhibiting increasingly complex spatiotemporal behaviours and undertaking grocery shopping as part of multi-purpose trips related to commuting, leisure or education (Berry et al. 2016; Waddington et al. 2017; Adcock 2016; Freedman; Hood, Clarke and Clarke 2015).

These behaviours and the subsequent slow-down in large-format store development programmes by many of the major retailers has changed the nature of store location-based decision making in the grocery sector. There is a focus on the growth of smaller format convenience stores, the siting of 'click and collect' facilities (as part of a drive to integrate e-commerce within a physical store estate) and network rationalisation programmes (which may include store refurbishments, relocations, or closures) (Reynolds and Wood 2010). Reynolds and Wood (2010) report that many retailers are placing less emphasis on the SIM for making some of these contemporary location-based decisions because its aggregate nature cannot capture the complex dynamics of these consumer interactions, which may not be driven by 'traditional' indicators of store attractiveness or proximity to their residential origin.

There is evidence that retailers are resorting to use of less sophisticated tools and techniques to supplement the predictions generated by their SIMs (Wood and Browne 2007). These approaches include analogues (comparisons) with existing stores which may have similar location-based or trading characteristics, relying on analysts' knowledge of the store estate in order to select appropriate analogous stores. This is particularly prominent for their convenience store estate (Wood and Browne 2007; Hood, Clarke and Clarke 2015) where consumer behaviours are less habitual and store choice decisions are complex and based on micro-location of the store relative to key drivers of demand such as workplaces, transport interchanges or other high footfall locations, which may not be captured within the SIM.

Whilst success has been achieved in model disaggregation to capture some demand side spatiotemporal behaviours (Newing, Clarke and Clarke 2014; Berry et al. 2016; Waddington et al. 2017) or the supply side dynamics of the discount, convenience or e-commerce sectors (Hood, Clarke and Clarke 2015; Clarke, Thompson and Birkin 2015; Thompson et al. 2012), these disaggregate SIMs struggled to fully capture the more nuanced and individualised nature of consumers' complex spatiotemporal behaviours. Parallel developments in the availability of near real-time consumer data capturing these behaviours (at the individual level) affords considerable potential for retail modelling. These data include those collected following the widespread introduction of loyalty cards by the major grocery retailers (see Burt, Sparks and Teller 2010).

These sources can provide considerable insight into complex and nuanced spatiotemporal store choice behaviours at the level of an individual loyalty card holder, including indicators of how frequently they visit a given store, the time of the day and day of the week that they typically shop, how much they spend, how far they have travelled (relative to a registered home address), and how they combine different store formats and channels (supermarket, convenience or online). These are crucial indicators which can support spatial model building and calibration. More recently, novel data sources capturing other forms of personal mobility and spatiotemporal behaviours (such as social media data, geo-located mobile phone positioning data or data collected from sensors [e.g. footfall] in urban areas) may provide further insights into spatiotemporal behaviours (Lovelace et al. 2015; Malleson and Birkin 2012, 2014) with implications for retail model building and calibration. Within this paper we draw exclusively on loyalty card data but return to these more recent novel sources in our discussion. In the following section we introduce agent-based modelling as a tool which could support individual-level modelling in a retail context.

Agent-based modelling

50 years ago, geographers were reliant on aggregate level data sets to inform their insights and theories. With the gradual increase in 'big data', including both traditional data sets such as national Censuses and more novel types, e.g. social media and mobile phone data (Crooks et al. 2016), new understanding and insights are being generated. Simulating the impact of individual decisions has become far more tangible than ever. This shift from aggregate to individual-level modelling has been compounded by the appearance of novel approaches from the computational sciences, most notably agent-based modelling (ABM). ABM is a methodology that places the individual at the centre of the simulation process. Heterogeneous individuals with bespoke rule sets are created, placed within an environment and given control over both their own decisions and interactions with other individuals (Crooks and Heppenstall 2012). This 'bottom-up' approach enables the exploration of system processes from the local (e.g. neighbourhood) to global (e.g. city).

Figure 1 shows the structure of a simple ABM. Here an agent (in this case a consumer) is given 'life-stage' attributes of age, sex, wealth and education. This is drawn from quantitative data such as the UK Censuses. Any number of characteristics could be used depending on the application, as well as any appropriate data set. Attitudes or behavioural characteristics are drawn from more qualitative data sources, such as surveys or interviews. Bringing together these seemingly disparate data sources results in a more holistic view of the individual and their likely decisions than previous methods have been able to achieve.

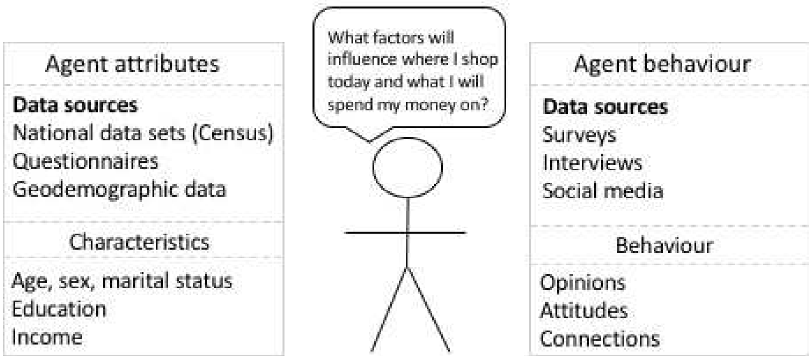

Figure 1: Schematic illustrating how agent attributes and behaviours can be constructed from different types of data.

Whilst ABM has enjoyed great popularity in the geographical sciences, with applications as diverse as crime modelling (Malleson, Heppenstall and See 2010) and traffic simulation (Manley et al. 2014), there are few examples of the application of ABM in retail. In an outline of the principal site evaluation tools and techniques presented by Wood and Reynolds (2011), drawn from interviews with location planners and their managers within UK retailers, the potential of ABMs is not mentioned. One of the earliest examples of ABM being applied to spatial retail markets is that of Heppenstall, Evans and Birkin (2005). Here an ABM was used to simulate the retail petrol (gasoline) market, in which individual petrol stations were given their own pricing rules (based on numerical analysis of data and interviews with managers). Petrol prices were determined by each station and determined reactively based on factors such as local competition and global factors such as the price of oil. Due to an absence of individual-level consumer data, consumer behaviour was simulated at an aggregate level using a SIM to determine which petrol station would be visited. Through the availability of a unique consumer data set at the individual level, the work within this paper advances on the work of Heppenstall, Evans and Birkin (2005) by creating individual consumers and simulating both their individual behaviours and their impacts on the supply side. The only other notable example of published work in this area is that of Vanhaverbeke and Macharis (2011). Here, an ABM was used to study consumer mobility, in particular the impact of commuting behaviour on consumer store choice. However, their model was not based on real-world data.

Clearly, ABM has vast potential for use in simulating behaviour in retail markets. Unlike 'traditional' statistical methods such as SIMs, ABM can represent individual decisions and preferences. Important behaviours, such as daily routine can also be embedded into each agent, creating a more realistic picture of individual movements, and thus store selection. However, creating individuals with their own characteristics and rule sets (that will drive their behaviour) comes at a very heavy data cost. The recent proliferation in big micro data has provided an opportunity for these models to be robustly calibrated and validated, however work within this area is still lacking and provides a considerable challenge for the modeller, as we address below. In the following sections we introduce a consumer-level dataset from our collaborating retailer and outline the development of our proof-of-concept ABM.

Extracting consumer behaviours

One of the crucial aspects of creating an ABM is getting the behaviour right. To do this, we explore a customer level dataset provided by our collaborating retailer and derived from their loyalty card scheme. We use these data to summarise the complex and individualised consumer store choice behaviours exhibited. We classify consumers according to those behaviours which then inform a series of 'rules' for application in our ABM. Our collaborating retailer (who wishes to remain anonymous) is a major player in the UK grocery market and operates a full range of store types and formats, including an online groceries operation.

<u>Exploring the loyalty card data</u>

Our collaborating retailer has provided data derived from their loyalty card transaction database relating to 348 customers with a home address in the Leeds local government area, capturing their store-choice behaviours over a 2 month period. Due to the commercially sensitive nature of these data, and data protection constraints restricting sharing of individual level data, the data used in this analysis have been simulated by our collaborating retailer. The simulated data are identical in format to the data our collaborating retailer routinely collect and reflects the range of consumer store choice behaviours that they wish to capture in an individual-level model. The simulated dataset has been created by our collaborating retailer specifically for our use. They have used genuine customer data and manually checked each record to ensure that it is representative of their typical loyalty card data. Leeds is a major UK city and was chosen as a demonstrator study area given the variety of store formats operated by our collaborating retailer in this area (large format, new build, major transport interchange, city-centre, suburban etc.).

The dataset contains records for ~4,000 transactions, capturing the store and channel (in-store and online) used and the date and time of the transaction. Orders placed online for home delivery or customer collection ('click and collect') represent less than 2% of the transactions within this dataset. In our subsequent discussion and model-building we consider only in-store transactions, where consumer store choice behaviours are driven by a well-understood range of factors (store size, store location etc.). The data contain an indicator of the transaction value and number of items purchased using a series of categories (low, low-med, med-high, high), preserving the commercial sensitivities within these data. Each transaction was attributed to an individual consumer and linked to the Lower Super Output Area (LSOA) for their residential location (registered loyalty card address). LSOAs represent a small area administrative geography in England and Wales used for dissemination of area based statistics. They have a mean usual resident population of around 1,500 and are commonly used for retail analytics, enabling us to append additional area-based population statistics from the 2011 Census of Population and Housing.

Using these data we derived a series of indicators summarising store choice behaviours at the level of the individual consumer (Table 1) with regard to the range and type of stores visited, frequency of visit, time of the day, shopping mission and distance travelled. We evaluated a broader range of potential indicators (particularly in relation to the temporal dimension and shopping mission), assessing their ability to distinguish different consumer behaviours and their correlation with one-another. We present here only those indicators which we used to classify these consumers within our database. Construction of these indicators required considerable data pre-processing and the challenges of upscaling this form of analysis to much larger and near-real time consumer transaction records should not be underestimated.

Store Choice Factor	**Indicator**	**Notes**
Frequency of visit	Total number of transactions	Derived from collaborating retailers' loyalty card data
Number of stores	Number of stores visited	
Shopping mission	Percentage of high value transactions Percentage of convenience store transactions	
Time of visit	Percentage of weekday transactions Percentage of evening transactions	
Distance	Distance to most frequently visited store	
Personal mobility	Percentage of households with no car	2011 Census variable KS404UK0002

Table 1: Derived indicators summarising individual level consumer store choice behaviours

The indicators highlighted in Table 1 capture key variations between consumers' observed behaviours. We can distinguish those customers who made numerous transactions and those that shopped less regularly, perhaps doing one weekly shop. We also distinguish between those consumers who shopped at a number of different stores versus those who tended to exhibit more habitual behaviours, shopping at only one store. An indication of the type of store visited and transaction value captures consumers' shopping missions, identifying evidence of consumers using larger supermarkets for 'top up' shopping, or more frequent use of convenience stores as an important part of their purchasing behaviours. We incorporate the proportion of high value transactions undertaken by each consumer, the distribution of which are observed to be positively skewed, indicating that the majority of customers made a small percentage of high value transactions.

Transactions were also categorised by their date and time stamp, identifying those that took place on a weekday and those at the weekend, alongside a time of the day indicator. Time of the day was categorised as morning (before midday), lunchtime (midday – 14.00), afternoon (14.00 – 17.00), early evening (17.00 – 19.00) or late evening (19.00 – 23.00). In conjunction with shopping mission these enable complex spatiotemporal store choice behaviours to be captured, such as a tendency for weekday top up shopping, larger weekly shops undertaken at the weekend, or the identification of consumers shopping from their place of work or on their commute. These consumers may have important implications for retailers in terms of store location, format, staffing, opening hours and product ranging (see Berry et al. 2016).

Extracting consumer mobilities

A measure of distance was incorporated to differentiate between customers shopping at stores close to where they live as opposed to consumers shopping at stores further from home, which may be in proximity to their place of work or study or as part of their commute. An origin-destination (O-D) matrix capturing the shortest distance (by road[1]) between consumers' residential locations and each store was derived. Consumers' residential locations were captured using the population-weighted centroid of the LSOA in which their home address falls, whilst store locations were captured using the GeoLytix OpenSupermarkets database[2]. A variety of distance measures were captured at the level of the individual consumer including distance to most frequently visited store (by number of transactions) or mean distance to all stores visited. Distance to store was also disaggregated by time of the day, type of store and shopping mission. We also incorporate the percentage of households with no car as this has been traditionally recognised as a factor known to affect a customer's ability to access stores (Clarke et al. 2006; Clarke, Eyre and Guy 2002). Car ownership (as a proxy for accessibility via private transport) is particularly important for consumers undertaking larger transactions (given the bulky and perishable nature of many grocery items) and the typical out of town locations of larger format food stores.

The final stage in this process used K-means clustering to segment these consumers based on their store-choice behaviours as captured by our 8 indicators (Table 1). In this case we sought to group consumers who exhibited similar store choice behaviours such that we could build these behaviours into our modelling framework. A detailed description of the classification process is beyond the scope of this paper, though a good overview of the process can be found in Rogerson (2015). In short, our indicators were standardised using z-scores to ensure that they were placed on the same scale of measurement and therefore carry the same weight within the clustering process. Standardisation is a common data transformation technique which rescales each variable based on its mean and standard deviation. Variables were also checked for polarity. K-means is a partitional clustering technique which groups observations (in this case individual consumers) into a pre-determined number of non-overlapping clusters. It is an iterative procedure which aims to allocate consumers to clusters which maximise variations *between* clusters and mimimise within cluster *variability*. The

[1] The Ordnance Survey Meridian 2 vector dataset was used, containing a series of road features enabling construction of an indicative road network.

[2] Geolytix 'Retail Points 2016'. Available: www.geolytix.co.uk © GeoLytix copyright and database right 2016

optimum number of clusters was determined by trialling a 5, 6, 7 and 8 cluster solution. The resultant clusters were assessed on the basis of cluster compactness and a-priori knowledge about likely consumer segments based on the individual behaviours exhibited within the loyalty card data. Through this process, a seven cluster solution was identified to offer a good spread of consumers across the clusters and conforms to our expectations in terms of broad consumer behaviours exhibited by each cluster. Our seven distinct consumer behaviours captured within our classification are summarised in Box 1.

Group 1 – High value supermarket customers
This customer group is defined by the presence of high value transactions, predominantly undertaken in the evening. There is an absence of transactions at convenience stores. The number of different stores visited by this group is below average as are the total number of transactions. Car ownership is highest amongst this group.

Group 2 – Less affluent weekday supermarket customers
Customers in this group predominantly shop in supermarkets on weekday daytimes, undertaking a low proportion of high value transactions. They are less likely to shop at convenience stores and the total number of stores visited and transactions made is low compared to other groups. Car ownership rates and the distance travelled to store is below average.

Group 3 – Convenience store customers
This customer group are defined by the presence of transactions at convenience stores. There is an absence of high value transactions amongst this group and they travel a short distance to store compared to other groups. Weekday and evening transactions are above average for this group.

Group 4 – Multiple-transaction customers travelling short distances
Customers in this group make a high number of transactions. They also tend to shop at a larger number of stores compared to other groups. The average distance travelled to store by this group is the shortest amongst all the customer groups. Weekday transactions are above average whereas high value transactions are below average.

Group 5 – Customers visiting multiple stores
This customer group is defined by a high number of different stores visited. They also make a higher than average number of transactions but these are less likely to be of high value. Car ownership is above average in the areas in which these customers live.

Group 6 – Weekend daytime customers
This customer group are defined by the absence of weekday and evening transactions. They make fewer transactions and visit fewer different stores compared to the other customer groups. High value transactions are also below average amongst this group.

Group 7 – Weekday evening customers shopping far from home
Customers in this group travel the furthest (on average) to store. There is a strong incidence of weekday and evening transactions amongst this group. The total number of transactions and number of different stores visited is below average as are high value transactions.

Box 1 – Summary of seven distinct customer groups (based on observed store choice behaviours and a census derived indicator of mobility) captured within our classification.

It is clear from Box 1 that this relatively small sample of consumers exhibit a broad range of consumer behaviours with regard to store choice, confirming some 'traditional' shopping behaviours akin to those observed by East et al. (1994) in relation to their regular weekly shop. Similarly, clusters 3 - 5 support our earlier notions regarding consumer behaviours in relation to frequent use of convenience stores for 'top up' shopping. Although not captured as distinct clusters, we also note evidence of channel blurring, with some evidence of consumers using supermarkets predominantly for smaller and more frequent 'top up' shopping (see Waddington et al. 2017), and also a propensity to use convenience stores for a larger weekly shop. The importance of personal mobility (and specifically car ownership) in influencing store choice is evident, particularly among the consumers in cluster 1. These consumers exhibit a propensity to undertake larger transactions and to utilise larger format (and predominantly out of town) stores. This is in contrast to cluster 5, whereby consumers are observed to be highly mobile, visiting multiple stores. By comparison, consumers in Group 2 exhibit lower rates of car ownership and tend to exhibit store-choice behaviours which favour routine behaviour and more limited personal mobilities, with lower transaction rates and a lower propensity to visit multiple stores.

Creating an ABM of consumer behaviour

The ABM was built using the open source modelling environment of Netlogo (Wilensky 1999). The model code can be freely downloaded via: http://tinyurl.com/ConsumerABM. Within this paper we were interested in the simulation of different types of consumer agents. The agents first populate a very simple and abstract spatial environment in order to test key behaviours of model agents (representing consumers and retail stores). Our agents subsequently populate a representation of the UK city of Leeds. As detailed below, this representation captures the diverse geodemographics and spatial pattern of store location within the city.

The ABM is populated by two types of agents: store and consumer agents, representing the supply and demand sides as captured within a traditional retail modelling framework. In the first iteration of the model, consumer agents were homogeneous containing the following basic properties: a home location (initially set randomly), a destination and a variable controlling the number of visits to a store. Stores were represented as two distinct agent types: supermarket and convenience. A convenience grocery store is conventionally defined as a store of less than 3,000 square foot sales area and is traditionally exempt from UK Sunday trading regulations which restrict stores in excess of 3,000 square foot to trading for a maximum of six hours on a Sunday. The 'convenience' (or secondary) and 'one stop' (larger supermarkets) sectors are distinct in serving different shopping missions and location types (Wrigley et al. 2009; Competition Commission 2000). It is thus important to represent this distinction in our individualised model of consumer store choice behaviours.

These variables were experimented with to check that the basic model framework was operating as expected prior to the consumer behaviour rules being embedded. Experimentation included increasing the number of store visits for each agent and placing a preference for either a supermarket or a convenience store. The store agents were programmed to record the ID of the consumer agents that have visited that store.

Consumer behaviours

Once the basic behaviours (i.e. making trips to stores) of the consumer agents had been tested, the next step involved increasing the complexity of their behaviour based on the information derived from the consumer loyalty data set. The shopping behaviours of the seven consumer groups detailed in Table 2 (drawn from Box 1) were converted into simple rules which were assigned to each agent of that type. The rules were based on the type of store, frequency of visits to a store, distance travelled, spend and time of shopping trip.

Consumer Type	**Store Type**	**Frequency**	**Time**	**Distance**	**Car ownership**	**Spend**
1	Supermarket/ Online	Low	Evening	Average	High	High
2	Supermarket	Low	Weekday daytime	Short	Low	High
3	Convenience	Average	Weekday evening	Short	Average	Low
4	Supermarket/ Convenience	Very high	Weekday	Very short	Average	Low
5	Supermarket/ Convenience	High	No preference	Average	High	Medium
6	Supermarket	Low	Weekend daytime	Average	Above Average	Medium
7	Supermarket/ Convenience	Low	Weekday evening	Long	Average	Low

Table 2: Summary of customer group characteristics

For example, an agent of consumer type 4 would operate the following rules:

```
If need food = true and weekday = true

     then travel to nearest supermarket or convenience store.
```

Whilst an agent of consumer type 6 would use the following:

```
If need food = true and weekday = false

     then travel to nearest supermarket store.
```

Store agents were assigned a spend variable which increased by a set amount each time a consumer agent visited the store. The amount spent depended on the type of store and the consumer type. From the analysis of the different consumer types, consumers in Group 1 (High value supermarket customers) spent more in store than the other customer groups. Within our proof-of-concept ABM, consumers in Group 1 were allocated a higher spend than all other consumer groups in order to reflect their observed purchasing behaviours. This enables us to demonstrate that the ABM can be used to identify store revenues resulting from consumer interactions with each store in our model. The incorporation of a notional (albeit crude) expenditure closely reflects the common application of SIMs as a location model where the objective is to predict store revenues rather than consumer patronage.

One of the key aspects where an ABM offers considerable potential is in the handling of the temporal dimension. Whilst SIMs are largely static, our ABM enables us to model a series of iterations or time steps, representing different days of the week (Monday through Sunday), with each day divided into three time periods, morning, afternoon and evening (a week thus contains 21 time steps). Each consumer type was given a probability of undertaking a shopping trip (store visit) during each modelled iteration (see Table 3). These probabilities are derived from our observed customer data and take account of the time of the day and day of the week of store visits by consumer type.

Day	**Day Part**	**Consumer Type**						
		1	**2**	**3**	**4**	**5**	**6**	**7**
Weekdays	Morning	0	50	20	90	50	0	0
Weekdays	Afternoon	0	50	20	90	50	0	0
Weekdays	Evening	75	0	75	90	50	0	40
Weekend	Morning	0	0	20	0	50	50	0
Weekend	Afternoon	0	0	20	0	50	50	0
Weekend	Evening	75	0	20	0	50	0	0

Table 3: Probabilities of undertaking a shopping trip (store visit) assigned to consumer agents by consumer type.

For those consumers undertaking a shopping trip in any given time period, the next aspect is to model is their actual store choice. This was based on the classic trade-off between store attractiveness and accessibility as captured within a SIM. Consumers' store choice was driven by the average distance travelled by that consumer type within our observed consumer data (see Table 2). Consumer agent types observed to travel the shortest distances to store (groups 2, 3, and 4) were allocated rule sets which forced them to visit their most proximate store which met their shopping mission (convenience vs. supermarket). Consumers which travel further (groups 1, 5, 6 and 7) were given the freedom to travel beyond their nearest store, again choosing a store attractive to their shopping mission.

Representing the city

For the initial testing of different consumer behaviours, a simplified environment was used with agents only having the choice of one or two stores at varying distances to choose from. Once these behaviours had been tested to ensure the basic model rules were operating as expected, the next stage increased the complexity of the spatial environment on both the demand and supply sides. Leeds was used an example city and an abstract but realistic geography of the north of the city was produced using the Office for National Statistics (ONS) Output Area Classification (OAC) (ONS 2014). The classification groups small-areas together according to key population characteristics derived from the 2011 Census in England and Wales. The 8 OAC Supergroups were mapped across Leeds (Figure 2a) and distinct areas were identified and translated into zones in the model (Figure 2b). For example, the student areas of Hyde Park and Headingley in the centre and north-west of the city (yellow patch agents), the inner city areas of Chapeltown and Harehills (blue patch agents), the deprived areas of Bramley and Seacroft (orange patch agents), the affluent suburbs of Horsforth, Chapel Allerton and Roundhay (pink patch agents) and the surrounding more rural towns and villages of Bramhope and Shadwell (green patch agents).

Our individual consumers were allocated a location within a specified part of our abstract 'city' based on the OAC Supergroup of their residential origin. Thus their location was driven by their observed characteristics, whilst their behaviours were driven by their consumer type (Box 1). The location of supermarket and convenience store agents within the model were fixed. Their locations were based on the location of our retail collaborators stores in north Leeds. In order to preserve the anonymity of our collaborating retail partner we are unable to reveal the specific locations of these stores.

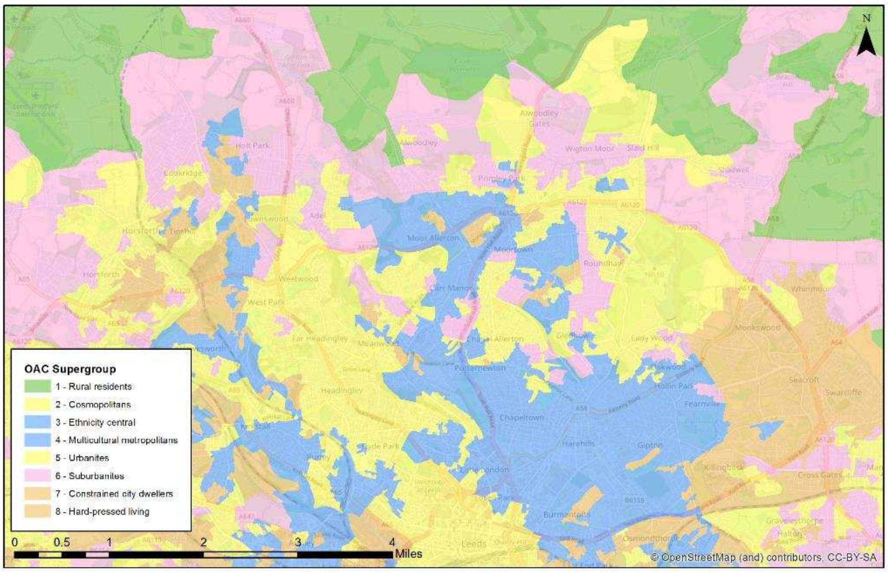

Figure 2(a): Geo-demographic map of the north Leeds area. Source: Constructed by authors using 2011 Output Area Classification (ONS 2014).

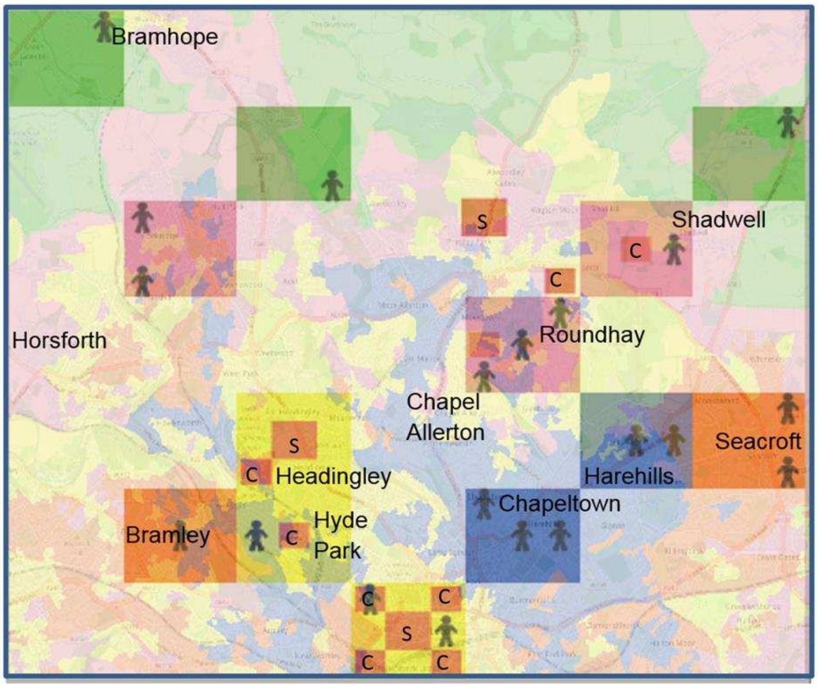

Figure 2(b): Geo-demographic map of the north Leeds area with the abstract, yet spatially realistic model environment (in Netlogo) overlaid. Store locations are indicated by red squares ('S' = supermarket and 'C' = convenience store) and people icons represent home locations.

Calibrating and testing our ABM

A number of measures were taken so that the behaviour of the consumer agents could be calibrated and validated against those observed in the customer data. The model was set up to simulate consumer behaviours over a weekly time period. Due to the element of randomness in the model, introduced by the probabilities of undertaking a store visit, the model was run multiple times to ensure greater statistical accuracy in the results. A hundred iterations of the simulation were run, for increasing numbers of agents (3, 100, 1000 of each consumer type) to check the model was robust when scaled up.

The number of visits made to a store was recorded for each consumer agent. Table 4 shows the average number of visits to a store by each consumer agent type. The relative number of store visits predicted within our model can be compared to the average number of transactions by each consumer group (a transaction generally represents a single store visit) from the observed customer data. The relative number of visits are used (rather than the actual numbers) as they cover different time periods. Consumer type 4 made the highest average number of visits to stores in the model. This is line with behaviours observed in the customer data in which this group made the largest number of transactions on average. Consumer type 5 also made a relatively high number of visits to store in the model and was the group with the second highest number of transactions in the customer data. Consumer groups 6 and 7 had the lowest number of visits to store in the model. This is also in line with the behaviours observed in the customer data in which these groups made the fewest number of transactions.

Consumer Type	**Observed (Customer Dataset)**	**Predicted (1000 agents)**
1	Medium	Medium
2	Medium	Medium
3	Medium	Medium
4	High	High
5	High	High
6	Low	Low
7	Low	Low

Table 4: Comparison of average number of visits to store by consumer type (observed and predicted data).

The average distance travelled by consumers on their visits to store was also calculated for each consumer type as an indicator of their trip making behaviours. These predicted average trip distances (ATDs) were compared to observed ATD by consumer type within our customer data. In its proof-of-concept form our ABM distance measurement (which is based on euclidean distance between consumers' residential location and their nearest store) doesn't have a metric associated with it as it is measured in an abstract model environment. This means that observed and predicted ATD cannot be directly compared in absolute terms, but their relative difference is indicative of model performance. We note that our ABM is broadly able to predict the relative distance travelled (by consumer type) in line with our observed customer data, enabling us to assess the models ability to replicate this key characteristic of consumers' trip making behaviours. Most noticeably, our ABM is able to reflect the propensity for consumers in Group 7 (Weekday evening customers shopping far from home) to exhibit the highest ATD. Our model is presently overestimating the ATD of consumers in Group 1 (relative to other consumer groups), and it may be that our model is giving too great an importance to car ownership in driving store choice behaviours for groups of consumers such as these, who exhibit a high number of transactions at larger-format stores.

During the model building stage we also loosely calibrated our ABM in relation to the day of the week and time of the day that consumers (by type) are observed to undertake their shopping trip(s), as outlined above. Following model calibration and testing we can be confident that our proof-of-concept ABM is able to replicate key characteristics of consumers store choice behaviours as captured by their frequency of visit and ATD. As we develop our proof-of-concept into a full prototype ABM it will also be possible to validate the models' ability to capture key supply side indicators of store patronage and revenues.

ABM for capturing consumer store choice behaviours

We have demonstrated the flexibility of an ABM in incorporating complex consumer interactions within a dynamic retail environment. In our proof-of-concept example we have incorporated a series of consumer behaviours as captured within our collaborating retailers' loyalty card database. We generated seven distinct consumer groups, each with associated agent 'rules', and used these to evaluate the type of store choice behaviours which could be captured in an individual-level modelling framework. We have evidenced that our model can recreate observed store choice behaviours with regards to frequency of visit, time of the day of visit and distance travelled. Thus, within our scaled down (and at times abstract) example, we have demonstrated that an ABM can capture the broad dynamics of the retail market. With increased availability of data capturing these behaviours at the individual level (and growing computational resources) it is entirely feasible to model these consumers and their unique behaviours as individual agents.

The novelty and innovation within our model is that the trade-off between attractiveness and accessibility incorporates a two-step decision making process with a crucial temporal dimension. Within each time step (time of the day and day of the week) our model first determines whether a given customer type is likely to undertake a shopping trip and, if so, identifies their broad shopping mission (large format supermarket or convenience store). Secondly, for those consumers undertaking a shopping trip, our ABM assesses the relative accessibility and attractiveness of each supply side destination (relative to their shopping mission), allocating these customers to appropriate stores. Thus, our model incorporates the key drivers of flows from within a SIM framework, with the additional benefits of capturing the temporal dimension, whilst also representing these interactions at the individual level. This enables a more complex set of store choice decision making processes to be captured, generating a truly dynamic model which incorporates key theoretical elements of the SIM, yet with far greater demand side and temporal disaggregation.

Ongoing model enhancements to move from proof-of-concept to prototype model include incorporation of a more realistic underlying geography. This will enable greater integration of retailers' existing demand and supply side datasets. Whilst our proof-of-concept is based on modelling consumer flows to only one retailer, the next phase of model development incorporates a full representation of the supply side, capturing the competition and brand attractiveness elements which are crucial in building and calibrating spatial models which reflect real consumer behaviours (e.g. see Newing, Clarke and Clarke 2014). Given the importance of the spatiotemporal dimensions in driving store choice behaviours (Newing 2013; Berry et al. 2016; Waddington et al. 2017), these represent the next demand side enhancements, incorporating consumers non-residential 'origins' at certain times of the day. These may include origins associated with workplaces or other locations visited as part of daily routines and from which interactions with the supply side can originate. The disaggregate spatial and temporal components of this model would enable these nuanced demand side features to be captured. This would generate a truly dynamic model which captures both the location and shopping mission of consumers at different times of the day and at the individual level.

Further model development will capture more sophisticated impedances by incorporating routing of consumer agents, recognising that there is an increased propensity for consumers to access grocery retail provision on foot, particularly where smaller format urban stores are in proximity to new forms of city centre residential developments or transport interchanges used by commuters. Ongoing model development focuses on alternative impedance measures, including routing of consumers on foot and by public transport. Where car-borne trade remains important (such as for larger transactions), there is also scope to improve our model's ability to capture the true cost of interaction by using a road network and road travel time data to capture store accessibility (Birkin, Clarke and Clarke 2010). An example of this is outlined in the work of Vanhaverbeke and Macharis (2011) on consumer mobility, in particular commuting behaviour.

Subsequent model enhancement will also capture the multi-channel nature of the supply side, incorporating consumer level indicators of e-retailing propensity (e.g. see Singleton et al. 2016) and adding e-commerce home delivery and click and collect channels into the models' supply side representation. In addition to the more complex nature of the demand and supply-side, incorporation of e-commerce within this modelling framework requires a more nuanced representation of interaction, recognising that the 'cost' of interaction is placed on the retailer (in the case of home delivery) or on the consumer (in the case of click and collect). Consumers' choice of home delivery vs. click and collect may itself be driven by the accessibility of collection points, availability of private transport and availability and affordability of home delivery, all of which could be captured within our modelling framework.

Our proof-of-concept model is based entirely on behaviours extracted from loyalty card data. These data enable us to capture a rich set of indicators related to a small subset of customers, with robust data on the actual stores used and their purchasing behaviours. Birkin, Clarke and Clarke (2017) highlight that these data provide considerable behavioural insight which extends well beyond those which can be derived from 'traditional' census or survey-based datasets. Whilst their use in academic research is rare, retailers (particularly those with long-established location analytics or customer insight functions) have been at the forefront of mining these data for behavioural insights (Burt, Sparks and Teller 2010; Humby, Hunt and

Phillips 2008). One crucial advantage of loyalty card data is the ability to link a given transaction to a named and geo-located consumer. Our own discussions with retailers suggest that they are investing in strengthening the role of customer insight within their businesses, developing a ‘single customer view’. This enables them to understand the behaviours and purchasing decisions of individual customers across all their store formats and channels (Giles 2015; Whitelegge 2014). Thus, retailers are increasingly equipped with the consumer level data and insights required in order to capitalise on the opportunities provided by ABMs for more nuanced and sophisticated location modelling.

Furthermore, the novel yet growing availability of non-traditional sources of data related to consumer mobilities and behaviours may afford new opportunities to enhance the development and validation of ABMs in this context. Lovelace et al. (2015), Birkin, Clarke and Clarke (2017) and Whitelegge (2014) present examples which suggest that we can track consumers movements by using new technologies such as social media data or mobile phone positioning. These could complement loyalty card data and provide a richer and more nuanced set of insights into consumer mobility and behaviour across the entire retail sector. Such data may not be restricted to customers of a particular retailer (as captured by retailer data) or be reliant on consumers actively engaging with a loyalty scheme. They could provide continuously updateable and detailed information on consumer behaviours and lifestyle preferences, movement and activity patterns and opinions and attitudes (Birkin and Malleson 2015). Notwithstanding potential ethical or privacy concerns, or issues related to the sample of consumers captured, or the considerable data cleaning and processing challenges (these issues are beyond the scope of this paper), incorporation of these data could considerably enhance our capacity to build and calibrate ABMs of consumer store choice behaviours. Model calibration and validation (in order to demonstrate the predictive capabilities of this model) are crucial stages in model building, yet present challenges in an ABM framework due to the complexity of these models and their parameters (Crooks, Castle and Batty 2008).

Whilst we acknowledge a number of data-driven enhancements which will be made to our model, we firmly believe that our proof-of-concept demonstrates considerable potential. We strongly argue that the hybrid nature of our ABM (incorporating the crucial SIM-like trade-off between accessibility and attractiveness) affords tremendous potential to capture complex consumer behaviours and support the retail location analytics process. These could enable retailers to move beyond the use of zonal origins (e.g. related to residential or workplace locations) capturing truly individualised spatiotemporal behaviours. The incorporation of near real-time data for model calibration and validation could enable us to develop a truly dynamic simulation model which is constantly re-calibrated against observed consumer behaviours captured from these data sources. Whilst this would offer a number of advantages over previously static models, development and validation of an ABM at a spatial and temporal scale suitable for retail location-based analytics would place limitations on the complexity of models. Thus the representation of agents in the model is an important consideration, ensuring that the level of abstraction and the spatiotemporal resolution and rule sets applied are sufficient for the intended purpose (Crooks, Castle and Batty 2008), and within the capabilities of the software itself (Crooks and Heppenstall 2012).

The extent to which the location planning sector possesses the skills to develop, calibrate, run and maintain these models is currently unknown. However, model development and application is one area where the academic sector offers considerable expertise. The link between academia and the grocery sector played an important role in developing early 'gravity models' into the SIMs that are widely applied today (Roy and Thill 2004; Reynolds and Wood 2010). Whilst many retailers later developed the capacity to build and calibrate these models in-house, the links with academia remain strong (Birkin, Clarke and Clarke 2010; Reynolds and Wood 2010). Burgeoning links between the consumer facing retail sector and academic expertise (such as through the Economic and Social Research Council funded Big Data Centres; notably the Consumer Data Research Centre [CDRC]) offers considerable scope for further development and calibration of our prototype model for application within a commercial context. Centres such as the CDRC may also offer a unique opportunity to capture the full complexity of consumer behaviours by acting as a 'trusted partner', enabling integration of behavioural insights captured across multiple commercial datasets (such as multiple retailers' loyalty card schemes) (see Reynolds and Wood 2010; and Birkin et al. 2014, for further discussion of the potential benefits of these forms of collaboration).

Wrigley and Lambiri (2015) suggest that we are witnessing a 'once in a generation' cultural shift in consumer shopping habits which are re-shaping the retail sector. Approaches such as agent-based modelling provide us a tool within which to capture and simulate these increasingly complex and individualised geographies of consumers' grocery shopping routines. Defacto approaches as used by the retail sector struggle to account for the full spatial and temporal range of individual behaviours and the work within this paper provides a simple proof-of-concept that offers a tantalising insight into the potential of this approach.

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