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# Geographical and Temporal Huff Model Calibration using Taxi Trajectory Data

**Shuhui Gong · John Cartlidge · Ruibin Bai⋆ · Yang Yue · Qingquan Li · Guoping Qiu**

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**Abstract** The Huff model is designed to estimate the probability of shopping centre patronage based on a shopping centre's attractiveness and the cost of a customer's travel. In this paper, we attempt to discover some general shopping trends by calibrating the Huff model in Shenzhen, China, and New York, USA, using taxi trajectory GPS data and sharing bikes GPS data. Geographical and Temporal Weighted Regression (GTWR) is used to fit the model, and calibration

⋆ corresponding author

Shuhui Gong
International Doctoral Innovation Centre, University of Nottingham Ningbo China, Ningbo, China
Department of Urban Informatics, School of Architecture and Urban Planning
Shenzhen University, Shenzhen China
E-mail: shuhui.gong@nottingham.edu.cn

John Cartlidge
Department of Computer Science, University of Bristol, UK
E-mail: john.cartlidge@bristol.ac.uk

Ruibin Bai
School of Computer Science, University of Nottingham Ningbo China.
E-mail: ruibin.bai@nottingham.edu.cn

Yang Yue
Shenzhen Key Laboratory of Spatial Smart Sensing and Services, Research Institute for Smart Cities
Department of Urban Informatics, School of Architecture and Urban Planning
Shenzhen University, Shenzhen China, 518060
E-mail: yueyang@szu.edu.cn

Qingquan Li
Shenzhen Key Laboratory of Spatial Smart Sensing and Services, Research Institute for Smart Cities
Department of Urban Informatics, School of Architecture and Urban Planning
Shenzhen University, Shenzhen China, 518060
E-mail: liqq@szu.edu.cn

Guoping qiu
School of Computer Science, University of Nottingham, Nottingham UK
E-mail: guoping.qiu@nottingham.ac.uk

results are compared with Ordinary Least Squares (OLS) regression, Geographical Weighted Regression (GWR), and Temporal Weighted Regression (TWR). Results show that GTWR gives the highest performance due to significant geographical and temporal variation in the Huff model parameters of attractiveness and travel cost. To explain the geographical variation, we use residential sales' and rental prices in Shenzhen and New York as a proxy for customers' wealth in each region. Pearson product-moment correlation results show a medium relationship between localised sales' and rental prices and the Huff model parameter of attractiveness: that is, customer wealth explains geographic sensitivity to shopping area attractiveness. To explain temporal variation, we use census data in both Shenzhen and New York to provide job profile distributions for each region as a proxy to estimate customers' spare leisure time. Regression results demonstrate that there is a significant linear relationship between the length of spare time and the parameter of shopping area attractiveness. In particular, we demonstrate that wealthy customers with *less* spare time are more sensitive to a shopping centre's attractiveness. We also discover customers' sensitivities to travel distance are related to their travel mode. In particular, people riding bikes to shopping areas care much more about trip distance compared with people who take taxi. Finally, results show a divergence in behaviours between customers in New York and Shenzhen at weekends. While customers in New York prefer to shop more locally at weekends, customers in Shenzhen care less about trip distance. We provide the GTWR calibration of the Huff model as our theoretical contribution. GTWR extends the Huff model to two dimensions (time and space), so as to analyse the differences of residents' travel behaviours in different time and locations. We also provide the discoveries of factors affecting urban travel behaviours (wealth and employment) as practical contributions that may help optimise urban transportation design. In particular, the sensitivity of residents to the attraction of shopping areas has a significant positive linear relationship with the housing price and a significant negative linear relationship with the residents' length of spare time.

**Keywords** GTWR · Huff model · shopping area analysis · shopping area's attractiveness

## 1 Introduction

The ubiquitous rise of shopping malls provides more shopping choices for customers. However, it also causes a series of issues for urban planners, such as high business competition, traffic congestion, and inefficient land use (Yue et al., 2011). To increase positive business competition, reduce traffic congestion, and improve land use efficiency, a possible countermeasure is to predict journeys to shopping areas (Bohnet and Gutsche, 2007). Previously, researchers have analysed travel behaviours to shopping areas to optimise the locations of shopping malls (Suárez-Vega et al., 2015), reduce traffic congestion (Tang et al., 2016), predict shopping demand (Cartlidge et al., 2018), and to model activity choices and spatial behaviours (Gong et al., 2019a,b). Often, shopping areas analysis is used to discover the key determinants that affect customers' spatial choices (Olsson, 1970; Southworth, 1983). By quantitatively modelling internal relationships between determinants and journeys to shopping areas, researchers are able to systematically understand travel behaviours, and ultimately, discover potential shopping demands for future urban planning.

Data, which is used to fit the model, is traditionally collected from surveys and interviews. These subjective collection methods are highly dependent on the participants' perceptions and assumptions (Suárez-Vega et al., 2015). In addition, the data collection process is labour intensive, time consuming, and costly (Gong et al., 2017). Apart from surveys and interviews, GPS data is another popular source for model calibration; with large-scale human mobility data being collected with relatively little cost (Wang et al., 2017). Previous studies on shopping areas analyses can be divided into two categories. The first category comprises *modelling*, which is used to discover influential factors of journeys to shopping areas (Yan et al., 2017). Examples include the gravity model (Huff, 1964), discrete choice model (Gracia and de Magistris, 2008), and logit model (Chu, 1989). The second category consists of the studies on model calibration. These studies increase the models' accuracy and are predicated on the fact that a model is essentially useless for either description or prediction without careful calibration (Rodrigue et al., 2013).

In this paper, Geographically and Temporally Weighted Regression (GTWR) is used to calibrate a traditional geographic model: the Huff model. The Huff model includes two attributes: a shopping centre's attractiveness, and customer's travel cost. Experiment showed that an attractive shopping mall is considered to have large area, including more requirements for a large range of goods, and is mostly located in city centres; while some people travel to relatively unattractive stores located far from city centres in order to benefit from lower prices (Yue et al., 2011). Previous research has demonstrated that shopping area size, traveller volume and customers' reviews on social media are able to represent shopping area's attractiveness with high performance (Gong et al., 2017; Gong et al., 2018). Therefore, we use three proxies (size, customer volume, and social media reviews) to estimate a shopping area's attractiveness, and use route distance to estimate travel cost. To test the generality of GTWR, we use taxi journeys in Shenzhen, and taxi journeys and sharing bikes journeys in New York to train and test the Huff model. Results demonstrate that the exponents of attractiveness, $\alpha$, and distance, $\beta$, are spatially and temporally variant.

To explain the geographical variation of parameters, we hypothesise that the values of $\alpha$ and $\beta$ are related to customers' wealth. In particular, the people who are more wealthy are more likely to: (i) select more attractive shopping areas, and (ii) travel farther to a shopping area. We test these hypotheses using two case studies in Shenzhen and New York. We collect open source house price sales' data and rental data in both Shenzhen and New York to estimate customers' wealth, and use Pearson's product-moment correlation and t-test to explore their relationship.

To explain the temporal variation of parameters, our hypothesis is: the length of people's spare time is negatively correlated to their sensitivities to attractiveness. In particular, people care more about attractiveness when they have less spare time. We estimate that the length of spare time is the length of time people do not work during the opening hours of the mall. We test the hypothesis both in Shenzhen and New York by using typical working schedules of different jobs to estimate people's time routine, and perform Pearson's product-moment correlation and t-test on two variables.

The rest of the paper is organised as follows. In Section 2, we review previous studies and state the motivation of this paper. In Section 4, the models used in the paper are introduced. In Section 5, we conduct the first case study, using Shenzhen taxi data to calibrate the Huff model. We use house price data (including house sales' data and rental data) and population census data to explain the spatial and temporal variation of parameters in the Huff model for Shenzhen. In Section 6, we conduct the second case study, using taxi data and sharing bikes data in New York to calibrate the Huff model. We use house price and people's spare time in New York to explain the variation of parameter $\alpha$ in the Huff model, and compare the results with Shenzhen taxi data. Finally, Section 7 concludes.

## 2 Literature review

First introduced in 1964, the Huff model is one of the most widely used models for shopping areas analyses (Huff, 1964). Following simple gravity assumptions, the Huff model estimates the probability of shopping centre patronage based on two factors: a shopping area's attractiveness and the passenger's cost of travel. Generally, an attractive store can be quantified by factors such as a shopping mall's size, the traveller volume (number of visits to the shopping area), and customers' reviews on social media platforms. Travel cost is often represented by travel route distance (Yue et al., 2012) or Euclidean distance (Brunsdon et al., 1996). Gong et al. (2017); Gong et al. (2018) discovered that customer volume has highest performance to estimate a shopping centre's attractiveness. Lu et al. (2014) set up a house price model and used Euclidean distance and route distance, respectively, to fit the model. The results suggested that using route distance in spatial models performs better than using Euclidean distance. In this paper, we apply the Huff model in two cities, Shenzhen and New York, to discover journeys to shopping areas in different time and locations.

Ordinary least squares (OLS) linear regression is a representative approach to unravel complex relationships (Ma et al., 2018). Nakanishi and Cooper (1974) demonstrated that the Huff model can be easily calibrated using OLS procedures. The basic assumption of OLS is that, in a model, variables are independent and spatially stationary. However, Lloyd (2010) showed the necessity and effectiveness to build regression methods for model calibration with dependent variables and non-stationary parameters. Therefore, the OLS approach is criticised for strong (and unrealistic) assumptions placed on variables and parameters. Since, according to the study by Gong et al. (2016), the two variables in the Huff model are closely related, we consider OLS insufficient to calibrate the Huff model accurately.

Alternative techniques have been proposed to overcome the drawbacks of OLS, including: distance-decay weighted regression (Gutiérrez et al., 2011), two-stage least squares regression (Estupiñán and Rodríguez, 2008), the passion model (Chu, 2004), and geographically weighted regression (GWR) (Suárez-Vega et al., 2015). Compared to other methods, GWR is specifically designed to deal with spatial data (Brunsdon et al., 1996). A weight matrix is used for each observation, such that the matrix depends on the distance between the locations of observations (Cardozo et al., 2012). Therefore, GWR can capture the spatial pattern of data via spatially varying parameters. Because of this, GWR has been widely used on urban planning, for instance: Suárez-Vega et al. (2015) used GWR to select an optimum location for a new store; Ma et al. (2018) developed a GWR model to explore the spatial variation of house prices; and Gong et al. (2017) demonstrated that GWR performs better than global OLS when calibrating the Huff model.

However, when dealing with temporally non-stationary variables, time is another critical dimension for which GWR is unable to capture. Cartlidge et al. (2018) showed that journeys to shopping areas have high time regularity and both spatial and temporal non-stationarity. Therefore, GWR has limitations when used to analyse journeys to shopping areas.

In recent years, a series of methods for spatio-temporal analysis have been proposed in studies on geographic information systems (GIS) and transport systems. Zhang et al. (2016) used Deep Neural Networks (DNN) to predict traffic flow spatially and temporally. Yue et al. (2009) proposed a clustering approach to discover attractive areas and movement patterns using taxi trajectory data. Mao et al. (2016) proposed a spatial clustering method using taxi data to discover spatio-temporal patterns of household travels. Wang et al. (2017) utilized taxi trajectory data to detect trip purpose with Hawkes processes. Li et al. (2019) proposed multinomial logit models for tourism destination choice analysis, which is able to analyse the temporal and spatial patterns of visitors. Rashidi et al. (2017) constructed a methodology to capture the temporal and spatial changes of emergency events from social media. Wang et al. (2018a) and Wang et al. (2018b) researched geographic consumption behaviour data with check-in data to understand urban vibrancy and popularity. In this paper, we use a spatio-temporal method (GTWR; introduced in Section 4.2.4) to calibrate the Huff model and to discover spatio-temporal patterns of journeys to shopping areas.

## 3 Problem definition

As introduced in Section 2, previous works on shopping areas analysis are constrained, since they did not consider multiple dimensions (both spatial and temporal) when analysing journeys to shopping areas. Moreover, the estimated shopping centre attractiveness is singular, and lack of comparison. The objectives of this study are: (i) to discover shopping patterns geographically and temporally; (ii) to discover whether the influential factors have spatial and temporal impacts on customers' choices (iii) to understand the reason why journeys to shopping areas are geographically and temporally different.

In this paper, we employ GTWR to fit the Huff model parameters of shopping centre attractiveness ($\alpha$), and parameter of travel cost ($\beta$). We consider two dimensions: location and time, and conduct two case studies using: (i) taxi data in Shenzhen; and (ii) taxi data and bike sharing data in New York. To make comparisons, we also use OLS (classical regression), GWR, and TWR to calibrate the Huff model.

## 4 Methodology

### 4.1 The Huff model

The Huff model (Huff, 1964) is designed to estimate shopping probabilities of customers when there exists more than one shopping areas. The classic form of the Huff model is:

$$P_{ij} = \frac{S_j^{\alpha} C_{ij}^{\beta}}{\sum_{j=1}^{m} S_j^{\alpha} C_{ij}^{\beta}} \tag{1}$$

where $P_{ij}$ represents the probability that customer from origin $i$ goes to shopping centre $j$; $C_{ij}$ stands for the travel cost from origin $i$ to shopping centre $j$; $S_j$ denotes the shopping centre $j$'s attractiveness; $\alpha$ and $\beta$ are the parameters associated with the attractiveness and the costing factors ($\alpha$>0, $\beta$<0); and $m$ is the number of shopping centres.

In this paper, we use GPS data to estimate shopping probabilities $P$ from location $i$ to shopping centre $j$ in time $t$:

$$p_{ijt} = \frac{n_{ijt}}{\sum_j n_{ijt}} \tag{2}$$

where $n_{ijt}$ means the number of customers who pick-up at location $i$ and drop-off at shopping centre $j$ at time $t$. We use O-D route distance returned from `baidu.com` to estimate $C$ in Shenzhen case study (Section 5), and from `google.com` to estimate $C$ in New York case study (Section 6). To calculate $S_j$, we use three variables: (i) shopping area size; (ii) the number of journeys (i.e., the number of taxi journeys with destination within the buffer radius of each shopping centre); and (iii) customers' reviews about shopping areas on social media (The reviews are the comprehensive evaluations of shopping malls and surrounding areas, while the overall evaluations of all shopping malls can be regarded as the comprehensive evaluations of a shopping area).

### 4.2 Huff model calibration

Parameters of the Huff model can be calibrated using trajectory data. Here, we compare four calibration methods: (i) OLS (Section 4.2.1), which gives one global best fit for the Huff model parameters, $\alpha$ and $\beta$; (ii) GWR (Section 4.2.2), which fits the model geographically such that parameters are a function of spatial locality; (iii) TWR (Section 4.2.3), which fits the model temporally such that parameters are a function of time; and (iv) GTWR (Section 4.2.4), which fits the model such that parameters are functions of both space and time.

To estimate the Huff model parameters $\alpha$ and $\beta$, O'Kelly introduced four combinations of attraction and cost functions (O'Kelly, 1999), to cover linear and exponential decay of variables $S$ and $C$. These cost functions are described as:

$$K1 : Ln(T_{ij}) = \alpha S_j + \beta C_{ij} \tag{3}$$

$$K2 : Ln(T_{ij}) = \alpha S_j + \beta Ln(C_{ij}) \tag{4}$$

$$K3 : Ln(T_{ij}) = \alpha Ln(S_j) + \beta C_{ij} \tag{5}$$

$$K4 : Ln(T_{ij}) = \alpha Ln(S_j) + \beta Ln(C_{ij}) \tag{6}$$

where $T_{ij}$ equates to the numerator in (1), with $\alpha$ and $\beta$ parameters a power of S and C, respectively. The four formulae linearise the Huff model equation (1) to enable calibration through regression. In his initial work, O'Kelly (1999) found K1 (3) resulted in best fit for global OLS calibration of the Huff model, when using shopping area size as a proxy for attraction $S$. However, a later study has shown that K2 (4) gives best fit for regression calibration when using number of journey drop-offs as a proxy for attraction $S$ (Gong et al., 2017). In this paper, we explore all four linearisations, to investigate their effect on regression calibration performance. To fit the Huff model parameters, $\alpha$ and $\beta$, calibration is performed using OLS regression, GWR, TWR, and GTWR.

#### *4.2.1 OLS regression*

Ordinary Least Squares (OLS) regression is a linear regression method. By minimising the sum of squared residuals, it estimates best fit parameters in a linear model. OLS calibration of the Huff model returns fixed values for $\alpha$ and $\beta$. The general form of OLS regression is:

$$y = \sum_{k=1}^{m} \beta_k x_k + \epsilon \tag{7}$$

where $y$ is the dependent variable; $x_k$ is the $k$-th independent variable; $m$ is the number of independent variables; $\beta_k$ is the regression coefficient for the $k$-th independent variable; and $\epsilon$ is the random error.

#### *4.2.2 GWR calibration*

GWR is a non-stationary technique that models spatially varying relationships. Compared with global regression, the coefficients in GWR are functions of spatial location (Brunsdon et al., 1996). The general form of GWR is:

$$y_i = \beta_{i0}(u_i, v_i) + \sum_{k=1}^{m} \beta_{ik}(u_i, v_i) x_{ik} + \epsilon_i \tag{8}$$

where $y_i$ is the dependent variable at location $i$; $x_{ik}$ is the $k$-th independent variable at location $i$; $m$ is the number of independent variables; $\beta_{i0}$ is the intercept parameter at location $i$; $\beta_{ik}$ is the local regression coefficient for the $k$-th independent variable at location $i$; and $\epsilon_i$ is the random error at location $i$. In particular, $u_i$ and $v_i$ represent the geographical location of $i$. Since the Huff model has two parameters (parameter of attractiveness, $\alpha$, and parameter of travel cost, $\beta$), so $m = 2$ for the Huff model and $\beta_{ik}$ in (8) corresponds to $\alpha$ and $\beta$ in (1).

#### *4.2.3 TWR calibration*

Similar to GWR, TWR is another non-stationary technique that models temporally varying relationships. The general form of TWR is:

$$y_i = \beta_{i0}(t) + \sum_{k=1}^{m} \beta_{ik}(t)x_{ik} + \epsilon_i \tag{9}$$

where $y_i$ is the dependent variable at time $t$; $x_{ik}$ is the $k$-th independent variable at time $t$; $m$ is the number of independent variables; $\beta_{i0}$ is the intercept parameter at time $t$; $\beta_{ik}$ is the local regression coefficient for the $k$-th independent variable at time $t$; and $\epsilon_i$ is the random error at time $t$.

#### *4.2.4 GTWR calibration*

Since GWR cannot deal with temporal variation of parameters, Ma et al. (2018) proposed GTWR (an extension of GWR), which assumes that variables are non-stationary in both time and space. GTWR is expressed as follows:

$$y_i = \beta_{i0}(u_i, v_i, t_i) + \sum_{k=1}^{m} \beta_{ik}(u_i, v_i, t_i)x_{ik} + \epsilon_i \tag{10}$$

where $y_i$ is the dependent variable at location $i$; $x_{ik}$ is the $k$-th independent variable at location $i$; $m$ represents the number of the variables in the model. Since there are two variables in the Huff model ($k_1 \equiv \alpha$, and $k_2 \equiv \beta$), therefore $m = 2$; $\beta_{i0}$ is the intercept parameter at location $i$; $\beta_{ik}$ is the local regression coefficient for the $k$-th independent variable at location $i$; and $\epsilon_i$ is the random error at location $i$; and $i$ represents each space-time location. In particular, $u_i$ and $v_i$ represent the geographical location of $i$; while $t_i$ represents the time location of $i$.

In this paper, we consider customers with the similar drop-off times and origin locations as a group, and estimate one pair of parameters in the Huff model (parameter $\alpha$ of shopping centre attractiveness, and parameter $\beta$ of travel distance) for each group. In this way, we use GTWR to calibrate the Huff model both spatially and geographically.

## 5 Case study using taxi trajectory data in Shenzhen

### 5.1 Data

In this case study, we use GPS taxi trajectory data in Shenzhen to analyse journeys to shopping areas. The taxi data includes taxi location (longitude, latitude), time (seconds), speed, direction angle, and status (0: taxi has no passenger; 1: taxi has passenger). For each taxi, the data collection time interval is between 30 seconds to one minute. One month of taxi data (24 hours/day) are collected from 24th September to 20th October in 2015, and there are 15,000 taxis in the data set. As 1st October is the Chinese National Day, the total number of journeys to shopping areas on 1st October is significantly larger than that of any other days. Although the number of journeys to shopping areas on 1st October have similar average trip

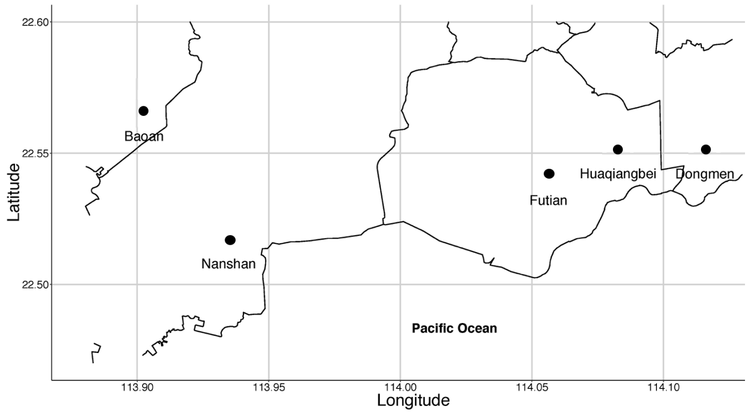



**Fig. 1** The locations of 5 shopping areas in Shenzhen, China

distance compared with normal weekends, we exclude taxi data on 1st October from our analysis to avoid bias and outliers.

We collect 712 questionnaires from the five study shopping areas in Shenzhen in 2015. The questionnaire surveys show that taxi journeys take 7.3% in all journeys to shopping areas. We initially segment Shenzhen and all taxi data into a grid of square cells of $400 \times 400$ metres (cell size chosen so that, each day, there are at least 50 taxi journeys in every cell; thus enabling statistical significance of analysis), with range boundary 113.80°–114.63° longitude and 22.46°–22.80° latitude.

Previously, researchers have selected taxi journeys that drop-off within 500 metres outside shopping malls as shopping journeys, and this method is called *buffer radius* (Yue et al., 2012; Gong et al., 2017). To validate the efficacy of this buffer radius, we tested four different buffer radii: 100, 300, 500, and 700 metres.

Once drop-off (or *destination*) points are selected, we extract their corresponding taxi pick-up points (i.e., the origins of the trips), which gives us a set of Origin-Destination (O-D) pairs. As most of the shopping centres in Shenzhen open from 10am to 10pm, O-D pairs are further filtered to remove those that occur outside of this window.

To verify the prediction accuracy of the calibrated Huff model, we split the data into two subsets: training data (used for calibrating the Huff model), and testing data (used to verify the prediction accuracy of the calibrated model). The data is initially sorted by time in origin location. Every tenth O-D pair is then selected for the test set, the other 90% of data are used for the Huff model calibration. Both sets are further segmented into two subsets: weekdays and weekends.

Here, we select five representative shopping areas in Shenzhen as our study area: Dongmen, Huaqiangbei, Futian, Nanshan, and Baoan. The location of each shopping area is shown in Fig. 1. Since the five shopping areas include most representative shopping malls in Shenzhen, we only consider these shopping areas in the experiments. There are multiple shopping malls inside each shopping area (see Table 1). Following the method of Yue et al. (2012), all shopping malls in the same area are aggregated to estimate attractiveness.

To calculate $S$, we use three variables: (i) shopping centre size; (ii) the number of journeys (i.e., the number of taxi journeys with destination within the buffer

**Table 1** Customers' rating data on Dianping

| Shopping centre | Number of malls | Number of reviews | Rating |
|---|---|---|---|
| Dongmen | 33 | 2496 | 4.76 |
| Huaqiangbei | 31 | 1941 | 4.94 |
| Futian | 10 | 1727 | 4.23 |
| Nanshan | 16 | 1401 | 4.44 |
| Baoan | 4 | 506 | 4.37 |

radius of each shopping centre); and (iii) customers' reviews on social media. (Gong et al., 2017; Gong et al., 2018). When using social media reviews to estimate shopping centre attractiveness, we collect reviews of 94 shopping malls in our study areas from `dianping.com`, a social media platform where customers can share their comments and give a rating up to five (where five represents the best review) to each shopping mall. We collect 8070 reviews in total. For each mall, we collect the number of reviews for each rating score.

A summary of reviews is presented in Table 1. To obtain the review ranking of the shopping areas, Bayesian Average is used to pre-process the data. Bayesian Average is a statistical method based on Bayes' Rules, which had been used to calculate the rating of the customer reviews (Yang and Zhang, 2013).[1] Bayesian Average is calculated as follows:

$$q = \frac{\sum_{i=1}^{n} r_i + B \times m}{B + n} \tag{11}$$

where $q$ is the rating value of each shopping centre, $r$ is the rating of each mall, $n$ is the number of votes for each shopping mall, $B$ is the mean number of votes across the whole set for each shopping centre (considering both shopping experiments and other POIs located around), and $m$ is overall average rating in the whole set.

We use Z-Score, presented in the final column of Table 1, to normalize the social media reviews. After normalization, the data is in the range [-1,1]. The form of Z-Score is calculated as follows:

$$z = (x - \mu)/\sigma \tag{12}$$

where $x$ is the input data, $\mu$ is the average value of $x$, and $\sigma$ is standard deviation of $x$. After normalization, we consider Z-Score values as an estimation of shopping centre attractiveness, $S$, in the Huff model. We label this estimation method as $S = S_{review}$.

To calibrate these models, we use $K1$–$K4$ to estimate parameters (Eq. (3)–Eq. (6)). In particular, five factors are considered, which are the shopping centre attractiveness ($S$), route distance ($C$), pick-up longitude, pick-up latitude, and drop-off time (hours).

After calibrating the Huff model, the prediction accuracy is verified using Mean Absolute Percentage Error (MAPE) on the test data. MAPE is defined as:

$$MAPE = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{y - f(x)}{y} \right| \tag{13}$$

where lower values indicate higher predictive accuracy.

[1] For example, Bayesian Average is used by Internet Movie Data Base (IMDB; `imdb.com`), the world's most popular source for movie, TV and celebrity content.

**Table 2** Global parameter calibration on training data using best estimators (highest $R^2$, lowest sum of squares) in 500 meters buffer radius (shown to have the best performance). K1 estimator has best performance when $S = S_{size}$ or $S = S_{review}$, and K2 has best performance when $S = S_{journey}$. Best fit presented in bold.

| Time | $S$ | Buffer radius | Est. | $\alpha$ | $\beta$ | S.E. | $R^2$ |
|---|---|---|---|---|---|---|---|
| weekday | size | 500 m | K1 | 0.79 | -0.58 | 1.43 | 0.76 |
| | **journey** | | **K2** | **0.92** | **-0.58** | **1.24** | **0.83** |
| | review | | K1 | 0.43 | -0.57 | 1.45 | 0.75 |
| weekend | size | 500 m | K1 | 0.61 | -0.18 | 1.42 | 0.74 |
| | **journey** | | **K2** | **0.66** | **-0.18** | **1.19** | **0.86** |
| | review | | K1 | -0.04 | -0.18 | 1.44 | 0.73 |

## 5.2 Huff model calibration results

We first perform a global calibration of the Huff model, with results shown in Table 2. The buffer radius of 500 metres gives best performance (with lowest residual S.E. and highest $R^2$ values), confirming the choice of buffer size used in previous studies (e.g., Yue et al. (2012)). Therefore, compared with results with 100m, 300m, and 700m buffer sizes, 500m buffer radius is most suitable to estimate shopping centre's influence area.

The global parameters, using a 500 metre buffer size, are $\alpha = 0.92$, and $\beta = -0.58$ in weekdays, and $\alpha = 0.66$, and $\beta = -0.18$ during weekends. We see that the absolute values of $\alpha$ and $\beta$ are much higher in weekdays than in weekends. This suggests that customers are more sensitive to a shopping centre's attractiveness and travel distance in weekdays. One interpretation of this could be that since people have less free time on weekdays (due to work constraints), for convenience, customers choose to shop at more attractive malls (that are larger, more popular, and more highly rated in reviews) to ensure that they are able to more quickly find the products they want; while cutting down on travel times by shopping at malls closer to their origin location. We further explore this interpretation in Section 5.6.

In Table 2, we see that all three proxies of $S$ (shopping centre size, customer volume, and social media reviews) have good performance—i.e., low errors—on estimating shopping centre attractiveness. Therefore, from the results, we infer that an attractive shopping centre is one that: (i) has large size and therefore sells a greater variety of products; (ii) is popular and has higher customer volumes compared with other malls; and (iii) is well liked and customers are satisfied with the available products and services. Moreover, using the number of customers, $S_{journey}$, to estimate a shopping centre's attractiveness provides best performance on the Huff model calibration compared with shopping centre size, $S_{size}$, and social media reviews, $S_{review}$.[2]

[2] A multiplicative model was also considered, such that attractiveness, $S$, is calculated as a linear function of size, reviews, and number of journeys. However, results showed that the three variables are colinear, thus rendering the model unusable.

**Table 3** Predictive accuracy on Shenzhen test data, using 500m buffer radius. Best accuracy presented in bold.

| Method | Est. | Time | MAPE (%) | Time | MAPE (%) |
|---|---|---|---|---|---|
| Global | K2 | weekday | 21.22 | weekend | 10.43 |
| GWR | | | 19.32 | | 9.40 |
| TWR | | | 15.15 | | 13.34 |
| **GTWR** | | | **14.67** | | **8.33** |

**Table 4** Shenzhen: number of significant local parameters from GWR calibration.

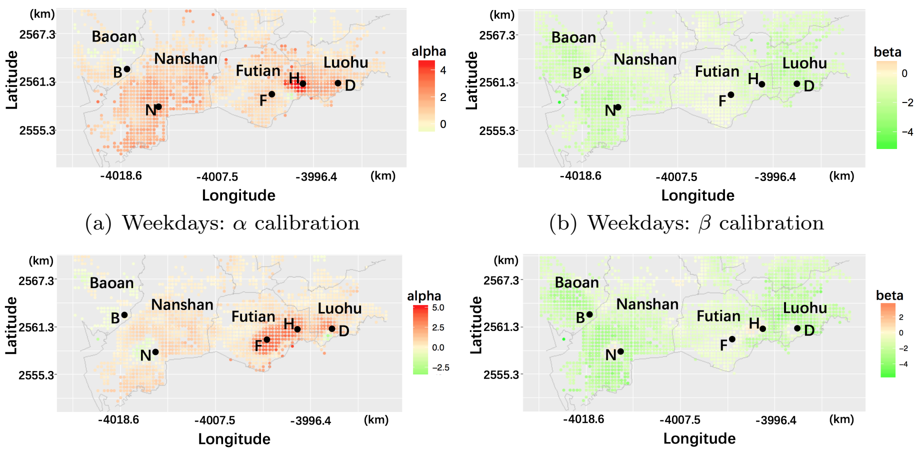
| 95% Significance | weekday | | weekend | |
|---|---|---|---|---|
| | $\alpha$ | $\beta$ | $\alpha$ | $\beta$ |
| Not significant | 1314 | 371 | 1711 | 500 |
| Significant | 6217 | 7160 | 5808 | 7019 |

## 5.3 Validation of Huff model calibration

Table 3 shows the predictive accuracy (MAPE) of the calibrated models on the test data, using a buffer radius of 500 metres. We can make the following observations: (1) the Huff model with GTWR calibration has highest prediction accuracy (smallest MAPE), while the Huff model calibrated with a single pair of global parameters performs worst (highest MAPE). This indicates that customers' sensitivities to both attractiveness and travel distance are closely related to time; (2) the predictive accuracy of the model is better for weekends than for weekdays. One interpretation is that since people are more likely to be working during weekdays, some taxi journeys that drop-off close to shopping malls are aimed for work rather than shopping—i.e., the "shopping journeys" pulled from the raw data for weekends is cleaner. The method of using a fixed buffer radius is unable to distinguish between shopping journeys and non-shopping journeys.

## 5.4 Spatial distribution of parameter $\alpha$ and $\beta$

Table 4 shows the number of significant parameters found in the GWR calibration, where significance is calculated using the multiple testing method (da Silva and Fotheringham, 2016). Fig. 2 presents the results of GWR calibration, such that only significant parameters are displayed. Four districts are mapped: Baoan, Nanshan, Futian, and Luohu. Fig. 2(a) shows the geographic variation in $\alpha$ for weekdays. We see $\alpha$ takes highest positive values (red) in Nanshan and Futian districts, and highest negative values in some areas in Baoan district. This suggests that people who live in Nanshan and Futian are more likely to prefer shopping at attractive stores, whereas people who live in Baoan care least on the attractiveness of stores. Compared with journeys to shopping areas in weekdays, customers' sensitivities to shopping centre attractiveness during weekends tend to be lower, apart from in Futian. People who live in Futian pay similar attention on shopping centre attractiveness in weekend and weekday. One interpretation is that Futian is the city centre, where there are many attractive shopping areas. People do not need to travel far to go shopping in attractive stores. Therefore, at anytime, citizens in




(a) Weekdays: $\alpha$ calibration

(b) Weekdays: $\beta$ calibration

(c) Weekends: $\alpha$ calibration

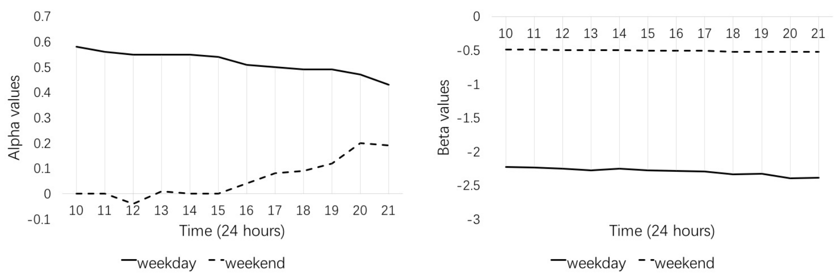
(d) Weekends: $\beta$ calibration

**Fig. 2** Spatial Huff model calibration for Shenzhen using GWR. Only significant parameters are shown. The Mercator projection (the standard map projection) is used to set up projected coordinates. Black points represent the locations of shopping areas.

Futian have quite high attention on shopping centre attractiveness. In particular, in Fig. 2(a), the value of $\alpha$ is close to zero in Nanshan, and negatively highest in most areas of Baoan. This suggests that people living in these areas in Shenzhen pay relatively less attention to shopping centre attractiveness during weekends. In some areas, people even prefer unattractive stores. We have previously discussed attractive malls in Section 5.2, which are large size, popular, and quality goods and services. On the contrary, unattractive stores are relatively small, with lower customer volume, and lower quality services. These shopping areas tend to be located far from city centres (where business competition is high), but close to suburban population centres, such as Baoan. Therefore, it is unsurprising that in some areas in Baoan, people prefer to select relatively unattractive stores in return for the convenience of shorter travel costs. In contrast, in city centre area such as Futian, the value of $\alpha$ is positively highest (red). This indicates that people who live in city centres, where multiple malls are in closer proximity, are likely to select the most popular centres to shop.

Compared with Fig. 2(a) and Fig. 2(c), we see that there is one area in Nanshan, where $\alpha$ value is positive in weekday and close to zero in weekend. From Google map, we see the Shenzhen University is located in this area. We therefore provide a possible interpretation: in weekday, University students study and live in school, they do not have much time for shopping, so they prefer to select a shopping mall that is large, and contain more items that they need; in weekends, students have more spare time, and their journeys to shopping areas are more random. We can also see this phenomenon in Fig. 2(b) and Fig. 2(d). In the same area in Nanshan, students in Shenzhen University have more spare time in the weekend than in weekdays, and they pay less attention on trip distance in weekends.

Fig. 2(b) and Fig. 2(d) display the geographic variation in $\beta$. We see that customers' sensitivities to travel distance are similar between weekdays and weekends. In particular, in most area in Baoan, Nanshan and Luohu, the value of $\beta$ is




(a) $\alpha$ (b) $\beta$

**Fig. 3** The temporal distribution of $\alpha$ and $\beta$, using GTWR calibration.

consistently high and negative, indicating that people living in this area prefer to shop a short distance from home. While in some area (e.g. Futian), the value of $\beta$ is close to 0. Given that Futian is a city centre district (large shopping malls are located near the region) this is perhaps unsurprising. This suggests that, in these regions, people do not need to travel far for necessities, but they are prepared to travel far to visit an attractive shopping centre. We infer that popular shopping centres have more individuality.

## 5.5 Temporal distribution of parameter $\alpha$ and $\beta$

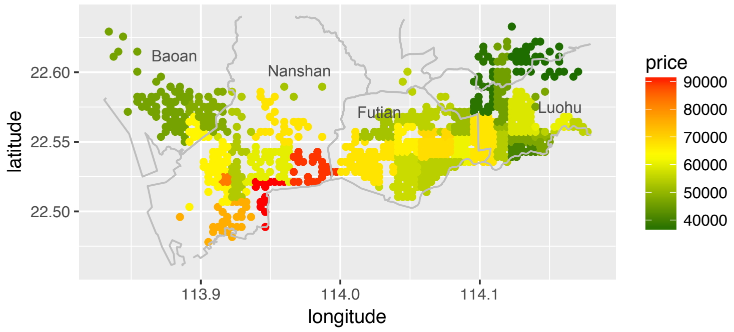
Fig. 3 shows the temporal distribution of $\alpha$ and $\beta$ using GTWR calibration results. From Fig. 3(a), we see that the value of $\alpha$ varies over time. In particular, on weekdays, $\alpha$ is highest in the morning and then gently falls. At weekends, $\alpha$ exhibits an opposite trend, starting very low in the morning, and then gently rising. Moreover, the value of $\alpha$ is much higher in weekdays than in weekends. Since people often work in weekday morning and afternoon, we infer that the customers' sensitivities to shopping centre's attractiveness is negatively related to the length of their spare time. We test this hypothesis in Section 5.6.2.

In Fig. 3(b), we see that when time is varying, $\beta$ values are relatively stable. However, customers' sensitivity to travel distance is negatively lower in weekends than in weekdays. One interpretation is that when people have more time, they care less about travel distance.

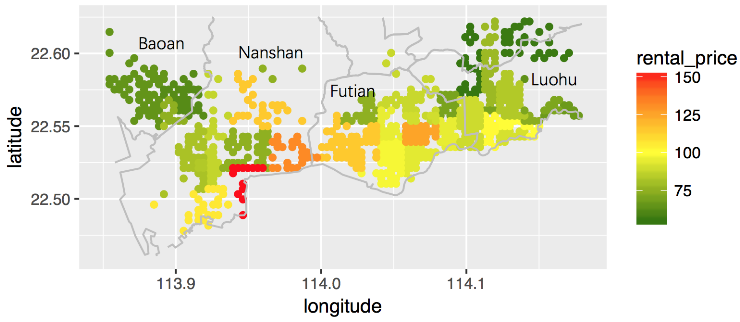
## 5.6 Factor analysis of travel behaviours in Shenzhen

### *5.6.1 Geographical distribution of parameters $\alpha$ and $\beta$*

We have seen that there is significant geographic and temporal variability in sensitivity to $\alpha$ and $\beta$. To explain this variability, we hypothesise that more affluent shoppers are more sensitive to $\alpha$ and $\beta$, such that people with more wealth are: (i) more likely to select a more attractive shopping mall; and (ii) more likely to travel farther to a shopping mall. To test our hypothesis, we consider house price sales' data and rental data for each region in Shenzhen as a proxy of wealth, and perform Pearson's product-moment correlation and t-test to identify whether




(a) Sales' prices




(b) Rental prices

**Fig. 4** Geographic distribution of residential sales' prices (RMB) and monthly rental prices (RMB/$m^2$) in Shenzhen, China. Sales and rental prices are strongly correlated ($r = 0.8$).

there is a relationship. We collect house price sales' data and rental data in Shenzhen during the first quarter of 2017.[3] The distribution of house price for each area is presented in Fig. 4, where Fig. 4(a) shows the distribution of sales' prices, and Fig. 4(b) presents the distribution of rental prices. We see that two distributions are visually similar. The proportion of rental properties for each region are presented in Fig. 5.

Pearson's product-moment correlation and t-test are performed using R's '*stats*' package. Results, shown in Table 5, show that there is a significant ($p < 0.01$) medium correlation ($r = 0.37$) between house sales' prices and $\alpha$, and a significant ($p < 0.01$) medium correlation ($r = 0.31$) between house rental prices and $\alpha$. The results also show the distribution of sales' prices and rental prices are significantly ($p < 0.01$) strongly correlated ($r = 0.80$). No significant relationship was discovered between house prices and $\beta$ (not presented).

### *5.6.2 Temporal distribution of parameters $\alpha$ and $\beta$*

GTWR calibration demonstrates high temporal variability in sensitivity to $\alpha$ (see Fig 3). To explain this variability, we hypothesise that people who have more spare

[3] These data were collected from an open source website `fang.com`, which is the largest and most comprehensive open source repository for house price sales in China.

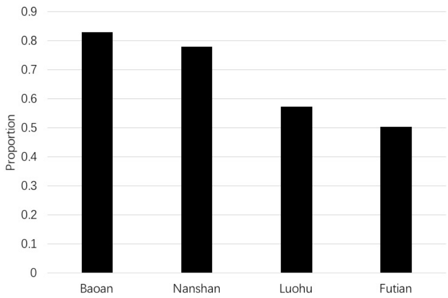



**Fig. 5** Rentals as a proportion of all residential property in four districts in Shenzhen.

**Table 5** Pearson's product-moment correlation and t-test results on geographical $\alpha$ values, residential sales' prices, and rental prices in Shenzhen. The results show medium correlation.

| Variable 1 | Variable 2 | Coefficient | 95% confidence interval | P value |
|---|---|---|---|---|
| $\alpha$ | sales price | 0.37 | (0.30, 0.44) | 2e-16 |
| $\alpha$ | rental price | 0.31 | (0.24, 0.37) | <2.2e-16 |
| sales price | rental price | 0.80 | (0.78, 0.83) | <2.2e-16 |

time (i.e., more time they are not working during shop opening hours) are less sensitive to shopping centre attractiveness. We test this hypothesis by discovering the relationship between the spare time of customers and the value of $\alpha$.

To calculate the length of spare time, we use time schedules of different job categories to estimate spare time in Shenzhen. The data is collected from the 6th national population census and `58.com`.[4] The proportion of employees working in different professions are presented in Fig. 6.

To estimate length of spare time, we select all types of jobs in Shenzhen from `58.com`, which is the largest job search website in China.[5] Based on working time in different jobs, we estimate the length of spare time as:

$$T_i = \sum_m (P_{mi} \times t_{mi}) \tag{14}$$

where $m$ means the job number, and in this study, the total number of job is 18. $T_i$ means the length of spare time at time $i$. For example, if a potential customer finishes work at $i = 5pm$, spare time for shopping is $10pm - 5pm = 5$, while spare time at 4 pm is 0 (since the potential customer is still at work).

$P_{mi}$ corresponds the percentage of people who work in job $m$ at time $i$, and $t_{mi}$ corresponds the length of spare time for job $m$ at time $i$. For example, a teacher often finishes work after 5 pm, and 3.46% of people in Shenzhen are engaged in education related jobs, therefore, $P_{education,4pm} = 3.46\%$, and $t_{education,4pm} = 0$. After calculating people's spare time distribution, we use Pearson's product-moment correlation and t-test to discover the relationship between the spare time distribution and the temporal distribution of $\alpha$.

[4] The data of the 6th national population census is available open source from `http://www.stats.gov.cn/ztjc/zdtjgz/zgrkpc/dlcrkpc/dlcrkpczl`.

[5] The open source website is: `sz.58.com`.


**Fig. 6** Employment distribution for Shenzhen residents, showing manufacturing accounts for nearly 50% of all employment, more than fifteen times the number employed in education. Data taken from `sz.58.com`.

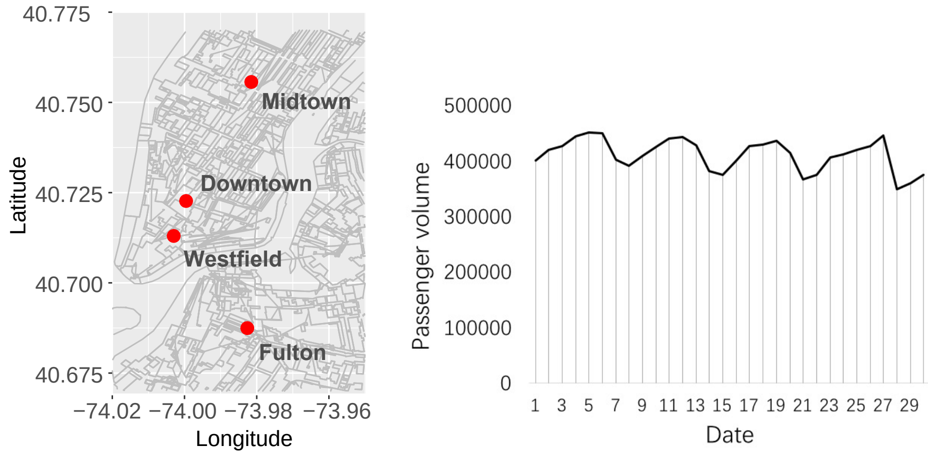
**Table 6** Pearson's product-moment correlation and t-test results on the length of spare time and temporal $\alpha$ values in Shenzhen.

| Variable 1 | Variable 2 | Coefficient | 95% confidence interval | P value |
|---|---|---|---|---|
| $\alpha$ | spare time length | -0.86 | (-0.94, -0.70) | 9.3e-08 |

The regression results are shown in Table 6. We see that there is a significant ($p < 0.01$) and strong negative correlation ($r = -0.86$) between the length of spare time and the customers' sensitivity to shopping centre attractiveness, $\alpha$. This suggests that people who have more spare time pay less attention on shopping centre attractiveness. One interpretation is that when people are urgent to buy a particular product (with less spare time), they are willing to choose a more attractive shopping mall (higher $\alpha$ value), since it is more likely to sell the product that they want. On the contrary, when people have more time for shopping (more spare time), they would shop in different malls, and do not pay much attention on shopping centre attractiveness (lower $\alpha$ value).

## 6 Case study in New York using taxi data and sharing bikes data

To test the generality of the Huff model calibration using GTWR, we use both taxi data and sharing bikes data in New York to perform Huff model calibration using OLS, GWR, TWR, and GTWR, before comparing results with those from Shenzhen. We select four representative shopping areas in New York as our study areas. The locations of the shopping areas are shown in Fig. 7(a), which are: Midtown Manhattan shopping area, Downtown Manhattan shopping area, Westfield trade centre, and Fulton shopping area. There are multiple shopping malls within one shopping area. We aggregate the different shopping malls in the same shopping area to estimate the attractiveness and calibrate Huff model.




(a) The locations of shopping areas (b) The passengers' volume in New York in June 2015

**Fig. 7** The shopping areas' locations and passenger volumes in New York.

**Table 7** New York: customers' rating data on shopping areas using Google map

| Shopping centre | Number of Malls | Number of Comments | Z-Score |
|---|---|---|---|
| Midtown | 26 | 93424 | 0.221 |
| Downtown | 15 | 3860 | -0.631 |
| Fulton | 18 | 14903 | -0.683 |
| Westfield | 12 | 28186 | -0.294 |

Similar to the case study in Shenzhen, we use 100 m, 300 m, 500 m, and 700 m as buffer radii to calibrate the Huff model using New York data. To estimate shopping centre attractiveness, $S$, we use the same three proxies of attractiveness used for the Shenzhen study: (i) shopping centre size; (ii) customer volume; and (iii) social media reviews. We collect customers comments directly from Google map, and the descriptions of the rating data in social media are shown in Table. 7. From the table we see that the shopping malls in Midtown Manhattan have the highest rating (highest satisfaction), while Fulton shopping area has the lowest rating (lowest satisfaction).

## 6.1 Huff model calibration using taxi data

For taxi data, we use over one million taxi journeys with destination near shopping malls (within 500 metres) to calibrate the Huff model. From 6003 trip diaries collected in New York in 2017, we see that taxi journeys take 3.2% of all journeys.[6] The taxi journeys are dated between June 3 and June 7 (three weekdays and two weekend days) in 2015. Although we only use five days' of taxi data, we employ Augmented Dickey Fuller Test on the passengers' volume in June 2015 in New York (shown in Fig. 7(b)). Results show that passengers' volume is stationary, and we therefore consider the 5 days' taxi data can represent passengers' travel behaviours

[6] The open source questionnaire website is: `opendata.cityofnewyork.us`

**Table 8** Global taxi calibration results for New York (highest $R^2$, lowest S.E.) using 500 metres buffer radius (shown to have best performance). Best fit presented in bold.

| Time | $S$ | Est. | $\alpha$ | $\beta$ | Residual S.E. | $R^2$ |
|---|---|---|---|---|---|---|
| weekday | size | K2 | 0.38 | -0.12 | 0.18 | 0.88 |
| | **journey** | | **0.26** | **-0.12** | **0.17** | **0.89** |
| | social media | | 0.39 | -0.12 | 0.17 | 0.88 |
| weekend | size | K2 | 0.38 | -0.36 | 0.16 | 0.89 |
| | **journey** | | **0.30** | **-0.36** | **0.15** | **0.91** |
| | social media | | 0.39 | -0.36 | 0.15 | 0.88 |

**Table 9** Predictive accuracy on test data for New York. Best accuracy presented in bold.

| Method | Est. | Time | MAPE (%) | Time | MAPE (%) |
|---|---|---|---|---|---|
| Global | K2 | weekday | 31.66 | weekend | 18.61 |
| GWR | | | 24.30 | | 15.39 |
| TWR | | | 24.82 | | 21.02 |
| **GTWR** | | | **19.08** | | **14.60** |

in New York. The global results are shown in Table 8, and the testing results are shown in Table 9. We see GTWR has highest accuracy (lowest MAPE) on the Huff model calibration, and customer volume has highest accuracy on estimating shopping centre attractiveness. These are consistent with the calibration results in Shenzhen. We therefore infer that GTWR has higher performance on the Huff model calibration than the other three methods.

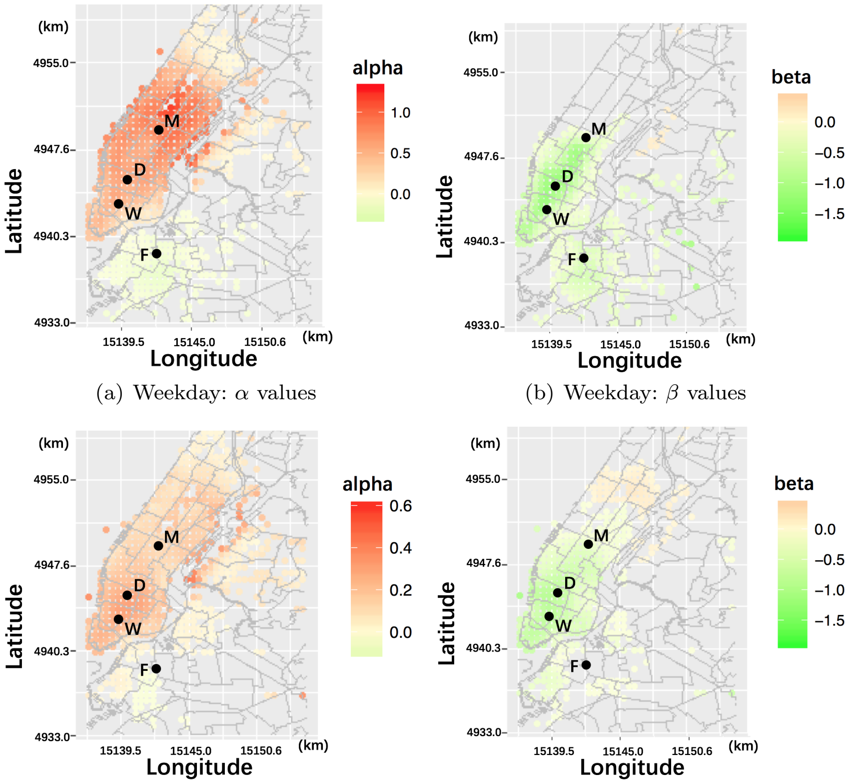
Comparing calibration results using New York taxi data (Table 8) and Shenzhen taxi data (Table 2), we see: (i) in weekdays, the value of $\alpha = 0.92$ in Shenzhen is much higher than $\alpha = 0.35$ in New York; (ii) the value of $\beta = -0.58$ in Shenzhen has greater magnitude than $\beta = -0.12$ in New York. This suggests that in weekdays, people who live in Shenzhen often have more considerations (more attractive shopping malls with short trip distance) when they go to shopping areas, while journeys in New York are less predictable, with New Yorkers caring less about shopping centre attractiveness and travel distance; and (iii) in weekends, the values of $\alpha = 0.43$ in Shenzhen and $\alpha = 0.35$ in New York are similar, while the value of $\beta = -0.16$ in Shenzhen has smaller magnitude than $\beta = -0.36$ in New York. This indicates that at weekends, people who live in Shenzhen prefer to travel farther to a shopping mall, while more citizens in New York prefer to select shopping malls that are closer to home.

This is an interesting finding, since it indicates that people who live in New York are more likely to purchase in different shopping areas in weekday, while people in Shenzhen spend more time travelling to shopping areas at weekends. This is perhaps indicative of the fact that, in Shenzhen, workers have fewer free hours during weekdays to shop.

We also use the trip diaries in New York to test our findings and interpretations. The trip diaries show that during weekends, 87% of taxi journeys that aim for shopping malls are within 30 minutes, while during weekdays, only 35% of taxi journeys that aim for shopping malls are within 30 minutes. We consider it as evidence to prove that people who live in New York care much about trip distance

**Table 10** New York: number of significant local parameters from GWR calibration.

| 95% Significance | weekday | | weekend | |
|---|---|---|---|---|
| | $\alpha$ | $\beta$ | $\alpha$ | $\beta$ |
| Not significant | 103 | 799 | 158 | 559 |
| Significant | 1677 | 981 | 1526 | 1125 |




(a) Weekday: $\alpha$ values (b) Weekday: $\beta$ values

(c) Weekend: $\alpha$ values (d) Weekend: $\beta$ values

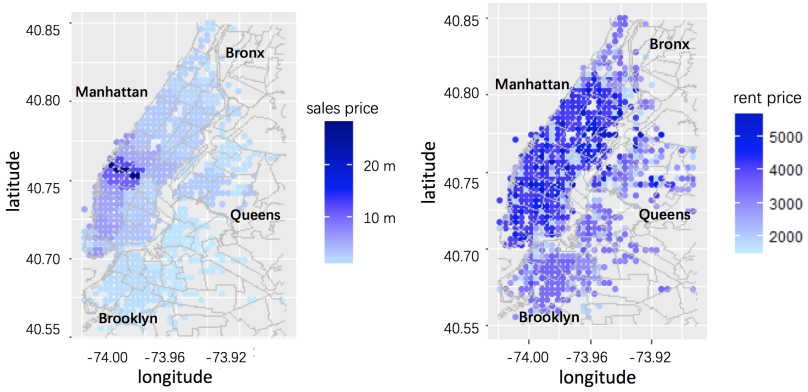
**Fig. 8** GWR calibration for New York. Only significant parameters are shown. The Mercator projection (the standard map projection) is used to set up projected coordinates. The black points represent the locations of shopping areas.

in weekends when they taking taxis. This is quite different to people in Shenzhen.

## 6.2 Factor analysis of travel behaviours in New York

### *6.2.1 Geographical distribution of parameters $\alpha$ and $\beta$*

Similar to the case study in Shenzhen, Table 10 shows the number of significant parameters found in the GWR calibration, where significance is calculated using




(a) Sales' prices (b) Rental prices

**Fig. 9** Geographical distribution of residential sales prices (USD millions) and monthly rental prices (USD) in New York. The correlation ($r = 0.46$) between sales' and rental prices is not as strong as that observed in Shenzhen (compare Fig. 4).

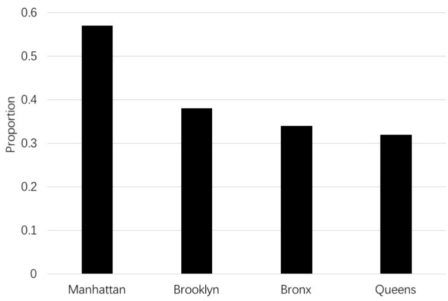



**Fig. 10** Rentals as a proportion of all residential property in four districts in New York.

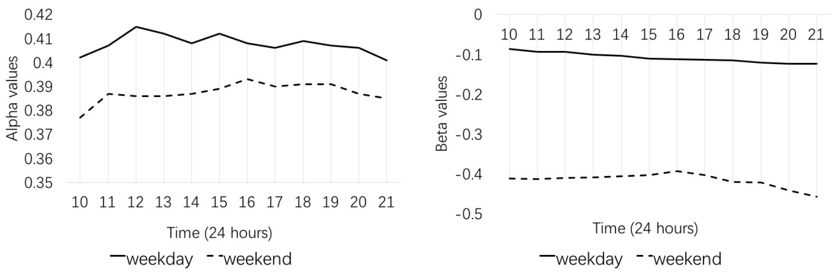
the multiple testing method (da Silva and Fotheringham, 2016). We only display the parameters in 95% significance in the figure. Fig. 8 shows the geographical distribution of $\alpha$ and $\beta$, where we see the values of $\alpha$ are highest in Manhattan (northwest in the map), and close to zero in other areas. On the contrary, the values of $\beta$ are negatively highest in Downtown Manhattan (in the west of the map), while close to zero in other areas. We therefore infer that people who live in Manhattan prefer more attractive stores and short trip distance when they go shopping.

Following the method used for the case study in Shenzhen, we use Pearson's product-moment correlation and t-test on geographical $\alpha$ values and house prices (sales' prices and rental prices) in New York. The house sales' price data in New York is collected from the government open source website, which includes house locations and sale prices.[7] The house rental prices data are collected from RENT-Cafe.com, which is a nationwide Internet Listing Service (ILS) that enables citizens

[7] https://www1.nyc.gov/assets/finance/downloads/pdf/rolling_sales/rollingsales_manhattan.pdf

**Table 11** Pearson's product-moment correlation and t-test results on geographical $\alpha$ values, residential sales' prices, and rental prices in New York. The results show medium correlation.

| Variable 1 | Variable 2 | Coefficient | 95% confidence interval | P value |
|---|---|---|---|---|
| $\alpha$ | sales price | 0.43 | (0.37, 0.48) | 2e-16 |
| $\alpha$ | rental price | 0.54 | (0.49, 0.59) | <2.2e-16 |
| sales price | rental price | 0.46 | (0.40, 0.51) | <2.2e-16 |




(a) $\alpha$ (b) $\beta$

**Fig. 11** The temporal distribution of $\alpha$ and $\beta$

to find apartments and houses for rent throughout the United States.[8] The spatial distribution of prices is shown in Fig. 9, and the proportion of rental properties for each region are presented in Fig. 10.

Pearson correlation and t-test results are shown in Table 11. We see that $\alpha$ and house prices have significant ($p < 0.01$) correlation. In particular, medium correlation between $\alpha$ and sales' prices ($0.3 < r = 0.43 < 0.5$), and strong correlation between $\alpha$ and rental prices ($r = 0.54 > 0.5$). We also discover the sales' prices and rental prices have significant ($p < 0.01$) medium correlation ($0.3 < r = 0.46 < 0.5$).

*6.2.2 Temporal distribution of parameters $\alpha$ and $\beta$*

Fig. 11 shows the temporal distribution of $\alpha$ and $\beta$. We see that the value of $\alpha$ varies over time, while the value of $\beta$ is relatively stable. Comparing temporal distribution of parameters in Shenzhen (Fig. 3) and New York (Fig. 11), we find similarities: in both Shenzhen and New York, people's sensitivities to shopping centre attractiveness varies over time. In particular, people pay most attention on shopping centre attractiveness on weekday morning, and least attention on weekend morning; moreover, sensitivities to trip distance are relatively stable in both Shenzhen and New York. However, journeys to shopping areas also differ. In Shenzhen, customers pay more attention to trip distance on weekdays than at weekends, while people who live in New York care more about trip distance at weekends than on weekdays.

Similar to case studies in Shenzhen, we test the relationship between the temporal distribution of $\alpha$ and people's spare time length. Fig. 12 shows the job distribution in New York, which is collected from the open survey data (NYC-OpenData, 2018). Following the method of Section 5.6.2, we use Pearson's product-moment

[8] `https://www.rentcafe.com`

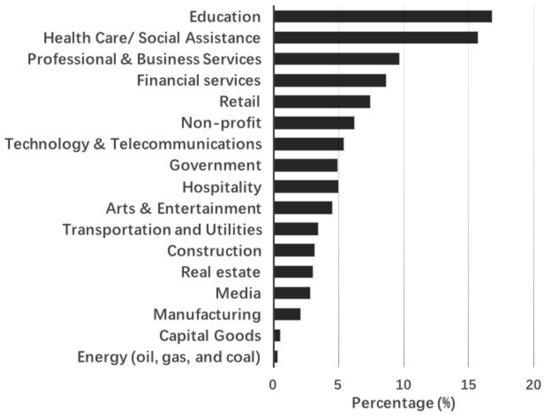



**Fig. 12** Employment distribution for New York residents, showing education accounts for 17% of all employment, approximately eight times larger than manufacturing. Data taken from open survey (NYC-OpenData, 2018), sample size $n = 1952$.

**Table 12** Pearson's product-moment correlation and t-test results on length of spare time and temporal $\alpha$ values in New York

| Variable 1 | Variable 2 | Coefficient | 95% confidence interval | P value |
|---|---|---|---|---|
| $\alpha$ | spare time length | -0.80 | (-0.91, -0.58) | <3.52e-6 |

correlation and t-test to discover the relationship between the parameter $\alpha$ and length of people's spare time (see Table 12). We see there is a significant ($p < 0.01$) strong negative correlation ($-1 < r = -0.8 < -0.5$).

### 6.3 Huff model calibration using sharing-bike data

Here, we use one million sharing bikes journeys from June 1 to July 4 in 2015 in New York for Huff model calibration. From 6,003 trip diaries collected in New York, we see that sharing bike journeys take 2.5% of all journeys. Since there are rental and return sites for sharing bikes next to shopping centres, we therefore directly select sharing bikes' journeys that drop-off near shopping centres. When $S = S_{journey}$, and linear format is K2, the results have best performance, which are shown in Table 13.

From the results, we see that MAPE is lowest for GTWR and highest for global calibration. Therefore, GTWR has best calibration for both taxi data and sharing bikes data in New York. This result is consistent with the Huff model calibration results for Shenzhen taxi data. We take this as conclusive proof that GTWR is the best approach of the three alternatives for calibrating the Huff model. Comparing sharing bikes and taxi journeys, we see that the value of $\alpha$ is lower and $\beta$ is much higher for sharing bikes than for taxis. This is intuitive. Since riding a bicycle takes physical effort, customers on bikes are much more sensitive to distance than shopping mall attractiveness. For taxi journeys, the opposite is true.

**Table 13** Sharing bike calibration results in global, GWR, TWR, and GTWR when $S = S_{journey}$. Mean Average Percentage Error (MAPE) is used to test the performance. K2 has best performance. Best results bold.

| Time | Global Huff Calibration | | | | MAPE | | | |
|---|---|---|---|---|---|---|---|---|
| | $\alpha$ | $\beta$ | Residual S.E. | $R^2$ | global | GWR | TWR | GTWR |
| weekday | 0.29 | -0.96 | 0.17 | 0.80 | 39.56 | 15.72 | 16.28 | **12.42** |
| weekend | 0.33 | -0.80 | 0.21 | 0.72 | 30.07 | 26.48 | 27.21 | **14.79** |

## 7 Conclusion

We have presented a Huff model calibration for shopping areas analysis using taxi data and sharing bikes data in the cities of Shenzhen, China, and New York, USA. Four calibration methods are used: OLS, which results in a single, global model fit; GWR, which returns localised calibration values for each geographical region; TWR, which returns temporal calibration values for each drop-off time (24 hours), and GTWR, which returns local and temporal calibration values for each local region and each drop-off hour. Results demonstrate that fitting the model geographically and temporally using GTWR provides much higher predictive power than other three methods, as parameter values for the Huff model are sensitive to both geographic location and time. We therefore suggest that GTWR is a superior regression technique that should be widely used on shopping areas analysis.

The results also demonstrate that the geographical variation of customers' behaviours can be largely explained by consumers' wealth, while the temporal variation of journeys to shopping areas can be explained by consumers' work patterns. Using residential sales' and rental prices to estimate customers' wealth, and population census data to estimate employee's spare time, we observe two highly significant linear relationships: (i) between wealth and sensitivity to store attractiveness, and (ii) between spare time and sensitivity to store attractiveness.

We also demonstrate that using 500 metres as buffer radius makes the Huff model more accurate compared with 100, 300, and 700 metres. This suggest that passengers that drop-off within 500 metres to shopping areas are potential customers. This corresponds with survey data in China (Bureau, 2009), which shows passengers often walk up to 500 metres to their destinations.

Furthermore, we compare the travel behaviours to shopping areas between people in Shenzhen and New York. The results show that customers in Shenzhen have more consideration on shopping areas (high attractive shopping area, close travel distance) in weekdays, while people who live in New York spend more time on shopping during weekdays and prefer shorter trip journey at weekends. We believe this to be due to cultural differences between Chinese and American shopping and employment patterns. We use survey data in New York in 2015 to prove that Americans pay much more attention on trip distance in weekends than in weekdays.

The findings in this paper have several potential applications. For example: (i) since travel behaviours to shopping areas vary spatially and temporally, GTWR could be widely used on spatio-temporal analysis on travel behaviours, which could benefit urban design. In particular, combined with data for housing costs, GTWR can be used to estimate spending habits at shopping centres in different time and areas. For new shopping malls, GTWR could help to estimate the residential locations of target customers, and therefore optimise the location selection of trading malls. (ii) For transportation analysis, this paper provides evidence that all points of interest (POI) attract passengers who drop-off within 500 metres from a taxi, which lead to the influence of travel demand. By analysing the activities in attractiveness zones, GTWR could help estimate the travel flow in order to reduce traffic congestion, and improve passengers' mobility; (iii) For commercial areas, since customers' sensitivities to stores' attractiveness are largely influenced by customers' income and spare time, we suggest shopping malls could use this result to optimise marketing strategies by targeting customers.

Future work will consider integrating the findings presented here into a dynamic agent-based model (ABM) to simulate individual behavioural patterns for shopping. City-scale dynamics will emerge from the complex interactions between individual agents, network infrastructure, and resources. A coevolutionary framework (e.g., see Cartlidge and Ait-Boudaoud (2011)) will be used to optimise shopping centre locations and transportation network design to minimise traffic congestion and reduce travel times across the city.

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