Trajectories of mobility reduction during England's first national COVID-19 lockdown[1]

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Highlights

- People's mobility levels have changed over the course of the pandemic
- Mobility levels in England declined substantially at first but already bounced back during the lockdown
- Trajectories of mobility reduction over the pandemic varied across local authorities in England
- Spatial differences in mobility trends are mainly associated with income, employment and car accessibility

Abstracts

The UK government imposed a lockdown across England in the spring of 2020 to reduce community transmission of COVID-19 and avoid health services becoming overwhelmed. The measures led to large reductions in everyday mobility, but not everywhere to the same extent. Using call detail records from more than 1.1m mobile phones, we analyse spatial differences between Local Authority areas in how mobility levels evolved in the period 1 March-1 July 20202. Four groups of Local Authorities are identified, which differ in terms of the minimum level of mobility after the imposition of England's first national lockdown and the extent to which mobility levels subsequently recover. Local Authorities' group membership is mainly associated with their levels of income, self-employed workers, and car availability, although ethnic/racial make-up of population and health-related neighbourhood features. The analysis shows that the greatest reduction in mobility after the imposition of the lockdown and continuation of low levels of mobility afterwards occurred in high-income areas with comparatively high levels of self-employed workers and cumulative COVID-19 infection rates before stay-at-home orders. It thus indicates that the greatest reductions have been achieved in areas where it is relatively easy for people to stay at home or in areas the risk of infection and severe illness was relatively high. More generally, the paper results highlight the need to consider the difference in the evolution of mobility levels, and it is explicitly linked to the ability to restrict everyday mobility.

Keywords: COVID-19; Everyday mobility; Lockdown; Dynamic time warping distance; Clustering; Classification.

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Introduction

COVID-19 is rapidly changing our everyday lives, and particularly our everyday mobility in daily life. Social distancing policies, such as travel restrictions and compliance with stay-at-home orders, has been widely implemented under the COVID-19 pandemic (Hale et al., 2021; Kishore et al., 2021). Working from home becomes the *new normal* to avoid social contact, and mitigate the risk while using public transport for work-related travel and on-site working (Beck & Hensher, 2020). Transport mode use has been strongly affected by the risk of travellers being exposed to the virus during their journey (Barbieri et al., 2021; De Vos, 2020). Inevitably, transit attractiveness down and massive service cuts on public transport systems while uptake in private vehicle use and active travel; walking and cycling (Department for Transport, 2020; Vickerman, 2021). In short, the risk of COVID-19 and travel-related measures rapidly reshaped our *mobility habits* (Cartenì et al., 2020). Although the magnitude of this change varies across and within cities and social groups.

UK government recognised the importance of rapid control to implement a series of social distancing measures to contain the epidemic since the COVID-19 reached in late January 2020 (Scally et al., 2020). However, the nationwide lockdown has been imposed as an emergency measure on 23 March 2020. In order to mitigate the transmission, and the new, more transmissible variant of the COVID-19 continues to spread. People's everyday mobility has to face new challenges and massive adaptions (Borkowski et al., 2021; Lee et al., 2021; Marsden & Docherty, 2021). Varying travel interventions and restrictions suppressed the mobility to diminish the physical interactions and instruct "stay-at-home". Greater attention should be paid to exploring change in mobility levels throughout the first COVID-19 lockdown to evaluate the effectiveness of social distancing measures.

To this end, this research addresses in detail and assess the effects of lockdown by monitoring the change in mobility levels over time using the call-detail records (CDRs) data collected from people's mobile phones. In other words, this research investigates the effects of government-mandated lockdowns on everyday mobility in England (Hale et al., 2021). To achieve this task, this research seeks to measure changes in mobility over time and quantify how it has been evolved. We utilised data mining techniques to reveal the significant socioeconomic and demographic factors likely to be correlated with the distinctive trajectories of mobility reduction under England's first nationwide lockdown. Specifically, the research addresses the following questions:

- How has mobility changed over time, and has it evolved under the lockdown?
- How and to what extent do socioeconomic and demographic factors that influence change in mobility levels?

Literature review

COVID-19 is transmitted between people in three main ways; contacts, droplets, and airborne transmission. A major transmission route is large infected droplets in line with the most respiratory virus (The Lancet Respiratory Medicine, 2020). The risk of droplet transmission by physical contact among people outlines scientific evidence suggesting social distancing guidelines to prevent the spread of COVID-19 (Rosti et al., 2020). Therefore, monitoring changes in mobility has become valuable to assess the effectiveness of government-imposed social distancing policies (Oliver, Lepri, Sterly, Lambiotte, Deletaille, et al., 2020).

Academic literature on transport and COVID-19 has burgeoned since the Spring of 2020. Many papers have focused on the reduction in mobility with people's attitudes and perceptions during the COVID-19 pandemic. By examining large-scale mobile phone data, and online panel surveys. There is abundant evidence that overall levels of mobility in physical space dropped significantly. Through traditional mobility metrics, such as daily distanced travelled per person (Hong et al., 2021; Lou et al., 2020; Pan et al., 2020; Weill et al., 2020; Xiong, Hu, Yang, Younes, et al., 2020), time spent travelling per person per day (Borkowski et al., 2021), and a total number of trips per day (Lou et al., 2020; Pan et al., 2020; Xiong, Hu, Yang, Younes, et al., 2020; Zhang et al., 2021).

There is now a substantial number of studies demonstrating the effects of government-mandated lockdowns on mobility, in terms of considerable decrease in everyday mobility, tracking the alternative mobility metrics generated from the mobile phone data (Hu et al., 2021). For instance, the share of stay-at-home depicts the percentage of people staying entirely at home and avoid leaving their house all day (Fu & Zhai, 2021; Hu et al., 2021; Jay et al., 2020; Pan et al., 2020; Weill et al., 2020) is robust evidence to assess the effectiveness of government interventions in people's everyday lives. Traffic flows reconstructed from mobile phone data measured changes in population movements between city pairs (Beria & Lunkar, 2021; Schlosser et al., 2020; Xiong, Hu, Yang, Luo, et al., 2020). Also, the radius of gyration is popularly used to measure the radial distance moved within a certain time period, such as a day (Gauvin et al., 2020; Hernando et al., 2020; Lee et al., 2021; Park et al., 2021; Pepe et al., 2020; Santana et al., 2020; Yabe et al., 2020).

As the study shows, the use of mobile data and tracking mobility metrics are helpful to investigate the impact of containment and closure policies, in the form of various travel disruptions and restrictions. Interestingly, people's mobility levels have sharply dropped first, and then gradually bounced back to normal in the early stage of the pandemic (J. Kim & Kwan, 2021; Lee et al., 2021). Recent studies also revealed how mobility changed in the different pandemic stages, and exhibited some notable differences in pre- to post-lockdown. *Spontaneous mobility reduction* (Linka et al., 2020; Xiong, Hu, Yang, Younes, et al., 2020) was observed in the time between pre-pandemic and implemented stay-at-home orders. It suggests that people would practice voluntary social distancing depend on the ability to self-regulate capacity (Cronin & Evans, 2020). Also, increased mobility observed people were going outside more while the coming months over the ease of the lockdown, entitled to *Quarantine fatigue* (J. Kim & Kwan, 2021; Kwan, 2021; Pan et al., 2020; Zhao et al., 2020).

However, limited attention has been given to a consideration of how mobility changed over time and its variation across space influenced by the shift in government response. Kwan (2021) noted that *temporal nonstationarity* in people's mobility levels. The change in mobility levels has been influenced by the prevalence of government measures, and individually perceived risk and ability to restrict everyday mobility together, all of which are time-varying. To further elucidate this issue, we examined the change in mobility throughout government-mandated lockdowns, coping with pre and post-lockdown period (i.e., ±2 months).

Data and methods

Data

Monitoring changes in mobility is a key indicator to assess the compliance of government-mandated lockdowns. This research deploys anonymised and aggregated GDPR-compliant CDRs[4] for 1,119,449 users in the period of 1 January – 1 July 2020 to compute the daily median radius of gyration for users in each LTLA area (*n*=317) in England[5]. The radius of gyration is widely used to capture mobility patterns through density metrics using the combined timestamp of CDRs (described above). We have estimated daily median mobility levels of 315 LTLA areas in England to use it as a comparison throughout our analysis. It can provide the useful insights into how changes in people's mobility levels are influenced by the implementation of travel and physical distancing interventions (Grantz et al., 2020; J. Kim & Kwan, 2021; Kishore et al., 2020). In these terms, it measures the range of activity space (Lu et al., 2021) though summation of the distance from all points of user i travels among the time-stamped (t) locations $l_{i,d,t}$ on day d from the trajectory's mean location c can be formulated as $l_{i,d}^{c} = 1/\mathrm{n}\sum_{t=1} l_{i,d,t}$ on that day. Locations l are approximated by the nearest mobile phone tower, and mobility will be underreported if individuals do not take their phone along. User-level $\mathrm{r_{i,d}}$ values are aggregated to the LTLA areas in which individuals reside.[6] Formally, the radius of gyration $\mathrm{r_{i,d}}$ can be expressed as:

$$\mathrm{r_{i,d}} = \sqrt{\frac{1}{n}\sum_{t=1}\left(l_{i,d,t} - l_{i,d}^{c}\right)^{2}} \qquad (1).$$

Using these data, we observed spatial and temporal variations in mobility (see Results section below). The generalised mobility level is suggested to track the trajectory of mobility reduction, by calculating the (percentage) change in mobility levels compared to a reference day. To do this, we replicate the approach taken by Lee et al. (2021). It suggests a single-day reference, Tuesday 3 March. This approach has been validated by conducting the sensitivity analysis with an alternative reference period.

Previous literature highlighted that socioeconomic (Huang et al., 2021; Lee et al., 2021) and demographic variables, particularly ethnicity compositions and age groups (Harris, 2020; Hong et al., 2021), have been explicitly linked to the reduction in mobility. This research deploys socioeconomic and demographic factors, including the ethnic composition of the LTLA areas. Data were retrieved

4 CKDelta, a company that collected, cleaned, and anonymised the mobile phone location data from a large British mobile phone provide.

5 At least two percent of the population has been sub-sampled from the users of a large British mobile phone provider, stratified by the 317 Lower Tier Local Authorities in England. City of London and Hackney are combined due to small population sizes, and Cornwall and Isles of Scilly as well.

6 The computation of home region of users exploits the night-time location when users are most likely to be at home. Home region detection followed three steps: a) filter observations from 10 pm to 6 am, b) finding the most common cell phone tower used at night-time, c) dropping users with fewer than 30 night-time observations per month. Each cell phone tower is assigned to its Lower Tier Local Authority area according to its location.

from the 2011 Census and other sources provided by the Office for National Statistics (ONS). We have aggregated data from the Lower Layer Super Output Area (LSOA) level to the LTLA area. The full list of variables used in the models is given in Table 2. Also, COVID-19 infection and mortality rates in a given spatial unit were included to consider the variation in everyday mobility affected by the perceived risk of COVID-19 before government-mandated lockdowns. COVID-19 activity metrics were retrieved from UK official COVID-19 dashboard open data API service (UK government, 2020) and processed.

Methods

1) Time-series clustering analysis

Clustering analysis was employed to identify the prominent clusters with a similar trajectory of mobility reduction under the lockdown (i.e., over the period of 23 March to 11 May 2020). Dynamic time warping (DTW) algorithm is chosen to compute an optimal (warping) distance between time-series (Berndt & Clifford, 1994) that minimise the alignment elements by iteratively stepping through the local cost matrix (Sardá-Espinosa, 2019). It is widely used for shape-based clustering to collect similar shapes of time series (Aghabozorgi et al., 2015). Because of the robustness (Chen et al., 2017; Petitjean et al., 2011) compared to other conventional measures, for instance, the Euclidian distance. Given two time-series, $S = \left(S_{1,}, S_{2,} \cdots, S_i, \cdots S_n\right)$ and $T = \left(T_{1,}, T_{2,} \cdots, T_j, \cdots T_m\right)$, DTW distance can be mathematically formulated as follows.

$$DTW(S,T) = \min_Q \left[\sum_{j=1}^{P} \delta\,(W_j)\right] \qquad (2).$$

The sequence of S and T can be arranged to form a n-by-m grid, where δ is a distance function, to represent the magnitude of the difference between the sequence elements (S_1, T_1) to (S_n,T_m). Q denotes a sequence of grid points (1 to j), P is a warping function to find the path through the grid. A warping path W aligns the elements of two sequences when the distance between them is minimised.

Hierarchical clustering methods were deployed to test different agglomerative hierarchical clustering algorithms with a DTW distance (Dau et al., 2016; Sardá-Espinosa, 2019). In order to group LTLA areas into clusters based on their similarity. We used the standardise cluster evaluation metric to determine the appropriate number of clusters, i.e., cluster validity indices (CVIs), using *dtwclust* package for R. We tested the different clusters, where *K*= [2, 20), and evaluated it using a Silhouette index (*Sil*). Arbelaitz (2013) notes that Sil is the best-performing CVIs for the validation of clustering. Whilst the *Sil* value ranges from -1 to +1, the high value denotes the overall clustering quality as the separation distance between the resulting clusters (Rousseeuw, 1987). It depicts how close each object is in one cluster (i.e. intra-cluster) by contrast to the nearest cluster (i.e. inter-cluster). By definition, *Sil* is calculated by using the average intra-cluster distance a, and the average nearest-cluster distance b. When each object l, in terms of any given LTLA area, belongs to cluster K, Sil_l can be expressed as follows.

$$Sil_l = \frac{b(l) - a(l)}{\max\{a(l), b(l)\}} \quad (3).$$

Where $a(l)$ is the average distance between l to other LTLA areas in the same the cluster K, $b(l)$ is the smallest average distance from l to other LTLA area(s) in the nearest cluster. For Sil_l to be close to 1, it requires $a(l) \ll b(l)$ that $a(l)$ is a measure of how dissimilar l is belongs to cluster K. Thus, a small value of a which means clustering analysis performed well.

2) Classification model

A penalised regression model is similar to linear regression but an additional penalty term to constrain (or regularise) the estimated coefficients. It can reduce the variance and decrease sample error to help generalise models (Boehmke & Greenwell, 2019). The LASSO (Least Absolute Shrinkage and Selection Operator) regression is a penalised regression model proposed by Tibshirani (1996). It minimises the residual sum of squared errors (RSS) while constraining the sum of the absolute values of the regression coefficients (Usai et al., 2009). In the mathematical form, the penalised likelihood function is given by

$$\hat{\beta}^{LASSO} = \arg\min_{\beta} \sum_{i=1}^{n} \left(y_i - \beta_0 - \sum_{j=1}^{p} \beta_j x_{ij} \right)^2 + \lambda \sum_{j=1}^{p} |\beta_j|, \quad (4).$$

Here t is a constraint as a tuning parameter ($t \geq 0$), p is the number of predictors, and λ is the penalty parameter that controls the amount of regularisation (i.e., the size of the coefficients). Setting λ to 1 allows the purely penalising the sum of the absolute values of the regression of coefficients β_j, i.e., the $\ell 1$ norm of coefficients. LASSO regression uses $\ell 1$ regularisation technique can result in sparse models with the coefficient of the unimportant features towards zero, and get eliminated in the model (Friedman et al., 2010).

The multinomial logistic regression model (MLR) utilises the logit link function to model the logarithm of the odds ratio for multi-category response variables (Krishnapuram et al., 2005). Let Y has multi categories to denote K number of clusters with a predictor vector X, the linear logistic regression model can be generalised to a multi-logit model (Friedman et al., 2010). The probability Pr for each cluster k to generalise the linear logistic regression into $K-1$ logits as Equation (5), and modifying term as Equation (6).

$$\log \frac{Pr\,(Y = k|x)}{Pr\,(Y = K|x)} = \beta_{0k} + x^{\mathbf{T}}\beta_k, \;\; k = \{1, 2, \ldots, K-1\}. \quad (5).$$

$$Pr\,(Y = k|X) = \frac{exp\left(\beta_{0k} + x^{\mathbf{T}}\beta_k\right)}{\sum_{i=1}^{K} exp\left(\beta_{0j} + x^{\mathbf{T}}\beta_i\right)} \quad (6).$$

Here β_k is a vector of coefficients, β_0 is a constant, and x is the predictors corresponding to cluster k, and $\mathbf{T}$ denotes vector/matrix transpose. Friedman et al. (2010) suggest fitting the model by regularised maximum (multinomial) likelihood. Denote $\mathbf{Y}$ be the $N \times M$ indicator response matrix, with elements $y_{ik} = I(Y_i = k)$. The log-likelihood part of $\mathcal{L}$ is given by

$$\mathcal{L}(K) = \frac{1}{N}\sum_{i=1}^{N}\left[\sum_{k=1}^{M} y_{ik}(\beta_{0k} + x_i^{\mathbf{T}}\beta_k) - \log\left(\sum_{k=1}^{M} exp\big(\beta_{0k} + x_i^{\mathbf{T}}\beta_k\big)\right)\right]. \qquad (7).$$

Krishnapuram et al. (2005) applied the $\ell 1$ norm into the log-likelihood function by replacing the residual sum of squares with the corresponding negative log-likelihood function $-\mathcal{L}$. For the multinomial LASSO logistic regression model (hereafter MLR LASSO), Hossain et al. (2014) summarised the penalised likelihood function can be expressed as Equation (8):

$$\widehat{\beta_\lambda}^{LASSO} = \arg\min_\beta \frac{1}{N}\left[-\mathcal{L}(K) + \lambda\sum_{k=1}^{K}\left|\beta_j\right|_1\right], \qquad (8).$$

Finally, the MLR LASSO can shrink and delete the coefficients (Hossain et al., 2014). Another advantage of this approach is ranking model predictors based on the absolute value of the coefficients, using an embedded feature selection process (K. Kim, 2018). It confirms the difference in predictor importance between distinct clusters of time-series data. The MLR LASSO is constructed to exhibit the significant factors between clusters using *glmnet* package for R (Friedman et al., 2010).

Results

Change in mobility levels over time in England

People's mobility has been inherently affected by the government's emergency response in the absence of a vaccine or efficient antiviral medication in the early stage of the pandemic (Haug et al., 2020). Mobility levels in England, i.e., the average daily median radius of gyration, have declined substantially over time (see Figure 1). In early March 2020, mobility levels had dropped significantly by about 50% before the pandemic (see Figure 3). This finding corresponds with Lee et al. (2021), and it is also broadly comparable with other studies using open-source mobility data (Apple Inc, 2020; Google LLC, 2020).

Further mobility reductions were indicated when England entered the first nationwide lockdown. The UK government was encouraged people to start working from home, and ban the mass gatherings and all unnecessary social contacts (Public Health England, 2020) since the mid of March. Whilst the lockdown has imposed in England on 23 March 2020, mobility levels in England have suppressed more, represented by less than 1km radial distance per day. However, after the lockdown, mobility levels gradually returned towards normal over time. In other words, lockdown lifting has certainly bounced back people's mobility in the post-lockdown period.

It confirms that mobile phone data will help to assess the efficacy of implemented policies through the monitoring of mobility (Oliver, Lepri, Sterly, Lambiotte, Delataille, et al., 2020). At the same time, it also shows the effects of the pandemic on mobility, not without limitations. No study has yet to uncover the evolution of mobility levels that would strongly depend on the socioeconomic and demographic factors, which varied markedly across space.

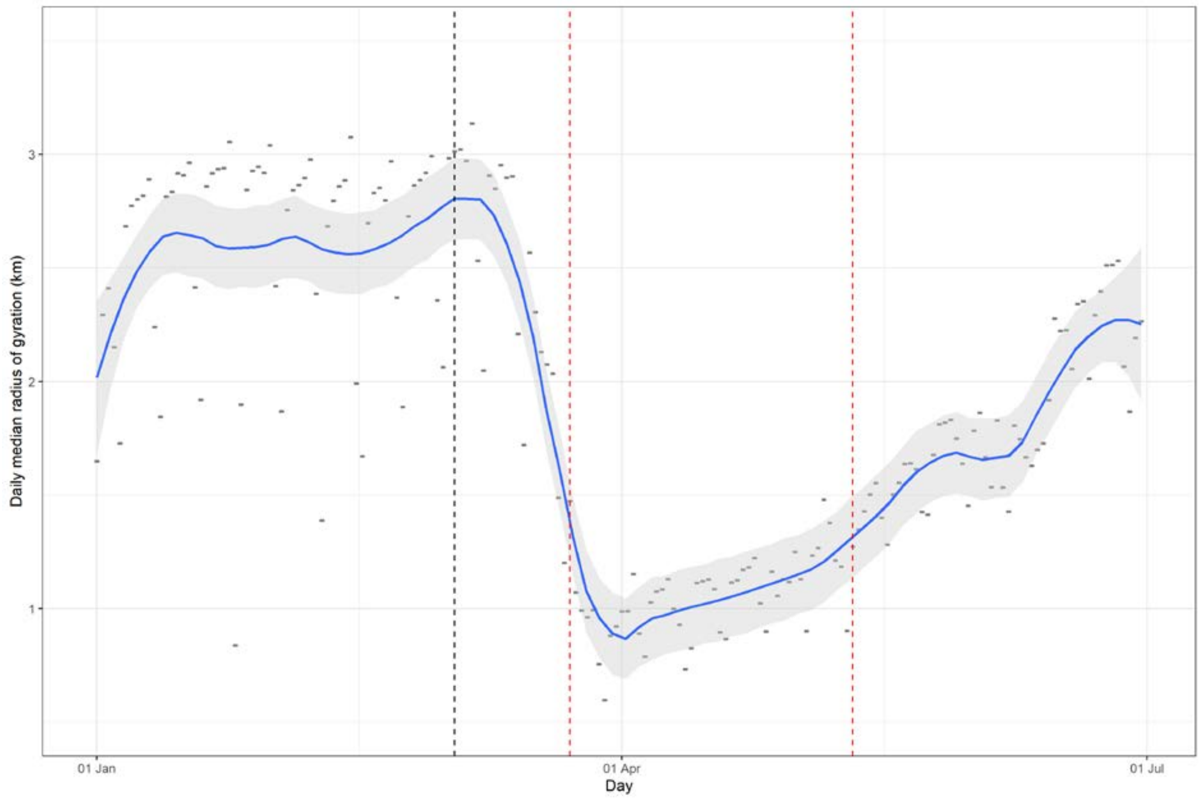

Figure 1. Change in mobility levels over time in England.

Note: Using the daily median radius of gyration (km), temporal trend estimated by using local polynomial regression function (with span *s*=0.2), and dotted lines highlighted the important days; black – baseline (3 March 2020), and red – 2020 Spring lockdown period in England.

Temporal evolution of mobility levels during lockdown

Time-series clustering analysis was suggested to quantify similar trajectories of mobility under the lockdown. 315 LTLA levels in England were grouped into *K* clusters tested by using eight different agglomerative hierarchical clustering algorithms[7]. The optimal number of clusters have been evaluated through the comparison of *Sil*. Figure 2 shows the variation in *Sil* against the number of clusters. *Sil* dropped when *K* increases (except *K*=6 and 9), in other words, the decrease of average inter-cluster similarity. Finally, the above-described cluster analysis generated four prominent clusters based on their similarities.

[7] Nearest-neighbour or Single-linkage Method ("single"), Furthest-neighbour or Complete-linkage Method ("complete"), Average-linkage Method ("average"), McQuitty's Method ("mcquitty"), Metric Methods; Centroid Sorting Method ("centroid"), Gower's Median Method ("median"), Ward's method ("ward.D", "ward.D2").

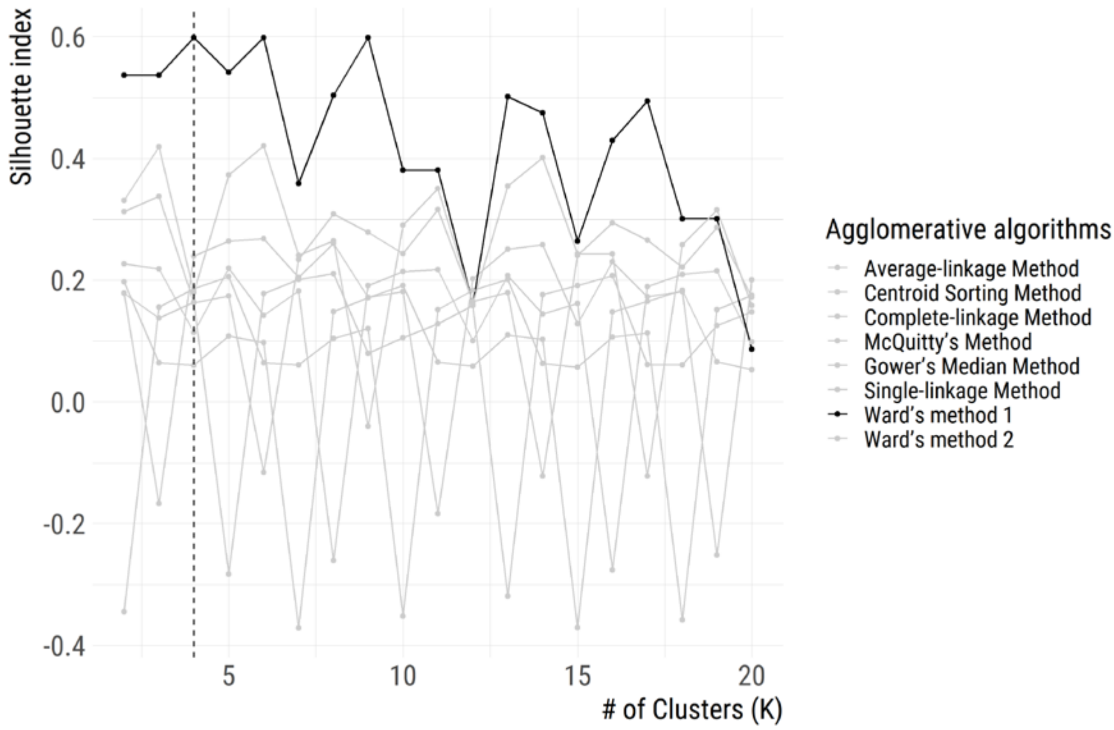

Figure 2. Variation in the Silhouette index against the number of Clusters (*K*= 2 to 20).

In overview, Figure 3 depicts identified clusters (*K*=4) based on the trajectory of mobility reduction under the lockdown. The evolution of mobility levels during lockdown is reflected in the timestamps of generated clusters in Figure 4. More importantly, Table 1 presents the characteristics of change in mobility levels during lockdown between clusters. We computed the median value of mobility levels for each cluster to avoid the bias in each tail of the distribution and disguise intra-cluster variations more accurately on a given day. By examining the relative magnitude of mobility levels throughout the lockdown to describe the heterogeneous nature between clusters.

Two observations can be made in these figures and table. First, cluster 3 have shown the largest reduction Mob_{min} on 29 March, in terms of day 7 of lockdown, 88.5% mobility reduction compared to normal levels before the pandemic. In contrast, cluster 1 have observed the lowest 67.3% mobility reduction on the same day. There was an accelerated mobility decline in cluster 1 (31.1%) relative to cluster 3 (21.4%) during the lockdown, by calculating the maximum mobility reduction during lockdown R_{max} compared to the mobility level on the first day of lockdown $Mob_{t=0}$. To date, lockdown measures were effectively diminished people's mobility levels for cluster 1 relative to cluster 3. Second, cluster 1 has shown the highest people's mobility bounce back during the lockdown as 40.6%, compared to the lowest mobility recovery at 15.3% in cluster 3.

The first observation confirms our hypothesis on heterogeneous trajectories of mobility reduction between clusters. Figure 5 illustrated the spatial cluster distributions when *K* is 4. Cluster 3 (45 LTLAs) consists of relatively wealthy and diverse local authorities mainly distributed over Inner London. In contrast, cluster 1 (69 LTLAs) is relatively deprived local authorities located in North West and Yorkshire and The Humber. In general, cluster 2 (105 LTLAs) and cluster 4 (96 LTLAs) represents the majority of the clusters. Cluster 2 resembles cluster 1, with the abundant clinical capacity (hospitals) and allowed premises (parks) in North West and East Midlands. While cluster 4 is more homogenous to cluster 3, fairly affluent local authorities in Outer London and Southern England. Descriptive statistics are evidenced to confirm the differences in local socioeconomic and demographic factors between clusters (see Table 2).

The second observation also revealed differences in the recovery of mobility levels during the lockdown between clusters. Lockdown measures had worked effectively for at least a week according to the minimum level of mobility indicated on seven-day of lockdown (i.e., 29 March). However, its effectiveness had declined over time, and was observed to lessen reduction in mobility over the course of the lockdown in Figure 3 and Figure 4. Also, we revealed the lowest mobility reduction before the lockdown, and the continuation of high levels of mobility recovery throughout the lockdown occurred in low-income areas in disadvantaged local authorities in Northern England. In contrast, a greater mobility reduction and marginal bounce back over time indicated in high-income areas with excellent health-related accessibility and a relatively high proportion of self-employed, particularly in Inner London.

Table 1. Characteristics of change in mobility levels during lockdown by clusters. .

Characteristics	G1 (69 LTLAs)	G2 (105 LTLAs)	G3 (45 LTLAs)	G4 (96 LTLAs)	National level (315 LTLAs)
Mobility level on the first day of lockdown ($\boldsymbol{Mob_{t=0}}$)	-36.2%	-44.2%	-67.1%	-57.7%	-47.7%
Minimum level of mobility ($\boldsymbol{Mob_{min}}$)	-67.3%	-75.4%	-88.5%	-82.6%	-78.4%
Maximum reduction ($\boldsymbol{R_{max} = (Mob_{min} - Mob_{t=0})/Mob_{t=0}}$)	31.1%	31.2%	21.4%	24.9%	30.7%
Mobility level on the last day of lockdown ($\boldsymbol{Mob_{t=T}}$)	-40.0%	-51.8%	-75.0%	-64.7%	-57.1%
Mobility recovery ($\boldsymbol{Mob_B = (Mob_{t=T} - Mob_{min})/Mob_{min}}$)	40.6%	31.3%	15.3%	21.7%	27.2%
Net reduction in mobility ($\boldsymbol{R_{net} = (Mob_{t=T} - Mob_{t=0})/Mob_{t=0}}$)	10.4%	17.2%	11.8%	12.2%	19.6%

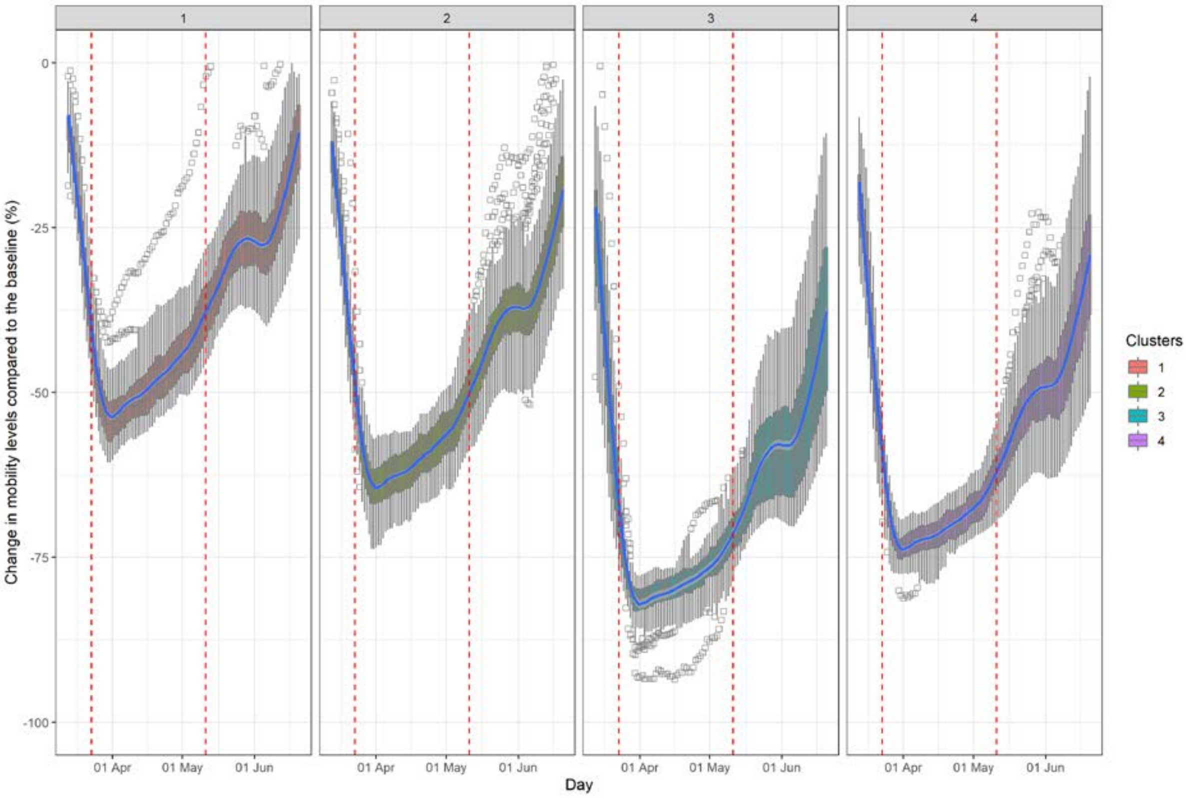

Figure 3. Temporal evolution of mobility levels between clusters.

Note: Using 14-day rolling average mobility levels, temporal trend estimated by using local polynomial regression function (with span *s*=0.2), and dotted lines highlighted the important days; black – baseline (3 March 2020), and red – 2020 Spring lockdown period in England.

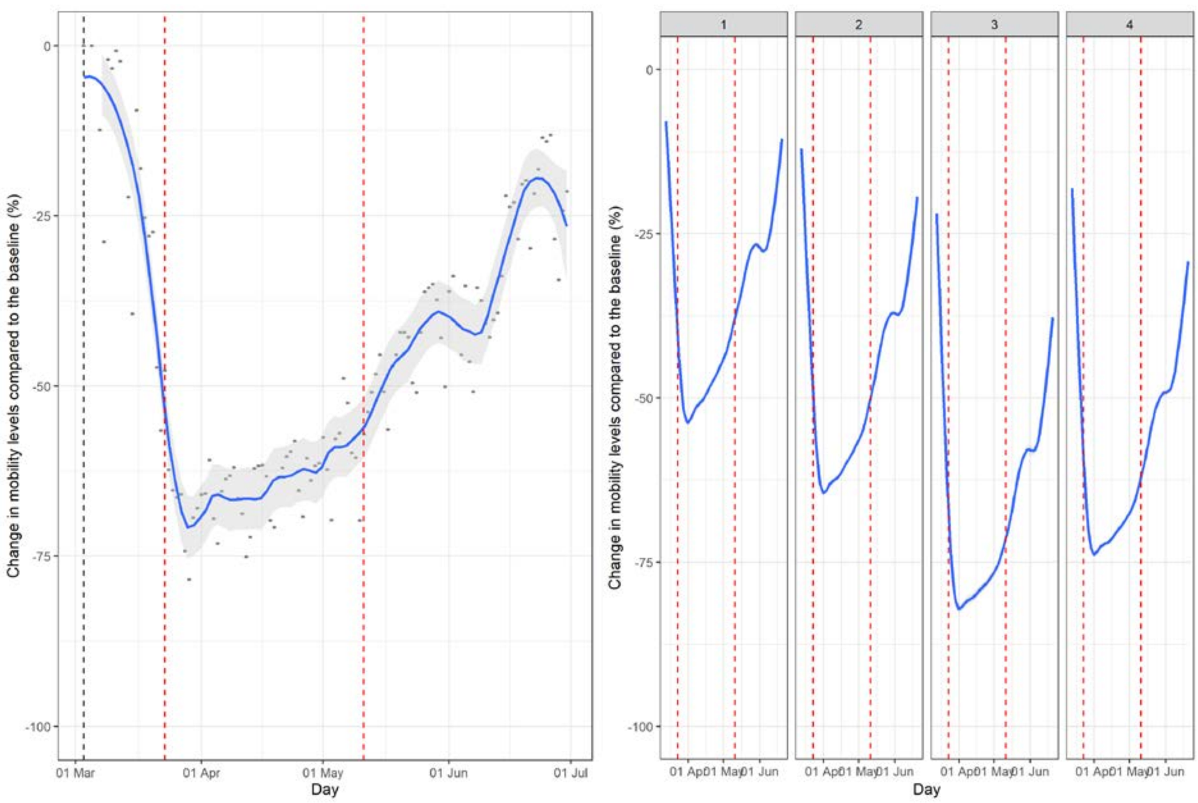

Figure 4. Trajectories of mobility reduction in England; national level (left), and differences in temporal trend between clusters (right).

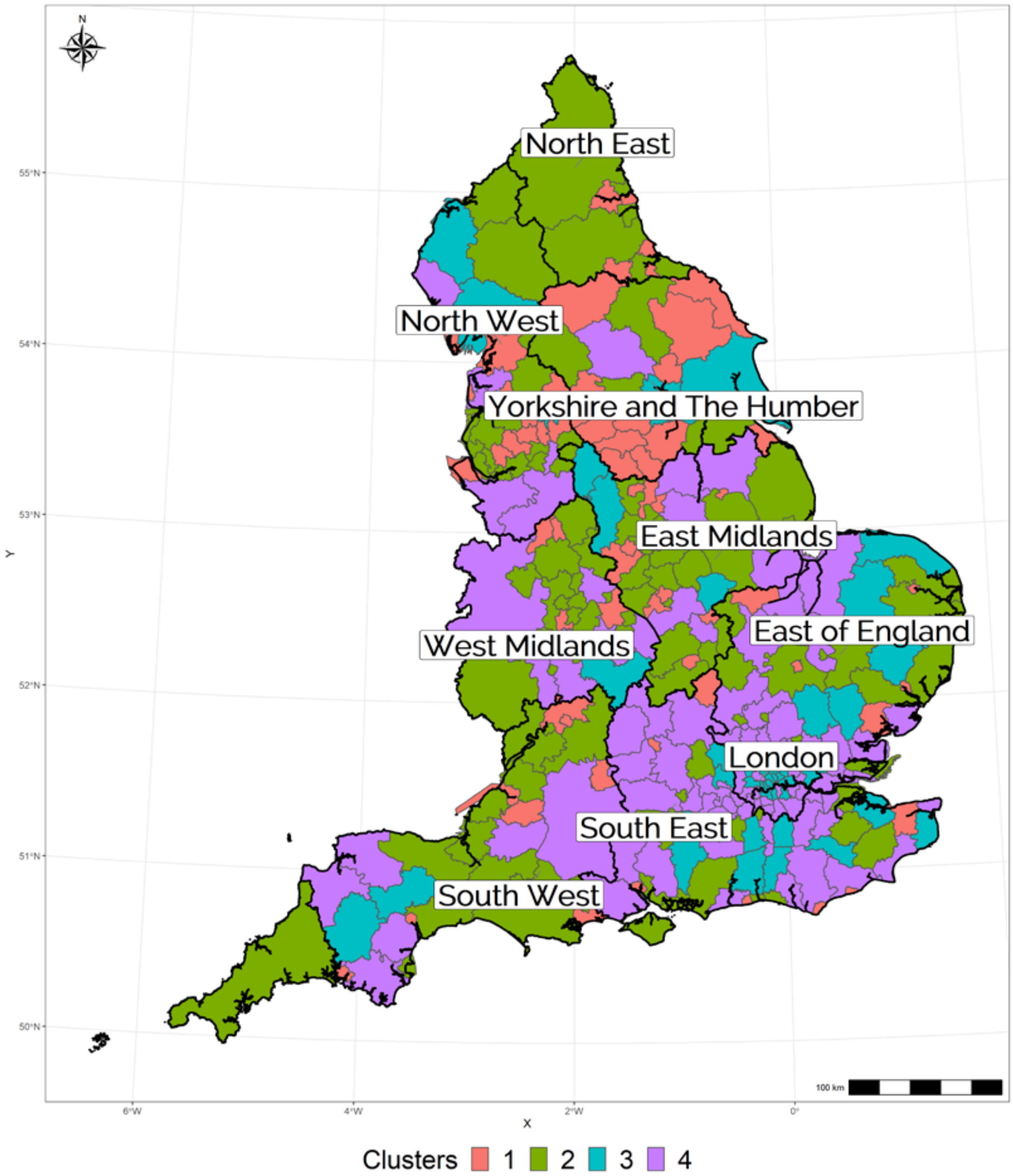

Figure 5. Spatial distribution of clusters (*k*=4).

Disparities in the effects of socioeconomic and demographic factors

In the following analysis, we deployed the classification model to examine the significant factors that help us to interpret the clusters identified through the time-series clustering analysis. MLR LASSO is applied to assess the effects of socioeconomic and demographic factors between clusters, which grouped into similar trajectories of mobility reduction during the lockdown. MLR LASSO can take advantage of reducing the dimension of input features or variable selection. Some socioeconomic and demographic factors might be irrelevant to explain and interpret the patterns of evolution of mobility levels. It also outperformed to eliminate the redundant collinear features to avoid multicollinearity (Gao et al., 2020). In MLR LASSO, estimated coefficients yielded the penalised coefficients for the standardised variables, a positive or negative sign is indicated as the direction of the relationship. MLR LASSO has no built-in model for ranking the model predictors (Abdel Majeed et al., 2018). Thus, the relative feature importance (RF) can be used to rank the importance of selected features according to their magnitude of MLR LASSO resulting coefficients, and it gave each feature a rank from 0 to 1 to estimate using *caret* package for R (Kuhn, 2008).

The model estimation results provided the estimated coefficients for selected factors between clusters. All explanatory variables were normalised to the range of [0,1] prior to model fitting. The best λ, penalty parameter, was selected by 10-fold cross-validation (CV). Seventeen factors were remaining through the embedded feature selection process in MLR LASSO. The share of high-income households, self-employed workers, and households with one vehicle were the most effective variables for the classification, yet the estimated coefficients varied between clusters (see Figure 6). The positive coefficients for the share of high-income households and self-employed workers were observed in cluster 3 and cluster 4. Based on the sign of coefficients, it can be inferred that those local authorities with particularly high levels of affluent populations and self-employed workers (are more likely to be low earners in London). Conversely, negative coefficients were indicated in cluster 1 and cluster 2 that high-income households and self-employed workers were negligible. In addition, the positive coefficients for the share of households with one vehicle were observed in cluster 1 and cluster 4, while negative coefficients were indicated in cluster 2 and cluster 3.

Table 3 details the estimated coefficients for selected factors that were correlated with the classification of generated clusters. It was generally classified as cluster 1, where the share of households with more than three vehicles, self-employed workers, and people in the lower middle class (i.e., social grade C1) were substantially lower. In contrast, cluster 3 was more likely located in the local authorities the share of high-income households, cumulative COVID-19 infection rates before the lockdown, and minority ethnic groups were comparatively high. Among the remaining clusters, high levels of the share of middle-income households, and more than three bedrooms in the house were more likely classified as cluster 2. At the same time, cluster 4 was more likely located in local authorities that the share of high-income households, lower middle class, and Black African were relatively higher.

Lastly, Figure 7 illustrates how RF emphasised the relative contributions of each feature to predict the clusters and how much each feature explains the output variance of MLR LASSO. In this case, the substantial explanatory variables are plotted against their relative importance from 0 to 1. The top 5 features for each cluster are described as follows:

- Cluster 1: Share of households with more than three vehicles (0.64), self-employed workers (0.26), more than three bedrooms in the house (0.23), cumulative COVID-19 mortality rates before lockdown (0.20), and percentage Black Caribbean (0.19).
- Cluster 2: Share of medium-income households (0.38), social grade C1 (0.25), high-income households (0.23), more than three bedrooms in the house (0.25), households with one vehicle (0.04), and self-employed workers (0.02).
- Cluster 3: Share of self-employed workers (0.71), households with one vehicle (0.35), cumulative COVID-19 infection rates before lockdown (0.24), high-income households (0.19), and percentage Other Black (0.12).

- Cluster 4: Share of high-income households (0.47), percentage Black African (0.43), households with more than three vehicles (0.39), more than three bedrooms in the house (0.30), and Hospital density per 1,000 population (0.15).

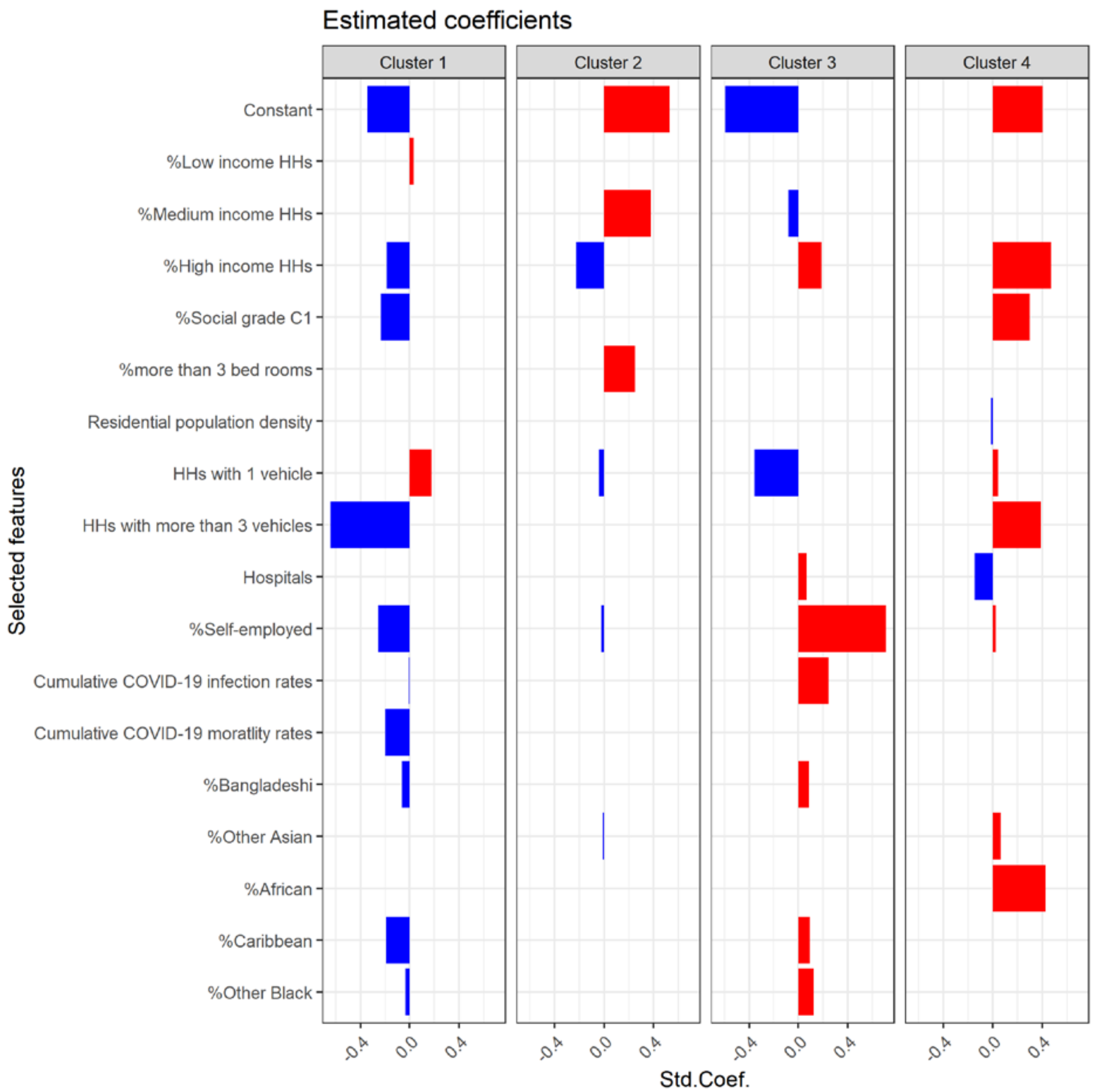

Figure 6. Estimated coefficients of explanatory variables to predict the clusters.

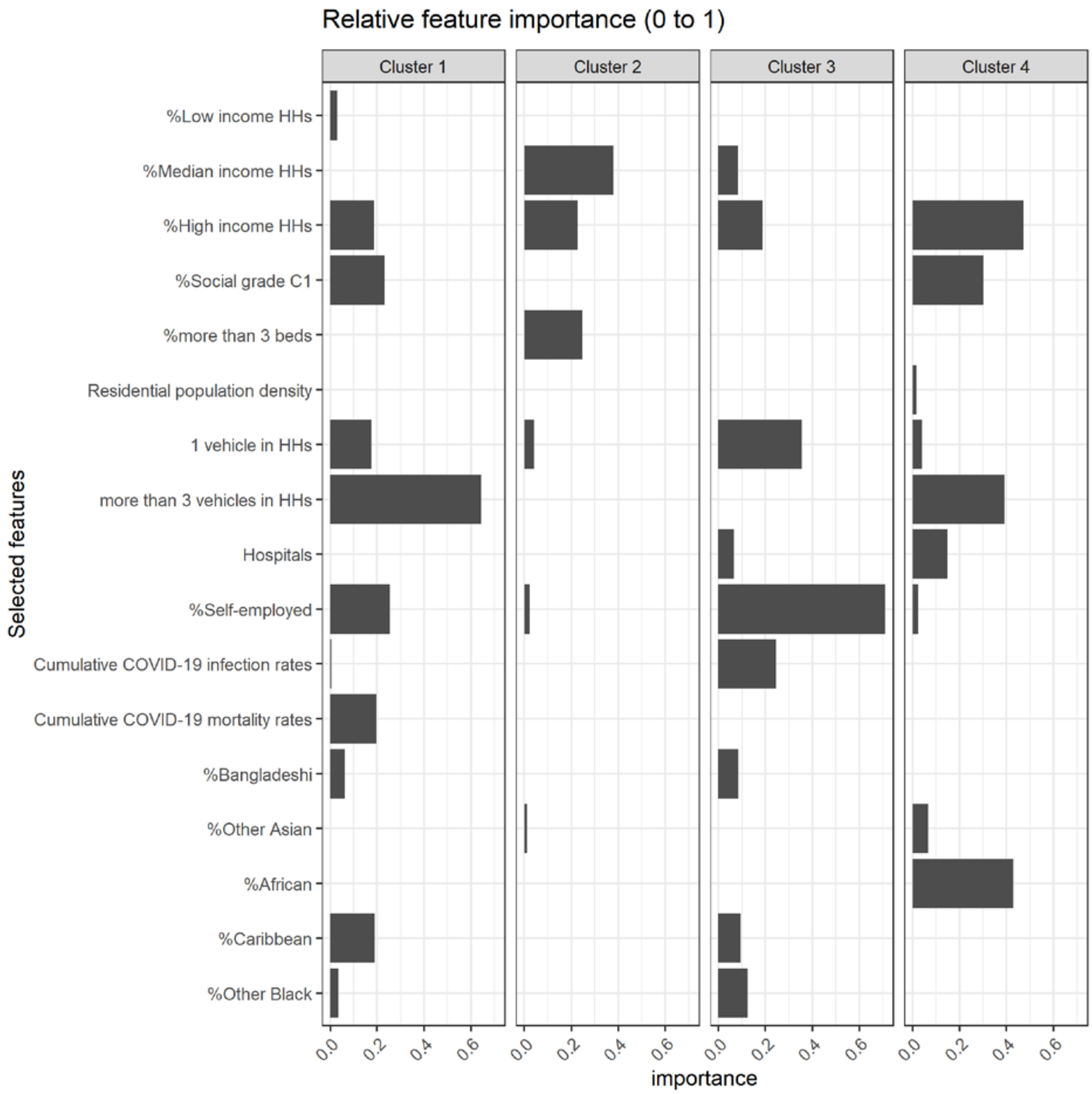

Figure 7. Ranking the relative feature importance to predict the clusters.

Table 2. Descriptive statistics of socioeconomic and demographic factors by clusters.

Domains		Variable	Cluster 1	Cluster 2	Cluster 3	Cluster 4	National level
			Mean (Std.)	Mean (Std.)	Mean (Std.)	Mean (Std.)	Mean (Std.)
Socioeconomic	**Income**	**Share of households in lowest household income quintile at national level**	**0.19 (0.03)**	**0.17 (0.02)**	**0.17 (0.02)**	**0.16 (0.02)**	**0.17 (0.02)**
		Share of households in median household income quintile at national level	**0.22 (0.02)**	**0.23 (0.02)**	**0.21 (0.02)**	**0.22 (0.02)**	**0.22 (0.02)**
		Share of households in top household income quintile at national level	**0.14 (0.04)**	**0.17 (0.05)**	**0.24 (0.07)**	**0.17 (0.05)**	**0.19 (0.07)**
	Education and skills	Share with no qualifications	0.25 (0.05)	0.24 (0.04)	0.19 (0.05)	0.21 (0.04)	0.22 (0.05)
		Share of non-English speakers	0.06 (0.05)	0.04 (0.04)	0.11 (0.12)	0.07 (0.07)	0.06 (0.07)
	Occupation	Share of Social Grade AB (upper middle class)	0.27 (0.05)	0.3 (0.06)	0.37 (0.07)	0.35 (0.07)	0.32 (0.07)
		Share of Social Grade C1 (lower middle class)	**0.21 (0.03)**	**0.23 (0.03)**	**0.23 (0.04)**	**0.24 (0.03)**	**0.23 (0.03)**
		Share of Social Grade C2 (skilled working class)	0.23 (0.03)	0.23 (0.03)	0.18 (0.05)	0.2 (0.04)	0.21 (0.04)
		Share of Social Grade DE (semi-skilled working class and non-working)	0.19 (0.05)	0.16 (0.04)	0.14 (0.04)	0.14 (0.04)	0.16 (0.05)
	Housing type	Share of social rented housing	0.18 (0.06)	0.15 (0.05)	0.18 (0.09)	0.15 (0.06)	0.16 (0.06)
		Share of dwellings with ≥3 bedrooms	**0.6 (0.06)**	**0.65 (0.06)**	**0.56 (0.15)**	**0.63 (0.07)**	**0.62 (0.09)**
Accessibility	**Residential density**	**Resident population density (1,000 inhabitants per km²)**	**0.01 (0.01)**	**0.01 (0.01)**	**0.03 (0.04)**	**0.01 (0.01)**	**0.01 (0.02)**
	Car availability	Share of households with 0 vehicle	0.27 (0.07)	0.21 (0.07)	0.28 (0.19)	0.19 (0.08)	0.23 (0.11)
		Share of households with 1 vehicle	**0.44 (0.02)**	**0.42 (0.02)**	**0.4 (0.04)**	**0.42 (0.03)**	**0.42 (0.03)**
		Share of households with 2 vehicles	0.23 (0.05)	0.28 (0.05)	0.24 (0.12)	0.29 (0.07)	0.27 (0.07)
		Share of households with ≥3 vehicles	**0.01 (0.01)**	**0.02 (0.01)**	**0.02 (0.02)**	**0.03 (0.01)**	**0.02 (0.01)**
		Hospitals (per 1,000 inhabitants)	**0.26 (0.15)**	**0.29 (0.16)**	**0.33 (0.2)**	**0.27 (0.11)**	**0.28 (0.15)**

	Clinical capacity and Allowed premises	Parks (per 1,000 inhabitants)	21.61 (10.54)	22.89 (11.82)	25.5 (10.95)	22.87 (10.32)	22.97 (10.98)
Activity commitment	**Economic activity**	Share of part-time workers in the resident population aged 16-74	0.14 (0.01)	0.15 (0.01)	0.13 (0.03)	0.14 (0.01)	0.14 (0.02)
		Share of full-time worker in the resident population aged 16-74	0.38 (0.04)	0.39 (0.03)	0.39 (0.04)	0.4 (0.04)	0.39 (0.04)
		Share of self-employed workers in the resident population aged 16-74	**0.08 (0.02)**	**0.1 (0.02)**	**0.13 (0.02)**	**0.11 (0.02)**	**0.1 (0.03)**
Population Health	General health status	Share of population in good health	0.8 (0.03)	0.81 (0.03)	0.83 (0.02)	0.83 (0.03)	0.82 (0.03)
		Share of population in fair health	0.14 (0.02)	0.14 (0.02)	0.12 (0.02)	0.12 (0.02)	0.13 (0.02)
		Share of population in bad health	0.06 (0.01)	0.05 (0.01)	0.05 (0.01)	0.05 (0.01)	0.05 (0.01)
Perceived risk of COVID-19	**Infection rates**	**Cumulative COVID-19 reported cases per 100,000 population before lockdown**	**9.49 (8.57)**	**11.29 (7.04)**	**24.6 (19.65)**	**15.72 (12.14)**	**14.11 (12.40)**
	Mortality rates	**Cumulative COVID-19 reported deaths per 100,000 population before lockdown**	**0.61 (0.81)**	**0.93 (1.26)**	**1.83 (1.87)**	**1.25 (1.44)**	**1.08 (1.39)**
Ethnic composition	White	Percentage of the residential population that identified as White British	0.9 (0.09)	0.93 (0.08)	0.82 (0.2)	0.88 (0.14)	0.89 (0.13)
	Mixed/multiple groups	Percentage of Mixed (joint) and Multiple ethnic groups	0.02 (0.01)	0.01 (0.01)	0.03 (0.02)	0.02 (0.01)	0.02 (0.01)
	Indian	Percentage Indian	0.02 (0.04)	0.02 (0.03)	0.03 (0.05)	0.02 (0.04)	0.02 (0.04)
	Pakistani	Percentage Pakistani	0.02 (0.04)	0.01 (0.03)	0.01 (0.02)	0.01 (0.03)	0.01 (0.03)
	Bangladeshi	**Percentage Bangladeshi**	**0 (0.01)**	**0 (0.01)**	**0.02 (0.05)**	**0 (0.01)**	**0.01 (0.02)**
	Chinese	Percentage Chinese	0.01 (0.01)	0 (0)	0.01 (0.01)	0.01 (0)	0.01 (0.01)
	Other Asian	**Percentage Other Asian**	**0.01 (0.01)**	**0.01 (0.01)**	**0.02 (0.03)**	**0.02 (0.02)**	**0.01 (0.02)**
	African	**Percentage Black African**	**0.01 (0.01)**	**0.01 (0.01)**	**0.03 (0.04)**	**0.02 (0.03)**	**0.01 (0.02)**
	Caribbean	**Percentage Black Caribbean**	**0 (0.01)**	**0 (0.01)**	**0.02 (0.03)**	**0.01 (0.02)**	**0.01 (0.02)**
	Other Black	**Percentage Other Black**	**0 (0)**	**0 (0)**	**0.01 (0.01)**	**0 (0.01)**	**0 (0.01)**
	Other ethnic groups	Percentage of any other ethnic group	0.01 (0.01)	0 (0)	0.02 (0.02)	0.01 (0.01)	0.01 (0.01)

***Notes*: Variables in bold (i.e., 17 selected features) have been included in the classification model below at least in one cluster.**

Table 3. Estimated coefficients of explanatory variables to classify clusters.

Domains		Variable	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Constant			-0.34	0.53	-0.59	0.41
Socioeconomic	Income	Share of households in the lowest household income quintile at the national level	0.03			
		Share of households in median household income quintile at the national level		0.38	-0.08	
		Share of households in top household income quintile at national level	-0.19	-0.23	0.19	0.47
	Occupation	Share of Social Grade C1 (lower middle class)	-0.23			0.30
	Housing type	Share of dwellings with ≥3 bedrooms		0.25		
	Residential density	Resident population density (1,000 inhabitants per km^2)				-0.02
Accessibility	Car availability	Share of households with 1 vehicle	0.18	-0.04	-0.35	0.04
		Share of households with ≥3 vehicles	-0.64			0.39
	Clinical capacity and Allowed premises	Hospitals (per 1,000 inhabitants)			0.07	-0.15
Activity commitment	Economic activity	Share of self-employed workers in the resident population aged 16-74	-0.26	-0.02	0.71	0.02
Perceived risk of COVID-19	Infection rates	Cumulative COVID-19 reported cases per 100,000 resident population before lockdown	-0.01		0.24	
	Mortality rates	Cumulative COVID-19 reported deaths per 100,000 resident population before lockdown	-0.20			
Ethnic composition	Bangladeshi	Percentage Bangladeshi	-0.06		0.08	
	Other Asian	Percentage Other Asian		-0.01		0.06
	African	Percentage Black African				0.43
	Caribbean	Percentage Black Caribbean	-0.19		0.09	
	Other Black	Percentage Other Black	-0.03		0.12	
Model criteria information						
AICc (Akaike's Information Corrected Criterion)						-222.91
BIC (Bayesian information criterion)						-161.18

Discussion

Each day, people make new decisions, and it translated into their mobility behaviour to move from place to place, carrying out their motivated activities. Pandemic has been forced to adapt to the *new normal* in our daily lives, the ways of work-from-home setting and parents home-schooling during waves of infection and government-mandated stay-at-home orders, lockdowns and social distancing, and longer-term impacts likely to outlast the COVID-19 pandemic. People start to see a new way to restore the activities differently in their everyday lives, such as relying on the internet for shopping (Mouratidis & Papagiannakis, 2021). However, on the one hand, people make journeys by walking or cycling to increase physical activity levels through active transport activity (Beck & Hensher, 2020).

In this vein, we explored the change in mobility levels over time by using long-term mobile phone data spanning seven months. We demonstrated how mobility has evolved in a spatially uneven manner through time-series clustering analysis. The clusters grouped into similar trajectories of mobility reduction under the lockdown. In order to address uncertainty how geographical contexts influence mobility (Schwanen, 2018), this study was considered to compare the characteristics of mobility changes over time, and assessed the distinctive effects of socioeconomic and demographic factors between generated clusters. Whilst previous literature has highlighted monitoring the change in mobility levels as an early observation in the pandemic. We believe this is the first study that seeks to unfold the evolution of mobility levels in view of the prolonged pandemic, and uncover its existence explicitly linked to the socioeconomic and demographic factors.

The results confirmed the reduction in mobility in the early stage of the pandemic, and the continuation of reductions following the national lockdown. However, when lockdown has lifted, mobility began to rise. People start to go back to normal life (Sun et al., 2020), and more people will want or need to move more with the support of warmer weather, tiredness of staying at home, and cost-of-living issues in a pandemic, recognised as *Quarantine Fatigue* (Zhao et al., 2020). Pan et al. (2020) observed that people tend to practice less social distancing immediately when they indicated decreasing the perceived risk of COVID-19. The evidence of post-lockdown mobility recovery appeared in line with England's up-to-date general reopening of retail shops and public-facing businesses in the post-lockdown period (i.e., 15 June 2020).

We also indicated the voluntary mobility reduction before government-mandated lockdowns. Xiong et al. (2020) suggested that people might be acting more actively when they perceived the threat to COVID-19, such as the rise of daily new COVID-19 cases and deaths where they are living. As a result, *Spontaneous mobility reduction* is quantified before lockdown measures have been introduced to suppress the mobility. People start to practice voluntary social distancing, in terms of self-regulation in the early stage of the pandemic (Khataee et al., 2021) depending on their ability to isolate and risk aversion on mobility. In overview, lockdown measures were effective for restricting people's everyday mobility, but only in the short term (J. Kim & Kwan, 2021). It is, however, a *nuclear option* that is "causing substantial collateral damages to society, the economy, trade and human rights" (Haug et al., 2020, p. 1309). Although the risk of new and more transmissible variant of the virus and the threat of second waves, people's mobility levels soon recovered throughout lockdown by considering people willing to socialise again and return to normality. It is plausible that the limited effectiveness of lockdown measures, even though travel restrictions and interventions to protect lives and communities under the lockdown. It is not a failure of policy but too late to contain the epidemic. People forecasted the ongoing and future situations cautiously in the wake of COVID-19 before social distancing policies were widely implemented. It might be making them regulate their social contacts and practice voluntary social distancing, which accounts for voluntary mobility reduction before the lockdown.

Conclusions

This paper has sought to provide rigorous evidence that trajectories of mobility reductions under the lockdown, and contribute to the methodological development to characterise the evolution of mobility levels. It is explicitly linked to socioeconomic and demographic factors. The research was founded on the integration of novel data and data mining techniques. In detail, the monitoring of mobility levels changes using mobile phone data spanning seven months. Clustering analysis and classification model were chosen to collect similar trajectories of mobility reduction and find the significant factors to predict the clusters, respectively. Two main conclusions can be drawn.

First, monitoring how people's everyday mobility has changed can be established as the best measure of the effectiveness of government interventions in times of the pandemic. In England, mobility levels already falling about 50% compared to the pre-pandemic in the early stage of the pandemic (i.e., the first day of lockdown). Mobility levels continuously declined towards 80% (i.e., 7-day on lockdown) but soon bounced back up to 50% over the course of the national lockdown. Lockdown easing supported the mobility recovery so that mobility levels returned to normal in the post-lockdown period. However, the trajectory of mobility reduction under the lockdown is not the same extent. Heterogeneous evolution of change in mobility levels was exhibited throughout time-series clustering analysis. It revealed differences in the recovery of mobility levels during the lockdown between generated clusters. The finding that areas with the greatest reduction in mobility levels before the government-mandated lockdown and marginal recovery during the lockdown have been observed in Inner London. In contrast, areas with the lowest reduction in mobility and rapid mobility bound back can be found in North West, and Yorkshire and the Humber.

Second, people's mobility levels have been influenced by government interventions, but it was also coupling with the individual ability to restrict everyday mobility (Lee et al., 2021). Unsurprisingly, high-income workers mainly were working from home, and felt to adapt successfully to the new normal (Office for National Statistics, 2021). Racial and ethnic minorities and poor people lived in crowded conditions and generally worked in essential industries (Huang et al., 2021). Additionally, Lou et al. (2020) found that stay-at-home orders did not significantly reduce low-income work trips. Thus, it is vital to demonstrate the effects of socioeconomic and demographic factors to predict the patterns of evolution of mobility levels in a pandemic. Our classification model, MLR LASSO, has examined the significant factors and assessed the importance of selected features between clusters. As a result, income, employment and accessibility are quantified as the most effective domains. Subsequently, housing type, perceived risk of COVID-19 (before the lockdown), and BAME (Black, Asian and minority ethnic) variables were also selected.

Availability of data and materials

All source R code and data necessary for the replication of our results and figures are available at https://github.com/wondolee/covid19-eng-lockdown.

Credit authorship contribution statement

Won Do Lee: Conceptualisation, Data Curation, Methodology, Formal analysis, Writing-Original draft preparation. Matthias Qian: Data Curation, Writing-Reviewing and Editing. Tim Schwanen: Conceptualisation, Writing-Original draft preparation, Supervision, Writing-Reviewing and Editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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