

A new resilience model for Hounslow

Commissioned by the Hounslow Together Board
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About this report

This report was commissioned by the Hounslow Together Board. The report has been written by Paul Goodship and Nicola Bacon, with statistical analysis by Alix Naylor.

About Social Life

Social Life was set up by The Young Foundation in 2012 to work on innovation and placemaking. All our work is about the relationship between people and the places they live. We work in the UK and internationally.

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Summary

This report describes the development of a model for assessing the resilience of local areas. It explores what the model tells us about change in the London Borough of Hounslow, and how it helps us understand the impact of population churn and new housing development on the resilience of local communities.

The model brings together data that predicts likely levels of resilience in neighbourhoods with data from official sources that describes local needs and circumstances.

The project has been developed by Social Life for the Hounslow Together Board through two phases of work, in 2015 and 2018-19.

Resilience - the ability of a community and individuals within it to cope and to support one another - is critical to understanding how communities manage and respond to stress and change at the local level, and how councils can best intervene to support local neighbourhoods.

The value of the resilience model

The resilience model's greatest strength is as a tool to flag the social aspects of small areas that may go under the radar, and that can often be hidden within official data.

Public sector resources are becoming increasingly stretched and many Londoners are living in poverty. Applying the resilience model reveals strengths and weaknesses in local areas. These insights can help direct public sector spending and intervention to support communities that are lacking the assets to thrive in the face of an uncertain future.

The resilience model

The data that predicts resilience - referred to as "predictive data" - has been modelled from Understanding Society Survey data. Factor and cluster analysis generated six "resilience clusters". Mapping these clusters to local neighbourhoods, or "Output Areas" (OAs), enables us to see where people with these characteristics are likely to live, and from this illustrate the predicted resilience of individual neighbourhoods.

The predictive data was compared to data from official sources that can be mapped to small statistical areas. This includes data on poverty and deprivation.

In the areas where the hard data and the predictive data move in different directions we can begin to explore the particular assets and vulnerabilities of different areas. Observations of local areas and conversations with residents and agencies help throw light on the detail of these very local dynamics.

Predicting resilience across Hounslow

The report reveals that predicted levels of resilience have changed across the London Borough of Hounslow.

- Between 2009 and 2015 the divide between the east and west of the borough widened, with the east becoming more resilient and the west less so.
- The east of the borough appears to have become absorbed into a more affluent inner London area while the west remains more deprived. Chiswick has become more similar to parts of Hammersmith, Ealing and Richmond.
- There are three distinct zones in the east of the borough: Chiswick and Osterley with predicted high levels of resilience, and Brentford with lower scores.
- The west of the borough changed very little between 2009 and 2015, with a scattering of strong and weak zones of predicted resilience.
- The west of the borough area is similar to the south of Hillingdon, here there is weaker resilience than in most of the outskirts of London.
- In the centre of the borough there are some more positive zones of resilience; this is separated from areas of high resilience in the south of the borough by the railway line.

The resilience clusters

1. **Low wellbeing:** lower satisfaction with life overall, income, amount of leisure time, and concerns about managing financially
2. **High wellbeing:** higher satisfaction with life overall, income, amount of leisure time, and concerns about managing financially
3. **Neighbourhood support:** high social solidarity and high belonging
4. **Competence:** high levels of capability and low levels of stress
5. **Isolation:** low levels of belonging and local levels of social solidarity
6. **Emotional fragility:** high levels of stress and low levels of capability.



Actual data describing small areas

A number of hard data sources were analysed and many broadly reflect the trends in the predictive data, including the Indices of Multiple Deprivation (IMD).

However at the very local level, disadvantage and deprivation do not always coincide with predicted resilience. For example the north west of the borough has high deprivation but predicted resilience is closer to average.

Resilience and population change

An important element of local life is the movement of people and groups in and out of an area. Numerous local and external dynamics influence these flows of population. Population churn can cause instability, which can undermine a neighbourhood's resilience; conversely churn can create a more diverse population which can be associated with stronger resilience.

New council tax registrations indicate where new households have moved into an area. Although there were few clear patterns in the relationship between new council tax registrations and the predictive data we did find that some of areas with the highest number of new council tax registrations (as a result of housing development) are also those with low predicted resilience. Many people moving into new homes will be from different social and economic backgrounds to the longer-standing residents of these more fragile areas.

Between 2009 and 2015 the number of registered HMOs grew in the centre of the borough, near Heathrow, and to a lesser extent in the east. The increase in HMO numbers is a possible threat to future resilience, introducing a more transient population, who may be unlikely to stay in the area. This could be particularly destabilising in areas where predicted resilience is low.

GP registration data includes details about ethnicity and place of birth. This reveals a large Asian, mostly Indian, population in the centre of the borough, with the white British population concentrated more in the east and west - and an "other white" population in central Hounslow.

International migration appears to be affecting the centre of the borough more than other areas. Our model predicts that these central areas of the borough are likely to have mid-range resilience, neither strong, nor weak. Analysis of individual clusters reveal that this part of Hounslow is likely to have strong neighbourhood support and low levels of isolation, suggesting that this Indian majority community is stable and neighbourly.

In the area that makes up the London Borough of Hounslow, international migration does not appear to be disproportionately concentrated in areas with low resilience.

Hounslow's experience compared to the rest of London

London has experienced a changing pattern of predicted resilience between 2009 and 2015.

- Predicted resilience weakened in the centre of the city. Conversely a swathe of outer London, in the southwest, southeast and east, plus the fringes of northwest London, are likely to have become more resilient.
- In inner London, some of the weakest areas of predicted resilience in 2009 had dispersed by 2015. This is especially noticeable around the edges of inner London, where resilience is likely to have become stronger in this period.
- The London Borough of Hounslow's experience mirrors the overall trends in the east of the city, with Chiswick becoming part of the more resilient inner London fringe.
- However at the edge of the borough we see a different trend to the majority of areas in the outskirts of the city, where predicted resilience strengthened over this period.

1. Introduction

This report describes Social Life’s work with the London Borough of Hounslow to develop and test a model for assessing resilience in local neighbourhoods. The project began with an initial study in 2015, and in 2018 Social Life developed and explored the model further, updating it with recent data and investigating changes over time.

This report sets out the findings of the work and the approach taken to analysing different kinds of data and mapping this to small areas. Our aim has been to paint a picture of the levels of resilience in Hounslow at the very local level, using existing data, and to understand how this changed between 2009 and 2015 (this was the most up-to-date relevant data available at the time of this analysis).

The key working assumption is that understanding resilience - the ability of a community and individuals within it to cope and to support one another - is critical to understanding how communities manage and respond to stress and change at the local level, and how councils can best intervene and support local neighbourhoods.

This is particularly relevant in the context of reductions in public sector spending, and for places like Hounslow where population growth, churn and change risk fragmenting communities and further undermining their ability to cope.

Our approach

Our work on resilience flows from the assumption that the neighbourhoods that thrive do so because of their local assets and social wealth, and that these factors are important in supporting people from all backgrounds, but particularly those who are vulnerable and disadvantaged.

In the same way that some individuals find it easier to deal with life’s difficulties, and bounce back in the face of problems that may stop others in their tracks, some places have over time proved more resilient to shocks and downturns than others.

2. Starting point

Our starting point has been a wish to make best use of openly available data describing local areas and how people feel about them, in order to better understand the different factors that support (or undermine) resilience and wellbeing.

Our resilience model brings together hard data about social needs and conditions with perceptions data about how people feel about their everyday lives.

The UK is well-served by extensive data about our population and social needs, and much of this is available at a very local level. This data covers everything from economic indicators and deprivation to measures of health and education. Large-scale national surveys also capture a volume of information about how we feel about our lives and how we perceive the places we live.

Measuring resilience allows us to identify the places where there are stronger social supports, acknowledging that these can exist alongside profound vulnerabilities. This approach is not a tool for traditional performance measurement, and cannot be used to simply rank different areas. Instead it is designed to support a better understanding of local areas and their community dynamics, and to support conversations, negotiations and decision making around resilience and wellbeing.

The World Health Organisation defines community resilience as “the ability of communities and groups to adapt and thrive in response to external stressors”. Elaborating on this, resilience is “the dynamic process of adapting well and responding individually or collectively in the face of challenging circumstances, economic crisis, psychological stress, trauma, tragedy, threats, and other significant sources of stress. It can be described as an ability to withstand, to cope or to recover from the effects of such circumstances and the process of identifying assets and enabling factors.”¹

Substantial work has been done on individual resilience to understand why some individuals bounce back or flourish in the face of adversity or risk. Research, particularly in relation to child and adolescent development, has tried to understand the interplay of “biological, psychological and socio-cultural” variables that allow successful adaptation in some individuals.



Research on community resilience is less developed, but extends these approaches, based on the premise that “place matters”.²

Sir Michael Rutter, a leading child psychiatrist who specialises in the interplay between genetic and psychosocial risk factors, distinguishes between moderating factors (which help a person or community thrive) before adversity, and moderating factors that help people cope at the time of or after adversity. The focus in our model is on understanding the factors that moderate risk prior to adversity, which we refer to as “assets”.³

This project

In 2014 the Hounslow Together Board initiated a body of work investigating the impact of population and demographic change on the borough, and on its communities and services. The Board’s hypothesis was that change and churn in the population was affecting the resilience of communities and their ability to cope with change, and that the resilience of communities can drive service demand and affect outcomes for individuals and for communities.

Social Life’s analysis of community resilience was first commissioned in 2015 alongside a pilot project, “Cranford Stronger Together”, which looked at local social networks and the impact on service use and wellbeing.⁴ Based on a network

analysis and ethnographic research in the Meadows Estate in Cranford by the Royal Society of Arts (RSA), this proof of concept project aimed to prove that by strengthening an individual’s social networks, people’s wellbeing and resilience might improve, and social isolation and reliance upon services might be reduced.

Social Life’s work updates The Young Foundation’s WARM - Wellbeing and Resilience Model - updating the data, refining the analysis, adding some new data.⁵ Our initial project in 2015 updated and refined the model, and in 2018 further work explored historical trends in the data and correlations with other datasets, particularly focusing on demographic change and international migration.

Our new framework tests a prediction of resilience in very local areas against actual data about the place, to reveal how well it is faring. We have explored individual small areas in detail, so that the change in wellbeing and resilience factors and “actual” data can be read over this period. This gives us insight into how the borough overall has changed, and the impact on specific local areas.

We have looked at data for Hounslow, but also London-wide, since citywide dynamics often impact on local communities.

3. The new resilience model

To begin to quantify resilience, we developed six typologies, or “resilience clusters”, describing key aspects of resilience. The detail about the analysis and how we approached it is in the Appendix.

If we analyse who lives in an area we can see how the different clusters are represented within the population. Mapping these clusters for 2009 and 2015 allows us to observe changes in the way the clusters are represented across the borough.

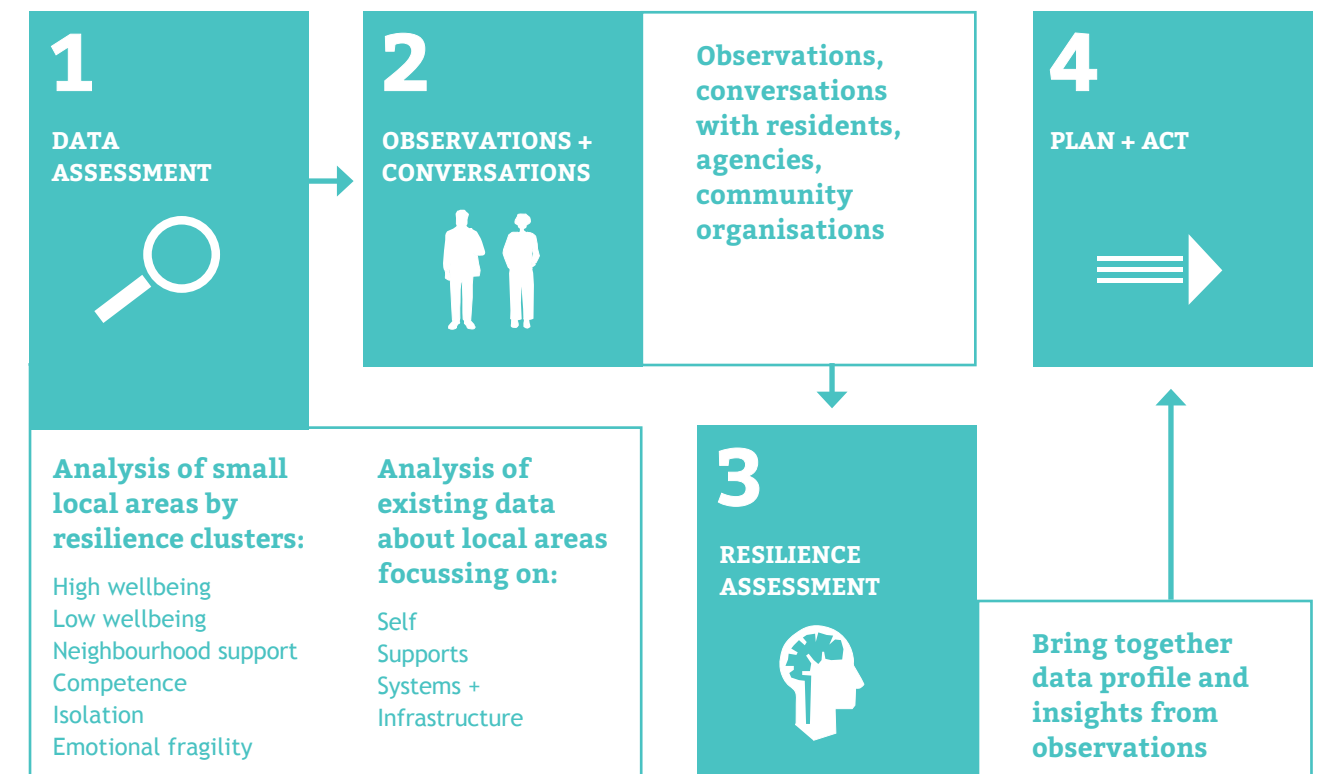
The resilience clusters

The different clusters describe areas where the notable characteristics are:

1. **Low wellbeing:** lower satisfaction with life overall, income, amount of leisure time, and concerns about managing financially
2. **High wellbeing:** higher satisfaction with life overall, income, amount of leisure time, and concerns about managing financially
3. **Neighbourhood support:** high social solidarity and high belonging
4. **Competence:** high levels of capability and low levels of stress
5. **Isolation:** low levels of belonging and local levels of social solidarity
6. **Emotional fragility:** high levels of stress and low levels of capability.

Mapping enables us to predict strengths and weaknesses within small local areas - identifying for example which areas have higher than average scores for a particular cluster (that is, there are larger number of people from that group living in the area), or which are lower (having fewer people from that group living in the area).

When we look over time, we can see the shifting patterns of local resilience. We can test this against actual data about the place to form a layered picture of Hounslow.

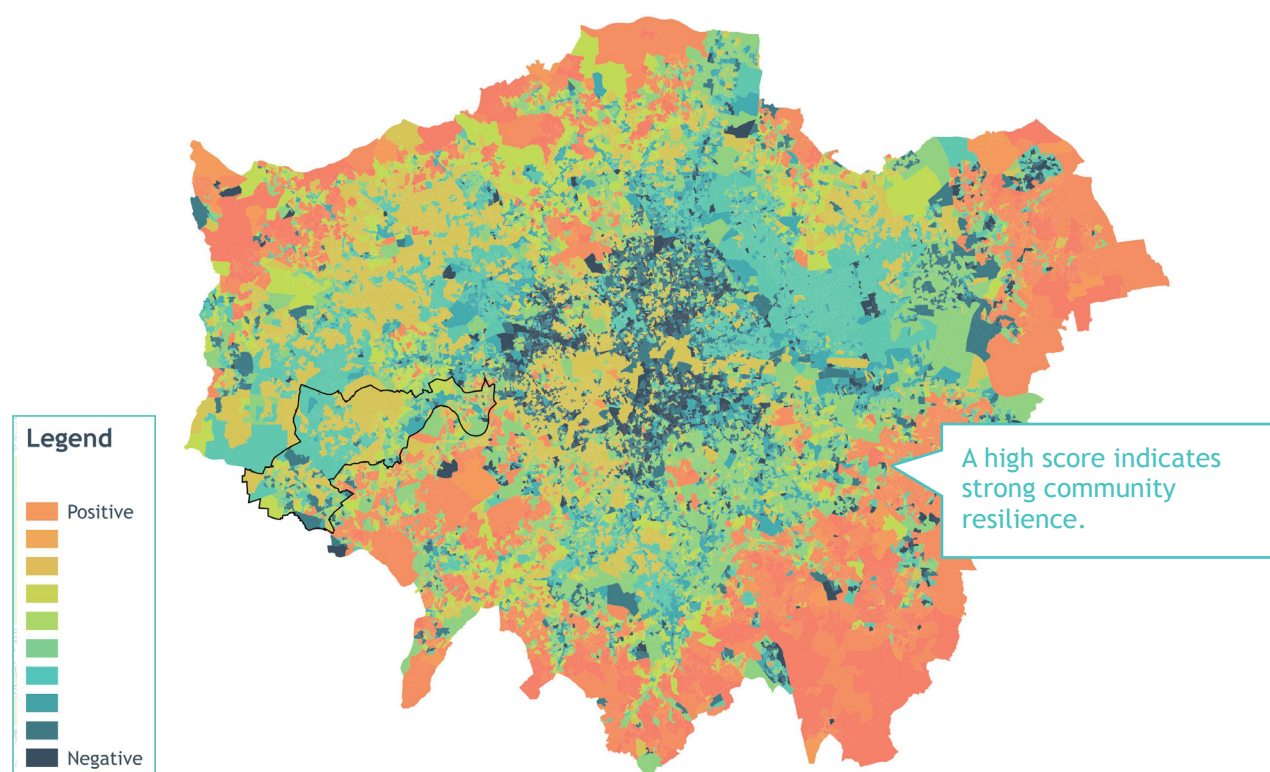


The resilience assessment for any particular area is in four stages. It brings together data from the resilience clusters that predicts levels of resilience, with existing data describing the circumstances of the area and the needs of the people living there. Next, the findings of the data analysis stages are investigated through observations of the area and conversations with local stakeholders. From this a resilience assessment can be made and a plan made to respond to the findings, to boost assets and help mitigate against vulnerabilities.

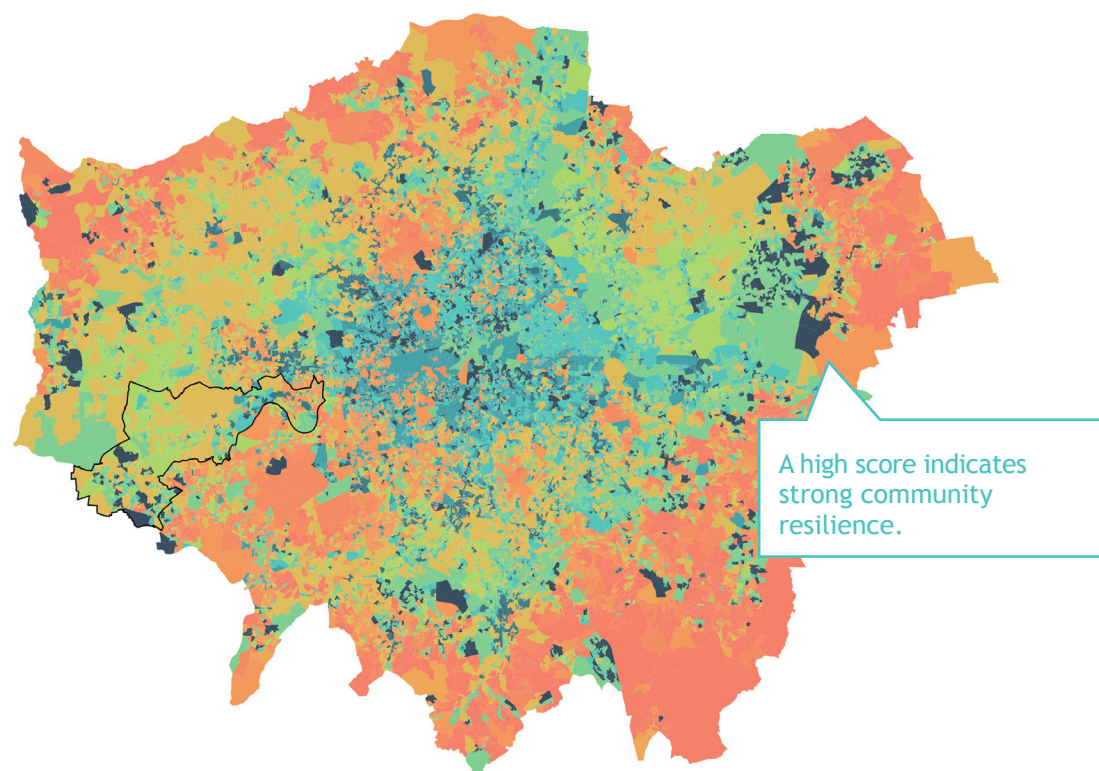
It is also possible to use the data to investigate particular issues or changes. In this report we investigate change over time and the impact of population churn and new housing development.

This is exploratory and experimental work. Hounslow’s initial pilots and tests - investigating the findings in depth in local areas, and examining how they relates to service data - have confirmed its value on two levels, as a borough-wide insight tool and within local areas to understand specific issues.

1 Predictive data scores, OA level, for London 2009



2 Predictive data scores, OA level, for London 2015



Developing resilience clusters

The six “resilience clusters” - groupings of people likely to have similar characteristics indicating resilience - were identified through factor analysis and cluster analysis of Understanding Society Survey (USS) data.⁶ This investigated the relationship between responses to different questions about how people feel about the places they live, as reported in USS.

The resilience clusters have been mapped by Hounslow’s Output Areas (or OAs), the smallest statistical areas used by the Office for National Statistics (ONS).⁷ We refer to this as to “predictive data”. We use the ONS’ Output Area Classification System (OAC) to map the data to small areas.⁸

The exercise was repeated for two years, 2009 (Wave A of USS) and 2015 (Wave F of USS).



Comparing predictive resilience clusters to actual data about a place

Actual data or “hard data” about small areas (from the census, benefits data, other administrative and public sector data) can be compared with the predictive data to show whether an area is conforming to its prediction - testing for example whether an area with high predictive resilience is faring well in terms of deprivation data, or social supports - or whether the predication and the actual data tell different stories. Where the hard and predictive data vary, this tells us that the area is either struggling, because it is faring less well than predicted,

or thriving, doing better than predicted. In each case it suggests that specific local factors are affecting resilience.

To compare the predictive and hard data, we combined the maps from the resilience clusters (showing where an area had scored poorly or well) and overlaid this with maps of the hard data. The aim is to reveal the local areas where individual hard datasets and the predictive data show the same pattern, either both being negative or both being positive; and to pinpoint the converse, to find areas with contradictory findings in the hard data and the predictive data.

Individual data profiles have been created for small areas to highlight underlying issues and trends over time.

To understand our findings in more depth, a series of walking assessments of selected areas were carried out, led by borough officers. Through these we investigated how local observations and conversations could be used to support the findings of the resilience model.

Using the findings

Our interest is in how this model can be used to understand changes in the borough. We looked at two issues: changes in population, particularly focusing on migration and diversity; and changes in housing provision.

Churn data

Hounslow Council provided data that illustrates population churn for the years between 2009 and 2015, some of which could be analysed by ethnicity and nationality. This came from historical Council Tax records and GP registrations. The data has been analysed to help understand the relationship between what is known about local resilience and wellbeing and population change, and the impact of migration on local communities and on demand for services.

Housing

Data about legal HMO (Houses in Multiple Occupation) registrations in 2009 and 2015, and recent constructed residential projects with planning consents were mapped to see how these relate to resilience. Both aspects of housing provision have the potential to disrupt community stability and established networks, and to generate tensions when they occur in area with fragile resilience.

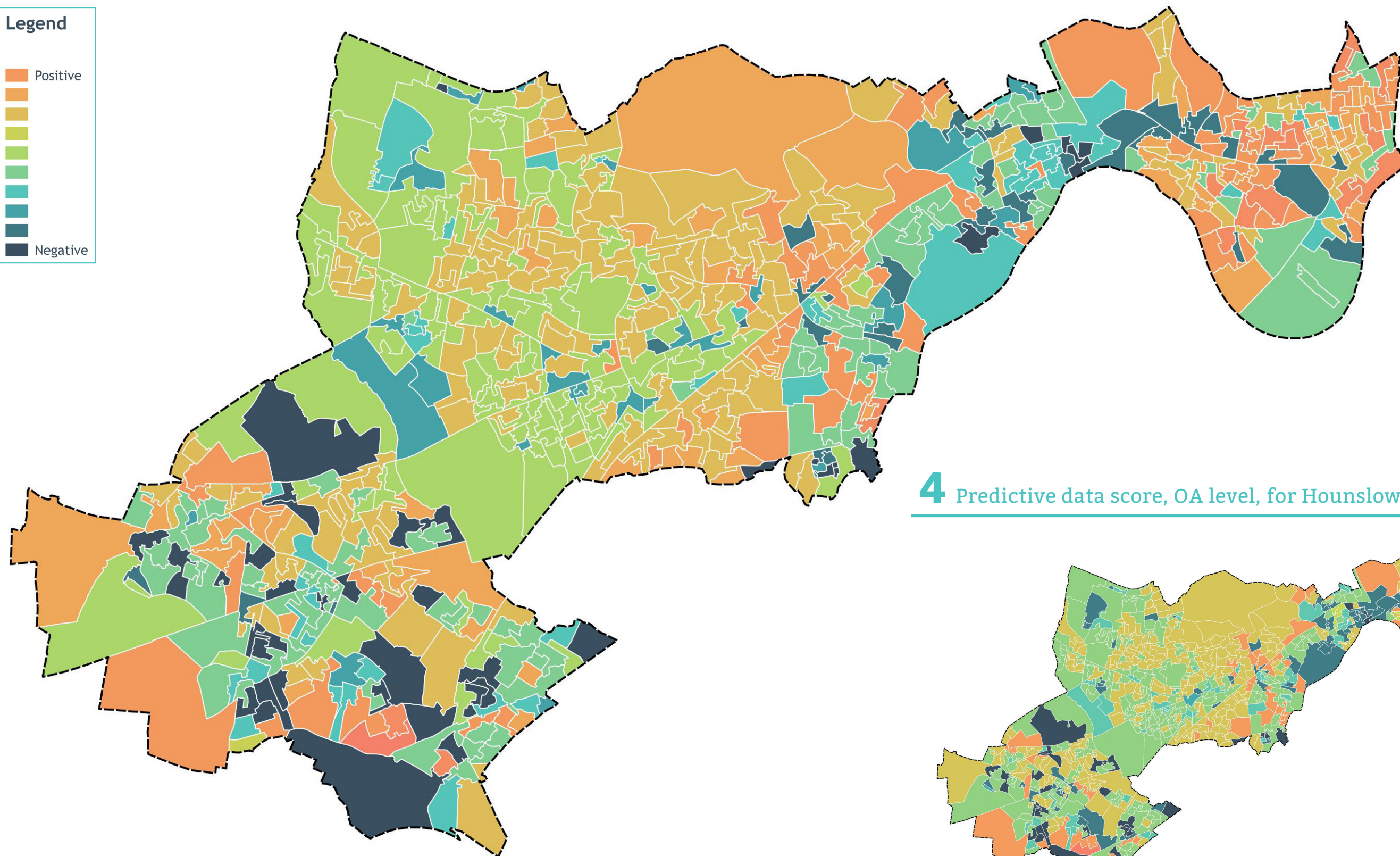
HMOs vary greatly in quality but there is a consensus that some of the worst housing conditions are often found in this sector.⁹ They can be home for many vulnerable people, with high levels of tenant turnover. An increase in their number within an area may therefore put a strain on services and community stability.

New housing development will also bring new residents into an area from different backgrounds to longer-standing residents. This may also disrupt social networks and community dynamics, including those that are supporting people who may be vulnerable and with few resources.

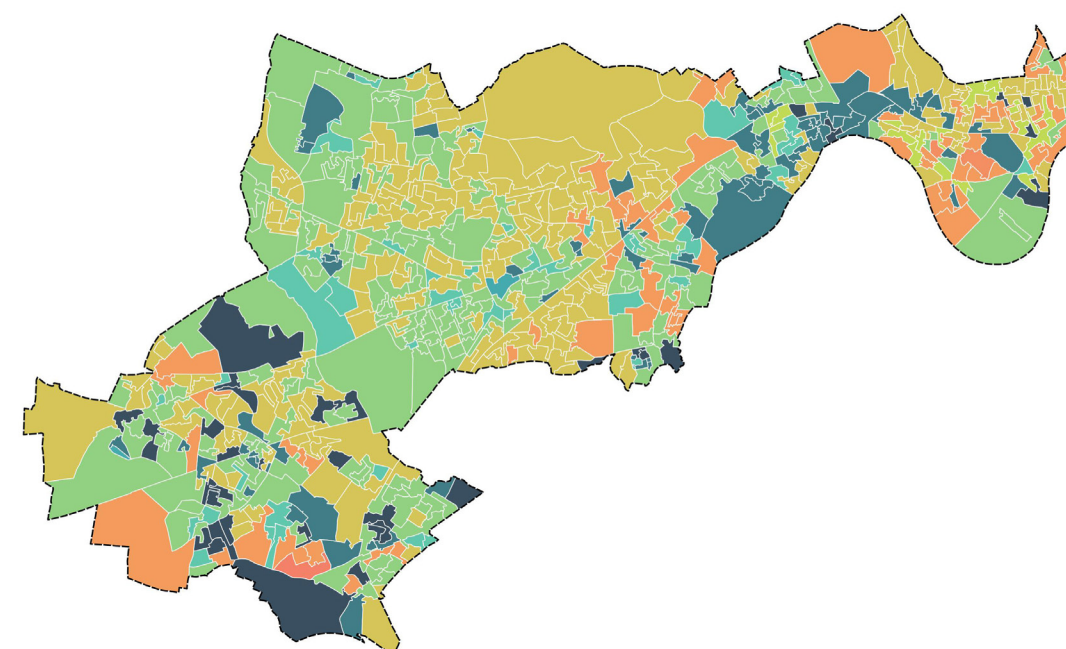
More detail about the analysis and how we developed our approach is in the Appendix.



3 Predictive data score, OA level, for Hounslow 2015



4 Predictive data score, OA level, for Hounslow 2009



A high score indicates strong community resilience

4. Our findings: the fragmentation of Hounslow

Predictive data: a division emerging



The predictive data illustrates that Hounslow fragments into positive and negative zones. This is most extreme in the east of the borough, around Chiswick, Brentford and Osterley, areas with good transport connections, close to central London. Here there are areas with strong and weak scores positioned side-by-side, and there are signs that these differences between strong and weak scores are growing over time.

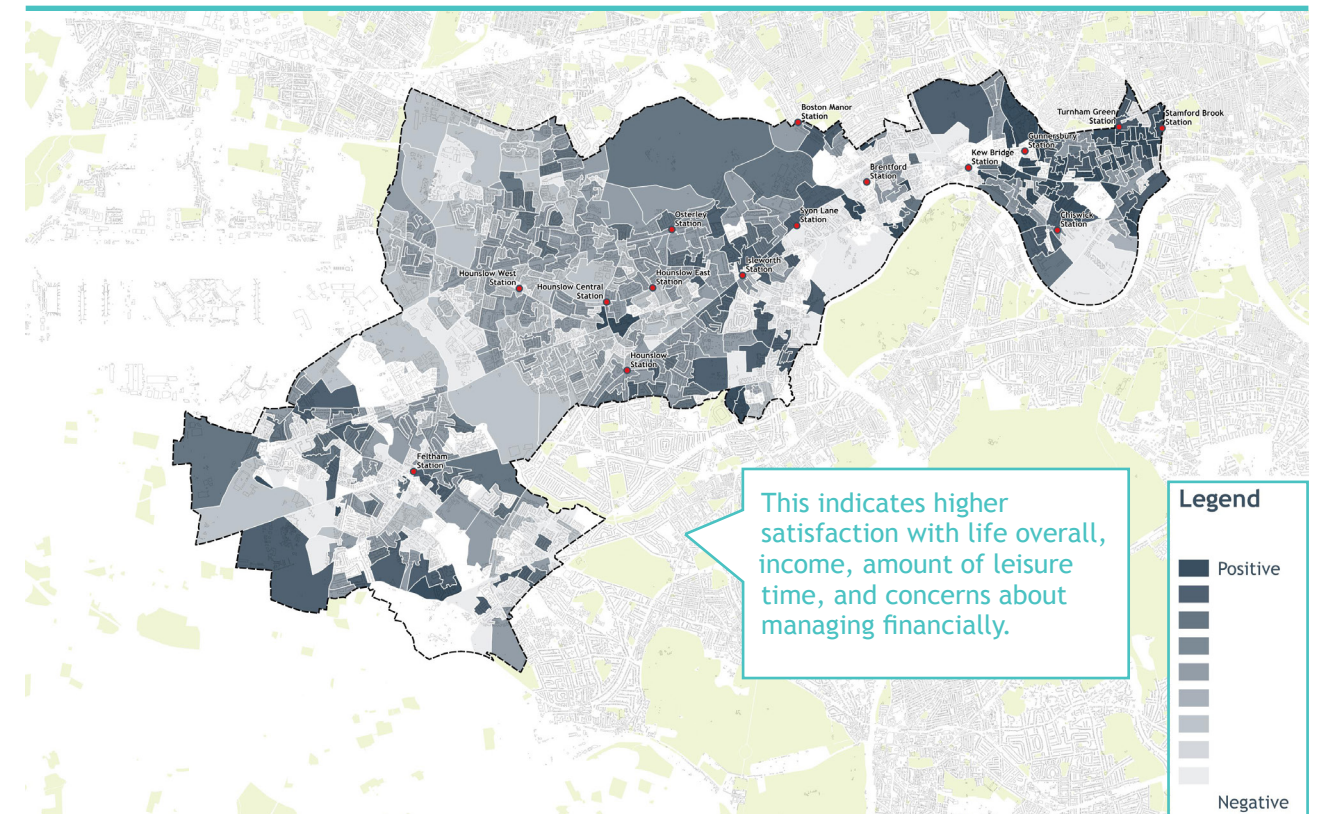
In the east of the borough:

- between 2009 and 2015 Chiswick is likely to have become more resilient, becoming more similar to parts of Hammersmith and Ealing and more distinct from the centre and west of the borough
- the predictive data shows three distinct zones in the east: Chiswick and Osterley with predicted high levels of community resilience and lower levels around Brentford.

The west of the borough:

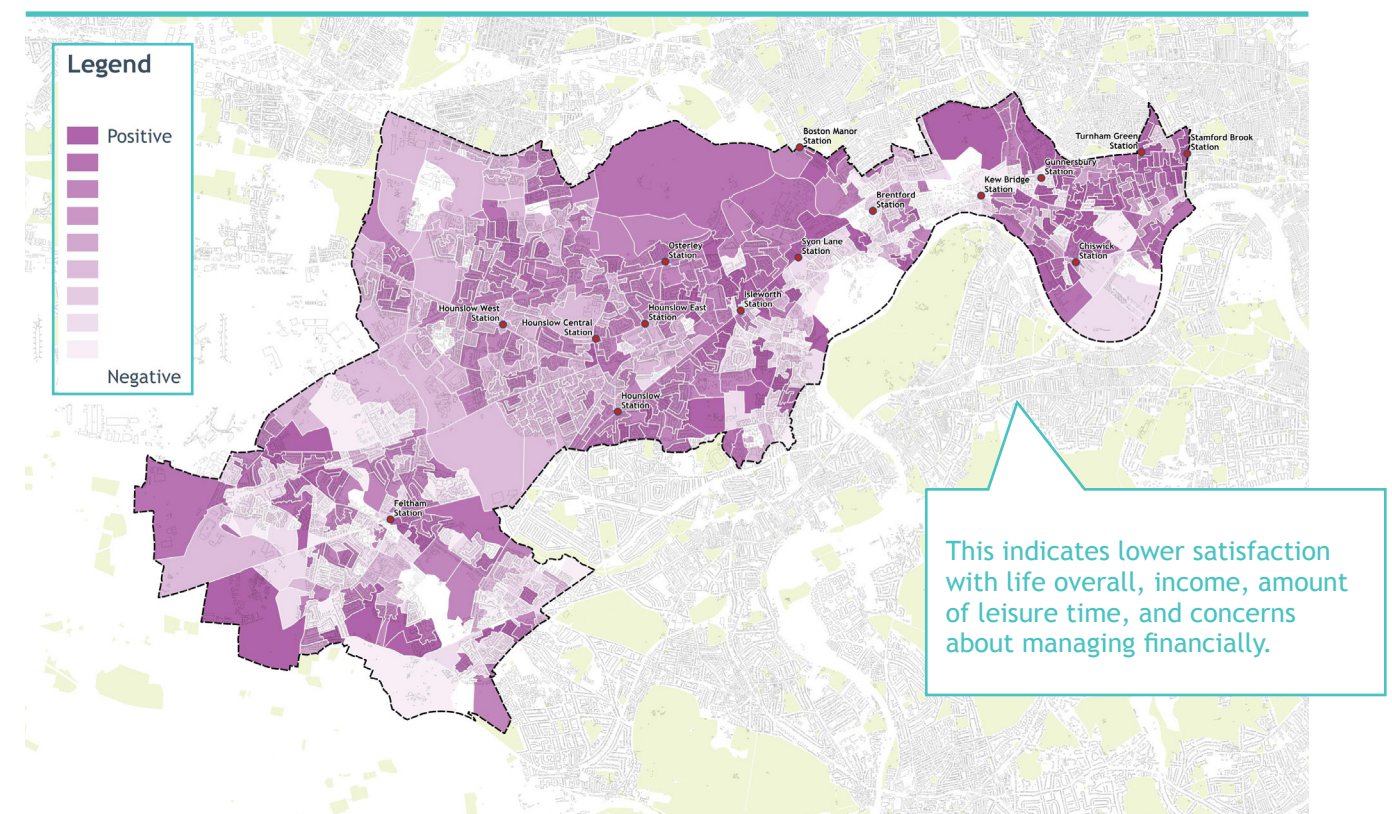
- the west remains largely the same between 2009 and 2015, a scattering of both strong and weak zones failing to form distinct areas
- this is an area with weak public transport connections bordering Heathrow Airport. It differs from many other areas on the outskirts of London where predicted resilience is stronger, although has similarities to the south of Hillingdon, also bordering Heathrow
- in the west the areas of strong and weak resilience are smaller than in the east, however there are still distinct divisions between these smaller areas, such as in Hanworth Park where strong and weak areas are positioned next to each other
- to the north-west of the borough, in Heston West, there are areas of weak resilience, there are signs these worsened between 2009 and 2015.

5 “High wellbeing” cluster, OA level, for Hounslow 2015



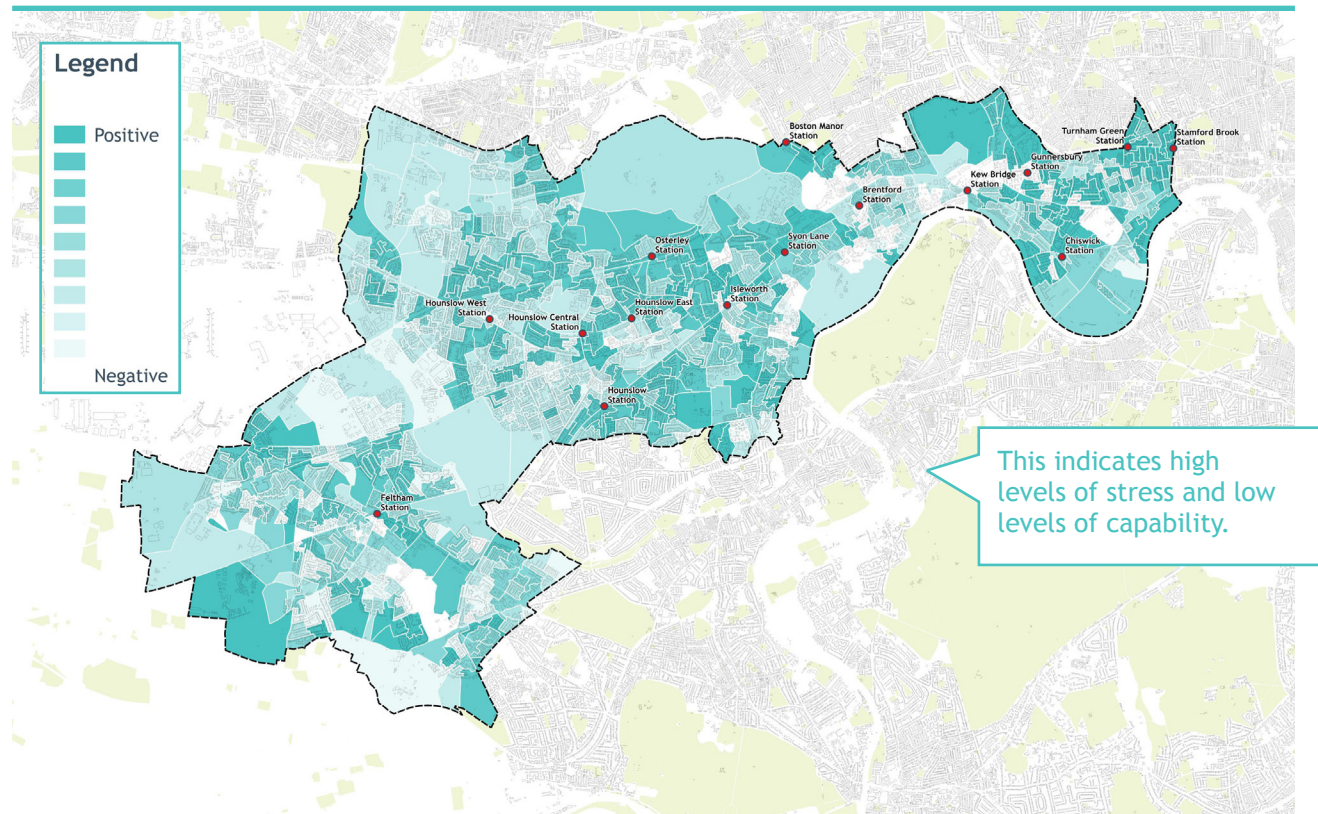
Positive being more high wellbeing and negative being less high wellbeing

6 “Low wellbeing” cluster, OA level, for Hounslow 2015



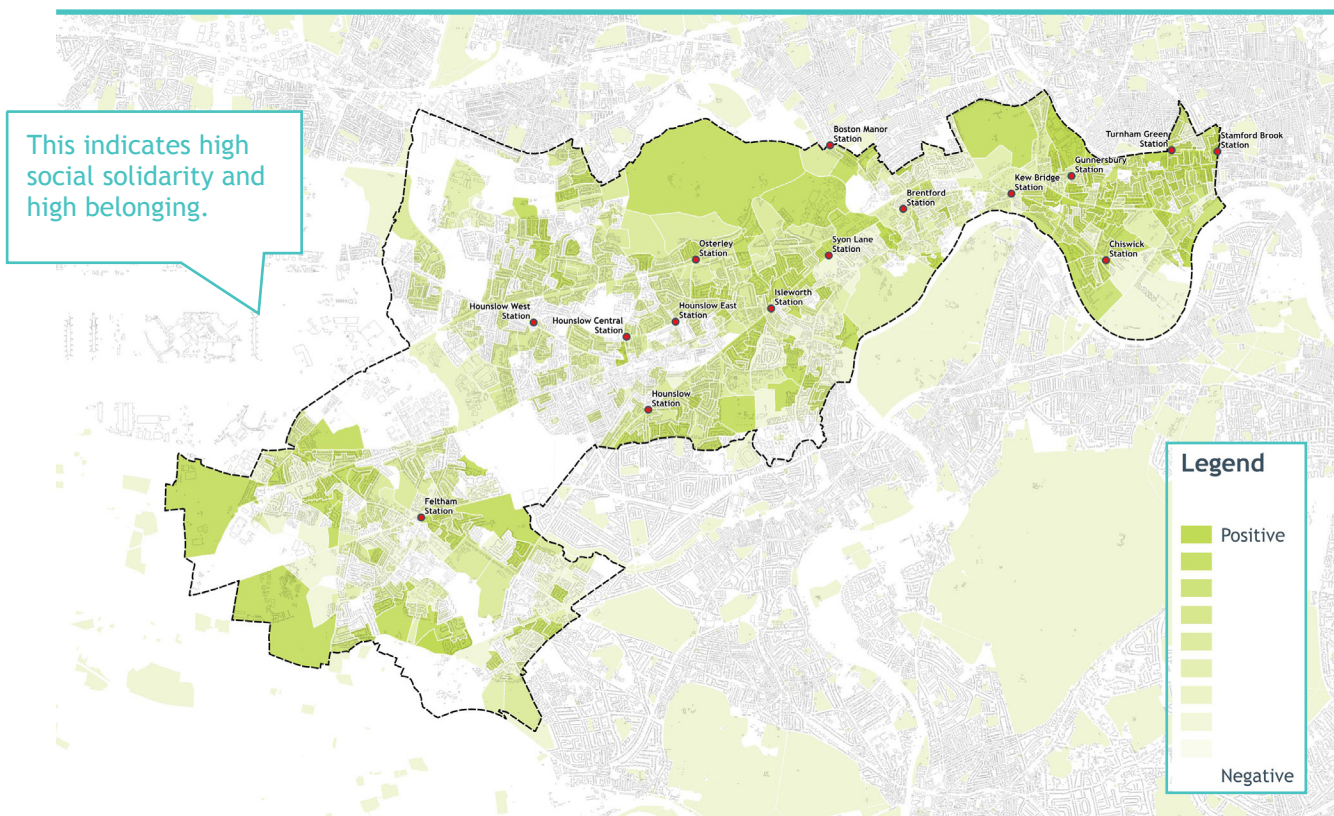
Negative being more low wellbeing and positive being less low wellbeing

7 “Emotional Fragility” cluster, OA level, for Hounslow 2015



Positive being less emotional fragility and negative being more emotional fragility

8 “Neighbourhood Support” cluster, OA level, for Hounslow 2015



Positive being more neighbourhood support and negative being less neighbourhood support



In the centre of the borough:

- resilience cluster mapping suggest some more positive zones in the centre of Hounslow, particularly when Competence and Isolation are mapped
- while south Hounslow show signs of high resilience there is a distinctive divide formed by the railway track, separating this area from Central Hounslow area, which has moderate resilience
- the railway tracks also appear to split areas of resilience between Osterley, which is strong and Syon to the south, which is weaker.

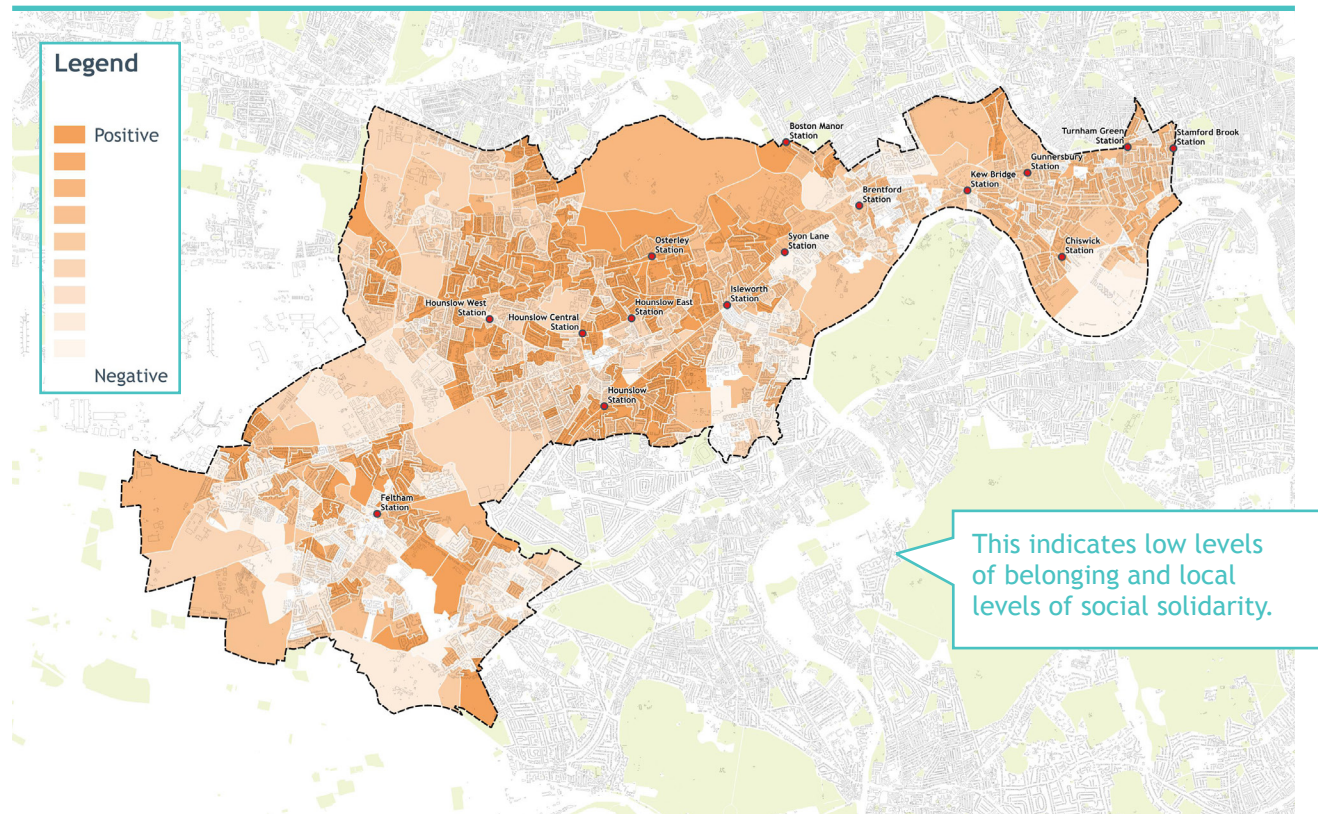
Looking at the individual clusters:

- similar patterns are repeated to the overall picture within the wellbeing clusters. There are some indicators that the divide between areas with predicted high and low wellbeing has increased
- the resilience clusters show less distinct divisions, however Emotional Fragility and Neighbourhood Support have some similarities in the distribution of negative and positive areas to the overall pattern. Scores vary between small local areas.

Mapping the predicted resilience of areas at the lowest level possible makes it possible to flag the local neighbourhoods where resilience is likely to be lower. If the predictive data is then tested against actual data, it becomes possible to identify places with particular vulnerabilities that may often go under the radar of traditional assessments.

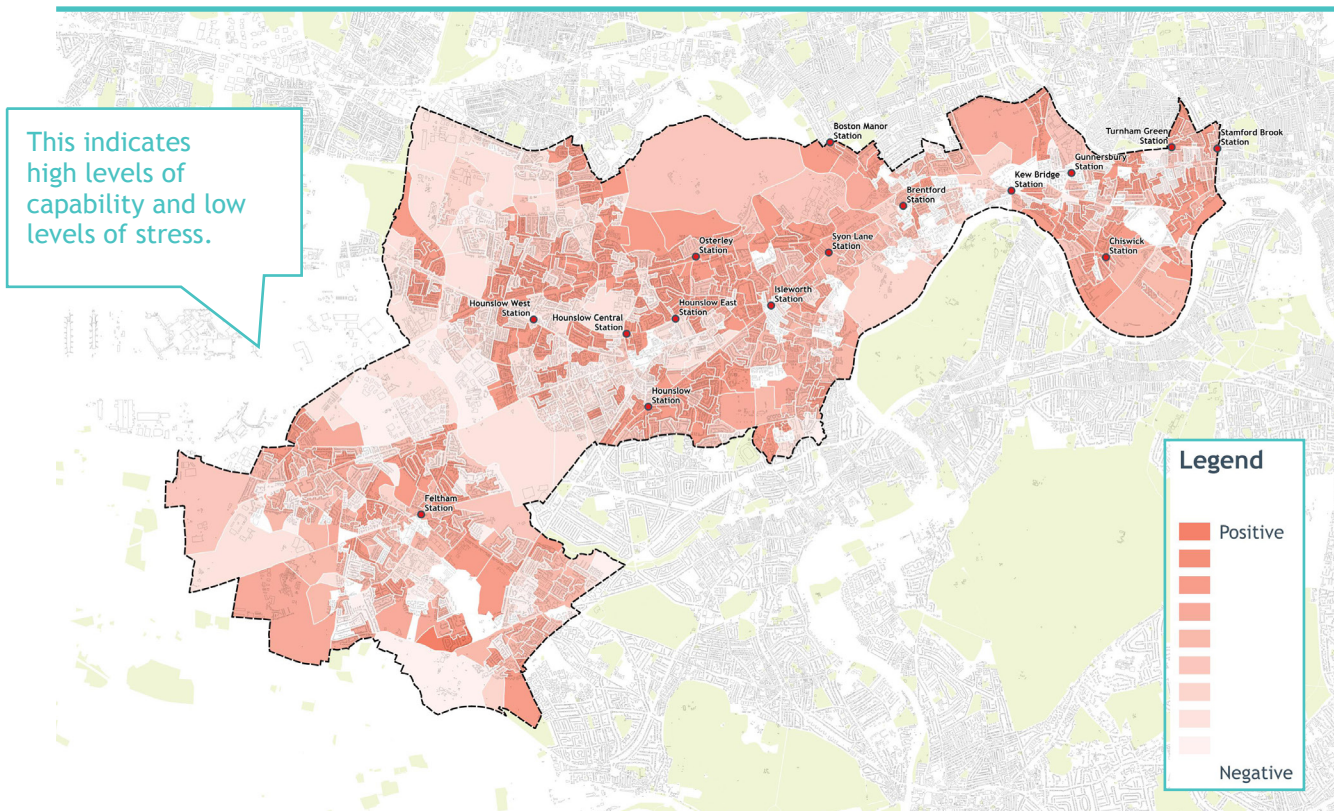
This provides the opportunity for local authorities and other public sector agencies to make best use of their limited resources to accurately target services to the areas that need it the most.

9 “Isolation” cluster, OA level, for Hounslow 2015



Positive being less isolation and negative being more isolation

10 “Competence” cluster, OA level, for Hounslow 2015



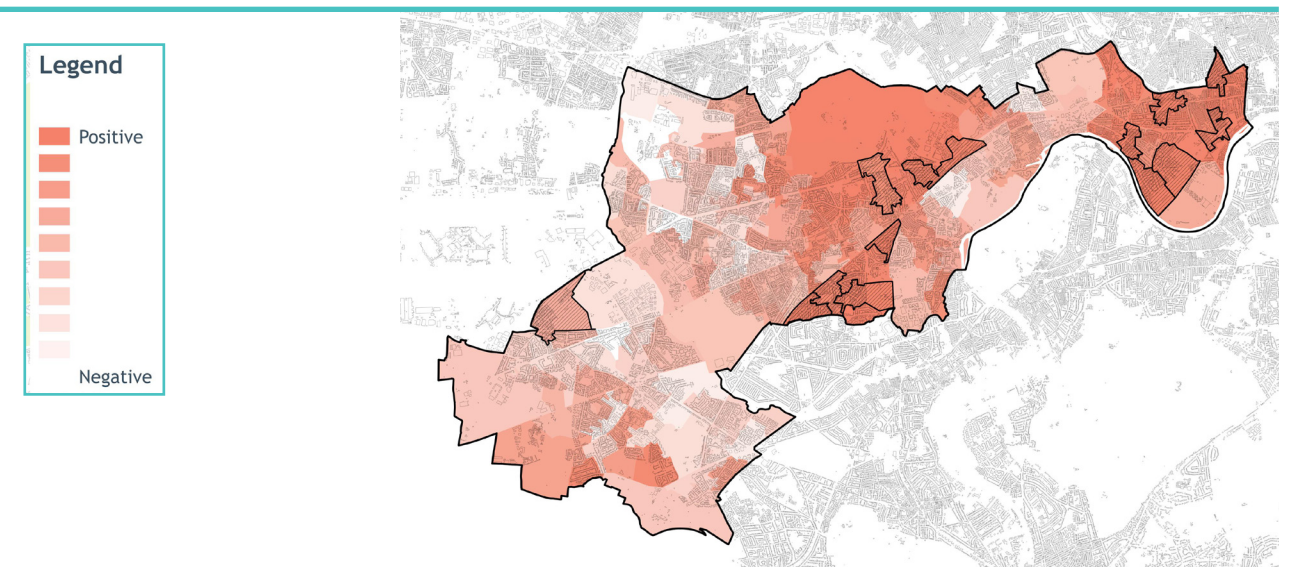
Positive being more competence and negative being less competence

Hard data: a divide in finance and deprivation

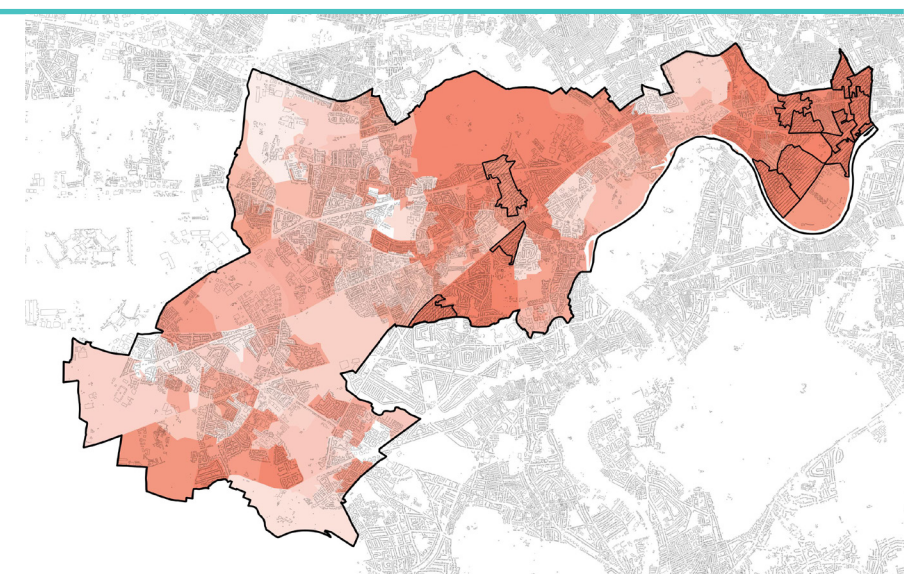
The predictive data and its individual clusters start to hint at an increasing divide between the east and west of the borough, the hard data can corroborate the specific differences.

We have looked at a range of different sources of hard data that paints a picture of social needs, for example, the number of elderly residents receiving pension credit and the number of children living in low-income families. We have explored which sources of hard data directly correlate to the predictive data results, and which show less of a connection (see Appendix, section 4). These have been aggregated together, and then explored as individual datasets.

11a Highest results in hard data, LSOA level, for Hounslow, 2009



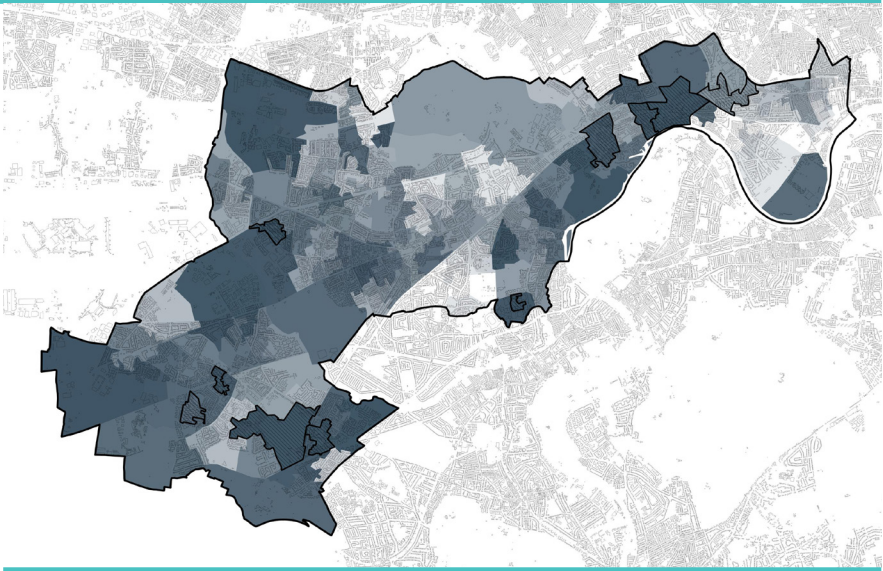
11b Highest results in hard data, LSOA level, for Hounslow, 2015



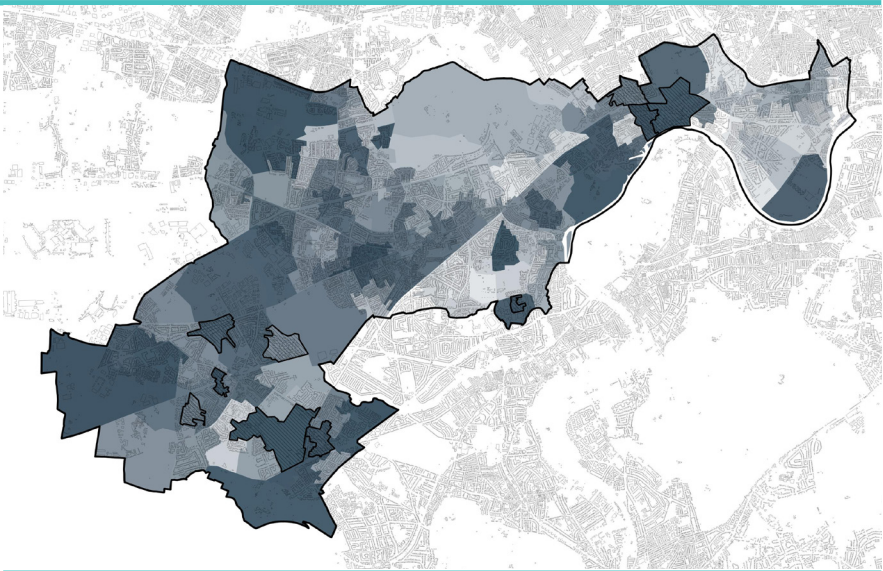
None of these datasets can be broken down to OA level, instead the larger Lower Layer Super Output Areas (LSOAs) are used as this is the smallest geographical level that most of the hard data can be mapped to.¹⁰

The highest and lowest areas of Hounslow are calculated from the combined analysis of each of the hard datasets, by overlaying the highest and lowest results for each. Areas outlined refer to the outlier LSOAs in the predictive data scores.

11c Lowest results in hard data, LSOA level, for Hounslow 2009



11d Lowest results in hard data, LSOA level, for Hounslow 2015



A strong correlation is clearly observed to IMD scores, which highlight the most and least deprived parts of the borough. Patterns are similar to the distribution of the predictive data. However at the very local level, IMD and predicted resilience do not always coincide. For example the north west of the borough has high deprivation but resilience is likely to be closer to average.

The Indices of Multiple Deprivation

IMD is a deprivation index at the small area level, devised for the UK government.¹¹ This captures distinct dimensions of deprivation, which can be recognised and measured separately, or aggregated into a single overall measure. This index is updated every five years, and was first created in 2000 as a continuation of the Local Index of Deprivation.

The Index is made up of seven domains, each built up from a series of different indicators:

- Income
- Education, skills and training
- Employment
- Barriers to housing and services
- Health and disability
- Living environment

While there are other pockets of deprivation elsewhere in the borough, Brentford is unique because spatially it sits between the least deprived area. It is well-served by public transport and and road connections and is close to inner London.

Very similar patterns are observed with other datasets such as children under 18 in low-income families, and residents over 60 on pension credit, both of which repeat the general distribution patterns of the resilience model, both in terms of the major zones of high and low resilience and in many small pockets.

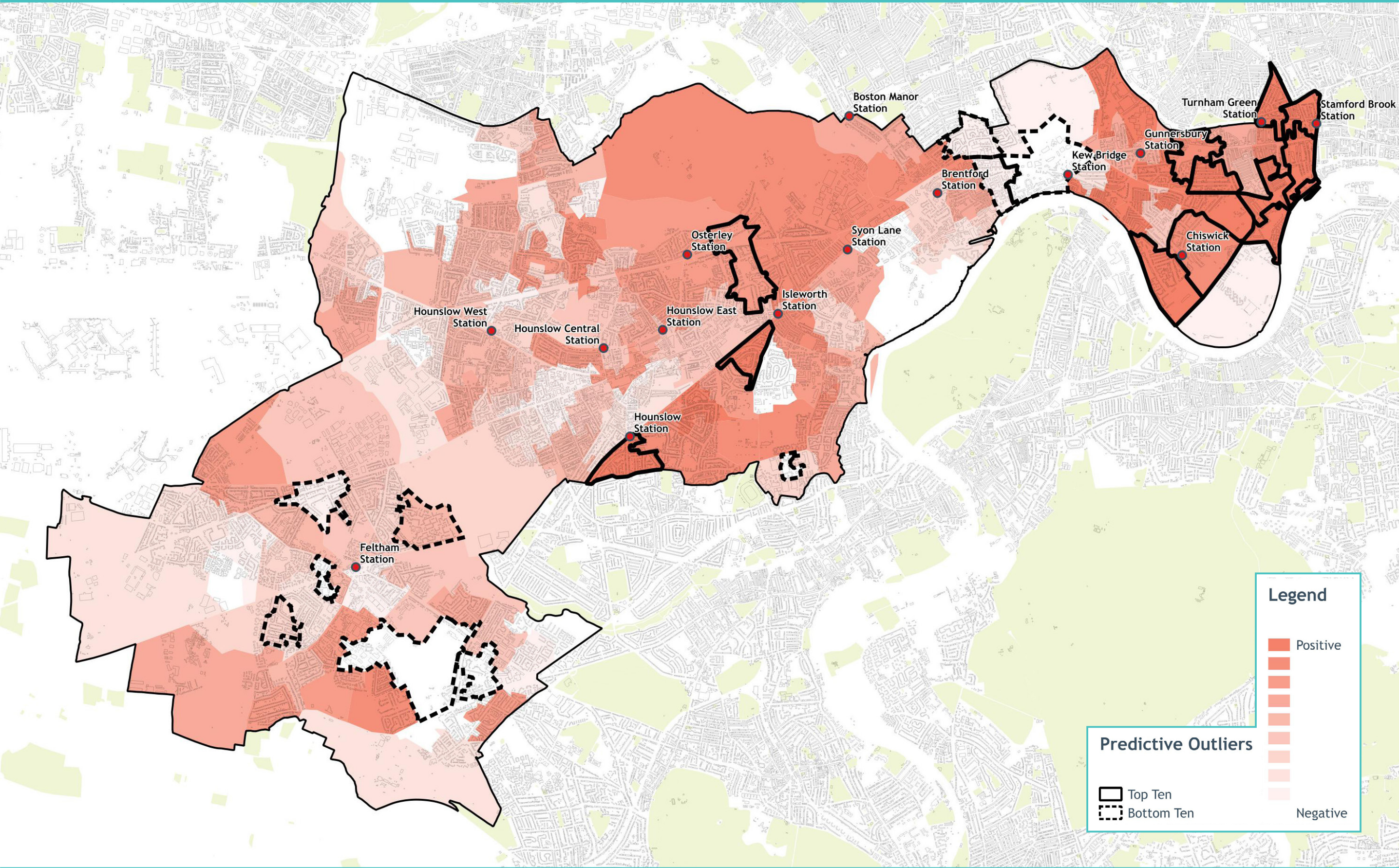


An additional dataset that repeats this very distinct east and west divide is childhood obesity at Reception (age 4 to 5). As with the other datasets, the results are more positive in the east, where there are distinctively fewer children considered obese than in the west. This relates to the general distribution patterns of resilience and to the financial and deprivation datasets. However, this dataset is measured at a larger geographic area - the Middle Layer Super Output Area (MSOA) - so direct local comparisons are hard.



Another financial dataset that repeats the same overall distribution patterns is median household income, however

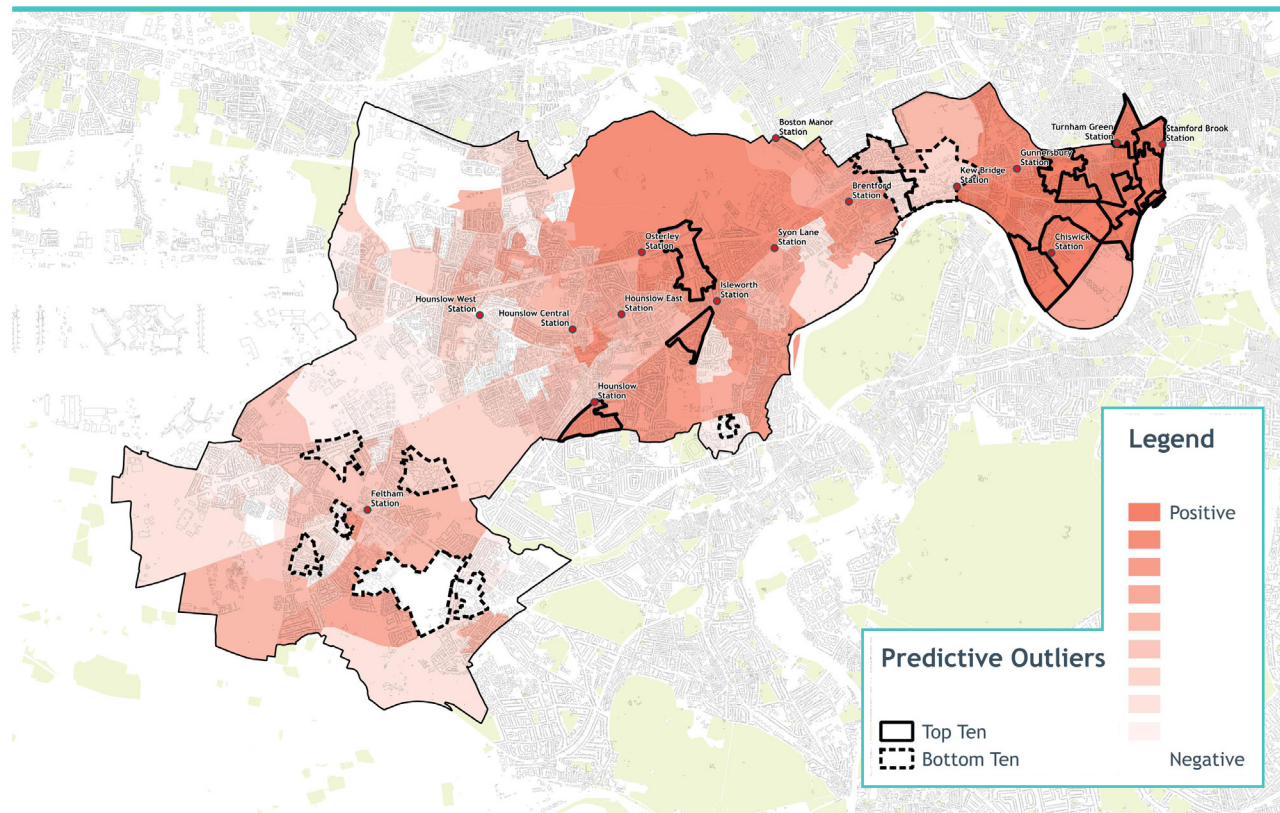
12 IMD Score for Hounslow, LSOA level, 2015



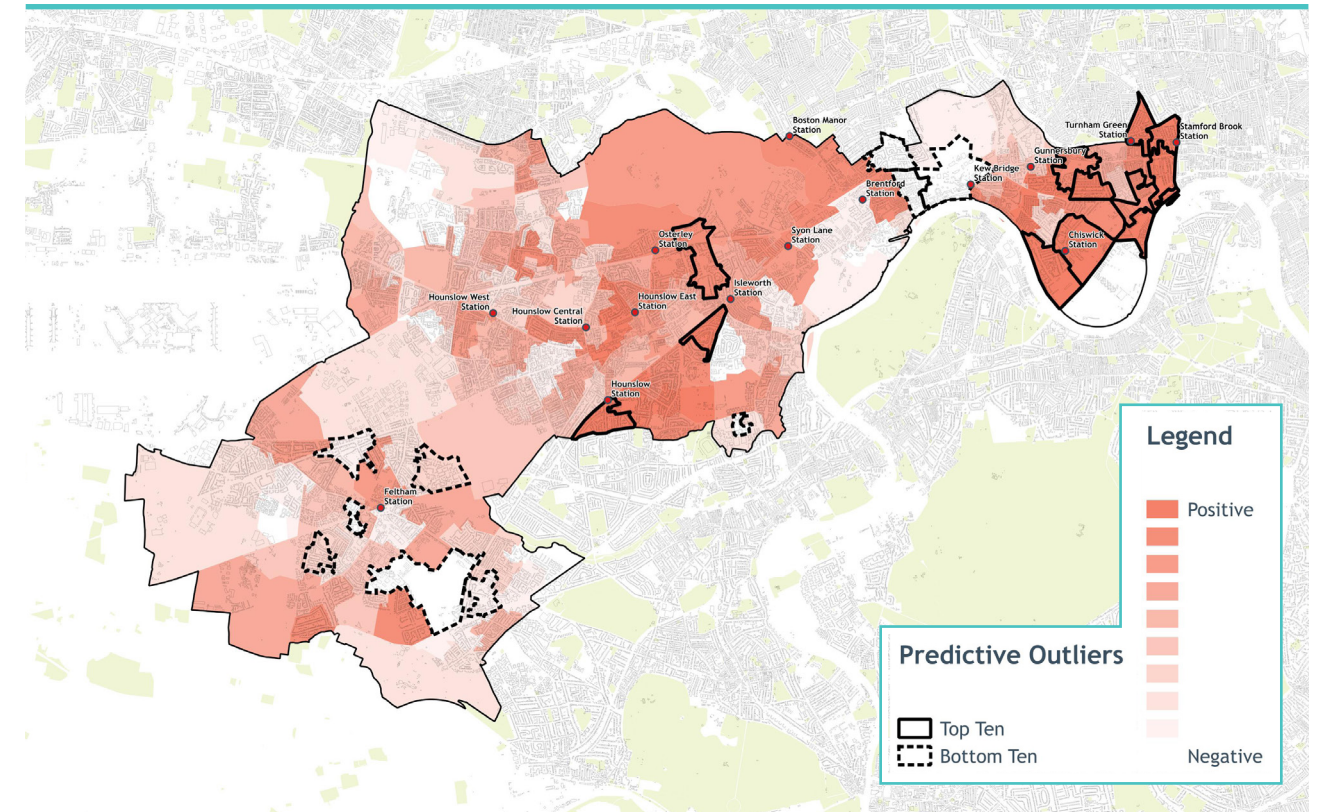
MAP 13

income does not map as closely to predicted resilience as other aspects of deprivation. Although the distribution of household incomes repeats the fragmentation patterns of the other hard and predictive datasets, it also illustrates a very distinct east-west divide in the borough. People living in the east earn more than in the west, even in Brentford, which is highlighted as being less resilient. Conversely, in the west, where income is lower, there are some areas with high resilience scores.

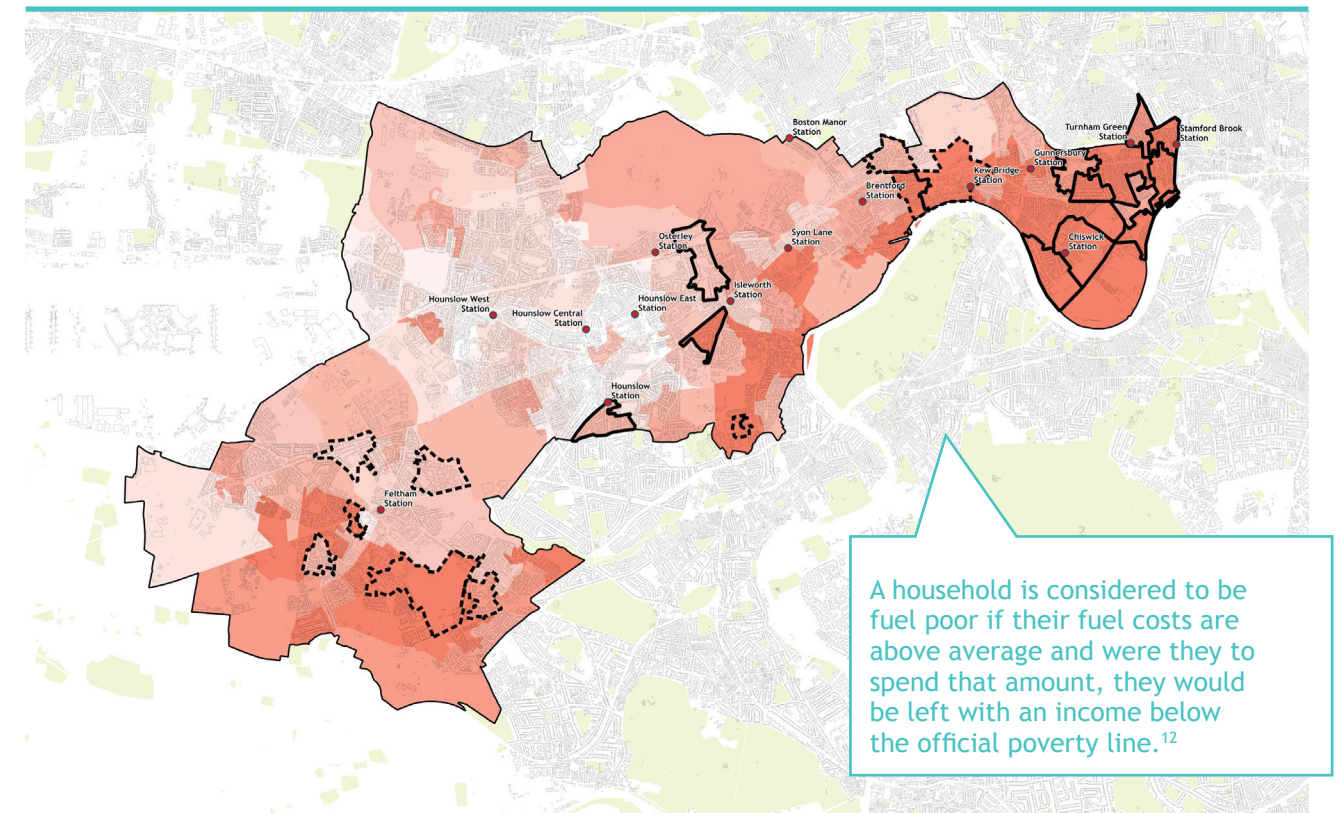
13 Median household income, LSOA level, for Hounslow 2015



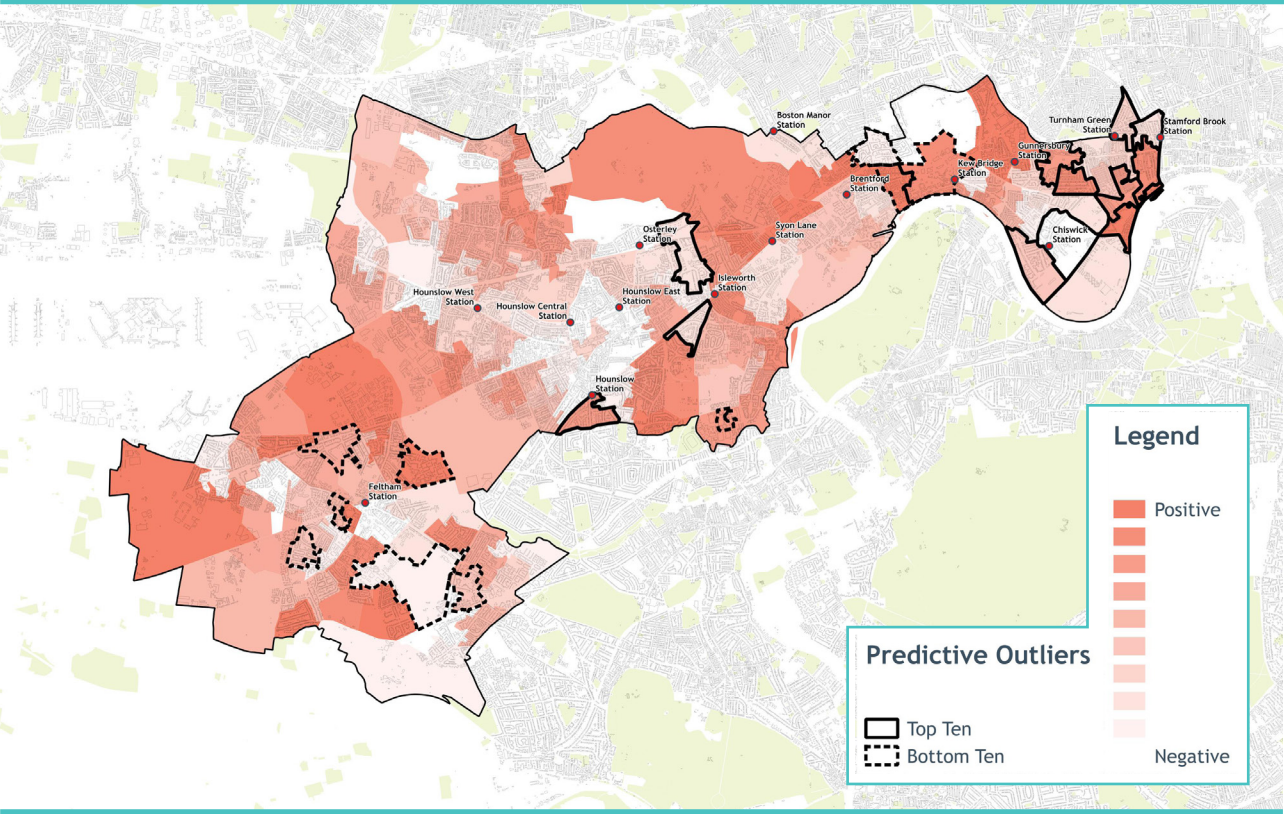
14 Children in low income families, LSOA level, for Hounslow, 2015



15 Fuel poverty, LSOA level, for Hounslow 2015



16 IMD Crime domain, LSOA level, for Hounslow 2015



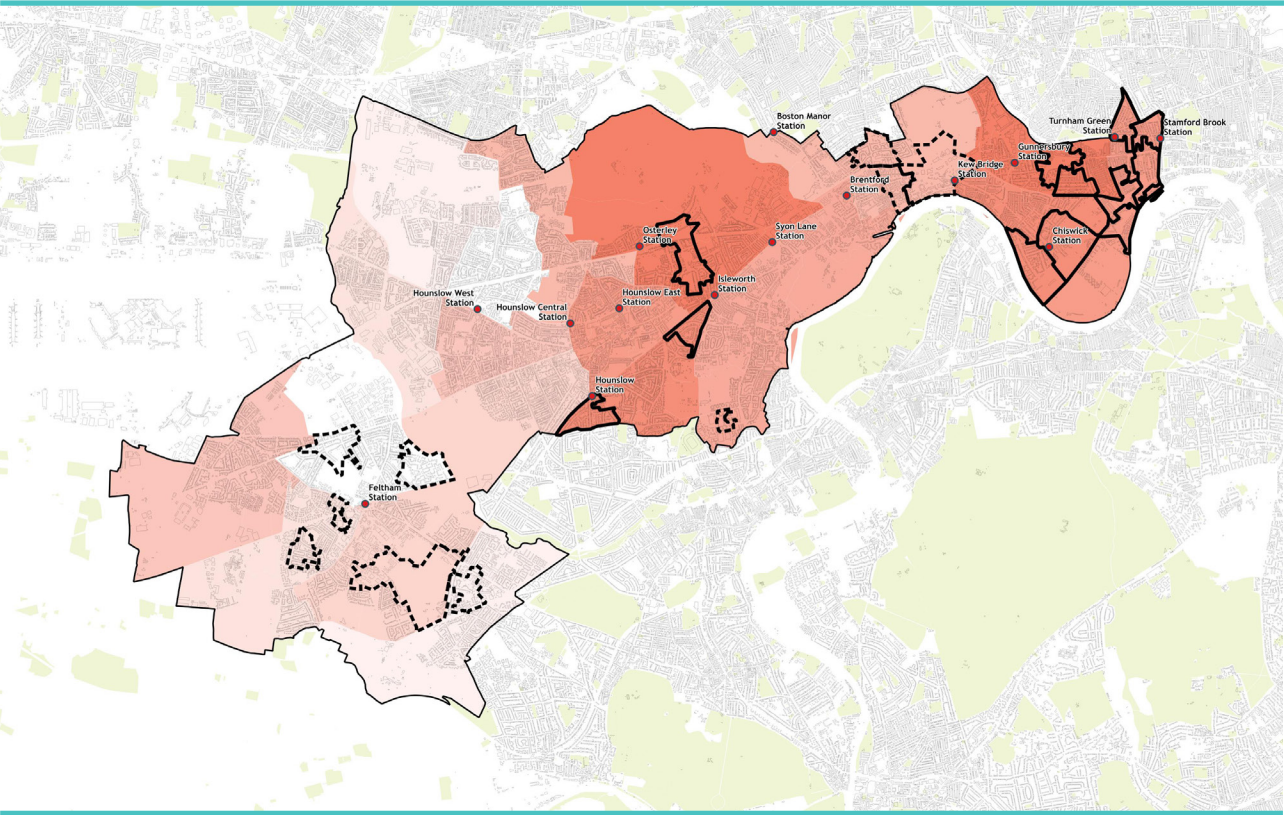
The IMD Crime domain, unlike the other domains, shows very few similarities to the resilience model or the individual clusters, as in general the strong and weak areas are unevenly scattered across the borough.

Though it is still possible to highlight the central parts of Hounslow as having the highest deprivation related to crime, there are also suggestions of a small negative area emerging in the east, where the wealthiest residents live. The distribution of crime appears to relate spatially to the locations of train stations, reflecting how crime is often concentrated in areas with high footfall.

Bringing together the resilience prediction and actual data

The predictive data highlights the neighbourhoods of Hounslow that are likely to be resilient, and the hard data corroborates some of these findings. However, by revealing the areas where the prediction and the actual data diverge, it is possible to see the areas where other aspects of local life are supporting residents or where there are unexpected vulnerabilities.

17 Child obesity at reception, MSOA level, for Hounslow 2015



The differences between predicted resilience and actual data flag important issues that the borough should investigate. These include the mismatch between high average incomes and low predictive resilience in Brentford, the variation in patterns of actual crime from predicted resilience, and the number of small local areas where predictive resilience and the hard data show contradictory patterns. This has implications for service delivery across agencies, flagging areas where communities may need more support to deal with change and with population churn.

5. Testing the relevance of the model: population churn and housing

An important element of local life is the movement of people, and groups of people, in and out of an area. Population churn can cause instability, which can undermine community resilience; conversely change in populations also supports the growth of a strong and diverse community, boosting community resilience. Numerous local and external dynamics influence flows of population. Correlating the predictive and hard datasets and the churn data adds another dimension to Hounslow's resilience model, and we can start to interpret where certain communities are positioned within these models of resilience.

As there is no comprehensive dataset describing population churn in local areas, we looked at different types of data that describe aspects of churn: patient registrations with GPs, planning consents for new developments¹³ and Hounslow's register of licensed HMOs (Hounslow Council operates an additional licensing scheme as well as the mandatory HMO licensing required by English and Welsh local authorities). These datasets can then act as a proxy for population churn in the borough.



Council tax registrations and new housing developments

When the total numbers of new council tax lead registrants are examined for 2009 and 2015 it is very hard to find overall patterns in the distribution of the data or relationships between this and the predictive data. However, when individual small areas are analysed alongside the resilience clusters we see that some of the areas that are least resilient also have the highest number of new council tax lead registrants. Between 2009 and 2015 parts of Hounslow experienced significantly larger rates of population growth than the borough average and much of this can be attributed to large new housing developments. This is evidenced in the council tax churn data, and there are similar findings in the new total number of GP registrants.



To analysis this further the location of (completed) planning consents for new developments for 2009 and 2015 were mapped, and plotted in relation to the number of new residential units completed.

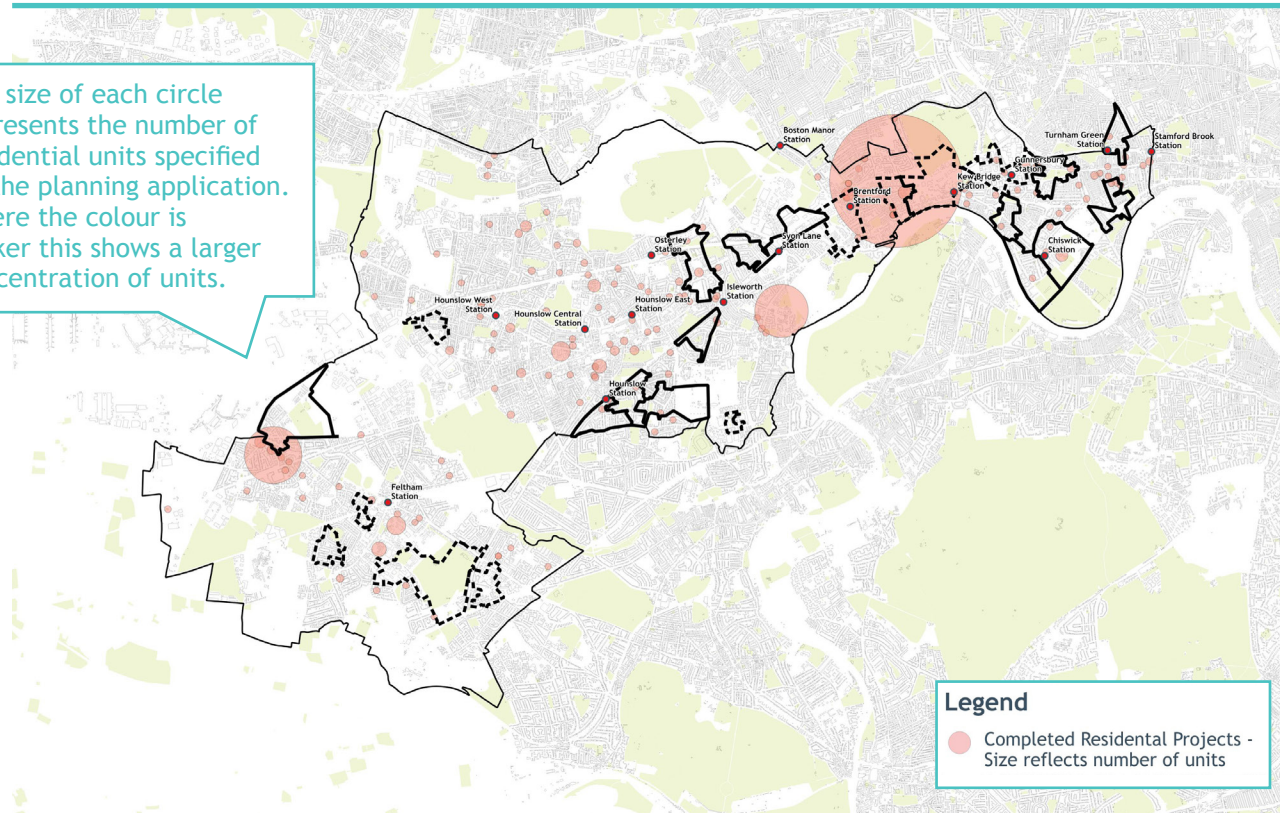
This shows that the largest concentration of new residential developments for both years occur in Brentford, specifically in and around the LSOA (Hounslow 003C) that is ranked lowest with the predictive data for both 2009 (Wave A) and 2015 (Wave F). This area also ranks very low in IMD and financial datasets. It appears that the part of Hounslow that is predicted to be the least resilient and emerges as very weak within the hard data is also the area that is being most heavily developed.

Housing development and regeneration tend to focus on areas where house prices and land values are low, where there are commercial opportunities and vacant sites to develop. These may be likely, by their nature, to be areas with more vulnerable populations and higher levels of deprivation. It is possible that other areas where new housing at scale is being developed, for example in central locations such as Canada Water and Elephant and Castle and areas such as Southall where transport is improving, may also be home to communities with fragile resilience.

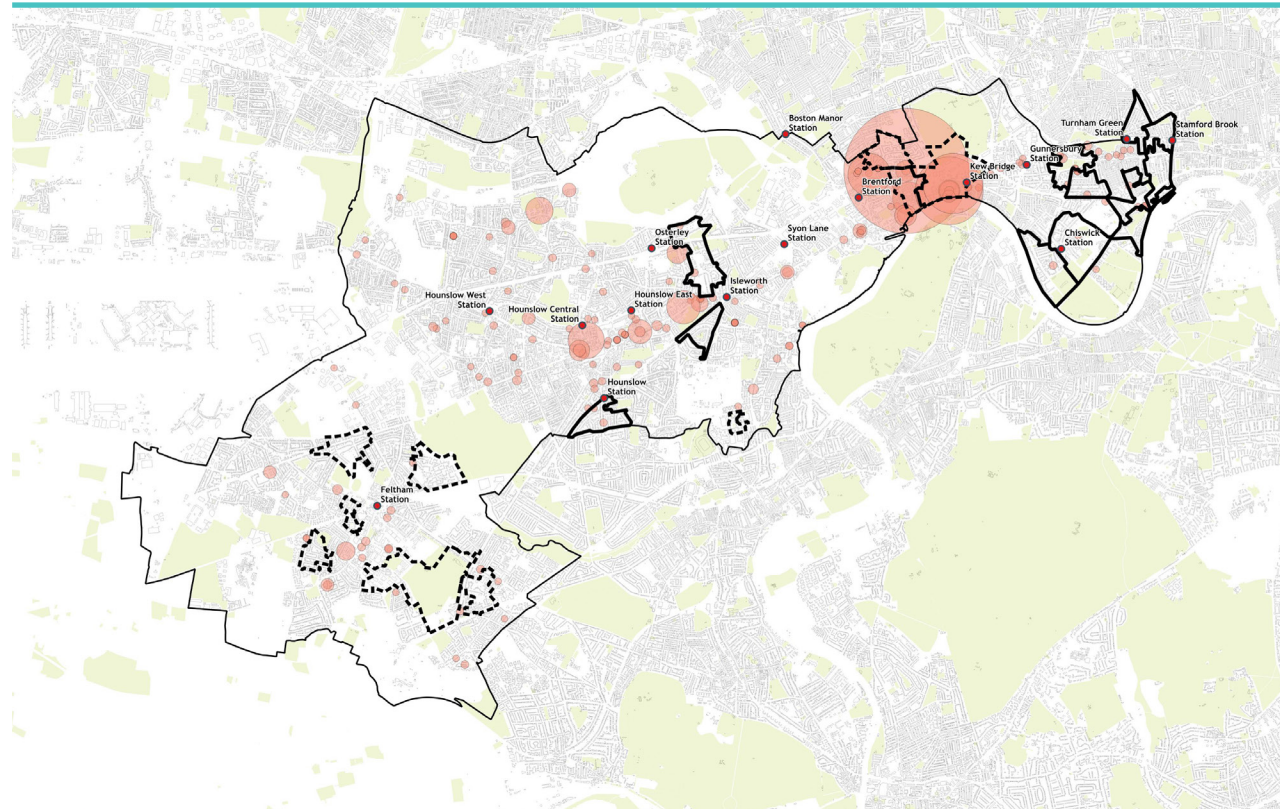
This finding has implications about the social supports and community infrastructure that need to be put in place to support long-standing residents at times of change, and to avoid disruption for existing communities when large numbers of new residents move into an area.

18 Completed residential projects, for Hounslow 2009

The size of each circle represents the number of residential units specified on the planning application. Where the colour is darker this shows a larger concentration of units.



19 Completed residential projects, for Hounslow 2015



Houses in Multiple Occupation (HMOs)

The total number of HMOs in Hounslow that are on the council's register of licensed HMOs increased between 2009 and 2015 from 198 to 615, an increase of 211 percent. The actual number of HMOs and rate of increase are most heavily concentrated in the centre of the borough, in Hounslow central. There is also a very noticeable sharp increase in the west in Cranford, where Hounslow borders Heathrow Airport, and in Hounslow Heath, on the side of the railway track that has weak predicted resilience. Both these locations include very few social housing estates. There is also a large number of HMOs in the east of the borough, although HMO numbers grew less in this area between 2009 and 2015.

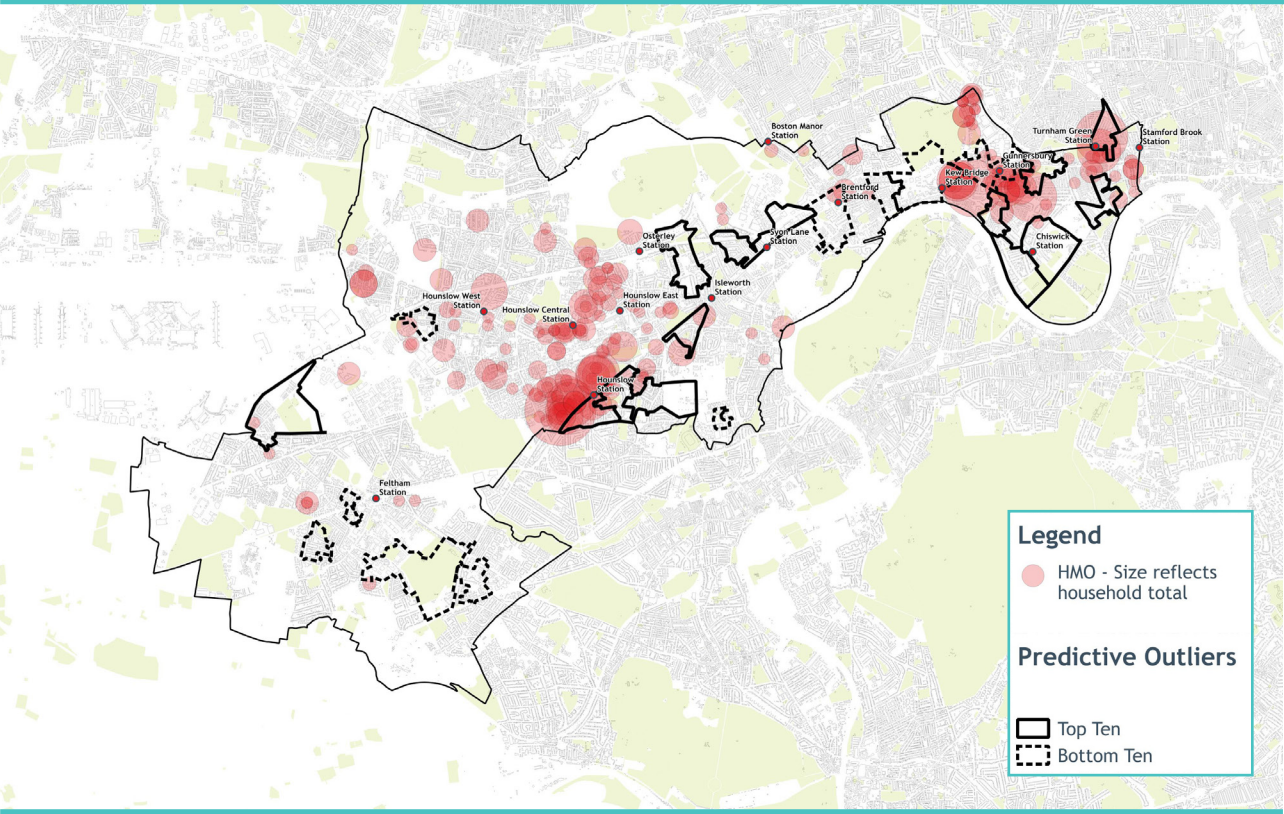
It is possible that there are different trends between areas, with more affluent young professionals moving to HMOs in Chiswick (with its higher housing costs) and more marginal lower income residents moving to lower rent HMOs in Hounslow. It could also be hypothesised that some HMO are located next to large-scale infrastructure and employment centres -for example near to the airport, the Golden Mile in Brentford or Chiswick Business Park - to take advantage of the cheap accommodation needs of a large workforce.



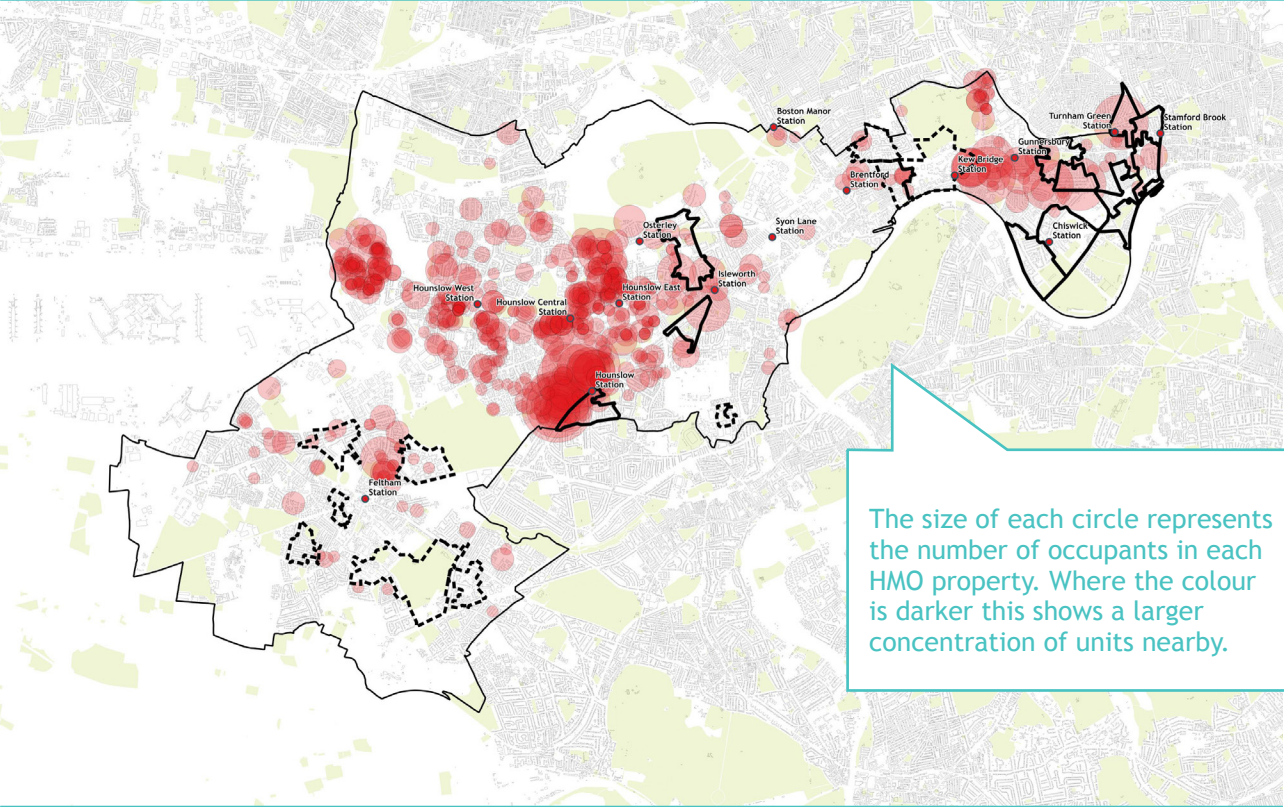
The increase in HMO numbers is a possible threat to future resilience - bringing in a more transient population, with low expectations of staying in the area in the longer term - particularly for the places where predicted resilience is low, such as in Hounslow Heath and Cranford.

These impacts are likely to be more acutely felt in areas where there are growing numbers of illegal HMOs. Hounslow Council is actively address this problem because of the negative impact on community life. Further investigation is underway into the prevalence of illegal HMOs in the west of the borough.

20 Registered HMOs, for Hounslow 2009



21 Registered HMOs, for Hounslow 2015



GP registrations

Changes in Council Tax registrations, newly completed housing and numbers of registered HMOs explain some changes in population churn, however they tell us little about who is moving into the borough. GP registrations can shine light on this, by revealing the demographic of new GP patients for both 2009 and 2015 and where they live in the borough.



When ethnicity and place of birth for new patients registering with Hounslow GPs are explored, we see a large Asian, mostly Indian, population in the centre of Hounslow, with the white population concentrated more in the east and west of the borough - and an “other white” population in central Hounslow. The proportion of new GP patients describing their ethnicity as “Indian”, mainly living in the centre of Hounslow, remained the same between 2009 to 2015 indicating a settled Indian-Asian community.



Our resilience model predicts that these central areas of the borough are likely to have mid-range resilience, neither strong, nor weak. The individual clusters reveal that this part of Hounslow scores well on Neighbourhood Support and low on Isolation, suggesting that this Indian majority community is stable, although not particularly affluent.

Between 2009 and 2015 new GP registrations illustrate broadly similar patterns of ethnicity and country of birth in the different parts of the borough. Over these years there was a slight increase in the proportion of registrations in the east from people describing themselves as white British and those



born in England. This area is predicted to have higher resilience and is the part of the borough that is the most prosperous, though unlike central Hounslow, in this area Neighbour Support cluster scores are weaker and Isolation is higher.

The number of people considering themselves to be white British in the west of the borough increased over this period. In this area the predicted resilience is weaker and the hard data more negative.

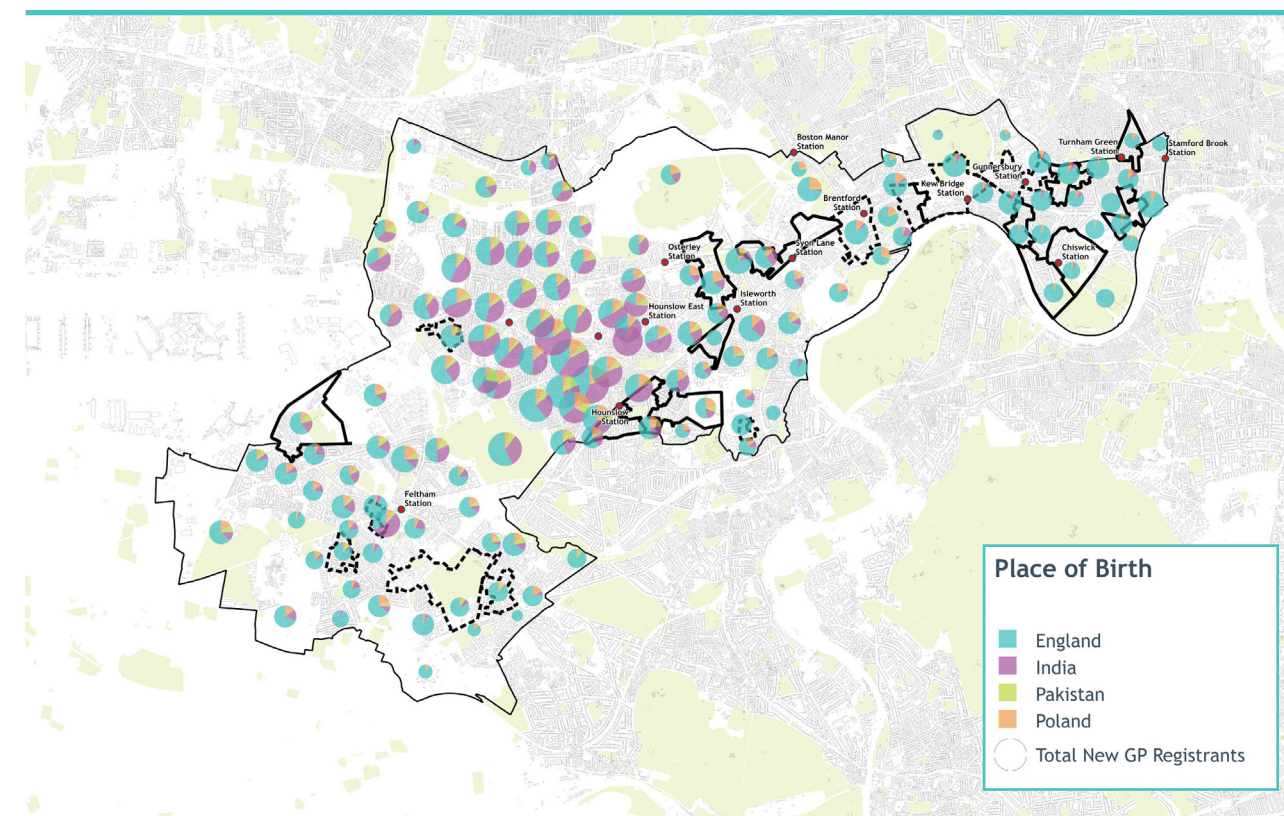
In 2015 there was a higher concentration of people from “other Asian” and “white other” backgrounds in Brentford than in 2009. This is predicted to be the area of weakest resilience and also scores low in the hard data. There was also a distinct decline in the number of people born in England in the north-west of the borough, near to Heathrow Airport.

Intriguingly, it is possible to connect the distribution of HMOs in both 2009 and 2015 with areas with a high “other white” population. This could be explained by the number of single people from eastern Europe moving to the borough.

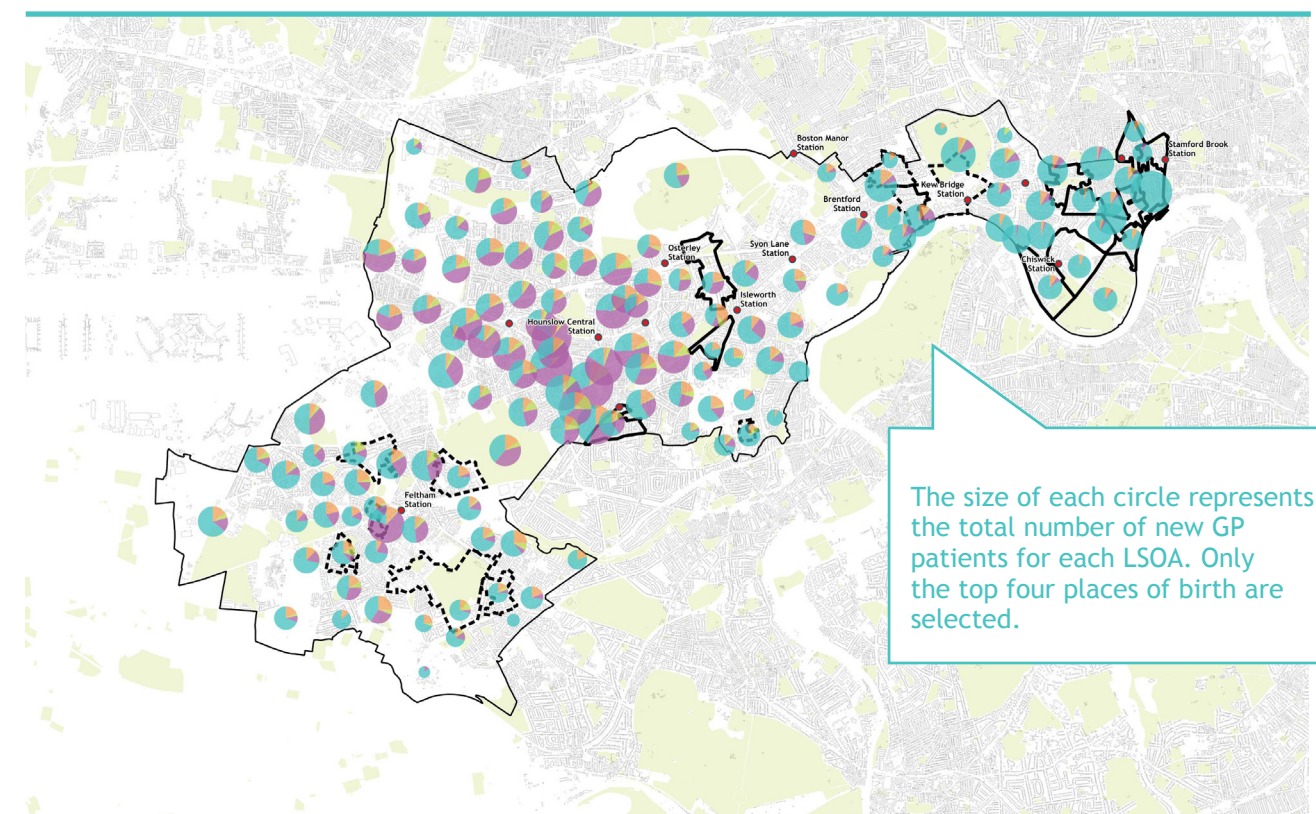
Some of the largest changes that the GP data reveals are in the age groups that represent traditional family bases (young children and middle-aged adults). A pattern emerges of families moving away from the centre of the borough and families (not necessarily the same ones) moving into the east of the borough. This has been corroborated by council officers’ conversations with estate agents. Younger adults continue to dominate the central and eastern locations. It is possible that the east of the borough is becoming more resilient as more families move in. There is also an increase in newborns in Brentford. This area is being heavily developed with new housing, so this could be an indication that young parents - both owners and renters - are moving into this area.

The fragmentation of the borough revealed in the predictive data and hard data is confirmed in the GP registration data. However, it does not appear that international migration correlates with predicted resilience. Overall, international migration does not appear to be concentrated in areas where predicted resilience is low, apart from some small groupings of people born in India and Poland living around Feltham.

22 New GP patients by place of birth, for Hounslow 2009



23 New GP patients by place of birth, for Hounslow 2015





6. The experience of local neighbourhoods

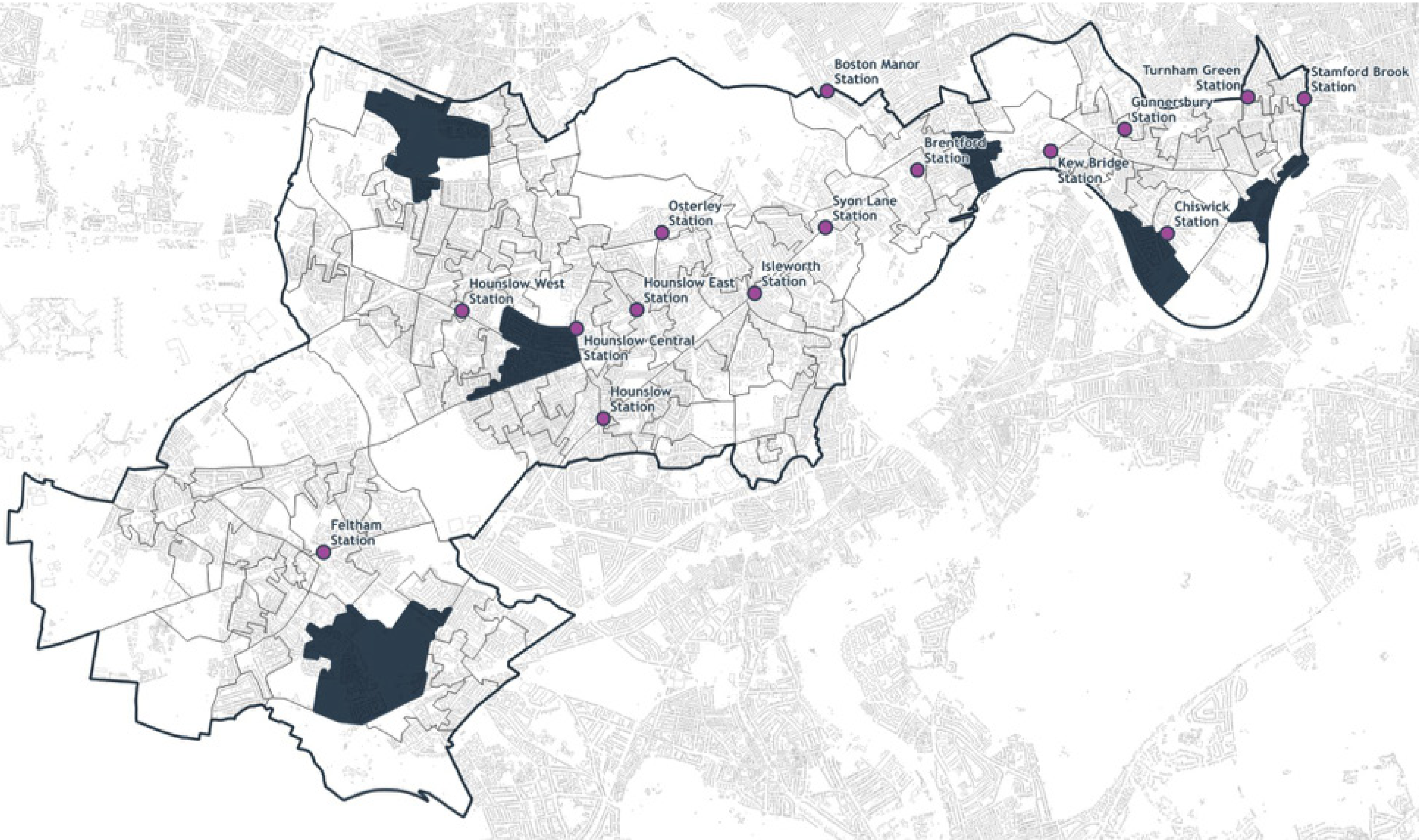
Many neighbourhoods in Hounslow show different patterns of positive and negative resilience in both the predictive and hard data. This is most visible where neighbourhoods with contrasting results are positioned next to each other. These results are noticeable at the OA and LSOA level.

To explore the reasons behind these sharp contrasts, some of the areas that were most significant in the predictive and hard data analysis were visited and compared with neighbouring areas. These onsite observations, led by Hounslow Council (see Appendix, section 6), helped the project team gain a better understanding of the data.

Some LSOAs were selected to demonstrate fragmentation, that is where there is a sharp contrast between the predictive data for neighbouring areas. Positive and negative outlier LSOAs were visited to explore why parts of the borough are more resilient than others. Areas were also selected to give a geographic spread. The areas visited were:

- an example of high fragmentation between Brentford and Chiswick
- an example of high fragmentation within Hounslow Central
- an example of a positive outlier in Hanworth Park area
- an example of positive change in Chiswick Homefields
- an example of a negative outlier in Hanworth Park
- an example of negative change in the Heston West area.

24 Locations of neighbourhoods visited and observed



East: Brentford and Chiswick

- Chiswick is a well-established affluent community, with an extensive range of private housing, and areas of exclusive land next to the river. Few signs of population churn, community assets or social interactions were observed, and there was little observable ethnic diversity in the local residents.
- Brentford appears to be a community in rapid transition with a high number of new residential developments under construction or recently completed, in an area that is dominated by high-rise social housing blocks. Recent population growth is likely to be affecting the socio-economic makeup of the area. There were visible signs of community assets and many pedestrians were seen during the day. There is noticeable ethnic diversity in the local population.
- Both the predictive data and hard data show the sharp contrasts between Brentford and Chiswick, with strong positive and negative results positioned next to each other. Observations confirmed that these are two very different neighbourhoods.



Photo from observations. Gated private housing in Chiswick on the riverside

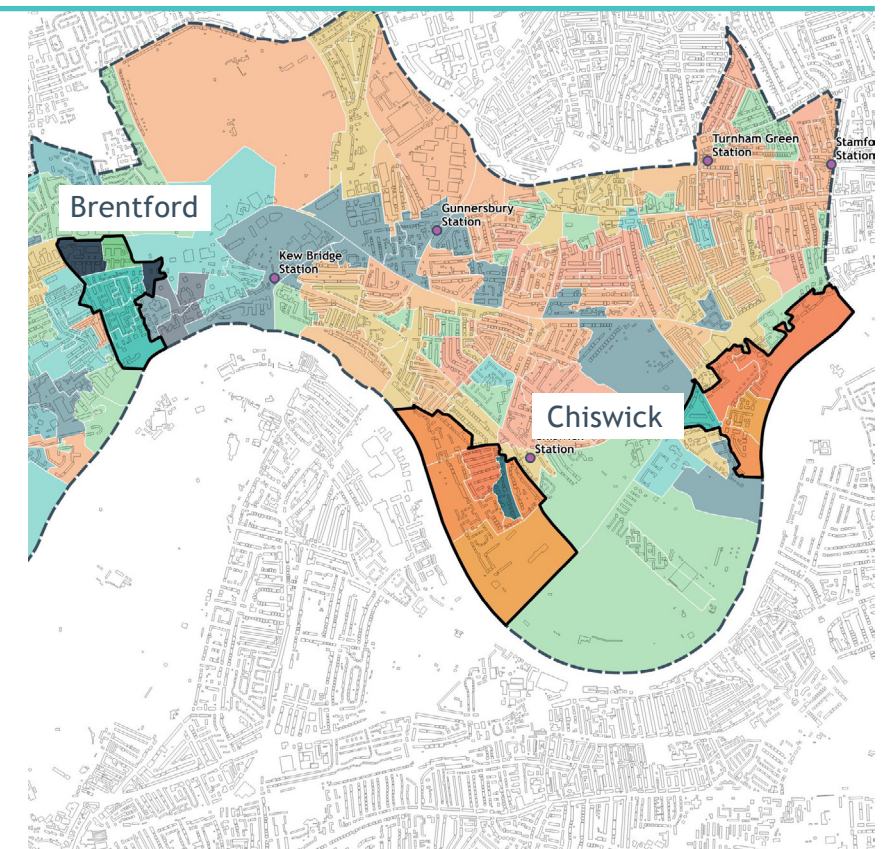


Photo from observations. Social housing tower blocks in Brentford

25a Brentford and Chiswick, aerial photo



25b Brentford and Chiswick, predictive data



Chiswick appeared significantly wealthier than neighbouring Brentford. This is noticeable in the built environment. In Chiswick private housing is low-rise and appears more affluent, commercial outlets are more likely to be independent. However in Brentford, social housing dominates the local built environment, including high tower block and large estates. Commercial outlets are more likely to be low-cost national chains.

There were contrasts too in other aspects of the environment. In Chiswick the community assets observed were a church and a boat house functioning as a community hall. In Brentford there were visibly more community assets and these were more evenly spread-out. In the observed area there was a school, and a community hall offering childcare and evening classes. The area appeared busy during the day, suggesting more people lived and worked here. In Chiswick fewer people were outside during the day, suggesting that many residents work in other parts of London.

It is also very noticeable that at Brentford change is happening very quickly, many new residential and commercial units are being built (this is also highlighted in the churn data), taking advantage of available land and good transport connections. However, intriguingly it was the older parts of the neighbourhood, such as the Haverfield Estate that appeared most lively. A local café owner highlighted how this rapid change is creating tension among the local community, and commented that more local residents are moving out of London as a result. In sharp contrast, in Chiswick there are far fewer large-scale changes to the built environment, suggesting that it is home to a more established and stable long-term community.

Within this small part of the borough there appear to be two very distinctly different communities, one thriving and affluent and another transitioning rapidly from social housing to mixed tenure housing. This starts to explain why the data indicates that Chiswick is significantly more resilient than Brentford.

26 LSOA profile, Brentford 003D

27 LSOA profile, Chiswick 008B

Profiles: hard data rank by LSOA

HARD DATA

	2009	2015	++
Household Income	120	109	+
Children in Low Income	140	138	+
60+ on Pension Credit	123	133	-
Job Seeker Allowance	141	139	+
Incapacity Benefit	139	124	+
Proportion of Claimants	142	142	=
Child Benefits	141	139	+
Households in Fuel Poverty	29	12	+
Alcohol Admissions	114	65	+
Child Obesity	22	65	-
Life Expectancy	65	58	+
Male Life Expectancy	59	102	-
Female Life Expectancy	51	36	+
Population Between 0-19	101	61	+
Population Over 65	47	24	+
HMOs Per 1000	73	40	+
Election Turnouts	107	98	+
Ambulance Callouts	130	136	-
Criminal Offences Per 1000	92	124	-
Pupils Achieving 5+ GCSEs	85	93	-
House Price	37	33	+
Public Transport Access	37	37	=
Total Population	137	142	-
Social Rent	140	142	-

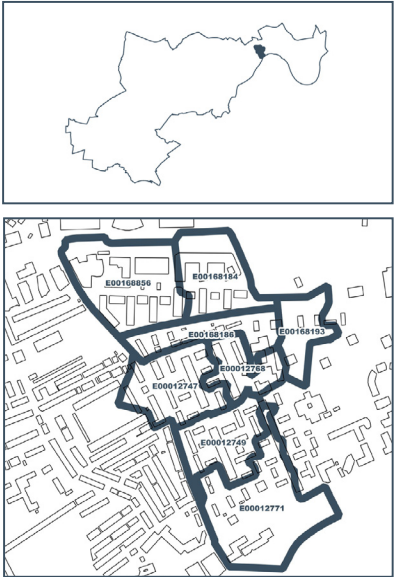
IMD DATA

	2009	2015	++
IMD	137	126	+
IMD Income	140	130	+
IMD Employment	139	109	+
IMD Health	139	141	-
IMD Education	122	92	+
IMD Housing	87	137	-
IMD Crime	12	12	=
IMD Environment	61	43	+

CHURN DATA

	2009	2015	++
Council Tax	1	2	-
HMO Total Occupancy	67	42	+
New Patients under 10	66	56	+
New Patients between 11-22	65	86	-
New Patients between 23-33	80	16	+
New Patients between 34-44	33	14	+
New Patients between 45-55	59	11	+
New Patients PoB India	10	10	=
New Patients PoB England	99	68	+
New Patients PoB Pakistan	88	88	=
New Patients PoB Poland	19	47	-
New Patient Other Asian	92	35	+
New Patient Indian	99	73	+
New Patient Other White	87	25	+
New Patient White British	6	18	-

Ward: Brentford



Profiles: Hard Data Rank by LSOA

HARD DATA

	2009	2015	++
Household Income	11	11	=
Children in Low Income	4	4	=
60+ on Pension Credit	17	18	-
Job Seeker Allowance	8	24	-
Incapacity Benefit	45	1	+
Proportion of Claimants	11	9	+
Child Benefits	3	4	-
Households in Fuel Poverty	15	4	+
Alcohol Admissions	29	30	-
Child Obesity	29	15	+
Life Expectancy	22	8	+
Male Life Expectancy	8	30	-
Female Life Expectancy	37	1	+
Population Between 0-19	28	13	+
Population Over 65	135	140	-
HMOs Per 1000	73	67	+
Election Turnouts	8	15	-
Ambulance Callouts	13	35	-
Criminal Offences Per 1000	31	65	-
Pupils Achieving 5+ GCSEs	65	37	+
House Price	12	17	-
Public Transport Access	51	64	-
Total Population	91	56	+
Social Rent	79	68	+

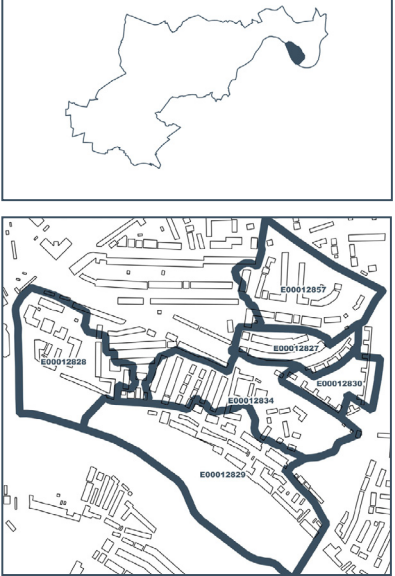
IMD DATA

	2009	2015	++
IMD	15	10	+
IMD Income	12	9	+
IMD Employment	31	29	+
IMD Health	16	14	+
IMD Education	17	3	+
IMD Housing	102	16	+
IMD Crime	26	76	-
IMD Environment	33	70	-

CHURN DATA

	2009	2015	++
Council Tax	41	64	-
HMO Total Occupancy	67	106	-
New Patients under 10	84	86	-
New Patients between 11-22	129	61	+
New Patients between 23-33	98	111	-
New Patients between 34-44	110	80	+
New Patients between 45-55	55	54	+
New Patients PoB India	43	41	+
New Patients PoB England	119	108	+
New Patients PoB Pakistan	88	97	-
New Patients PoB Poland	117	91	+
New Patient Other Asian	118	116	+
New Patient Indian	99	98	+
New Patient Other White	36	85	-
New Patient White British	47	34	+

Ward: Chiswick Riverside



Profile: predictive data score by OA																							
Output Area	Combined Score			High wellbeing			Low wellbeing			Emotional fragility			Neighbourhood Sup			Isolation			Competence				
	a	f	++	a	f	++	a	f	++	a	f	++	a	f	++	a	f	++	a	f	++		
E00012747			+			+			+			+			+			-			-		
E00012749			+			+			+			+			+			-			-		
E00012768			+			+			+			+			+			-			-		
E00012771			+			+			+			+			+			-			-		
E000168184			+			-			+			+			-			+			+		
E000168186			+			+			+			+			+			-			-		
E000168193			-			-			+			-			-			+			-		
E000168856			-			-			+			+			-			-			+		

Profile: predictive data by OA																							
Output Area	Combined Score			High wellbeing			Low wellbeing			Emotional fragility			Neighbourhood Sup			Isolation			Competence				
	a	f	++	a	f	++	a	f	++	a	f	++	a	f	++	a	f	++	a	f	++		
E00012851			=			-			+			-			-			+			+		
E00012852			+			+			+			-			-			-			-		
E00012853			-			-			+			-			-			+			+		
E00012821			-			-			-			-			+			+			+		
E00016822			=			-			+			-			-			+			+		
E00016849			+			+			+			+			+			+			+		

47

48

West: Hanworth Park

- The area defined by LSOA 028D appeared affluent. Residents appeared to be very protective about their neighbourhood, referring to it as “Hanworth” and not as a part of the borough of Hounslow.
- In sharp contrast the neighbouring area, LSOA Hounslow 026E, did not have many distinguishing features apart from the park. The sparse housing on the edges of the park does not relate to the expensive neighbouring area, because it is either closed off Ministry of Defence (MOD) housing or council homes.
- The area observed to the west has strong predicted resilience, but the adjoining area to the east is likely to have significantly weaker resilience.
- While this is very similar to the fragmented patterns observed in Brentford and Chiswick, the difference here is the geographical scale, as this is a very small isolated area.

The area to the west (Hounslow 028D) appears very affluent. Homes are low-rise two- to three-storey detached houses, often “Tudor” in appearance and the surrounding area is very green and spacious. Visually this could easily be a rural village in Surrey. Local residents often refer to the area as Hanworth Park, and not Hounslow or Feltham (its Parliamentary constituency), highlighting a strong attachment to this small area.

“It’s a well-to-do area... I am a Feltham boy really, but here you have to say Hanworth Park, not Feltham”.

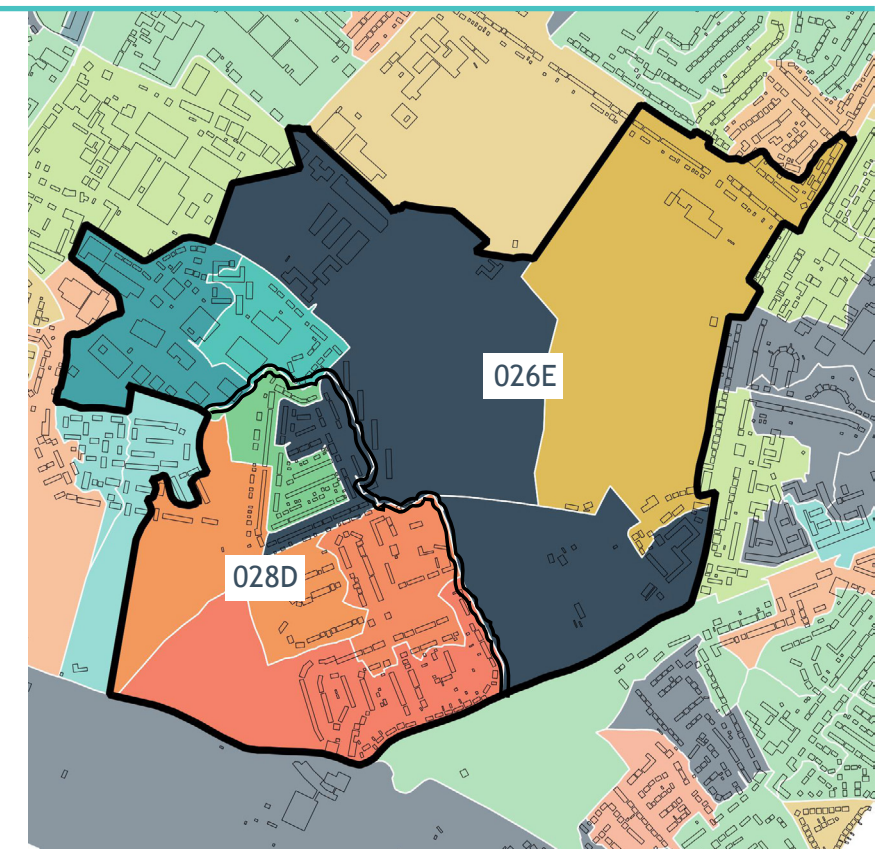
This area has a tight-knit community, and sense of pride in the historic Tudor Courts. There is an active community organisation, the Tudor Residents Association. People selling homes are advised to sell to families, not developers.

While the park spatially divides the area, it is also an important asset for the community and is a space that has much historic importance. Henry VIII hunted in the park and Anne Boleyn lived here before her execution. The historic references are seen throughout the area, particularly in the area observed to the west, where streets are named “Shakespeare Way”, “Tudor Court” and “Castle Way”. This presents the image of a prestigious neighbourhood, socially and economically distinct from neighbouring area.

28a Hanworth Park, aerial photo



28b Hanworth Park, predictive data



Within the observed area there is a range of community assets, such as community centres, a mosque and a church, local football clubs, a school, social clubs and a village.

Though some of these may not be well maintained, they provide good facilities for the community. There are basic small shops and a petrol station for groceries and everyday shopping. Residents have to drive to the nearest supermarkets. This reinforces the independent village feel, the poor public transport connections mean living here comfortably without a car would be difficult, something that may put extra pressure on residents on lower incomes.



Photo from observations. Hanworth housing near Ministry of Defence



Photo from observations. Housing opposite Hanworth Park.

The built environment in the area next to this (Hounslow 026E) was very different. Much of this was because of the large park or heath that centrally dominates the area, breaking up the different types of residential blocks located around its edges. The area can feel isolated and there is one bus route passing through it. The division in this area is heightened by the different types of housing, with a council estate providing traditional

social rent and closed-off secure MOD housing creating a large physical barrier.

While the contrast in the data between Brentford and Chiswick can be related to development trends in London, the very localised division in the data at Hanworth is a result of specific local factors.

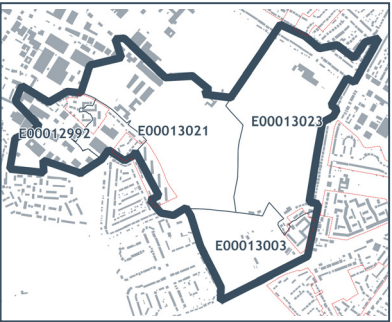
29 LSOA profile, Hanworth 026E

Profiles: Hard Data Rank by LSOA

	2009			2015	+-
	a	f	+		
HARD DATA	Household Income	131	130	+	
	Children in Low Income	120	128	-	
	60+ on Pension Credit	123	130	-	
	Job Seeker Allowance	41	84		
	Incapacity Benefit	130	43		
	Proportion of Claimants	55	93		
	Child Benefits	135	134	+	
	Households in Fuel Poverty	29	12		
	Alcohol Admissions	128	72		
	Child Obesity	50	86		
	Life Expectancy	102	95	+	
	Male Life Expectancy	52	60	-	
	Female Life Expectancy	95	36		
	Population Between 0-19	109	96		
	Population Over 65	63	55	+	
	HMOs Per 1000	73	93		
	Election Turnouts	43	36	+	
	Ambulance Callouts	121	111		
	Criminal Offences Per 1000	111	113	-	
	Pupils Achieving 5+ GCSEs	99	136		
HARD DATA	House Price	128	97		
	Public Transport Access	78	85	-	
	Total Population	12	15	-	
	Social Rent	136	133	+	

	2009			2015	+-
	a	f	+		
IMD DATA	IMD	138	139	-	
	IMD Income	130	134	-	
	IMD Employment	138	132	+	
	IMD Health	142	139	+	
	IMD Education	139	137	+	
	IMD Housing	122	123	-	
	IMD Crime	106	116		
CHURN DATA	IMD Environment	83	27		
	Council Tax	54	86		
	HMO Total Occupancy	67	106		
	New Patients under 10	101	116		
	New Patients between 11-22	53	125		
CHURN DATA	New Patients between 23-33	136	111		
	New Patients between 34-44	115	110	+	
	New Patients between 45-55	41	93		
	New Patients PoB India	69	110		
	New Patients PoB England	86	110		
	New Patients PoB Pakistan	63	39		
	New Patients PoB Poland	117	99		
	New Patient Other Asian	61	106		
	New Patient Indian	106	80		
	New Patient Other White	94	126		
CHURN DATA	New Patient White British	47	74		

Ward: Brentford



Profile: predictive data by OA

Output Area	Combined Score			High wellbeing			Low wellbeing			Emotional fragility			Neighbourhood Sup			Isolation			Competence		
	a	f	+	a	f	+	a	f	+	a	f	+	a	f	+	a	f	+	a	f	+
E00012992																					
E00012993																					
E00013003																					
E00013021																					
E00013023																					

30LSOA profile, Handsworth Park 028D

Profiles: Hard Data Rank by LSOA

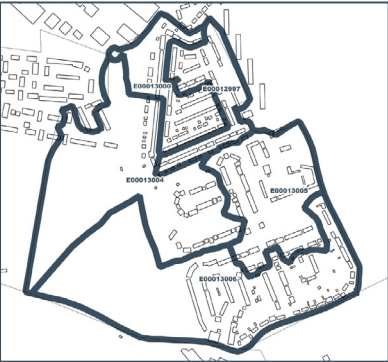
	2009	2015	+-
Household Income	50	44	+
Children in Low Income	15	18	-
60+ on Pension Credit	5	7	-
Job Seeker Allowance	22	9	+
Incapacity Benefit	22	1	+
Proportion of Claimants	20	1	+
Child Benefits	43	19	+
Households in Fuel Poverty	42	10	+
Alcohol Admissions	128	72	+
Child Obesity	50	86	-
Life Expectancy	102	95	+
Male Life Expectancy	52	60	-
Female Life Expectancy	95	36	+
Population Between 0-19	44	37	+
Population Over 65	112	118	-
HMOs Per 1000	73	93	-
Election Turnouts	43	36	+
Ambulance Callouts	18	4	+
Criminal Offences Per 1000	13	5	+
Pupils Achieving 5+ GCSEs	99	136	-
House Price	99	62	+
Public Transport Access	78	85	-
Total Population	40	21	+
Social Rent	13	24	-

TOP 10% 10%-25% 75%-90% BOTTOM 10%

	2009	2015	+-
IMD	41	27	+
IMD Income	7	9	-
IMD Employment	16	25	-
IMD Health	18	60	-
IMD Education	107	91	+
IMD Housing	135	110	+
IMD Crime	15	8	+
IMD Environment	28	14	+

	2009	2015	+-
Council Tax	65	126	-
HMO Total Occupancy	67	94	-
New Patients under 10	110	116	-
New Patients between 11-22	87	134	-
New Patients between 23-33	86	137	-
New Patients between 34-44	127	133	-
New Patients between 45-55	28	127	-
New Patients PoB India	6	127	-
New Patients PoB England	93	123	-
New Patients PoB Pakistan	88	88	=
New Patients PoB Poland	94	64	+
New Patient Other Asian	80	113	-
New Patient Indian	84	137	-
New Patient Other White	23	89	-
New Patient White British	82	118	-

Ward: Handsworth Park



commercial and retail outlets. There are many transport connections to the rest of London. These factors generate a lot of movement on the streets. There is a wide mix of housing, from social housing to recently developed private housing to shared accommodation options in HMOs all near to busy commercial streets and good transport. This makes this area an attractive place to live for people moving to London, and inevitably population churn is high.

The experience of local areas

Our observations explored the everyday experience of small areas, comparing them with the data profiles and using the insights from our visits to explain the findings of our resilience model.

Our visit to Hanworth Park revealed the large spatial disconnect imposed by the local park and affluent self-preservation of the Hanworth Village. In Brentford, the scale of the rapid change becomes more apparent through observation and we also saw the striking contrast between Brentford and the stability of neighbouring Chiswick. In Heston we saw the impact of geographic boundaries on local identity.

These examples add a level of understanding to our resilience model. They demonstrate the detail of how the fragmentation of resilience across the borough is affecting local neighbourhoods and the people who live in them.

Profile: predictive data score by OA

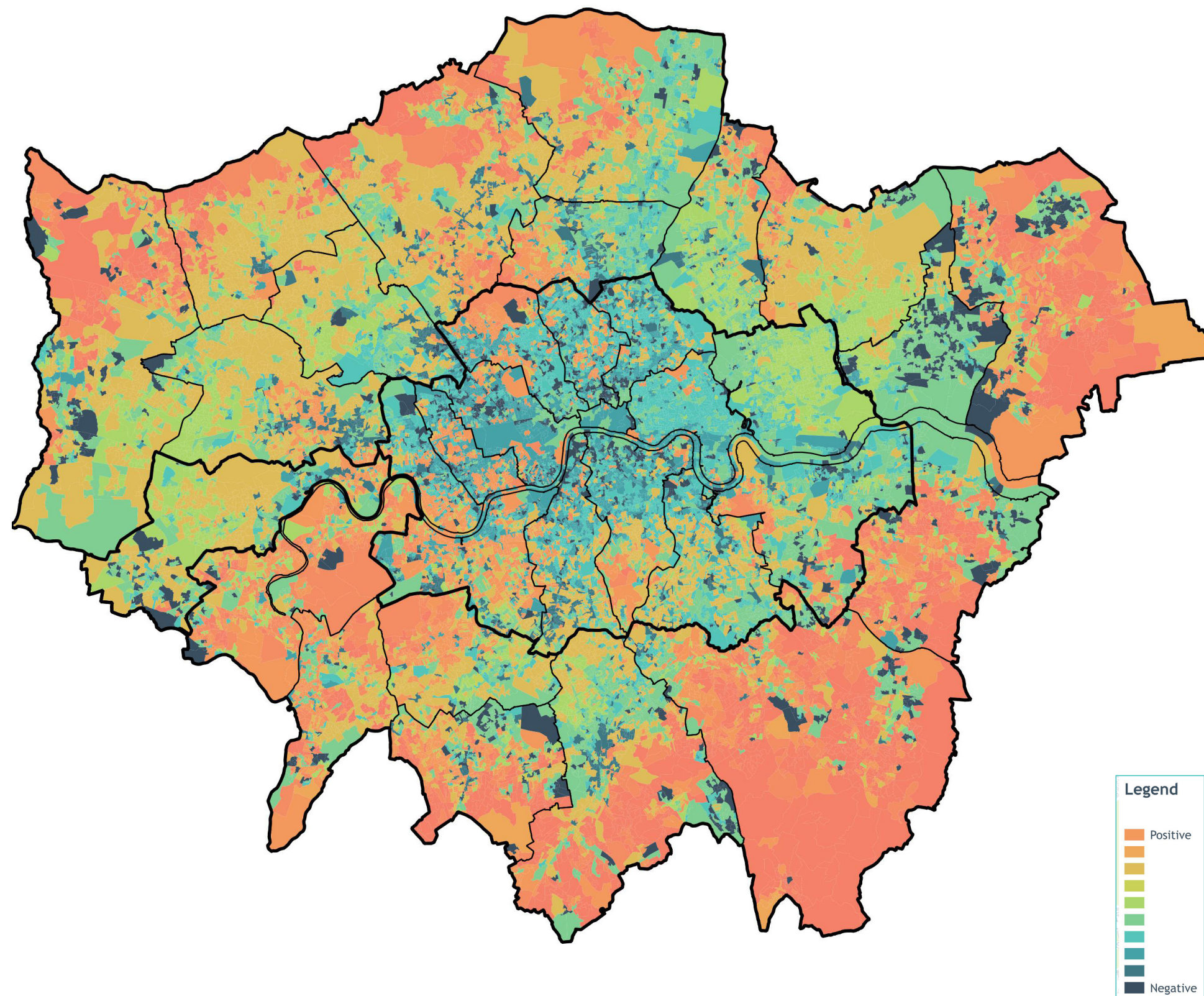
Output Area	Combined Score			High wellbeing			Low wellbeing			Emotional fragility			Neighbourhood Sup			Isolation			Competence		
	a	f	+-	a	f	+-	a	f	+-	a	f	+-	a	f	+-	a	f	+-	a	f	+-
E00012997			-			+			+			+			-			+			+
E00013000			-			+			+			+			-			+			+
E00013004			=			+			+			+			-			+			+
E00013005			+			+			-			+			-			-			+
E00013006			=			+			+			=+			-			+			+

Other parts of the borough

A selection of other locations, including Heston West and the centre of Hounslow were also observed to explore the wider issues affecting the borough.

At Heston West, in the north-west of the borough, observations highlighted spatial divisions caused by a golf course and the M4, and a motorway service station that is not accessible by foot. To the north of this divide, the neighbourhood appears to be more closely connected to Southall, with a large observable Asian population. Housing in this area appears to be in reasonable condition, with a mixture of expensive private and social housing. This demonstrates how a very small area can become heavily divided by large spatial obstacles, to travel between the north and south parts takes 30 minutes by bus.

Hounslow Central is ethnically diverse, the built environment is dense and compact and there is a wide array of different



7. Conclusion

Our assessment of the changing resilience of the London Borough of Hounslow between 2009 and 2015 reveals that the borough is continuing to fragment into different parts, with the east developing a more resilient community that connects to neighbouring Hammersmith, Ealing and Richmond, and the west and central parts of the borough seeing less change. The west remains akin to the southern part of Hillingdon, both neighbouring Heathrow Airport.

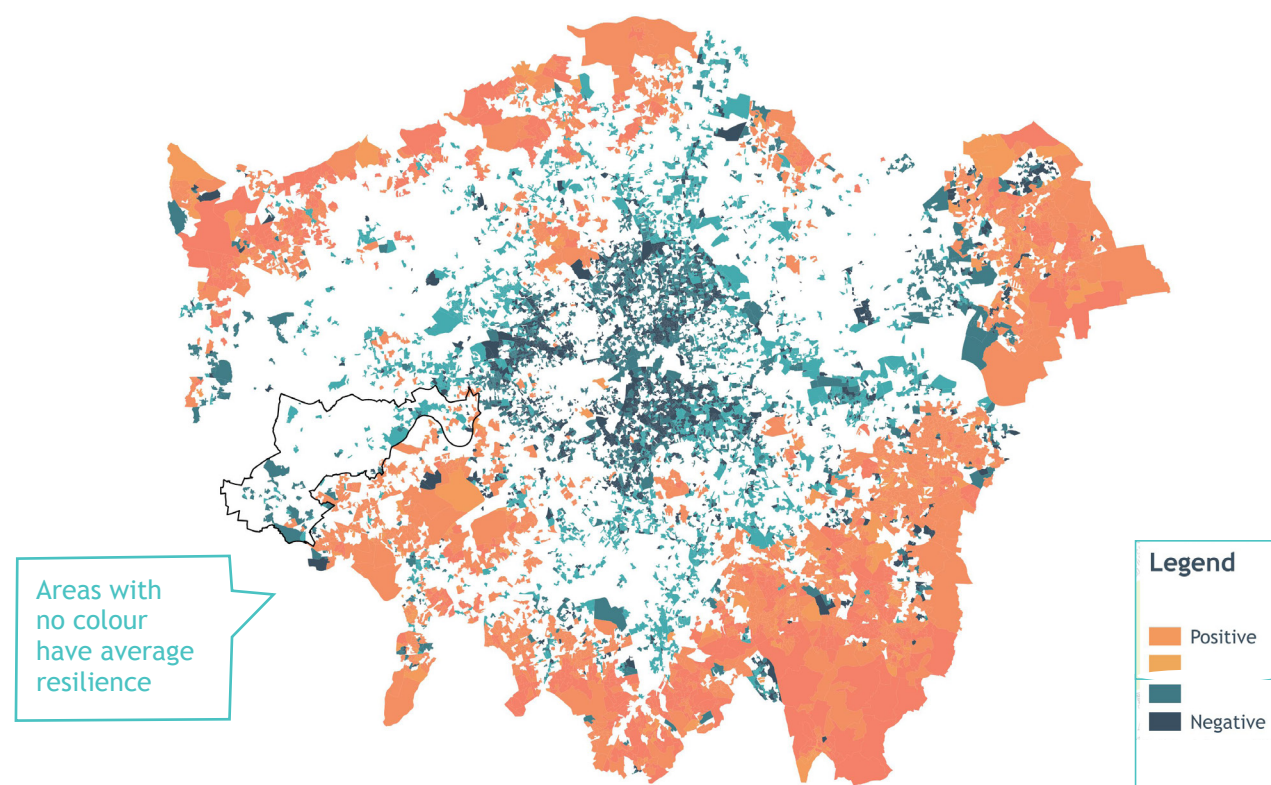
Local government boundaries do not always either map onto natural neighbourhoods or map to the social trends described by our data. The shape of the borough of Hounslow, with its narrow curvature to the east, effectively allows the eastern end to disconnect from the rest of the borough and become a larger part of a wider west London area where predicted resilience has strengthened. The trend is exacerbated by the disparity in financial resources and deprivation across the borough, between the more affluent east and less affluent west and centre.

Exploring how these local changes relate to the London-wide picture helps to explain some of these trends. A changing pattern in predicted resilience can be observed throughout London, especially in Inner London, where some of the weakest areas of predicted resilience in 2009 dispersed by 2015, suggesting this area is slowly becoming more resilient. This is especially noticeable around the fringes of inner London, including Chiswick in the east of the borough.

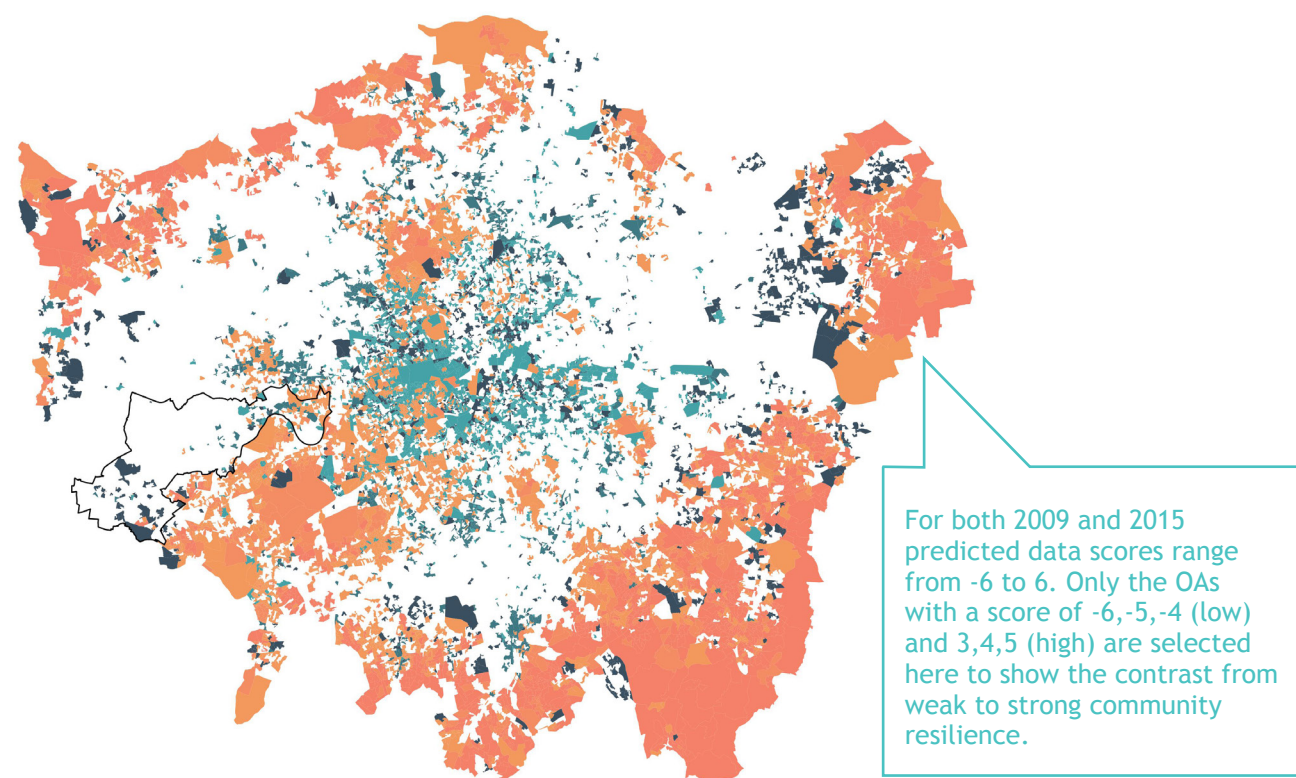
In 2015 the centre of London overall shows lower predicted resilience than in 2009, conversely over the same period a swathe of outer southwest, southeast and east London, plus the fringes of northwest London are predicated to have become more resilient. One possible explanation explaining why many areas on the fringes of London may be more resilient than central London is that they have been less affected by demographic change.

The divide in the London Borough of Hounslow in predicted levels of resilience is reflected in the overall distribution of wealth and deprivation. Between 2009 and 2015 the east became financially more secure and the west more deprived. With this overall

32 Predicted high and low scored OAs for London 2009



33 Predicted high and low scored OAs for London 2015



pattern there are pockets of inequality. We can see these in small areas, such as around Hanworth Park in the west of the borough. However, these are starkest in the east, particularly around Brentford where low predicted resilience is boxed in by some of the most resilient and wealthy neighbourhoods in the borough. In this area of low resilience new housing development is bringing new people from different backgrounds into the area to live alongside longer-standing residents.

Against this background, we ask whether population churn and international migration could be undermining the resilience of local communities. We found trends that could impact positively and negatively on resilience: the significant increase in the number of registered HMOs in the central parts of the borough suggesting future vulnerabilities; the increase in families evident in GP data in the east of the borough suggesting possible strengths. However, we have concluded across the borough, migration from both within the UK and internationally does not seem to correlate significantly with changes in predicted resilience.

The strength in the resilience model is to demonstrate what is happening beneath these wider trends and to identify neighbourhoods where the hard data and predictive resilience show different patterns: where a neighbourhood appears to be thriving in spite of predicted weaknesses, or where a neighbourhood is likely to be resilient but in reality appears to be struggling.

This analysis can reveal local trends and sensitivities that may not be revealed through more familiar data, throwing a new light on the impact of policy and practice. An example of the power of this approach is demonstrated in mapping new housing development against the resilience clusters, illustrating how new homes are being built in areas where resilience is likely to be fragile.

Our resilience model reveals the unexpected strengths and weaknesses of an area, highlighting neighbourhoods that may slip under the radar during more standard assessment processes. The major strength of this tool is its ability to flag areas where these vulnerabilities, and assets exist, allowing local authorities to target the areas that are most in need of their limited resources.

Footnotes

¹ South, J., Jones, R., Stansfield J. and Bagnall, A. (2018) What qualitative and quantitative measures have been developed to measure health-related community resilience at national and local level? WHO Health Evidence Network synthesis report 60. World Health Organisation

² Lupton, R. (2003) “Neighbourhood Effects”: Can we measure them and does it matter? CASE paper 73, London: Centre for Analysis of Social Exclusion, London School of Economics

³ Constantine, N., Benard, B., and Diaz, M. (1999) Measuring Moderating Factors and Resilience Traits in Youth: The healthy kids resilience assessment, paper presented at the Seventh Annual Meeting of the Society for Prevention Research, New Orleans, LA

⁴ <https://www.thersa.org/action-and-research/rsa-projects/public-services-and-communities-folder/hounslow---cranford-stronger-together>

⁵ Mguni, N. and Bacon, N. (2010) Taking the temperature of local communities: The Wellbeing and Resilience Measure, London: The Young Foundation

⁶ For more information about USS see <https://www.understandingsociety.ac.uk/about>

⁷ <https://www.ons.gov.uk/methodology/geography/ukgeographies/censusgeography>

⁸ <https://www.ons.gov.uk/methodology/geography/geographicalproducts/areaclassifications/2011areaclassifications/abouttheareaclassifications>

⁹ ODPM (2006) Explanatory memorandum to the licensing of Houses in Multiple Occupation (prescribed descriptions) (England) Order 2006

¹⁰ <https://www.ons.gov.uk/peoplepopulationandcommunity/populationandmigration/populationestimates/datasets/lowersuperoutputareamidyearpopulationestimates>

¹¹ <https://www.gov.uk/government/statistics/english-indices-of-deprivation-2015>

¹² For a full definition see <https://www.gov.uk/government/collections/fuel-poverty-statistics>

¹³ Planning permissions on the London Development Database, provide by Greater London Authority - <https://data.london.gov.uk/dataset/planning-permissions-on-the-london-development-database--ldd->

1. Predictive data

In 2014-15 Social Life was commissioned by the London Borough of Hounslow to update The Young Foundation's Wellbeing and Resilience Measure (WARM) framework to update the underlying data, and to explore how the framework could be made more relevant, accessible, and simpler to use.

The development of the new model has been carried out in two stages: an initial project in 2015 updated the original WARM framework, that dated back to 2010; and in 2018 further work explored historical trends in the data and correlations with other datasets.

The framework used data from the Understanding Society Survey (USS), the largest longitudinal household survey of its kind. USS is based on annual interviews with a panel of households to explore how their lives are changing over time. USS explores different aspects of life in the UK capturing information about people's social and economic circumstances, attitudes, behaviours and health. It is funded by the Economic and Social Research Council (ESRC) and several government departments.

The USS data was analysed to reveal patterns that indicate wellbeing and resilience. This was then matched to the Office of National Statistics' (ONS) Output Area Classifications (OACs), enabling us to predict what the likely level of wellbeing or resilience is in a specific local area.

Area classifications for Great Britain have been produced by ONS after every census since 1971. Using socio-economic and demographic data from each census, they aim to identify areas of the country with similar characteristics. This information is useful to many groups, including government departments, local authorities, health authorities and academics. Area classifications can be generated at different geographies, for Output Areas (OAs), around 125 households, and Lower Level Super Output Areas (LSOAs) between 400 and 1,200 households.

Analysis

The aim of the analysis was to explore patterns within the data to establish what explains wellbeing and resilience at the local level. **Factor analysis** was used to investigate how different

USS questions relate to the core concepts of wellbeing and resilience and to identify the questions that make up the wellbeing and resilience measures. A **cluster analysis** was then used to group the questions and factors together to develop clusters of respondents with different levels of wellbeing and resilience.

Backdating

Our aim was also to explore change over time in clusters. The same method of analysis was repeated for the most recent year available, and for the earliest year that comparable USS data was available. This provided an opportunity to test the method and for changes in wellbeing and resilience to become apparent.

The most recent data available at the time the analysis took place was for 2015 (Wave F). The earliest year that the model could be backdated to was 2009, the first year (or Wave A) of USS. The previous British Household Panel Survey, which USS largely replaced, could not be used to backdate further because it did not unfortunately use enough of the questions in our analysis.

Our new framework tests a prediction of resilience in very local areas against actual data about the place, to reveal how well it is faring. We have explored individual small areas in detail, so that the change in wellbeing and resilience factors and “actual” data can be read over this period. This gives us insight into how the borough overall has changed, illustrating the specific local areas that have absorbed the largest changes.

We have looked at data for the borough of Hounslow, and also London-wide, since city-wide dynamics often impact on local communities.

1.2 Factor analysis

The factor analysis was run on the USS data for 2009 (Wave A) and 2015 (Wave F) to identify wellbeing and resilience factors.

After discussion with Hounslow officers, it was decided to keep one wellbeing scale but to separate the different factors that had emerged relating to broader resilience issues and this is repeated for this updated model. This is because resilience is a more disparate concept, and complex statistical relationships emerged from the factor analysis. There is a danger that conflating all the different factors relating to resilience into one scale would lose sensitivity from the analysis.

Four factors emerged strongly from the data:

- wellbeing
- emotional stress
- capability
- belonging and social solidarity.

In our first analysis relationships within the data also emerged around physical health, political involvement and perceptions of crime. These were not included in the final list of factors because they were felt to be less important to Hounslow and were also duplicated issues that could be measured through actual data.

Testing the model with two waves of USS data allowed us to see if the results are comparable across time, and to examine the results longitudinally to see if the analysis can be used retrospectively with historic data.

The USS questions that correspond to each of the factors identified are in Table A1.

A1 Output from factor analysis

Understanding Society Survey (USS) Questions	
Wave A (2009)	Wave F (2015)
Wellbeing	Wellbeing
satisfaction with health	satisfaction with health
satisfaction with income	satisfaction with income
satisfaction with amount of leisure time	satisfaction with amount of leisure time
satisfaction with life overall	satisfaction with life overall
financially_now	financially_now
Emotional stress	Emotional stress
last 4 weeks: mental health meant accomplished less	emotional problems: accomplished less
last 4 weeks: mental health meant worked less carefully	emotional problems: less carefully than usual
felt_calm	felt_calm
last 4 weeks: felt downhearted and depressed	felt downhearted and depressed
ghq_loss_sleep	ghq_loss_sleep
ghq_under_strain	ghq_under_strain
ghq_depressed	ghq_depressed
ghq_lose_confidence	ghq_lose_confidence
ghq_selfworth	ghq_selfworth
Capability	Capability
had_energy	had_energy
last 4 weeks: physical or mental health interfered with social life	health or emotional problems interfered with social activities
ghq_concentrate	ghq_concentrate
ghq_useful	ghq_useful
ghq_decisions	ghq_decisions
ghq_overcome_difficulty	ghq_overcome_difficulty
ghq_enjoy_daytoday	ghq_enjoy_daytoday
ghq_face_problems	ghq_face_problems

1.3 Cluster analysis

Again, a two-step cluster method was used to group respondents based on similarity in answering the questions included in the clustering.

The final clusters chosen were those that have the best balance between separation and cohesion: respondents within the cluster are as similar to each other whilst maintaining difference between clusters.

To analyse **wellbeing** the five questions that make up the wellbeing measure were entered into the cluster method and to analyse **resilience** the four factors - wellbeing, emotional stress, capability, belonging and social solidarity - were entered.

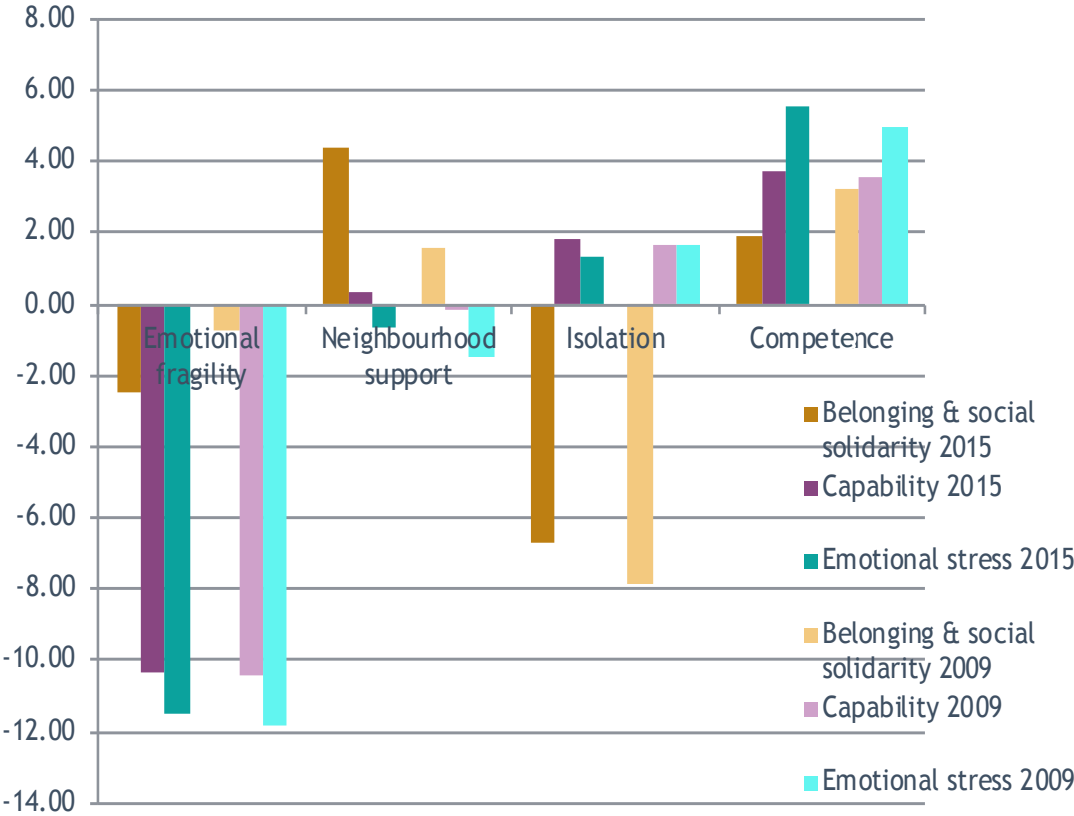
The following graphs (A2 and A3) show the cluster composition for both 2009 and 2015 (the scores at each point are standardised).

The clusters

The different clusters describe areas where the notable characteristics are:

- **Low wellbeing:** lower satisfaction with life overall, income, amount of leisure time, and concerns about managing financially
- **High wellbeing:** higher satisfaction with life overall, income, amount of leisure time, and concerns about managing financially
- **Neighbourhood support:** high social solidarity and high belonging
- **Competence:** high levels of capability and low levels of stress
- **Isolation:** low levels of belonging and local levels of social solidarity
- **Emotional fragility:** high levels of stress and low levels of capability

A2 Wellbeing clusters



A3 Resilience clusters



A2a Wellbeing cluster scores, by factor

USS wave F clusters (2014-15)			
	High	Average wellbeing	Low
Financially now 2015	0.38	0.43	-0.93
Health 2015	0.73	-0.96	-0.54
Income 2015	0.63	0.2	-1.19
Leisure 2015	0.45	-0.11	-0.74
overall	0.58	-0.16	-0.83
No of responses	16456	6656	10070
% of responses in cluster	50%	20%	30%

USS wave A clusters			
	High wellbeing	Average wellbeing	Low wellbeing
Financially now 2009	0.60	-0.37	-0.88
Health 2009	0.61	-0.17	-1.17
Income 2009	0.78	-0.34	-1.35
Leisure 2009	0.54	-0.13	-1.20
overall	0.62	0.01	-1.66
No of responses	16942	14785	6718
% of responses in cluster	44%	38%	17%

A3a Broader resilience cluster scores, by factor

USS wave F clusters				
	Emotionally fragile	Neighbourhood support	Isolated	Competence
Belonging & social solidarity 2015	-2.50	4.35	-6.71	1.90
Capability 2015	-10.32	0.34	1.79	3.71
Emotional stress 2015	-11.51	-0.63	1.33	5.54
No of responses	5357	10171	6790	10576
% of responses in cluster	16%	31%	21%	32%

USS wave A clusters				
	Emotionally fragile	Neighbourhood support	Isolated	Competence
Belonging & social solidarity 2009	-0.77	1.59	-7.84	3.25
Capability 2009	-10.40	-0.13	1.67	3.55
Emotional stress 2009	-11.84	-1.46	1.68	4.95
No of responses	5538	10784	6645	13920
% of responses in cluster	15%	29%	18%	38%

1.4 Matching clusters to local areas

Clusters were matched to different OAC classifications for both Waves A and F (Tables A4 and A5). The most extensive classification available, the subgroup, was used for this.

The OAC cluster breakdown shows the percentage of the clusters within the OAC. The aim is to see whether there are any OACs where the proportions of people within each cluster are significantly different from the overall proportions, whilst being aware of the small numbers of survey respondents in some of the OACs.

The results can then be mapped (see A6) using the appropriate OAs for Hounslow, allowing the results of each cluster to be visualised. To allow each cluster map for 2009 and 2015 to be viewed together the colour range for each cluster is calculated from both years. This means the lowest and highest cluster values are taken from the results of both years, not just one. This allows changes to be visualised better across the two years.

A test of statistical significance was applied to the results, so insignificant data could be highlighted and disregarded from the analysis if required. Often this is because of the small number of respondents in certain OAC sub-groups.

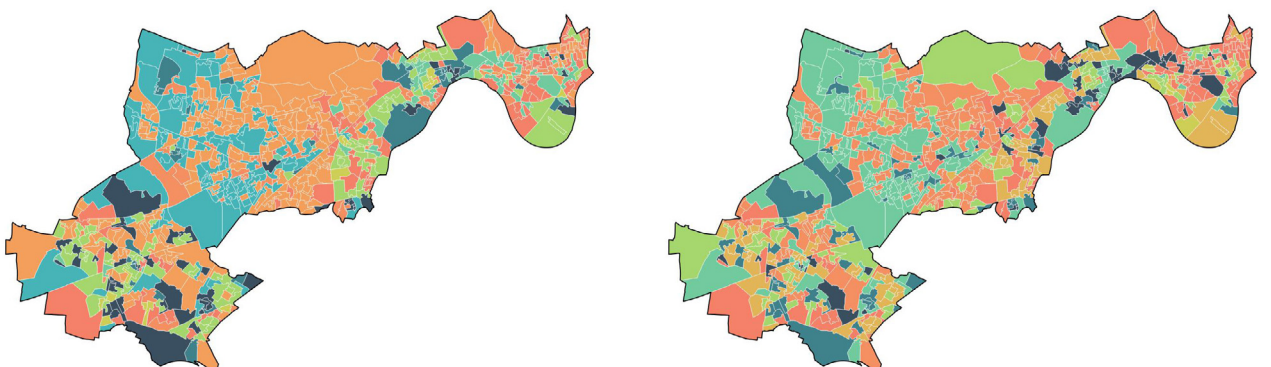
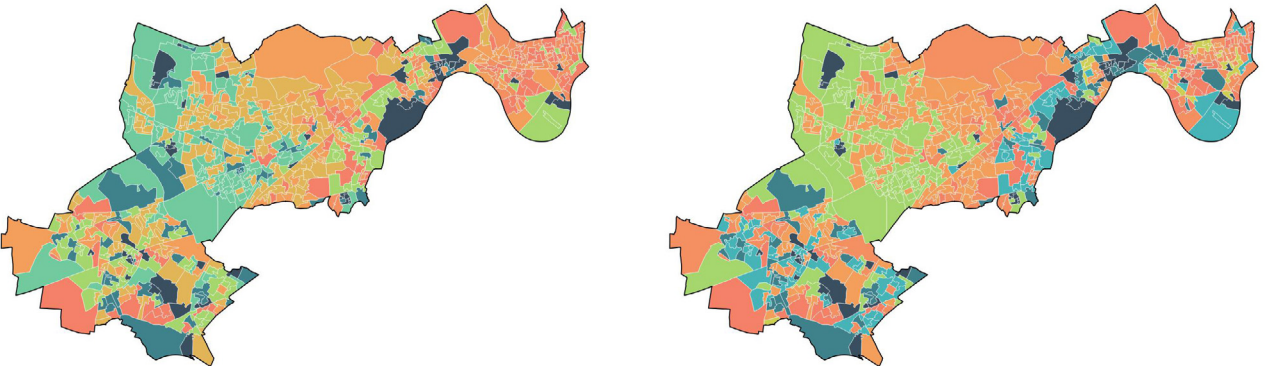
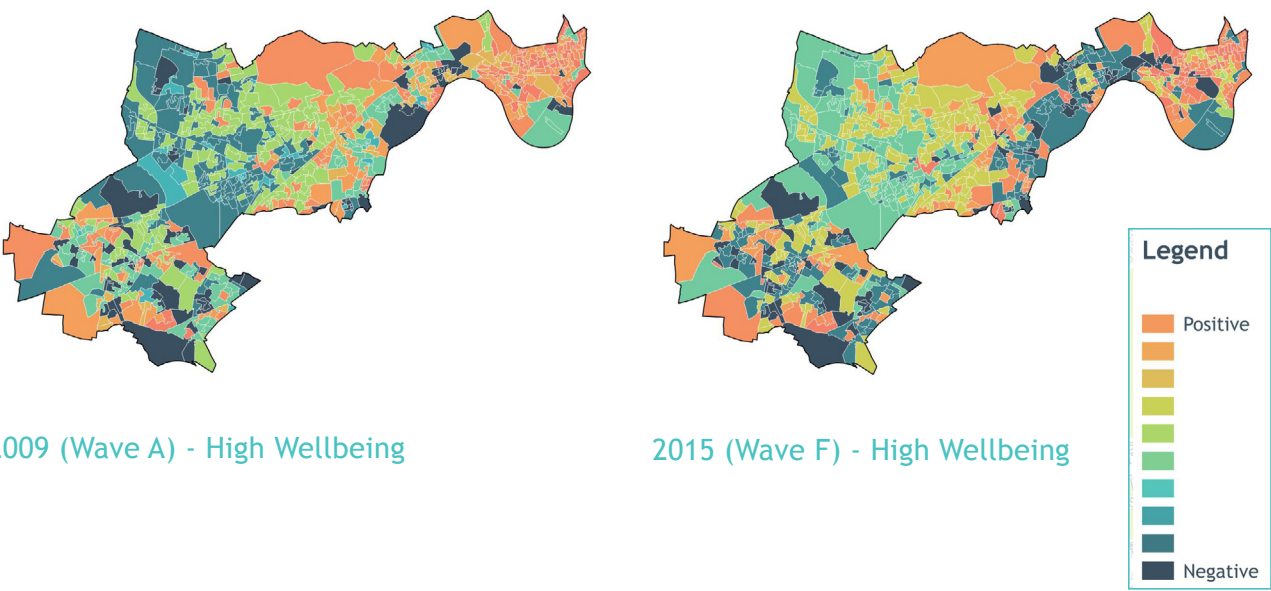
A4 Wellbeing and resilience clusters scores, by OAC, 2009

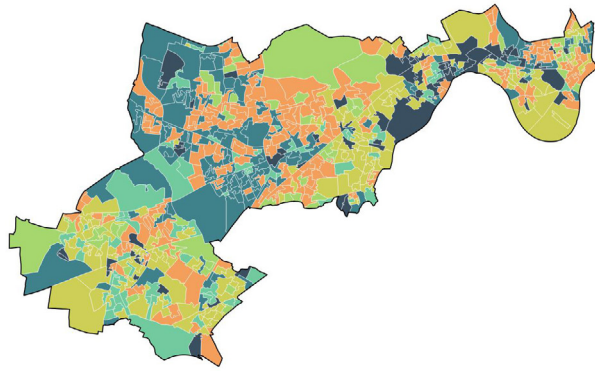
	Wellbeing clusters - WAVE A				Resilience clusters - WAVE A			
	Difference from overall				Difference from overall			
	High	Average	Low		Competence	Emotionally fragile	Neighbourhood support	Isolated
OAC	44.1%	38.5%	17.5%	OAC	37.7%	15.0%	29.2%	18.0%
1A1	8.6%	-2.2%	-6.5%	1A1	14.7%	-5.1%	-0.5%	-9.2%
1A2	11.5%	-6.2%	-5.4%	1A2	5.9%	-4.4%	3.0%	-4.6%
1A3	13.8%	-9.8%	-4.0%	1A3	9.1%	-2.9%	-0.1%	-6.1%
1A4	8.5%	-3.0%	-5.5%	1A4	11.8%	-1.9%	0.9%	-10.7%
1B1	4.2%	-1.4%	-2.7%	1B1	7.3%	-1.8%	0.7%	-6.2%
1B2	13.1%	-8.0%	-5.1%	1B2	10.2%	-6.9%	2.5%	-5.9%
1B3	4.2%	-4.1%	-0.2%	1B3	7.5%	-0.3%	-1.5%	-5.6%
1C1	9.4%	-6.7%	-2.7%	1C1	11.5%	-2.1%	-1.8%	-7.5%
1C2	6.2%	-1.7%	-4.5%	1C2	3.9%	-0.2%	2.8%	-6.5%
1C3	18.0%	-10.8%	-7.2%	1C3	5.5%	-4.3%	2.9%	-4.1%
2A1	2.9%	-6.6%	3.7%	2A1	-2.4%	3.4%	-15.4%	14.3%
2A2	7.9%	-1.4%	-6.4%	2A2	-9.6%	-5.5%	-6.8%	21.9%
2A3	2.5%	-0.3%	-2.2%	2A3	-12.3%	0.8%	-6.5%	17.9%
2B1	-1.7%	1.8%	-0.1%	2B1	-12.2%	-2.8%	-10.3%	25.3%
2B2	0.6%	2.9%	-3.4%	2B2	-19.9%	4.5%	-11.4%	26.9%
2C1	-2.7%	3.4%	-0.7%	2C1	-2.4%	-0.6%	-10.3%	13.3%
2C2	-6.4%	6.5%	-0.1%	2C2	-19.0%	6.9%	-4.2%	16.4%
2C3	12.4%	-6.2%	-6.2%	2C3	-0.6%	-2.1%	-1.8%	4.6%
2D1	3.1%	-1.8%	-1.3%	2D1	-4.4%	-2.0%	-3.9%	10.2%
2D2	11.1%	-8.9%	-2.3%	2D2	-14.0%	-6.0%	1.9%	18.1%
2D3	6.3%	1.7%	-8.0%	2D3	-6.5%	-0.4%	-2.2%	9.1%
3A1	-19.4%	10.1%	9.3%	3A1	-2.6%	3.5%	-7.8%	7.0%
3A2	-13.1%	6.3%	6.9%	3A2	-5.0%	-1.6%	-2.6%	9.3%
3B1	-17.6%	3.7%	13.9%	3B1	-12.5%	5.2%	1.8%	5.5%
3B2	-20.6%	13.3%	7.3%	3B2	-4.6%	4.6%	3.5%	-3.5%
3B3	-4.4%	-2.4%	6.8%	3B3	-16.9%	4.4%	-4.4%	16.9%

A5 Wellbeing and resilience cluster scores, by OAC, 2015

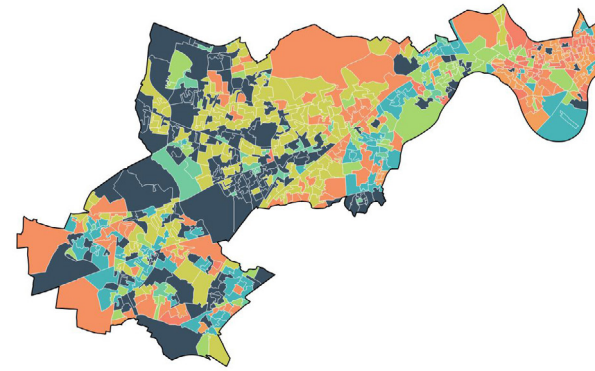
	Wellbeing clusters - WAVE F				Resilience clusters - WAVE F			
	Difference from overall				Difference from overall			
	High	Average	Low		Competence	Emotionally fragile	Neighbourhood support	Isolated
OAC	49.6%	20.1%	30.3%	OAC	32.2%	16.3%	30.9%	20.6%
1A1	4.4%	-0.8%	-3.6%	1A1	-0.5%	-4.6%	14.0%	-8.9%
1A2	10.1%	-0.1%	-10.0%	1A2	4.9%	-4.9%	7.7%	-7.6%
1A3	3.3%	0.4%	-3.7%	1A3	0.5%	-3.7%	7.8%	-4.6%
1A4	9.3%	4.2%	-13.5%	1A4	7.5%	-3.1%	6.3%	-10.7%
1B1	0.3%	1.2%	-1.5%	1B1	2.7%	0.1%	3.7%	-6.5%
1B2	8.3%	-2.5%	-5.7%	1B2	4.1%	-5.3%	7.5%	-6.3%
1B3	0.7%	2.0%	-2.7%	1B3	-0.5%	-1.7%	6.4%	-4.2%
1C1	8.1%	1.9%	-10.0%	1C1	6.1%	-4.9%	11.4%	-12.5%
1C2	2.4%	0.8%	-3.2%	1C2	-1.7%	-3.1%	9.5%	-4.7%
1C3	11.5%	1.2%	-12.7%	1C3	6.5%	-1.9%	0.5%	-5.2%
2A1	-11.9%	8.2%	3.6%	2A1	-2.0%	8.2%	-13.9%	7.7%
2A2	0.4%	-3.4%	3.0%	2A2	-7.2%	4.5%	-17.0%	19.6%
2A3	4.6%	-1.3%	-3.3%	2A3	-6.6%	2.5%	-10.1%	14.3%
2B1	2.8%	-1.8%	-1.1%	2B1	-14.9%	-2.7%	-13.6%	31.2%
2B2	7.9%	-3.8%	-4.1%	2B2	-13.2%	-2.4%	-24.6%	40.1%
2C1	5.3%	-6.5%	1.2%	2C1	1.9%	-4.2%	-17.3%	19.5%
2C2	-9.2%	14.0%	-4.8%	2C2	-21.5%	5.0%	-16.0%	32.5%
2C3	8.2%	3.4%	-11.6%	2C3	2.2%	-6.9%	0.3%	4.4%
2D1	13.6%	-4.3%	-9.3%	2D1	-3.4%	-2.5%	2.1%	3.8%
2D2	-1.3%	-2.8%	4.1%	2D2	-8.0%	2.7%	-18.9%	24.2%
2D3	6.8%	-2.2%	-4.6%	2D3	-5.4%	-4.4%	7.7%	2.1%
3A1	-9.8%	-5.3%	15.1%	3A1	-3.7%	4.5%	-6.2%	5.4%
3A2	-9.1%	-2.6%	11.7%	3A2	-5.2%	5.8%	-6.8%	6.3%
3B1	-7.8%	-7.0%	14.8%	3B1	0.3%	6.2%	-14.4%	7.8%
3B2	-8.6%	-7.8%	16.3%	3B2	-11.1%	4.2%	1.2%	5.7%
3B3	-10.4%	-2.4%	12.8%	3B3	-10.2%	13.7%	-12.9%	9.4%

A6 Cluster maps

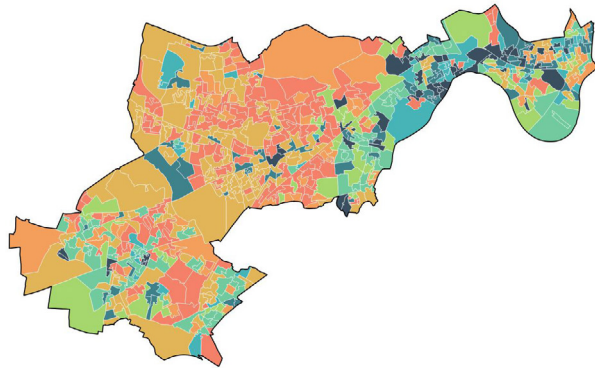




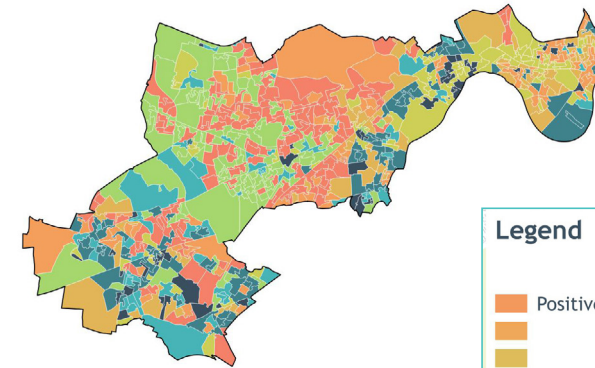
2009 (Wave A) - Neighbourhood support



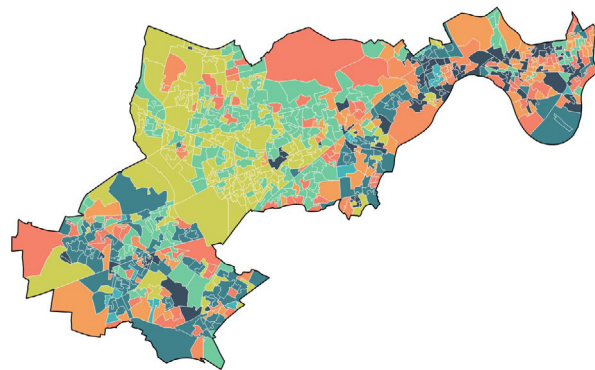
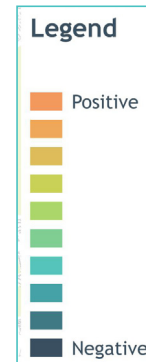
2015 (Wave F) - Neighbourhood support



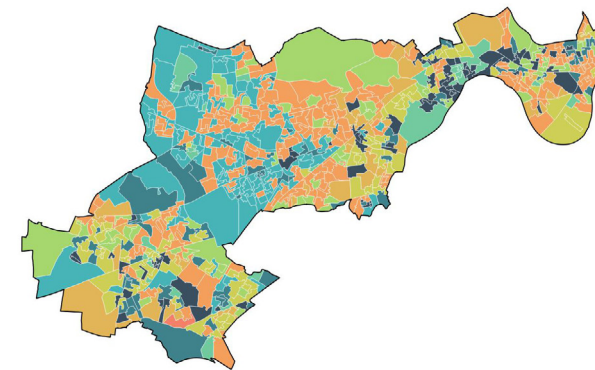
2009 (Wave A) - Isolation



2015 (Wave F) - Isolation



2009 (Wave A) - Competence



2015 (Wave F) - Competence

1.5 Scoring the predictive data

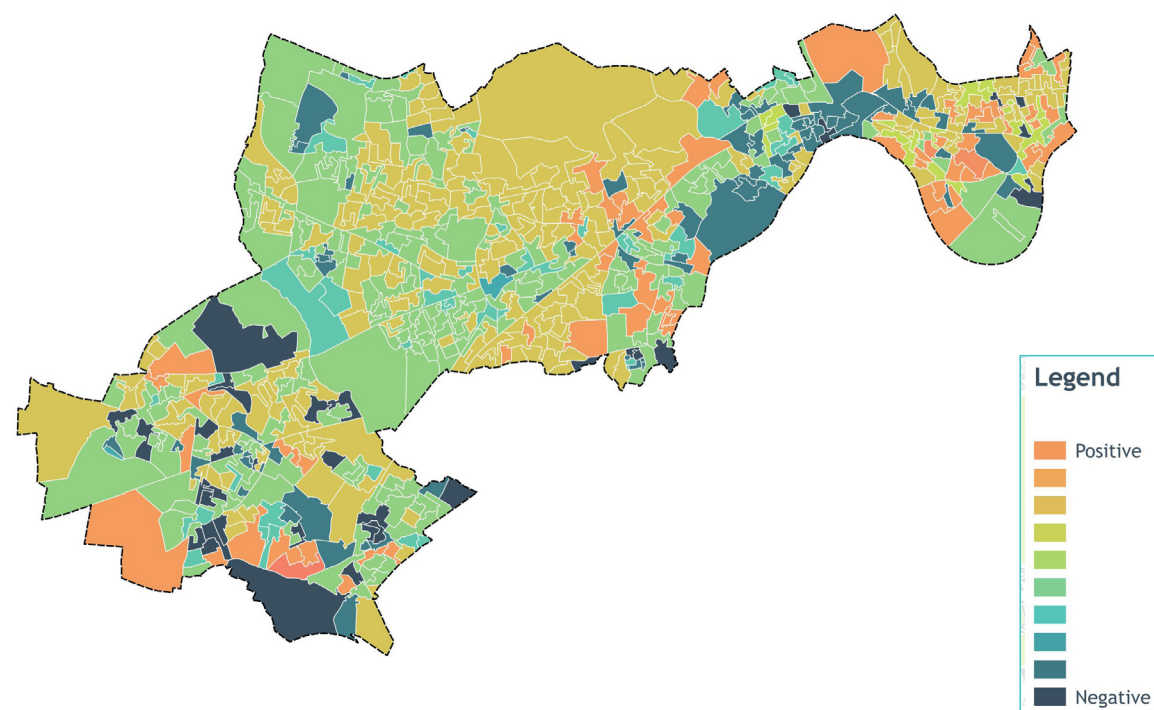
Stage 1: Putting the clusters into quartiles within OAs

The predictive data for each OA was scored to develop a set of positive and negative OAs for each cluster, and then to develop an overall predictive data score for all the clusters combined. This was again done by finding the upper and lower quartile for each cluster and then each quartile was either scored positively (indicating higher resilience and scoring +1) or negatively (indicating lower resilience and scoring -1). Where the cluster is neither positive nor negative it is left alone (scoring 0).

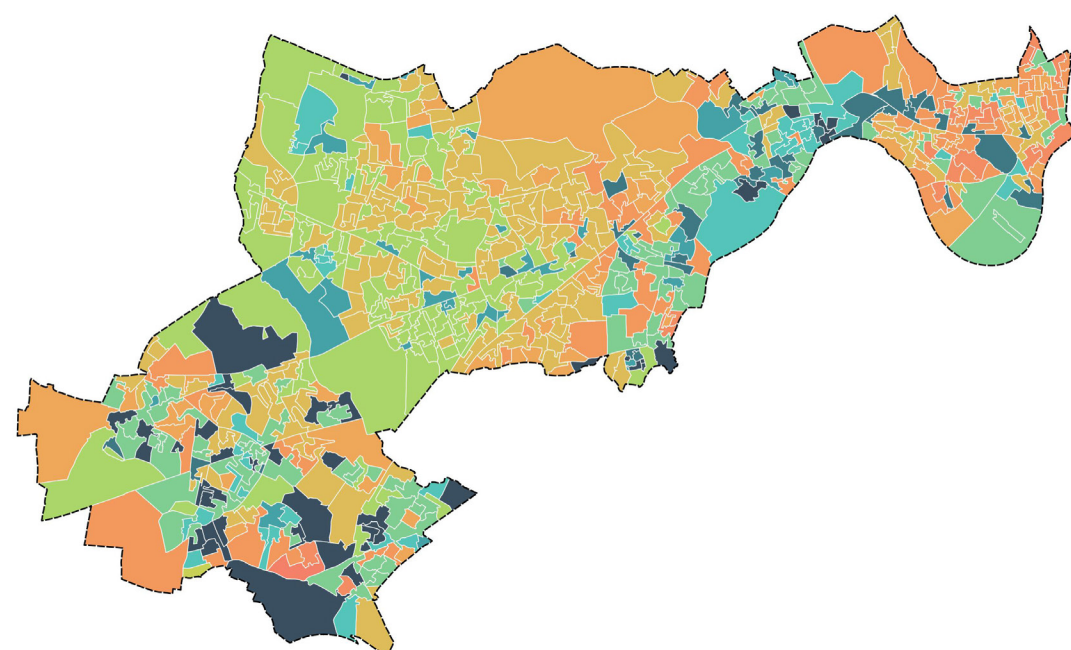
The upper or lower quartiles do not necessarily correspond directly to positive or negative scores depending on the meaning of the particular cluster, for example a high score for Neighbourhood Support is positive (the upper quartile), but a high score for Isolated is negative (the lower quartile).

The scores for each cluster can then be aggregated for each OA to develop an overall predictive data score, thus allowing the most positive and negative areas of Hounslow to be mapped for each year. This is also possible for the whole of London and for any other part of the UK.

A7 Predictive data score, OA level, 2009



A7a Predictive data score, OA level, 2015



Stage 2: Aggregating the OA data to LSOAs

To compare the predictive data, which is at OA level, with the actual or hard data describing a place, which is mostly at LSOA level, a way was needed to interpret the predictive data at LSOA level.

To do this the scores for each OA is aggregated for each LSOA, so either the upper or lower quartiles of data were counted by adding the scores allocated with each cluster, either +1, -1 or 0.

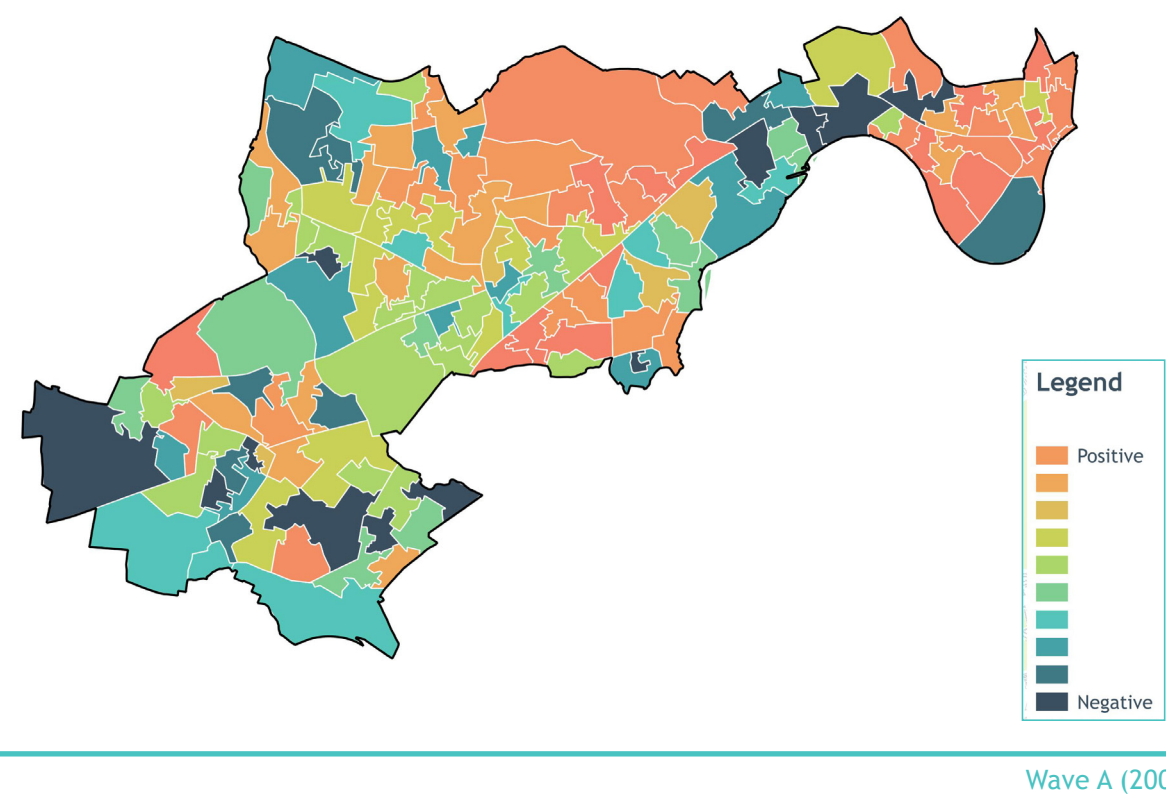
This enables each LSOA to be assessed by the number of OAs scoring positive or negative within each cluster and for each year (Tables A4 and A5). This provides a different score for each cluster and OA for both years (2009 and 2015) allowing change to be recorded and visualised in maps and then compared to data at the same level. This is also a method that could be scaled up to MSA level or ward level to assess larger areas - such as whole cities or large urban areas where a fine grained analysis is not needed.

However, caution is needed: in scaling up the predictive data from OA to LSOA level some fine-grained analysis will inevitably be lost in this process. This could include such as individual pockets of local variation where small areas of negative scores might be lost next larger areas of positive scores, or vice versa.

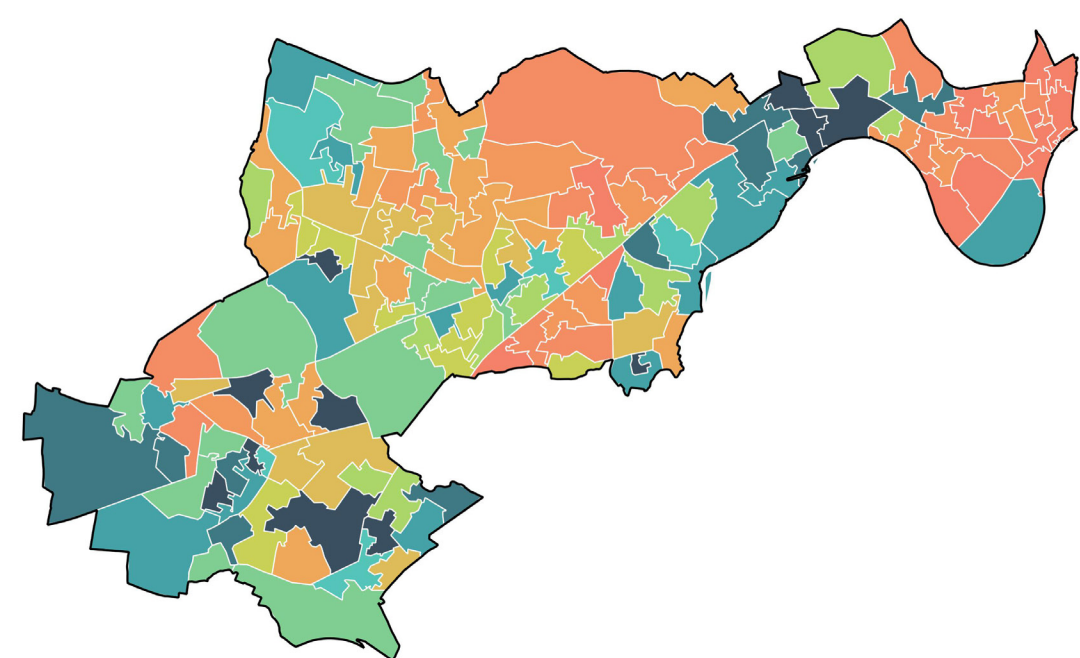
It is important to remember that the predictive data is always best analysed at the OA level and should only be scaled up when the comparison to another dataset is needed and where the two data sources cannot be visually overlaid onto a map.

In the future it may be worthwhile exploring the mean value of the combined scores for each LSOA, as this may reflect a more balanced result for each LSOA as the number of OAs in each often varies.

A8 Predictive data score, LSOA level, 2009



A8a Predictive data score, LSOA level, 2015

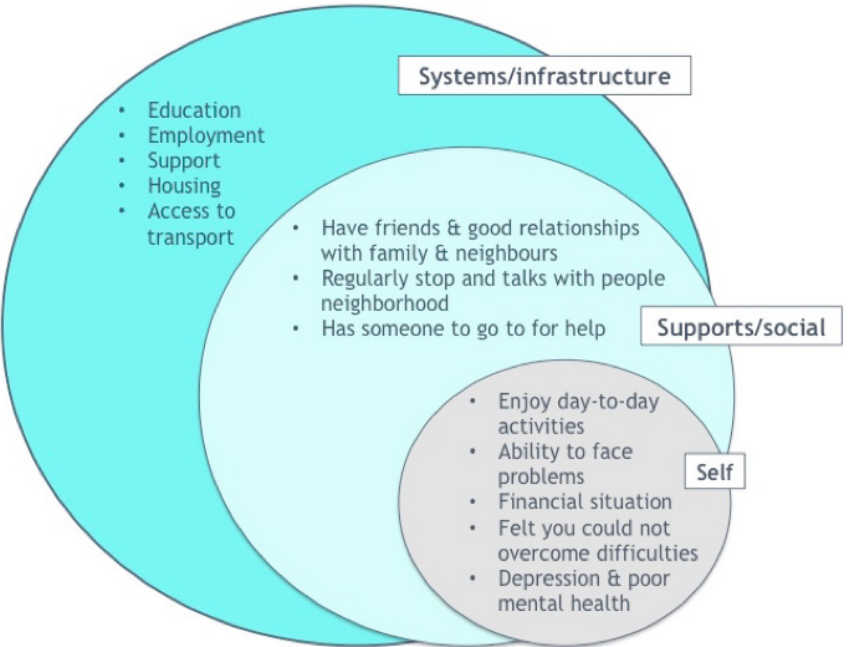


2. Hard data

The original WARM framework structure used data from a number of different sources under three dimensions: “self”, “supports/social” and “systems/infrastructure”.

The initial aim at the start of the 2018 project was to use this structure in the new model and to populate each dimension with data for both 2009 and 2015. Substantial flexibility was included in the data sourcing to allow datasets from other years to act as proxies. However, after exploring different options in detail, the conclusion was reached that it was not possible to achieve the same level of coverage for both years.

A9 Resilience domains



Only 24 data sources (Table A10) were found that could be used for both years, compared to 50 data sources that were sourced in 2015. Enough data was found to sufficiently cover the “self” dimension, however the other dimensions were poorly covered and what data there was often at MSOA or ward level. This provided much weaker connections to the predictive data, which is at the much smaller OA level. A particular limitation was that census data could not be updated, and that the

borough’s residents survey in its current format does not pre-date 2012.

As the three dimensions could not be adequately populated for both 2009 and 2015, this framework could not be used to structure the hard data. Instead, individual datasets were investigated separately in their own right.

A10 Available hard data for both 2009 and 2015

2009	2015
SELF	
Household Income estimates median 2008/09	Household Income estimates median 2012/13
Council tax percent difference 2009	Council tax percent difference 2015
% of children under 18 in low income families (CLIFLM)	% of children under 18 in low income families (CLIFLM)
% of residents aged 60+ on Pension Credit	% of residents aged 60+ on Pension Credit
Job seekers allowance for small areas, Nov 2009	Job seekers allowance for small areas, Nov 2015
Incapacity and Severe Disability Allowance benefit claimants, Nov 2009	Incapacity and Severe Disability Allowance benefit claimants, Nov 2015
Claimants as a proportion of residents aged 16-64, by LSOA 2009	Claimants as a proportion of residents aged 16-64, by LSOA 2015
% of households on Child Benefit households tax credits	% of households on Child Benefit claiming tax credits
Modeled % of households in fuel poverty (low income high costs measure)	Modeled % of households in fuel poverty (low income high costs measure)
Alcohol related harm hospital admissions (standardised admissions ratio) by ward	Alcohol related harm hospital admissions (standardised admissions ratio) by ward
% of Reception-age children who were obese, by ward	% of Reception-age children who were obese, by ward
Life expectancy by ward 2005-09	Life expectancy by ward 2009-13
Male life expectancy 2007-11 by ward-	Male life expectancy 2011-15 by ward
Female life expectancy 2007-11 by ward	Female life expectancy 2011-15 by ward
% population aged 0-19 (projected) by ward	% population aged 0-19 (projected) by ward
% population aged 65+ (projected) by ward	% population aged 65+ (projected) by ward
SUPPORT	
Registered HMOs per 1,000 dwellings, by ward	Registered HMOs per 1,000 dwellings, by ward
Local elections statistics % per wards, 2010	Local elections statistics % per wards, 2014
SYSTEMS & STRUCTURE	
IMD rank (where 1 = most deprived)	IMD rank (where 1 = most deprived)
Ambulance callouts per 1,000 residents	Ambulance callouts per 1,000 residents
Crime rate (modifiable offences per 1,000 population in financial year 2009), by ward	Crime rate (modifiable offences per 1,000 population in financial year 2015), by ward
% of pupils achieving 5+ GCSEs including English & Maths at grades A*-C, by MSOA of residence	% of pupils achieving 5+ GCSEs including English & Maths at grades A*-C, by MSOA of residence
Median house prices	Median house prices
Public transport accessibility level (PTAL)	Public transport accessibility level (PTAL)

2.1 Scoring the data

Stage 1: Scoring the hard data (if a combined model is needed)

The hard data covering both 2009 and 2015 is patchy, however it was scored in a similar manner to the predictive data to explore change over time.

The data was first assembled at LSOA level, allowing direct correlations to the predictive data to be made. Then the top and bottom quartiles of each data source were analysed to produce more consistent scores for each LSOA.

The scoring system for the hard data reflects the way the predictive data is scored.

Stage 2: Exploring the change

To examine changes between the two years a coherent method for normalising the data was needed. This was important because the same data source for different years (2009 and 2015) often produced hugely different values for each LSOA. For example, the election turnouts differed because the results for 2009 are from a general election and the results for 2014 from a local election. Similar disparities can also be observed for benefit claimants because of the introduction of universal credit and the changes in child benefit.

This presented the opportunity to examine two different methods of normalisation (Table A11):

- each LSOA was ranked from the most positive to least positive. This created a ranking list between 1 (most positive) and 142 (least positive) for each data source. This makes it possible to rank the hard-data scores, allowing different datasets to be compared to each other and to the predictive data for each neighbourhood. This is a very common method used for large areas and is used by IMD to rank all LSOAs between the least and most deprived areas in the UK
- however, this method does not take into account major deviations between neighbouring ranking positions. Therefore, a second option creates a normalised range for each LSOA from 0 to 1.0, where 0 is the lowest and

1.0 is the highest. Unlike the previous ranking system the deviation between two values is dependent on the raw data. For example, if the differences in the data source between the 9th and 10th placed LSOAs are significant larger than 8th to 9th this will be represented in the normalised value (Table A12).

While both methods show the same positive and negative distribution of LSOAs, the second method provides more accurate and reliable results.

A11 Hard data scores, LSOA level, 2009 and 2015

LSOA	2009 Score	2015 Score	LSOA	2009 Score	2015 Score	LSOA	2009 Score	2015 Score	LSOA	2009 Score	2015 Score
Hounslow 011D	1	1	Hounslow 017E	0	-5	Hounslow 023A	-1	-2	Hounslow 024B	-3	-4
Hounslow 011E	2	0	Hounslow 016E	-3	-3	Hounslow 023B	0	-1	Hounslow 024C	0	0
Hounslow 012A	4	0	Hounslow 021E	-2	-1	Hounslow 023C	-5	-2	Hounslow 022E	-2	-1
Hounslow 004E	0	-1	Hounslow 020A	-1	0	Hounslow 023D	-2	-5	Hounslow 027A	1	0
Hounslow 010C	-1	0	Hounslow 014A	0	0	Hounslow 023E	-6	-7	Hounslow 025B	-2	-2
Hounslow 005A	-14	-14	Hounslow 014B	-6	-6	Hounslow 003A	-1	0	Hounslow 025C	-3	-3
Hounslow 005B	-15	-11	Hounslow 020B	1	0	Hounslow 006A	0	0	Hounslow 025D	-2	-4
Hounslow 010D	-1	3	Hounslow 020C	0	0	Hounslow 003B	-3	-4	Hounslow 027B	-2	-1
Hounslow 010E	-1	2	Hounslow 020D	-6	-1	Hounslow 006B	2	3	Hounslow 027C	3	2
Hounslow 005C	-7	-7	Hounslow 020E	-13	-15	Hounslow 003C	-5	-6	Hounslow 025E	-1	-3
Hounslow 005D	-8	-6	Hounslow 012D	9	7	Hounslow 006C	3	2	Hounslow 026A	-12	-13
Hounslow 012B	5	1	Hounslow 009A	13	6	Hounslow 003D	-9	-9	Hounslow 026B	-7	-2
Hounslow 012C	5	6	Hounslow 012E	5	9	Hounslow 001A	11	12	Hounslow 026C	-13	-10
Hounslow 018A	-2	0	Hounslow 015E	2	5	Hounslow 001B	9	7	Hounslow 026D	-1	1
Hounslow 015A	0	2	Hounslow 009B	8	8	Hounslow 007A	20	17	Hounslow 028A	-6	-5
Hounslow 015B	-3	-2	Hounslow 009C	8	6	Hounslow 007B	-1	-1	Hounslow 028B	-1	2
Hounslow 015C	-3	1	Hounslow 009D	2	2	Hounslow 001C	16	14	Hounslow 028C	-4	-2
Hounslow 017B	-5	-6	Hounslow 014C	-1	0	Hounslow 001D	13	15	Hounslow 024D	-1	-3
Hounslow 021A	-1	-1	Hounslow 014D	0	0	Hounslow 001E	16	14	Hounslow 024E	0	-1
Hounslow 018C	-4	1	Hounslow 014E	2	3	Hounslow 008A	2	2	Hounslow 024F	1	0
Hounslow 018D	0	0	Hounslow 006D	0	2	Hounslow 007C	7	14	Hounslow 027D	1	0
Hounslow 021B	-2	-3	Hounslow 006E	-6	-7	Hounslow 007D	11	11	Hounslow 026E	-11	-12
Hounslow 021C	-1	-1	Hounslow 029A	7	12	Hounslow 008B	10	12	Hounslow 027E	-1	1
Hounslow 021D	-2	1	Hounslow 007E	3	4	Hounslow 008C	2	0	Hounslow 028D	2	4
Hounslow 019A	2	3	Hounslow 007F	11	14	Hounslow 008D	7	11	Hounslow 011A	0	-1
Hounslow 019B	3	4	Hounslow 029B	7	7	Hounslow 008E	12	13	Hounslow 010A	-1	-2
Hounslow 019C	2	5	Hounslow 029C	4	5	Hounslow 013A	-1	-2	Hounslow 004A	2	-2
Hounslow 019D	3	3	Hounslow 029D	2	4	Hounslow 013B	-2	0	Hounslow 011B	0	-2
Hounslow 018E	7	10	Hounslow 025F	-2	-11	Hounslow 013C	-3	-1	Hounslow 010B	0	0
Hounslow 029E	12	15	Hounslow 025G	0	2	Hounslow 013D	-2	0	Hounslow 011C	-2	-3
Hounslow 015D	10	11	Hounslow 003F	5	4	Hounslow 016A	-1	0	Hounslow 017A	-1	-1
Hounslow 019E	-2	4	Hounslow 003G	4	0	Hounslow 016B	-16	-15	Hounslow 004B	-2	0
Hounslow 016C	-1	1	Hounslow 018F	4	8	Hounslow 013E	-1	-1	Hounslow 004C	1	-1
Hounslow 016D	-2	2	Hounslow 018G	5	3	Hounslow 022C	0	-1	Hounslow 004D	-1	-8
Hounslow 017C	3	4	Hounslow 022A	-1	0	Hounslow 024A	-2	-1			
Hounslow 017D	-2	-3	Hounslow 022B	-1	0	Hounslow 022D	-2	0			

A12 Normalising data source for comparison between 2009-15

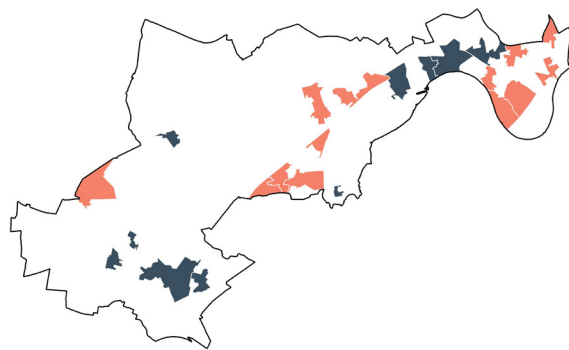
LSOA	IMD Ran king	IMD Normal ised	LSOA	IMD Ran king	IMD Normal ised	LSOA	IMD Ran king	IMD Normal ised	LSOA	IMD Ran king	IMD Normal ised
Hounslo w 007A	1	0	Hounslo w 012D	37	0.2341 64744	Hounslo w 011E	73	0.3591 88774	Hounslo w 025C	109	0.5235 00577
Hounslo w 001E	2	0.0724 00038	Hounslo w 028B	38	0.2352 46059	Hounslo w 010B	74	0.3599 57709	Hounslo w 023A	110	0.5278 25836
Hounslo w 018E	3	0.0856 16109	Hounslo w 012E	39	0.2358 70819	Hounslo w 026D	75	0.3672 62591	Hounslo w 016A	111	0.5280 66128
Hounslo w 008E	4	0.0958 28527	Hounslo w 027D	40	0.2450 49981	Hounslo w 017D	76	0.3726 21107	Hounslo w 028C	112	0.5289 5521
Hounslo w 007F	5	0.1032 53556	Hounslo w 009D	41	0.2458 18916	Hounslo w 015A	77	0.3798 05844	Hounslo w 025B	113	0.5303 96963
Hounslo w 008D	6	0.1050 79777	Hounslo w 018F	42	0.2524 99039	Hounslo w 015B	78	0.3848 03922	Hounslo w 022E	114	0.5370 77086
Hounslo w 001D	7	0.1117 11842	Hounslo w 012A	43	0.2585 30373	Hounslo w 024D	79	0.3921 08804	Hounslo w 018G	115	0.5379 18108
Hounslo w 015D	8	0.1138 02384	Hounslo w 027B	44	0.2601 6436	Hounslo w 022D	80	0.3941 75317	Hounslo w 024E	116	0.5576 46098
Hounslo w 001A	9	0.1208 18916	Hounslo w 006C	45	0.2642 25298	Hounslo w 015E	81	0.3952 56632	Hounslo w 011C	117	0.5652 15302
Hounslo w 008B	10	0.1247 59708	Hounslo w 012C	46	0.2668 68512	Hounslo w 018C	82	0.4105 39216	Hounslo w 003B	118	0.5659 12149
Hounslo w 001C	11	0.1275 47097	Hounslo w 022B	47	0.2704 24837	Hounslo w 024B	83	0.4159 21761	Hounslo w 007B	119	0.5986 15917
Hounslo w 029A	12	0.1490 0519	Hounslo w 006A	48	0.2707 61246	Hounslo w 008A	84	0.4214 48481	Hounslo w 003A	120	0.6070 50173
Hounslo w 007C	13	0.1510 71703	Hounslo w 029D	49	0.2729 71934	Hounslo w 018A	85	0.4339 91734	Hounslo w 013C	121	0.6099 57709
Hounslo w 029B	14	0.1534 50596	Hounslo w 004B	50	0.2790 27297	Hounslo w 003F	86	0.4354 57516	Hounslo w 017B	122	0.6177 91234
Hounslo w 019A	15	0.1582 80469	Hounslo w 010C	51	0.2822 95271	Hounslo w 011B	87	0.4369 23299	Hounslo w 026B	123	0.6208 42945
Hounslo w 009A	16	0.1647 92388	Hounslo w 020C	52	0.2833 52557	Hounslo w 025E	88	0.4375 24029	Hounslo w 004D	124	0.6209 15033
Hounslo w 029E	17	0.1660 65936	Hounslo w 021E	53	0.2909 69819	Hounslo w 006D	89	0.4397 34717	Hounslo w 023D	125	0.6229 33487
Hounslo w 019B	18	0.1698 62553	Hounslo w 024F	54	0.2937 81238	Hounslo w 004E	90	0.4406 47828	Hounslo w 003D	126	0.6422 04921
Hounslo w 009C	19	0.1739 71549	Hounslo w 029C	55	0.2961 60131	Hounslo w 024C	91	0.4408 64091	Hounslo w 017E	127	0.6660 89965
Hounslo w 014E	20	0.1745 00192	Hounslo w 014D	56	0.2970 01153	Hounslo w 027A	92	0.4515 57093	Hounslo w 005D	128	0.6666 42637
Hounslo w 007D	21	0.1842 80085	Hounslo w 013D	57	0.3062 04344	Hounslo w 017A	93	0.4520 61707	Hounslo w 005C	129	0.6882 92964
Hounslo w 019C	22	0.1918 97347	Hounslo w 010E	58	0.3063 72549	Hounslo w 025D	94	0.4552 57593	Hounslo w 003C	130	0.6887 49519
Hounslo w 019D	23	0.1937 71626	Hounslo w 010A	59	0.3127 88351	Hounslo w 013A	95	0.4623 94271	Hounslo w 028A	131	0.6934 35217
Hounslo w 001B	24	0.1955 49789	Hounslo w 022C	60	0.3180 02691	Hounslo w 014C	96	0.4636 91849	Hounslo w 023E	132	0.7203 71972
Hounslo w 009B	25	0.2078 52749	Hounslo w 025G	61	0.3229 7674	Hounslo w 021B	97	0.4731 35333	Hounslo w 006E	133	0.7235 91888

Hounslo w 011D	2 6	0.21100 0577	Hounslo w 027E	6 2	0.32434 6405	Hounslo w 020D	98	0.47363 9946	Hounslo w 005B	13 4	0.76110 1499
Hounslo w 028D	2 7	0.21128 8927	Hounslo w 004C	6 3	0.32730 1999	Hounslo w 016E	99	0.48404 4598	Hounslo w 014B	13 5	0.76732 5067
Hounslo w 006B	2 8	0.21474 9135	Hounslo w 021D	6 4	0.32790 273	Hounslo w 003G	10 0	0.49002 7874	Hounslo w 025F	13 6	0.77631 1995
Hounslo w 020B	2 9	0.21679 1619	Hounslo w 016C	6 5	0.33282 872	Hounslo w 004A	10 1	0.49483 3718	Hounslo w 026A	13 7	0.78621 2034
Hounslo w 019E	3 0	0.22090 0615	Hounslo w 024A	6 6	0.33366 9742	Hounslo w 008C	10 2	0.49517 0127	Hounslo w 026C	13 8	0.81276 4321
Hounslo w 027C	3 1	0.22414 456	Hounslo w 021C	6 7	0.33400 6151	Hounslo w 021A	10 3	0.49675 6055	Hounslo w 026E	13 9	0.81778 6428
Hounslo w 011A	3 2	0.22568 243	Hounslo w 016D	6 8	0.33508 7466	Hounslo w 023B	10 4	0.50367 6471	Hounslo w 005A	14 0	0.85313 341
Hounslo w 012B	3 3	0.22717 2241	Hounslo w 007E	6 9	0.34789 504	Hounslo w 023C	10 5	0.50545 4633	Hounslo w 016B	14 1	0.93709 1503
Hounslo w 017C	3 4	0.22885 4287	Hounslo w 020A	7 0	0.35157 1511	Hounslo w 018D	10 6	0.50567 0896	Hounslo w 020E	14 2	1
Hounslo w 022A	3 5	0.23034 4098	Hounslo w 010D	7 1	0.35832 3722	Hounslo w 013E	10 7	0.50607 9393			
Hounslo w 014A	3 6	0.23197 8085	Hounslo w 013B	7 2	0.35906 8627	Hounslo w 015C	10 8	0.50643 9831			

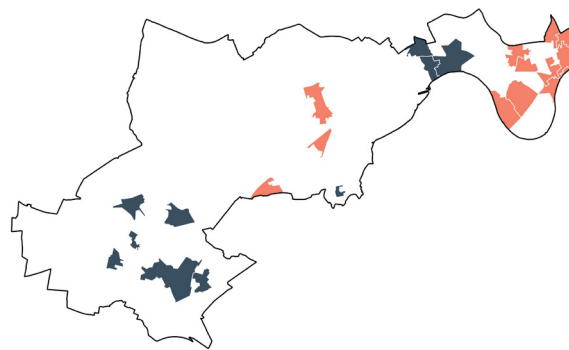
3. Combining hard and predictive data

LSOA outliers for the hard data (A13) for both 2009 and 2015 have been examined in detail alongside a handful of pre-selected hard datasets. This provides the opportunity to compare and contrast the predictive and hard data for individual LSOAs and to allow changes to be observed.

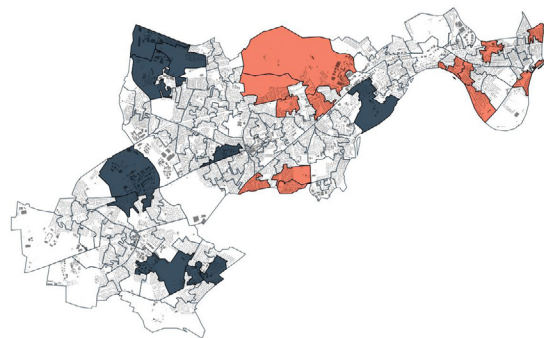
A13 Location of data outliers, LSOA level, 2009 and 2015



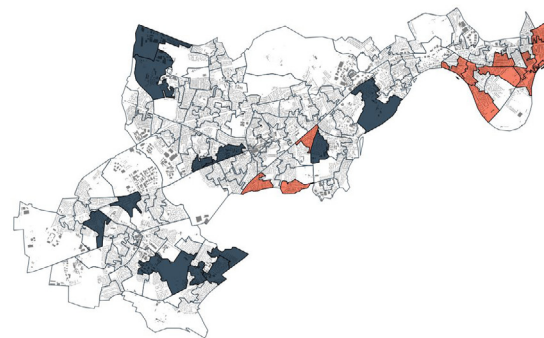
Predictive data, Wave A (2009)



Predictive data Wave F (2015)



Hard data Wave A (2009)



Hard data Wave F (2015)

4. Measuring change

While change can be visually mapped for the hard and predictive data to show statistical changes between the two, interpreting the significance of the positive and negative changes for each LSOAs is often much more difficult, especially over short periods of time. For example an area could see a big negative shift in predicted resilience, yet overall remain relatively strong compared to other areas. Conversely predicted resilience could increase, yet the areas still show significant vulnerabilities. Therefore, the way change is represented is very important.

The danger of mapping change for the whole of the borough is that it may misrepresent significant areas of the borough, therefore change was presented recorded locally within individual LSOA profiles (See Appendix, section 5). These profiles highlight where changes in the hard and predictive data have occurred at both OA and LSOA levels.

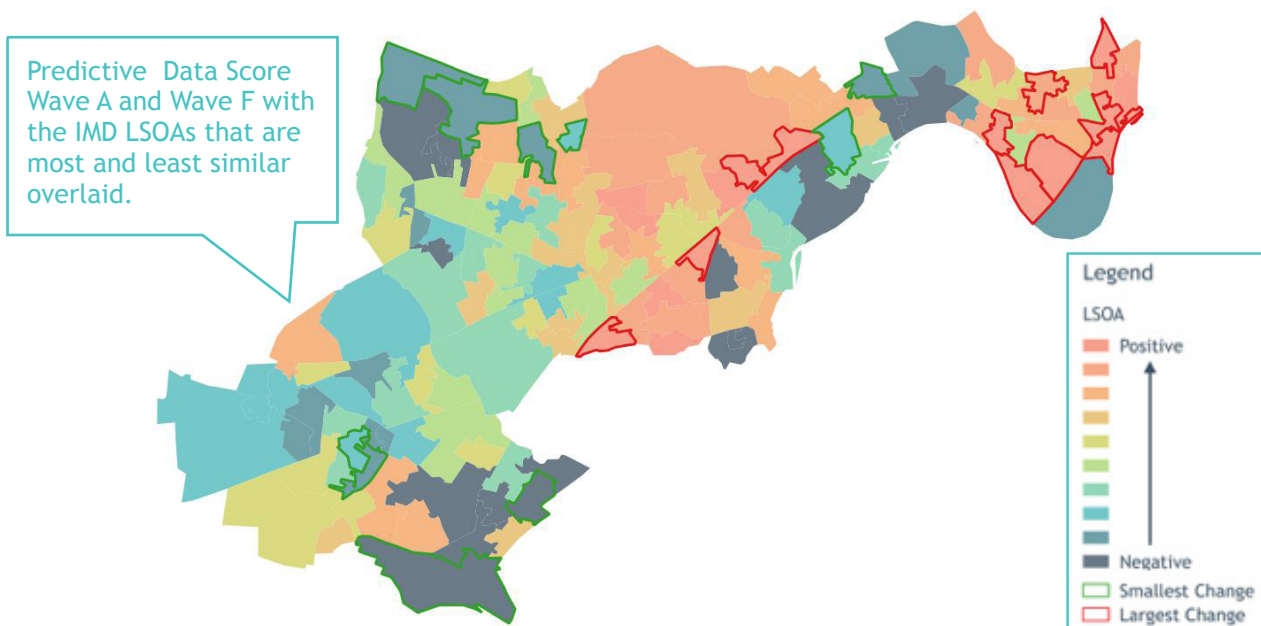
To understand change over the whole borough, the predictive data, which has proven to be reliable and robust for the two different years examined, was analysed alongside individual hard datasets. This allowed specific relationships between the predictive scores (and each cluster) and individual hard data sources to be explored.

This gives the potential for a narrative to be developed for the period between 2009 and 2015 for each relationship, and for a clear and concise conclusion to be established from this study. It also reveals which data sources that do not connect with the predictive data.

Each data source was related to each predictive cluster using linear regression. This method is used because it allows two datasets to be related to each other and the likeliness of their relationship to predict change (both positively and negatively) to be established. Linear regression draws an average line between all the plots line to produce a predictive r-square value between 0.0 and 1.0. When this forms a 1.0r2 result the combination of the two datasets produces a perfect prediction, when it is 0.0r2 the combined datasets produces zero likeliness of any prediction. This is useful for examining the relationship between two different dataset and highlights when changes occur between 2009 and 2015.

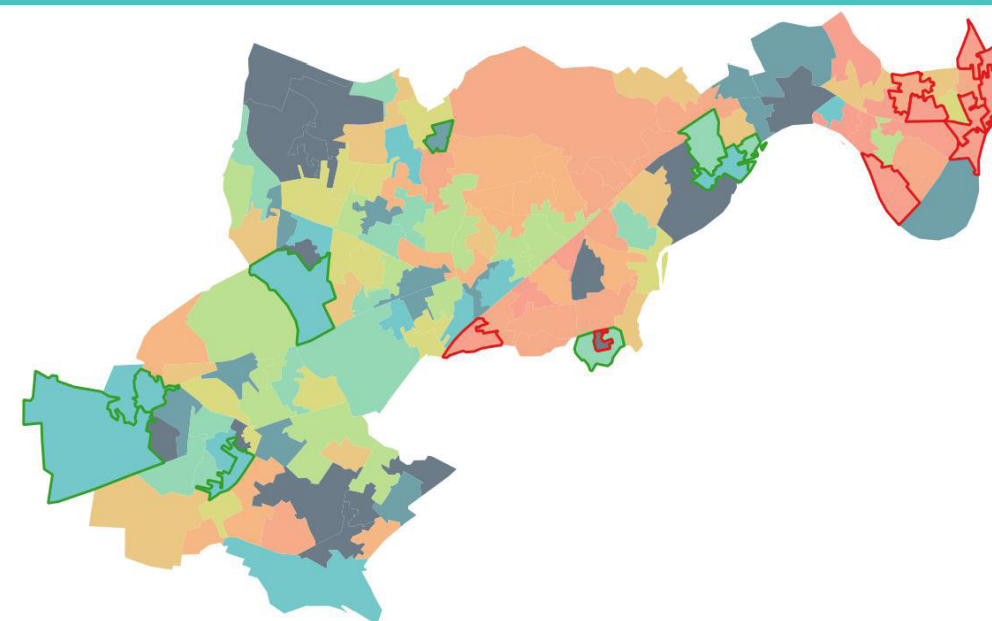
This enables the hard data that relates most strongly to the predictive data to be identified, and where the predicted and the hard data give contradictory results.

A14 Combining data, LSOA Level, 2009



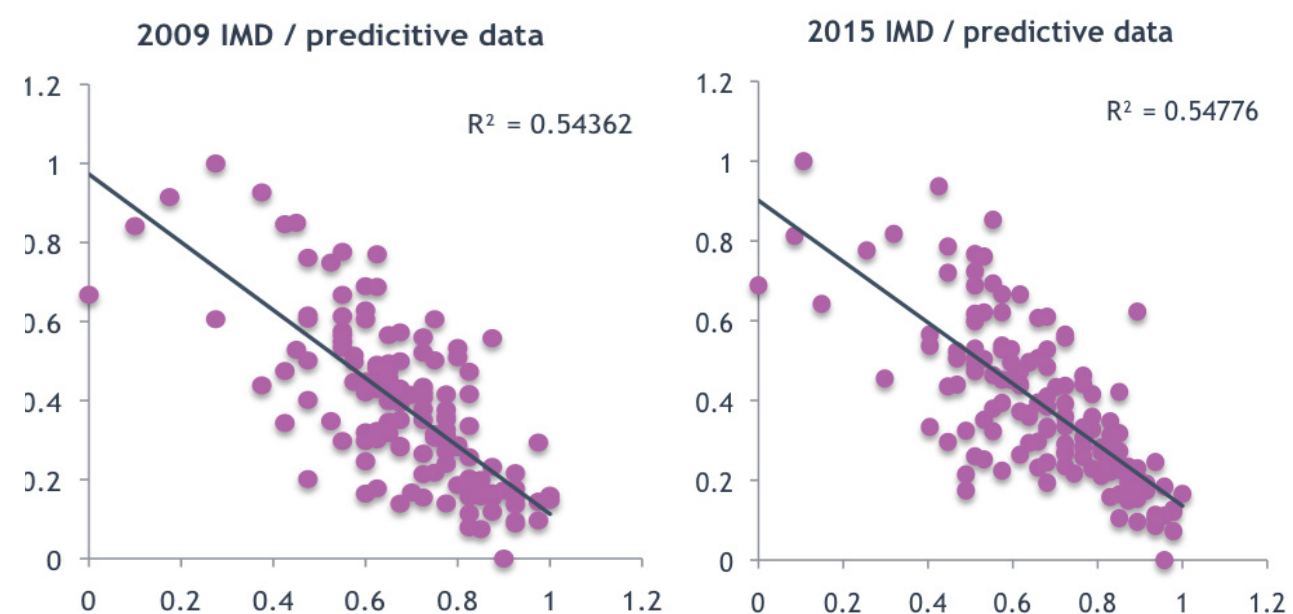
Predictive data, Wave A (2009)

A14a Combining data, LSOA level, 2015



Predictive data, Wave F (2015)

A15 Linear regression: IMD and predictive data



IMD Score to overall predictive data score

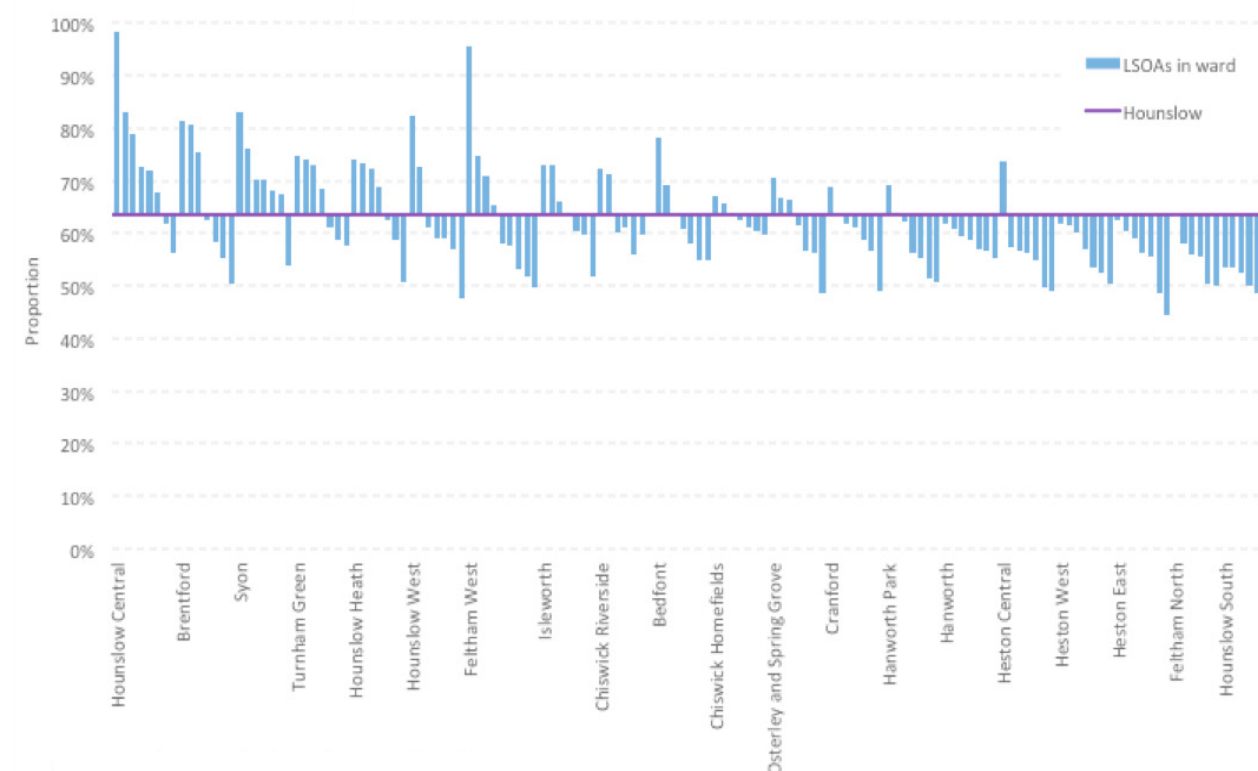
5. Churn data

The churn data was analysed in the same way as the hard data. There are numerous datasets for new GP patients so that actual datasets to be analysed were reduced to give more focus. To do this each dataset is correlated between the respective results for 2009 and 2015 to highlight where there have been significant change, using linear regression. Where the values return a correlation coefficient close to 1.0r2 very few changes have occurred, but where the results are closer to 0.0r2 the have been larger changes. This is useful for understanding where communities have changed or remained the same.

These results, along with the general aggregated results that show where there are good sample sizes, are then used to decide what dataset to analysis (Table A17).

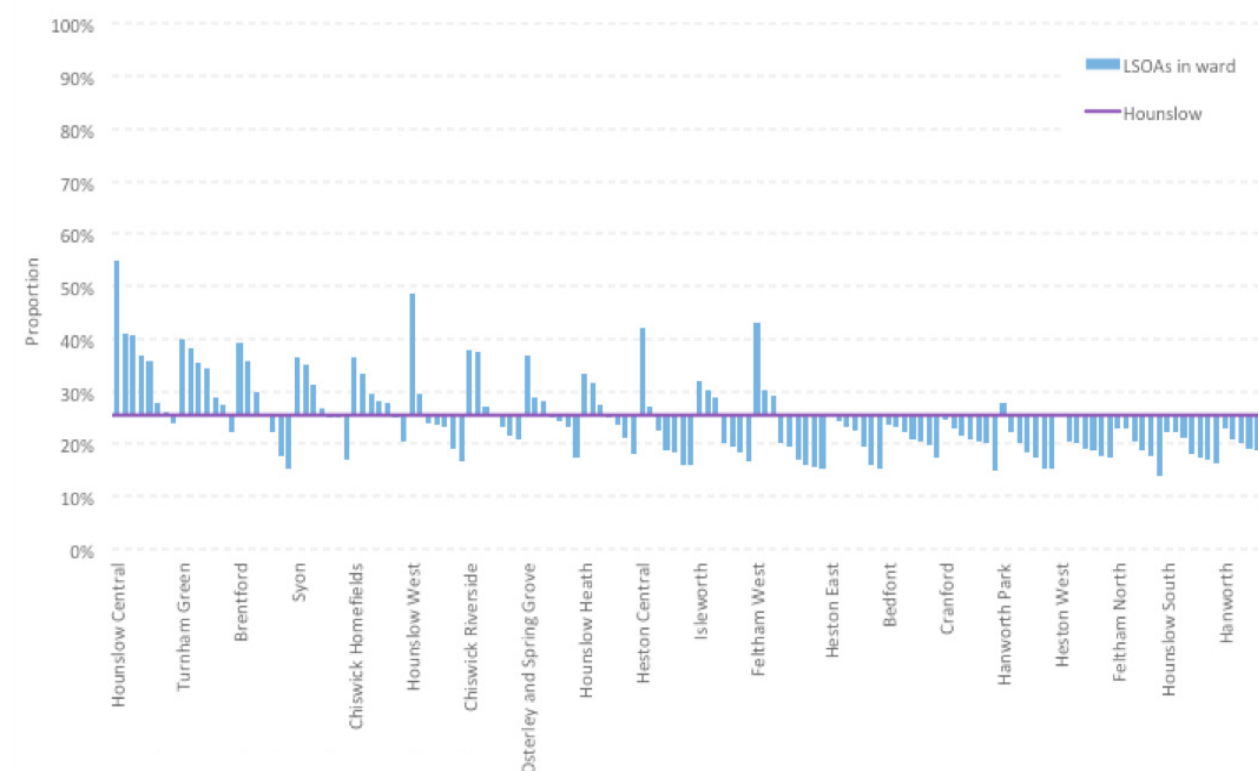
The churn data is ranked to show the top and bottom LSOAs in the borough. This shows the number of people who have moved in and out of the area, without making any judgement about whether high or low scores are positive or negative.

A16 Council tax turnover data since 2006



Source: London Borough of Hounslow

A16a Council tax turnover data since 2016



Source: London Borough of Hounslow

A17

Selected churn data for 2009 and 2015

	2009 & 2015
1	New council tax registrants
2	Total HMOs
3	Total occupants in HMOs
4	Total number of GP patients
5	Total number of GP patients - newborn
6	Total number of GP patients - under 10
7	Total number of GP patients - age 11-22
8	Total number of GP patients - age 23-33
9	Total number of GP patients - age 34-44
10	Total number of GP patients - age 45-55
11	Total number of GP patients - age 56-66
12	Total number of GP patients - age 67-77
13	Total number of GP patients - age 78-88
14	Total number of GP patients - PoB India
15	Total number of GP patients - PoB Pakistan
16	Total number of GP patients - PoB Poland
17	Total number of GP patients - PoB England
18	Total number of GP patients - ethnicity Asian Indian
19	Total number of GP patients - ethnicity Asian Pakistan
20	Total number of GP patients - ethnicity Asian Bangladesh
21	Total number of GP patients - ethnicity Asian China
22	Total number of GP patients - ethnicity Asian Other
23	Total number of GP patients - ethnicity black Africa
24	Total number of GP patients - ethnicity black Caribbean
25	Total number of GP patients - ethnicity black other
26	Total number of GP patients - ethnicity other mixed
27	Total number of GP patients - ethnicity other Arab
28	Total number of GP patients - ethnicity white British
29	Total number of GP patients - ethnicity white Irish
30	Total number of GP patients - ethnicity white other

The datasets highlighted were analysed as these covered a wide range of residents and also provided a reasonable sample size.

6. Neighbourhood profiles

Assessments of local neighbourhoods starts with mapping the assets of the community. This gives a sense of what is there on the ground before visits are made.

Visits include a walkabout of the area, paying attention to particular markers of community. This can include assets, such as churches or charities, the wording of signs and whether communal and shared spaces are used and well-kept. Levels of affluence or disadvantage can also be observed, for example by paying attention to the upkeep of houses and age of cars. Taken together these can indicate how a community is faring.

To select the profiles for this report the LSOAs with the most positive and negative scores from both the predictive and hard data analysis were used, plus some areas where there was a specific interest.

The profiles (A19) show the ranking positions of all the hard data available for both 2009 and 2015 in each LSOA (1 = strongest, 142 = weakest), coloured to highlight the strongest data (green) and weakest (red). This is also completed for all the different IMD domains. The same principle is applied to the churn data, however, the ranking here shows high and low churn instead of strong or positive and weak or negative. A “+” or “-” symbol for each data row is added to indicate if there has been a positive or negative change between the two years. Where the symbol is highlighted the ranking has changed more than 10 positions.

The same principle is used for the predictive data, but instead of showing the aggregated results for the LSOAs, the results are shown for the OAs that makes up the LSOA profile. Because of the smaller level of analysis and because there are considerably more OAs, these are not numerically ranked in the same way, instead the top and bottom quartiles of each cluster (including the combined score) are colour positively or negatively so that these can be visually compared to the coloured rankings of the hard, IMD and churn data.

A18 Neighbourhood assessment process

1.Desk-based scoping (assets, maps, profiles)

- Mapping physical assets eg parks, schools, religious venues (GIS Earthlight, Google Maps)
- Analysis of available demographic data (eg Local Insights, ONS)
- Assessing community resilience profile of the LSOA
- Scoping local individuals to interview

2."Walkabout"

- In at least pairs, walk around the area with a map, camera and notebook.
- Where possible, talk to passer-bys, shopkeepers etc. asking questions such as: do you like it here? do people know each other here? has the area changed since you have lived/worked here? suggest a place you like/don't like here for us to visit.
- Write up notes. At this stage it may be possible to form a hypothesis about what the data is showing and causes and effects explaining why levels of resilience have increased or decreased.

3.Interviews with local leaders and residents

- Interview people who are familiar with the area. Local leaders, community activists and local services are a good place to start.
- Use this process to triangulate analysis of the desk research, resilience maps and walkabouts.
- At this stage, it may be possible to confirm the hypothesis developed in stage 2.

Continue to move between stages 3 and 4 to refine and confirm the hypothesis.

4.Targetted "walkabout"

- With the hypothesis confirmed at stage 3, it is worth returning to the area to focus on a particular local asset, street or community to test the findings.

A19 Example LSOA profile, Heston West

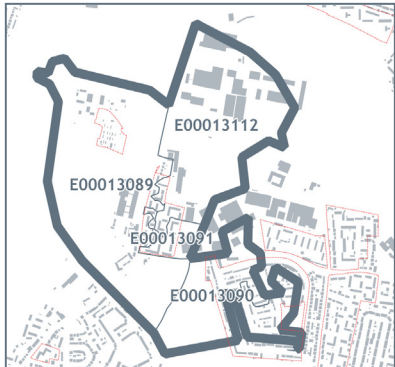
Profiles: Hard Data Rank by LSOA

	2009	2015	+-
Household Income	138	140	-
Children in Low Income	133	141	-
60+ on Pension Credit	103	129	+
Job Seeker Allowance	138	117	+
Incapacity Benefit	133	43	+
Proportion of Claimants	139	118	+
Child Benefits	126	133	-
Households in Fuel Poverty	80	75	+
Alcohol Admissions	52	44	+
Child Obesity	136	123	+
Life Expectancy	44	81	-
Male Life Expectancy	74	81	-
Female Life Expectancy	102	79	+
Population Between 0-19	136	128	+
Population Over 65	63	36	+
HMOs Per 1000	73	93	-
Election Turnouts	50	8	+
Ambulance Callouts	126	132	-
Criminal Offences Per 1000	115	109	+
Pupils Achieving 5+ GCSEs	51	86	-
House Price	134	139	-
Public Transport Access	122	122	=
Total Population	48	53	-
Social Rent	135	132	+

	2009	2015	+-
IMD	134	140	-
IMD Income	135	140	-
IMD Employment	136	140	-
IMD Health	100	134	-
IMD Education	115	136	-
IMD Housing	132	133	-
IMD Crime	85	62	+
IMD Environment	89	55	+

	2009	2015	+-
Council Tax	18	16	+
HMO Total Occupancy	67	106	-
New Patients under 10	61	45	+
New Patients between 11-22	58	54	+
New Patients between 23-33	87	88	-
New Patients between 34-44	110	99	+
New Patients between 45-55	52	98	-
New Patients PoB India	43	51	-
New Patients PoB England	69	61	+
New Patients PoB Pakistan	35	19	+
New Patients PoB Poland	80	78	+
New Patient Other Asian	80	68	+
New Patient Indian	63	60	+
New Patient Other White	94	102	-
New Patient White British	93	60	+

Ward: Heston West



Profile: predictive data score by OA

Output Area	Combined Score			High wellbeing			Low wellbeing			Emotional fragility			Neighbourhood Sup			Isolation			Competence		
	a	f	+-	a	f	+-	a	f	+-	a	f	+-	a	f	+-	a	f	+-	a	f	+-
E00013089			=			+			+			+			+			+			+
E00013090			=			+			+			+			+			+			+
E00013091			+			+			+			+			+			+			+
E00013101			=			+			+			+			+			+			+
E00013112			+			+			+			+			+			+			+

These profiles could easily be completed for any LSOA of interest to show a quick visual representation of the local area. They could be completed for all the LSOAs in Hounslow, or any other borough, to create a local resilience atlas.

Social Life

Social Life is an independent research organisation that aims to put people at the heart of places. We work with local authorities, developers and local community groups in the UK and across the globe to find practical ways to build stronger communities.

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