Assessing resilience in Hounslow's communities

The approach

10th December 2015

Social Life was commissioned by Hounslow Council earlier in the summer of 2015 to develop a framework for assessing resilience in local neighbourhoods.

This note sets out the approach taken to analysing different kinds of data and mapping this to small areas, with the aim of painting a picture of the predicted and actual levels of resilience in Hounslow at the very local level.

Maps of the data, and profiles of four small areas, are in a separate document, "Assessing resilience in Hounslow's communities: the data".

This work has been carried out to a tight budget, and has generated a method and approach to understanding resilience, and some initial visualisations of the data. Social Life hopes in the future to be able to take this work further to understand how this complex data can be made most useful to local agencies,

1 The starting point

The new resilience measure created for Hounslow has taken the structure of the 2010 WARM (Wellbeing and Resilience Measurement) framework[1] (updated in 2012[2]), developed by the Young Foundation, as the starting point. The WARM framework has been reviewed and revised to take account of new data, Hounslow's particular needs, and to make the framework more streamlined and accessible.

The resilience measure developed for Hounslow draws on two types of data:

- **Hard data**, or data that describes the circumstances of small areas in terms of service use, or social needs. This is generally broken down to lower level super output (LSOA) or ward area
- **Predictive data**, drawn from national surveys held by government or research councils. This has been modelled to predict key elements of resilience at the very local level. This is at output area (OA) level.

2 Hard data

The original WARM framework structures data from a number of different sources under three dimensions: "self", "supports" and "systems/infrastructure". This structure has been carried forward into the new model. Data sources were selected to populate these dimensions from a wide range of sources.

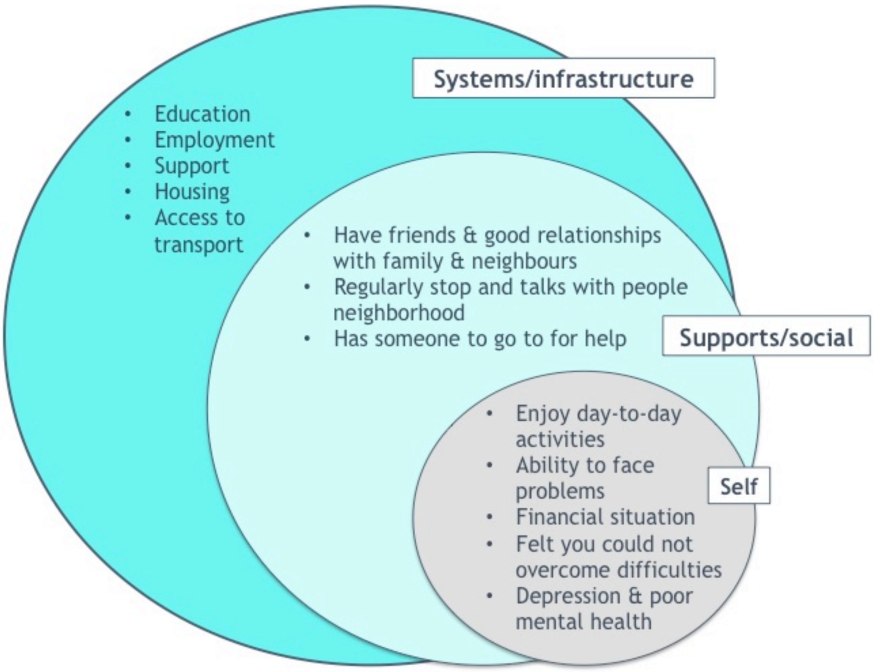

Fig 1: resilience domains

The data used includes data from the census, from services, and from other public sector sources, including Hounslow's own data. This data describes the characteristics of the area, its social needs and demographics, and the use of services. This data has been broken down to the LSOA wherever possible.

Table 1: hard data used, with sources, by domain and theme

SELF		
Age	% population aged 65+ (projected) by ward, 2015	GLA
Benefits	% of residents aged 60+ on Pension Credit, February 2015	DWP
	% of Child Benefit households claiming tax credits, August 2013	HMRC
	% of residents aged 16-64 who are JSA claimants, February 2015	DWP/ONS
Deprivation	% of households deprived in >= 2 dimensions, 2011	ONS Census
	IMD rank 2015 (where 1 = most deprived)	DCLG
Education	% of pupils achieving 5+ GCSEs including English & Maths at grades A*-C, 2014, by MSOA of residence	DfE
Health	% Households with ≥1 member with limiting long term illness, 2011	ONS Census
	Ambulance callouts per 1,000 residents, Oct 2014-Sep 2015	GLA
	% in bad or very bad health, 2011	ONS Census
	% day to day activities limited a little or a lot, 2011	ONS Census
	Hospital admissions for self-harm (standardised admissions ratio) by ward, April 2008-March 2013	PHE Local Health
	Alcohol related harm hospital admissions (standardised admissions ratio) by ward, April 2008-March 2013	PHE Local Health
	% of Reception-age children who were obese, 2011/12-2013/14, by MSOA of residence	NCMP
	All age all cause mortality (standardised mortality ratio) by ward, 2008-2012	PHE Local Health
	Male life expectancy by ward, 2008-2012	PHE Local Health
	Female life expectancy by ward, 2008-2012	PHE Local Health
Income	Median household income 2014 (modelled)	PayCheck
Fuel Poverty	Modelled % of households in fuel poverty, 2013 (Low income high costs measure)	DECC
Qualifications	% of residents with level 2 or higher qualifications (including apprenticeships, other quals), 2011	ONS Census
Work	% speaking English badly or not at all, 2011	ONS Census
	% economically active, 2011	ONS Census
	% Adults with disabilities in employment, 2011	ONS Census
SUPPORTS		
Housing	% of houses overcrowded (<0 on rooms measure), 2011	ONS Census
Participation	Voter turnout by ward, May 2015 General Election	Hounslow data
Social Action	% who have volunteered in local area over the last year (as of October 2014), by locality	Hounslow residents survey
Support	% of residents who are divorced/ separated, 2011	ONS Census
	% religious (100% minus non-religious and minus did not answer), 2011	ONS Census
	% of pop providing 20+ hrs unpaid care/wk, 2011	ONS Census
	% HHs are Lone parent HHs with dependent children, 2011	ONS Census
	Adult social care clients per 1,000 adult residents 2015, by ward	Hounslow ASC
Transience	% of residents living at another address 12 months before Census	ONS Census
	% HHs private renting, 2011	ONS Census
	Registered HMOs per 1,000 dwellings, by ward	Hounslow data/GLA
SYSTEMS & INFRASTRUCTURE		
Accesibility	% commuting on foot, 2011	ONS Census
	Average distance travelled to work (km), 2011	ONS Census
	Travel time in minutes to nearest employment centre by public transport/on foot, 2011	GLA
	Travel time in minutes to nearest primary school by public transport/on foot, 2011	GLA
	Travel time in minutes to nearest secondary school by public transport/on foot, 2011	GLA
	Travel time in minutes to nearest GP surgery by public transport/on foot, 2011	GLA
	Travel time in minutes to nearest food shop by public transport/on foot, 2011	GLA
Environment	Air quality: PM2.5 Concentration (µg/m3), 2008	GLA
Public services	% residents satisfied with LA by locality, October 2014	Hounslow residents survey
	% residents satisfied with local area by locality, October 2014	Hounslow residents survey
Safety	Crime rate (notifiable offences per 1,000 population in financial year 2014/15), by ward	Met Police/GLA
	London Fire Brigade callouts to fires per 1,000 residents by ward, Oct 2012-Sep 2015	GLA/LFEPA
	% residents feeling safe or very safe during the day by locality, October 2014	Hounslow residents survey
	% residents feeling safe or very safe after dark by locality, October 2014	Hounslow residents survey
Transport	Road accident casualties per 1,000 population by ward, 2014	GLA
	Public transport accessibility level (PTAL 2014) where 0=worst and 8=best	GLA/TfL

Scoring the self-structures and supports domain data

Stage 1: ***scoring the domains***

The data was assembled by LSOA and the top and bottom 10% for each data source were deemed "outliers", ie lower or higher than would be expected. These were scored positively (green) or negative (red).

Stage 2: ***finding the outliers***

The number of negative and positive outliers in each source was counted. If more (or equal to) a third of the total number of data sources were positive outliers the domain was scored positive (green); if more than (or equal to) a third of the total number of data sources were negative outliers, the domain was scored negative (red).

This process enabled LSOAs to be scored by domain (self, structures and supports).

Overall, 28 LSOAs emerged as having overall negative scores; and 25 LSOAs emerged that had overall positive scores.

Stage 3: ***exploring the outlier LSOAs***

The 53 LSOAs with overall positive and negative scores were analysed to explore patterns in the underlying data.

This enables an assessment to be made within each domain of the strengths and weaknesses indicated by the different data sources.

3 Predictive data

Social Life updated the Young Foundation's WARM framework to ensure that the underlying predictive data is up to date, and to explore how to make the data can be made more relevant, accessible, and simpler to use.

The framework uses 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. USS is funded primarily by the Economic and Social Research Council (ESRC), with significant additional funding from government departments.[3]

USS data was analysed to reveal patterns that indicate wellbeing and resilience, and then matched to Output Area Classifications (OACs). **This enables us to predict what the likely level of wellbeing or resilience is likely to be in a local area.**

Lower Level Super Output (LSOA) OAC classifications will not be released by ONS until 2016, so the data was therefore analysed at the Output Area (OA) level. OAs are around 125 households[4], and LSOAs are between 400 and 1,200 households[5]. OAs cannot be simply aggregated to LSOA scores, so the predictive data needs to be viewed at this very local level.

The aim in the initial analysis was to explore patterns within the data to establish what explained wellbeing and resilience at the local level. We carried out a **factor analysis** to investigate how different USS questions relate to the core concepts of wellbeing and resilience and to identify the questions that will make up the wellbeing and resilience measures; and then a c**luster analysis** to group the questions and factors together to develop clusters of respondents with different levels of wellbeing and resilience.

1 Factor analysis

Factor analysis was run on USS data, primarily to identify wellbeing and resilience factors. Wellbeing is an integral part of resilience, feeling positive about the quality of our lives now is a protective factor against future shocks.

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. 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 loose sensitivity from the analysis.

Four factors emerged strongly from the data:

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

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 also duplicated issues included elsewhere in the framework.

The USS questions that correspond to each of the factors identified are below.

Table 2: output from factor analysis

Wellbeing
c_sclfsat2 satisfaction with income
c_sclfsat7 satisfaction with amount of leisure time
c_sclfsato satisfaction with life overall
c_sclfsat1 satisfaction with health
how managing financially_now
Stress
c_scsf6c last 4 weeks: felt downhearted and depressed
ghq_depressed
ghq constantly under_strain
c_scsf4a last 4 weeks: mental health meant accomplished less
ghq_loss_sleep
ghq_losing_confidence
last 4 weeks: felt_calm and peaceful
ghq_belief in selfworth
c_scsf4b last 4 weeks: mental health meant worked less carefully
Capability
Ghq ability to face_problems
ghq_enjoy_day to day activities
ghq capable of making decisions
ghq_general happiness
ghq playing a useful role
ghq_concentrate
ghq_overcome_difficulty
c_scsf7 last 4 weeks: physical or mental health interfered with social life
last 4 weeks: had a lot of energy
Belonging and social solidarity
local_friends mean a lot
advice obtainable locally

regularly stop and talk
borrow things and exchange favours
feel like I belong [neighbourhood]
similar to others [neighbourhood]
willing_improve [neighbourhood] – not sure if this quite fits??
Plan to stay [neighbourhood]
Number of friends locally
close_knit [neighbourhood]
people willing_to_help neighbours
people in this_neighbourhood can be trusted
c_nbrcoh4 people in this neighbourhood don t get along with each other
Likes present neighbourhood

2 Cluster analysis

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

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.

To analyse **resilience** the four factors – emotional stress, competence, belonging and social solidarity – were entered.

All the clusters – whether focusing on wellbeing or broader resilience issues

The cluster profiling looks at the distribution of respondents across the clusters with the aim of looking at the characteristics of people within each cluster. For example – whether the percentage of men and women was balanced across each cluster.

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

The graphs below show the cluster composition [the scores at each point are standardised]. The clusters focusing on wellbeing have been computed using the individual five questions, whereas the clusters indicating broader resilience have been computed using the four overall resilience measures. At the top of each cluster is the number of people in it, because it is important when forming the solutions that there is a reasonable balance across the clusters.

Fig 2: wellbeing clusters

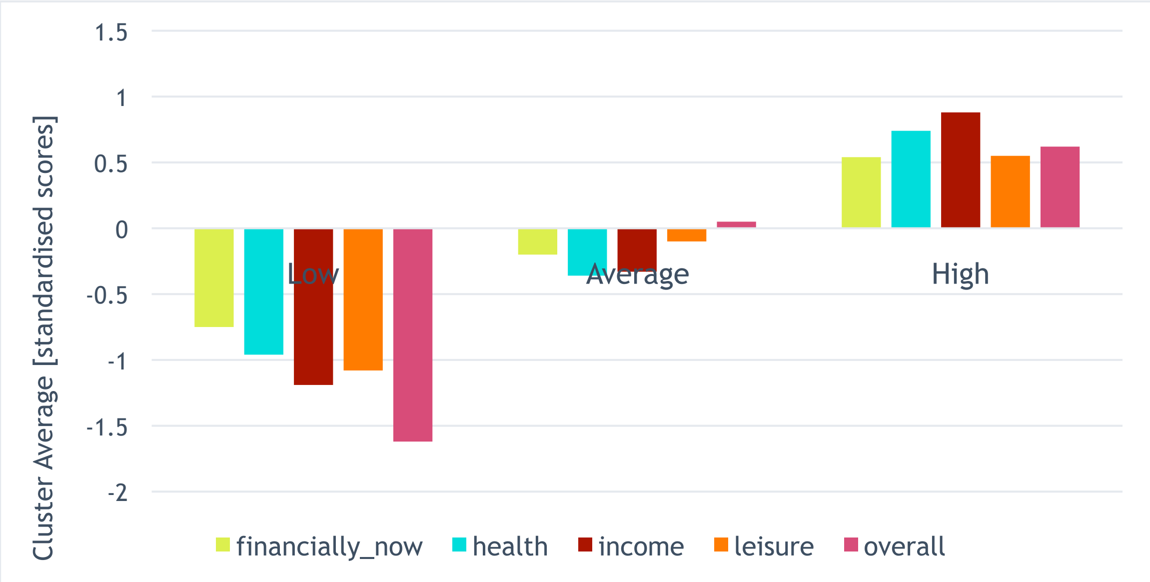

Table 3: wellbeing cluster scores, by factor

	Low	Average	High
financially_now	-0.75	-0.2	0.54
health	-0.96	-0.36	0.74
income	-1.19	-0.33	0.88
leisure	-1.08	-0.1	0.55
overall	-1.62	0.05	0.62
Number of responses	*7,021*	*16,482*	*17,073*

Fig 3: broader resilience clusters

Table 4: broader resilience cluster scores, by factor

	Neighbourhood support	Competence	Isolation	Emotional fragility
Belonging	4.65	-0.3	-6.8	-1.79
Capability	1.33	3.77	0.97	-10.7
Stress	1.33	4.96	-0.29	-11.33
Social solidarity	2.44	0.05	-3.84	-0.94
Number of responses	*14,842*	*10,843*	*7,594*	*6,040*

3 Matching clusters to local areas

These clusters were then matched to different OAC classifications.

The OAC cluster breakdown shows the percentage make up of the clusters within each OAC – with the aim of seeing 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 in some of the OACs.

A test of statistical significance was applied to the results, so insignificant data could be excluded from the analysis.

Table 5: wellbeing and resilience cluster scores by OAC

WELLBEING CLUSTERS

very low	low	average	high	very high

Difference from overall

OAC	1 Low	2 Medium	3 High
1A1	-4.0%	-5.3%	9.4%
1A2	-5.8%	-1.4%	7.2%
1A3	-4.6%	-4.2%	8.7%
1A4	-5.5%	-7.9%	13.4%
1B1	-2.4%	0.7%	1.7%
1B2	-4.6%	-5.3%	10.0%
1B3	-2.5%	0.5%	1.9%
1C1	-4.1%	-1.7%	5.8%
1C2	0.1%	-0.5%	0.4%
1C3	-5.5%	-6.9%	12.4%
2A1	-0.1%	2.5%	-2.4%
2A2	-2.7%	-4.7%	7.4%
2A3	2.1%	-2.9%	0.8%
2B1	-4.0%	4.4%	-0.4%
2B2	0.5%	-6.0%	5.4%
2C1	-2.1%	0.7%	1.4%
2C2	4.4%	4.4%	-8.7%
2C3	1.0%	-1.6%	0.6%
2D1	-2.8%	-9.9%	12.6%
2D2	-2.5%	2.6%	0.0%
2D3	-2.6%	-1.1%	3.7%
3A1	8.2%	5.6%	-13.8%
3A2	8.4%	1.7%	-10.0%
3B1	12.2%	-2.4%	-9.8%
3B2	4.0%	11.7%	-15.7%
3B3	4.7%	-3.9%	-0.8%
3C1	13.8%	0.1%	-13.9%
3C2	18.7%	-0.6%	-18.1%
3D1	0.3%	1.1%	-1.4%
3D2	8.3%	-2.6%	-5.6%
3D3	3.5%	3.1%	-6.6%
4A1	8.4%	5.8%	-14.2%
4A2	2.9%	1.3%	-4.1%
4A3	4.8%	4.5%	-9.3%
4B1	7.4%	4.1%	-11.5%
4B2	10.6%	2.6%	-13.2%
4C1	2.8%	0.2%	-3.1%
4C2	6.3%	3.2%	-9.5%
4C3	0.4%	-5.0%	4.6%
5A1	-2.5%	-1.8%	4.3%
5A2	-3.3%	-0.7%	4.0%
5A3	-1.0%	1.2%	-0.2%
5B1	-5.1%	-4.7%	9.7%
5B2	-2.0%	-1.9%	3.9%
5B3	-4.7%	-1.4%	6.2%
6A1	-6.0%	-5.8%	11.8%
6A2	-3.1%	-7.3%	10.4%
6A3	-7.5%	-5.4%	13.0%
6A4	-4.6%	-7.0%	11.7%
6B1	-4.0%	-4.0%	8.1%
6B2	-4.9%	-2.5%	7.4%
6B3	-4.4%	0.2%	4.2%
6B4	-3.7%	-1.7%	5.4%
7A1	1.1%	3.2%	-4.3%
7A2	4.4%	3.4%	-7.8%
7A3	8.7%	6.5%	-15.2%
7B1	9.7%	2.6%	-12.3%
7B2	11.9%	8.0%	-19.9%
7B3	3.4%	7.1%	-10.5%
7C1	3.9%	9.5%	-13.5%
7C2	10.9%	3.0%	-13.9%
7C3	3.4%	3.4%	-6.8%
7D1	0.8%	-0.9%	0.1%
7D2	1.5%	6.4%	-8.0%
7D3	3.4%	-0.4%	-3.0%
7D4	-9.6%	-2.2%	11.8%
8A1	0.1%	3.0%	-3.0%
8A2	5.6%	2.9%	-8.6%
8B1	-0.1%	4.6%	-4.5%
8B2	6.5%	2.2%	-8.7%
8C1	2.4%	-1.6%	-0.8%
8C2	3.0%	3.6%	-6.5%
8C3	1.7%	5.1%	-6.8%
8D1	8.8%	4.9%	-13.7%
8D2	3.1%	5.6%	-8.7%
8D3	4.8%	4.2%	-9.0%

RESILIENCE CLUSTERS

very low	low	average	high	very high

Difference from overall

OAC	Local support	Compet-ence	Isolated	Emotion-ally fragile
1A1	18.2%	-4.3%	-10.1%	-3.9%
1A2	16.9%	-2.9%	-10.1%	-3.9%
1A3	16.4%	-7.6%	-9.2%	0.5%
1A4	17.7%	-0.3%	-9.4%	-7.9%
1B1	14.5%	-2.8%	-8.5%	-3.2%
1B2	16.7%	-4.0%	-8.7%	-4.0%
1B3	13.2%	-3.5%	-8.1%	-1.5%
1C1	25.8%	-2.6%	-14.3%	-8.9%
1C2	13.1%	-5.9%	-5.4%	-1.8%
1C3	7.6%	5.8%	-8.5%	-4.9%
2A1	-14.0%	-8.9%	11.2%	11.8%
2A2	-27.4%	2.3%	29.0%	-3.9%
2A3	-21.3%	4.1%	14.4%	2.7%
2B1	-24.1%	4.0%	17.4%	2.6%
2B2	-24.5%	-2.1%	26.6%	-0.1%
2C1	-17.3%	11.7%	6.5%	-0.8%
2C2	-29.0%	-6.5%	29.8%	5.7%
2C3	-19.8%	9.6%	12.7%	-2.5%
2D1	-14.7%	2.5%	14.3%	-2.1%
2D2	-15.0%	4.2%	13.6%	-2.9%
2D3	-2.3%	-3.2%	0.4%	5.1%
3A1	-16.2%	-0.8%	12.4%	4.7%
3A2	-19.5%	2.8%	14.7%	2.0%
3B1	-26.5%	0.2%	17.8%	8.5%
3B2	-1.7%	-7.5%	5.6%	3.6%
3B3	-29.0%	3.5%	29.2%	-3.7%
3C1	-18.7%	-3.9%	10.5%	12.1%
3C2	-29.7%	-11.6%	28.7%	12.6%
3D1	-17.5%	7.3%	11.6%	-1.3%
3D2	-15.3%	-2.0%	17.5%	-0.2%
3D3	-9.7%	-1.3%	7.4%	3.6%
4A1	-14.8%	-1.3%	11.6%	4.6%
4A2	-14.8%	-2.1%	14.8%	2.1%
4A3	-11.1%	2.4%	8.7%	0.0%
4B1	-15.5%	1.0%	11.3%	3.2%
4B2	-1.7%	-6.9%	0.5%	8.1%
4C1	-7.3%	1.1%	5.4%	0.8%
4C2	-8.7%	1.7%	4.1%	3.0%
4C3	-4.1%	3.3%	3.3%	-2.5%
5A1	0.1%	3.6%	-1.7%	-2.0%
5A2	-1.6%	2.5%	0.8%	-1.8%
5A3	-3.6%	2.8%	1.6%	-0.7%
5B1	1.0%	3.9%	-1.0%	-3.9%
5B2	1.0%	2.3%	-0.4%	-2.9%
5B3	5.3%	2.3%	-5.6%	-2.0%
6A1	6.2%	2.6%	-4.6%	-4.1%
6A2	6.7%	3.8%	-7.5%	-2.9%
6A3	11.3%	1.6%	-9.0%	-3.8%
6A4	12.3%	2.6%	-9.7%	-5.2%
6B1	1.3%	4.2%	-4.0%	-1.5%
6B2	6.0%	1.5%	-3.7%	-3.8%
6B3	5.2%	2.8%	-5.7%	-2.3%
6B4	5.0%	3.0%	-4.6%	-3.4%
7A1	-15.6%	0.7%	9.3%	5.5%
7A2	-7.5%	-4.3%	7.7%	4.1%
7A3	-15.7%	-3.4%	10.5%	8.5%
7B1	-23.0%	0.4%	13.0%	9.6%
7B2	-12.0%	-11.9%	9.3%	14.6%
7B3	-11.3%	-0.2%	8.0%	3.5%
7C1	-1.1%	-4.6%	3.0%	2.6%
7C2	-10.7%	-5.6%	5.8%	10.6%
7C3	-3.5%	-3.1%	1.6%	5.0%
7D1	7.4%	-4.0%	-4.3%	1.0%
7D2	-5.7%	-5.8%	7.6%	3.9%
7D3	-8.7%	3.8%	-1.9%	6.7%
7D4	16.1%	-12.2%	-11.6%	7.7%
8A1	4.8%	-1.4%	-3.2%	-0.2%
8A2	-2.8%	-4.7%	3.2%	4.3%
8B1	-4.3%	-1.9%	1.4%	4.8%
8B2	1.3%	-3.0%	-1.7%	3.4%
8C1	-0.9%	0.6%	-1.4%	1.7%
8C2	3.9%	-2.4%	-3.1%	1.6%
8C3	-2.7%	-0.2%	1.8%	1.1%
8D1	-13.6%	-3.9%	6.9%	10.5%
8D2	-8.7%	-0.2%	8.0%	0.9%
8D3	-10.0%	-1.2%	7.3%	3.8%

4 Scoring the predictive data

Stage 1: ***putting the clusters into quartiles within OAs***

The predictive data for each output area was analysed to find the upper and lower quartile for each cluster. Each quartile was scored either positive (indicating higher resilience, and marked green) or negative (indicating lower resilience, and marked red). 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, but a high score for Isolation is negative.

Stage 2: ***aggregating the OA data to LSOAs***

To compare the predictive data, which is at OA level, with the hard data, which is at LSOA level, a way needed to be found to interpret the predictive data at LSOA level.

The data was manipulated to develop a scoring of OAs within any given LSOA. The number of clusters in each output area that were in either the upper or lower quartiles of data were counted.

This enables each LOSA to be assessed by cluster, by the number of OAs scoring positive or negative within each cluster.

Stage 2b: ***aggregating the OA data to LSOAs, an alternative method***

An alternative method of scoring is to assess each LOSA by the number of OAs in total that contained positive or negative scores.

4 Combining hard and predictive data

To bring together the hard data and the predictive data, two methods have been created.

- The first is to map the predictive data, showing also the LSOAs where the hard data suggests weaknesses or strengths of resilience.
- The second has been to create a spreadsheet of the 53 LSOAs where the hard data is either positive or negative, and to present this alongside the predictive data scored by LSOA.

The aim was to reveal the LSOAs where the hard data and the predictive data show the same patterns – overall negative or overall positive.

> *For example, Hounslow 026C is below average in hard data, and the predictive data suggests many clusters score poorly.*

> *For example, Hounslow 015D is above average in hard data, and the predictive data suggests many clusters score well.*

And the LSOAs where the hard data and the predictive data are contradictory, suggesting different levels of resilience.

> *For example, Hounslow 003A is below average in hard data, but the predictive data suggests few negatives.*

Table 6: hard data and predictive data combined, by 53 selected LSOAs

Key:

Above average in the hard data
Below average in the hard data
Contains both high and low scoring factors in hard data

	Predictive data		Hard data	
lsoa11nm	Number of positive scores within OAs within LSOA	Number of negative scores within OAs within LSOA	Above average	Under average
Hounslow 001A	22	8	Y	N
Hounslow 001B	13	8	Y	N
Hounslow 001C	24	1	Y	N
Hounslow 001D	20	3	Y	N
Hounslow 001E	20	3	Y	N
Hounslow 003A	12	0	N	Y
Hounslow 003B	8	8	N	N
Hounslow 003C	4	18	N	N
Hounslow 003D	0	24	N	N
Hounslow 003F	0	6	N	N
Hounslow 003G	9	10	N	N
Hounslow 004A	0	18	N	N
Hounslow 004B	6	0	N	Y
Hounslow 004C	5	5	N	Y
Hounslow 004D	2	19	N	Y
Hounslow 004E	3	13	N	Y
Hounslow 005A	0	27	N	Y
Hounslow 005B	1	19	N	Y
Hounslow 005C	0	20	N	N
Hounslow 005D	1	23	N	Y
Hounslow 006A	20	1	N	N
Hounslow 006B	10	8	N	N
Hounslow 006C	7	10	N	N
Hounslow 006D	10	8	N	N
Hounslow 006E	8	6	N	Y
Hounslow 007A	20	4	Y	N
Hounslow 007B	5	14	N	N
Hounslow 007C	24	3	Y	N
Hounslow 007D	21	3	Y	N
Hounslow 007E	16	13	Y	N
Hounslow 007F	24	3	Y	N
Hounslow 008A	14	13	Y	N
Hounslow 008B	32	2	Y	N
Hounslow 008C	19	6	Y	N
Hounslow 008D	21	7	Y	N
Hounslow 008E	20	7	Y	Y
Hounslow 009A	12	0	N	N
Hounslow 009B	12	0	N	N
Hounslow 009C	15	0	N	N
Hounslow 009D	18	0	N	N
Hounslow 010A	9	5	N	N
Hounslow 010B	4	10	N	Y
Hounslow 010C	6	5	N	Y
Hounslow 010D	4	10	N	Y
Hounslow 010E	6	10	N	Y
Hounslow 011A	10	0	N	N
Hounslow 011B	4	10	N	N
Hounslow 011C	4	10	N	N
Hounslow 011D	8	5	N	N
Hounslow 011E	7	10	N	N
Hounslow 012A	6	5	N	N
Hounslow 012B	8	0	N	N
Hounslow 012C	4	10	N	Y
Hounslow 012D	11	0	N	N
Hounslow 012E	9	0	N	N
Hounslow 013A	6	5	N	N
Hounslow 013B	0	20	N	N
Hounslow 013C	2	15	N	N
Hounslow 013D	6	5	N	Y
Hounslow 013E	2	21	N	N
Hounslow 014A	22	1	N	N
Hounslow 014B	8	2	N	N
Hounslow 014C	6	5	N	N
Hounslow 014D	16	0	N	N
Hounslow 014E	6	4	N	N
Hounslow 015A	4	16	N	Y
Hounslow 015B	8	10	N	N

Hounslow 015C		6	16	N	N
Hounslow 015D		18	0	Y	N
Hounslow 015E		15	5	N	N
Hounslow 016A		2	20	N	N
Hounslow 016B		3	21	N	Y
Hounslow 016C		6	5	N	N
Hounslow 016D		4	10	N	N
Hounslow 016E		2	15	N	Y
Hounslow 017A		1	18	N	N
Hounslow 017B		2	21	N	N
Hounslow 017C		6	0	N	N
Hounslow 017D		3	18	N	Y
Hounslow 017E		3	13	N	N
Hounslow 018A		7	8	N	N
Hounslow 018C		2	15	N	N
Hounslow 018D		5	13	N	N
Hounslow 018E		16	0	N	Y
Hounslow 018F		3	3	N	Y
Hounslow 018G		1	13	N	Y
Hounslow 019A		9	0	Y	N
Hounslow 019B		14	0	N	N
Hounslow 019C		15	0	N	N
Hounslow 019D		8	4	N	N
Hounslow 019E		9	0	N	N
Hounslow 020A		15	5	N	N
Hounslow 020B		18	0	N	N
Hounslow 020C		20	5	N	N
Hounslow 020D		8	17	N	N
Hounslow 020E		1	23	Y	Y
Hounslow 021A		0	30	N	N
Hounslow 021B		2	10	N	N
Hounslow 021C		2	15	N	N
Hounslow 021D		2	15	N	N
Hounslow 021E		4	5	N	N
Hounslow 022A		16	5	N	N
Hounslow 022B		9	2	N	N
Hounslow 022C		14	6	N	N
Hounslow 022D		6	15	N	N
Hounslow 022E		4	15	N	N
Hounslow 023A		9	5	N	N
Hounslow 023B		8	0	N	N
Hounslow 023C		3	10	N	N
Hounslow 023D		17	0	N	Y
Hounslow 023E		6	5	N	N
Hounslow 024A		7	10	N	N
Hounslow 024B		10	0	N	N
Hounslow 024C		6	10	N	N
Hounslow 024D		10	5	N	N
Hounslow 024E		17	5	Y	N
Hounslow 024F		9	9	N	N
Hounslow 025B		8	6	N	N
Hounslow 025C		5	13	N	N
Hounslow 025D		2	15	N	N
Hounslow 025E		4	5	N	N
Hounslow 025F		4	0	N	N
Hounslow 026A		2	16	N	Y
Hounslow 026B		10	5	N	N
Hounslow 026C		0	26	N	Y
Hounslow 026D		6	10	N	N
Hounslow 026E		3	19	N	Y
Hounslow 027A		12	3	N	N
Hounslow 027B		6	5	N	N
Hounslow 027C		9	9	Y	N
Hounslow 027D		8	9	N	N
Hounslow 027E		5	10	N	N
Hounslow 028A		10	10	N	N
Hounslow 028B		15	0	N	N
Hounslow 028C		10	11	N	N
Hounslow 028D		20	5	N	N
Hounslow 029A		24	8	Y	N
Hounslow 029B		12	1	Y	N
Hounslow 029C		24	10	Y	N
Hounslow 029D		19	9	Y	N
Hounslow 029E		26	7	Y	N

[1] Nina Mguni and Nicola Bacon (2010), "Taking the temperature of local communities", Young Foundation http://youngfoundation.org/publications/taking-the-temperature-of-local-communities-the-wellbeing-and-resilience-measure-warm/

[2] Nina Mguni and Nicola Bacon (2012), "The wellbeing and resilience paradox", Young Foundation http://youngfoundation.org/?s=wellbeing+paradox

[3] for more information about USS see https://www.understandingsociety.ac.uk/about

[4] http://www.ons.gov.uk/ons/guide-method/geography/beginner-s-guide/census/output-area--oas-/index.html

[5] http://www.ons.gov.uk/ons/guide-method/geography/beginner-s-guide/census/super-output-areas--soas-/index.html