Digital Exclusion as a barrier to accessing healthcare: A summary composite indicator and online tool to explore and quantify local differences in levels of exclusion.

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Abstract

Digital exclusion leads to marginalization and inequality. A lack of tools to measure local exclusion hampers targeted interventions. In this study a composite indicator for digital exclusion and associated toolkit was developed. Indicator variables were normalised and aggregated. Factor analysis determined indicator weightings. Local levels of claiming Guaranteed Pension Credit, unemployment and low socioeconomic status showed strong mutual correlation. Underlying constructs were identified related to socioeconomic deprivation, poor academic qualifications, lack of activity and barriers to digital access. In general, coastal areas in Lincolnshire, UK had higher levels of digital exclusion, with significant local disparities within urban areas. The Lincolnshire Digital Health toolkit assists decision-makers in understanding and addressing digital exclusion.

Key Words

Digital Exclusion, Access, Composite indicator, Marginalisation, Inequity, Social Deprivation

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Introduction

The provision of key services online and the impact of inequity in digital access is attracting increasing international interest. The COVID-19 pandemic and lockdown measures resulted in a step-change in the provision and adoption of digital tools. In the United Kingdom (UK) and other high income countries online provision became the norm for medical appointments, engagement with social support services, and education at all levels. As a consequence pre-existing inequalities in access and take-up of digital technology were exacerbated (Holmes and Burgess Gemma, 2022). While the pandemic was a once in a lifetime event, globally there has been a major change in the adoption of digital technology with evidence pointing towards sustained changed patterns of remote or flexible working. Given these important trends, there is a critical need to explore the significant section of the population who face digital exclusion. These groups faced major digital disadvantage prior to the pandemic, but during the pandemic and in a post pandemic world they experienced an increased level of marginalisation that amplified their exclusion (Andrew et al., 2020; Litchfield et al., 2021; Watts, 2020).

Ofcom, the UK communications regulator, describe digital exclusion as having three inter-linked dimensions relating to access, ability and affordability (Ofcom, 2022). Access describes exclusion due to a lack of internet provision at home or elsewhere. Affordability is closely linked and relates to the financial cost of accessing the internet or purchasing appropriate devices for access. Ability describes barriers due to lack of digital literacy. Digital exclusion results in major disadvantage, marginalisation, and inequality, particularly for those who are geographically isolated and have health-related limitations or impairment (Litchfield et al., 2021). There is a lack of tools to determine the relative digital exclusion of people at fine-grained local geographic levels which makes the development of targeted interventions difficult.

Those living in geographically isolated communities may experience inequitable access to services, often due to a lack of public transport. Geographic barriers are further intensified for individuals with a disability or illness which restricts their mobility, for whom face to face access to a medical practice can be challenging (The Good Things Foundation, 2021). Online service provision is often put forward as a solution for those facing geographic isolation, but lack of digital connectivity, low levels of digital literacy, and a lack of access to digital resources limits the take-up of such services for these groups (Ofcom, 2021). UK data indicates that only 78% of individuals with a health-related limitation or impairment make use of the internet compared to 94% of individuals in the general population (Ofcom, 2021). While there is a lack of granular data on internet usage amongst people who face both ill-health or impairment and geographic isolation, it could be hypothesised that the internet access differences would be even wider.

Digital inclusion can be characterised as a basic human right (United Nations General Assembly Human Rights Council, 2018) with those who are digitally excluded facing major challenges including in seeking employment, accessing banking and managing money, and taking-up online learning opportunities (Bonner, 2021). There is a clear connection between digital exclusion and social isolation (Age UK, 2020; Care Connect, 2019; Moroney and Jarvis, 2020). It is also clear that interventions which promote digital inclusion need to be tailored to the needs of the individual or community and the type of services they need to access. In this paper we describe the development of a composite indicator and associated online tool to quantify the relative digital exclusion of each Lower-layer Super Output Area (LSOA) in the County of Lincolnshire in the UK. This study addresses a methodological gap in the development of composite indicators which quantify digital exclusion. We describe the approach taken to choose the underlying indicator variables and statistical methods used to normalise and aggregate them into a single composite index balancing the contribution of the underlying constructs within the individual indicators. The composite indicator and its method of development has potential applicability across the UK and internationally. The Lincolnshire Digital Health Toolkit (https://lhih.org.uk/lincolnshire-digital-health-toolkit/) provides a web-based user interface to explore geographic variations in digital exclusion.

Background

Lincolnshire is a large rural and costal, geographically dispersed county, which poses challenges for health and other service provision. The UK Chief Medical Officer highlighted the lack of digital infrastructure as a key challenge in coastal communities in his 2021 annual report, and included Lincolnshire as a case study (Whitty C, 2021). Lincolnshire has an ageing population in a widely rural area with the more deprived areas of Lincolnshire seen on the coast and the inner towns and cities.

Lincolnshire County Council (LCC) worked with other Local authorities on the 'Digital Access for All' study. (Local Government Association, 2022) As a Council, LCC were committed to addressing digital exclusion for adults with social care needs. A framework was developed showing the steps which local authorities and health and social care providers might take to develop locally tailored digital inclusion strategies. Key to the implementation of such a framework is the development of metrics that quantify levels of exclusion and identify individuals and local geographic areas of greatest need. A variety of underlying factors have been identified which contribute to digital exclusion in addition to limitations in the provision of physical access to online resources. These include age , gender, income level, type of or lack of employment and level of educational attainment (van Deursen and van Dijk, 2019).

Composite Indicators

Many composite indicators have been developed across a multitude of domains including deprivation, national economic performance, human development, and health service delivery (Barclay et al., 2019; Burke and Jones, 2019; Terzi et al., 2021). These indicators are potentially useful in analysing the immediate and longer-term impact of policy change. However, poorly constructed indices may lead to misleading policy messages and in turn ineffective policy development and implementation(OECD, 2008).

Criticism has been directed at a lack of methodological transparency in the development of composite indices which can lead to users being unable to properly understand the rationale behind their development. Significant issues include the rationale for selecting the component variables and the methods used to apply relative weightings to them in the derivation of the composite (Barclay et al., 2019). If a composite index includes several indicators which describe the same underlying construct, and are thus highly correlated, there is a risk that these constructs may dominate other components in the overall score.

The Digital Exclusion Risk Index (DERI) Tool (Greater Manchester Office of Data Analytics, 2022) was developed by the Greater Manchester Combined Authority research team in the UK to enable local authorities to better understand digital exclusion at a local level in order to target interventions to the areas of most need. The DERI tool combines a range of indicators to provide an overall DERI score for each Lower-level Super Output Area (LSOA) [1] across England, with visualisations of the relative scores

[1] LSOAs are small areas designed to be of a similar population size, with an average of approximately 1,500 residents or 650 households. There are 32,844 LSOAs in England. They were produced by the Office for National Statistics for the reporting of small area statistics.

provided for all LSOA's in Greater Manchester. The overall score is a composite measure of the risk of digital exclusion ranging from 0 (low risk) to 10 (high risk) based on nine individual indicators[2]. Underlying indicators are grouped into three broad categories describing demography (age structure), deprivation, and broadband access. Indicators are standardised on a range of 0 to 10, they are then combined in to three composites: age, broadband and deprivation using an empirical weighting scheme. The three composites are then given equal weighting in the final composite (Greater Manchester Office of Data Analytics, 2021).

The Lincolnshire Digital Health Toolkit has been created in a bid to reduce digital exclusion in Lincolnshire by highlighting the areas most at risk of being left behind with digitalisation by including indicators that give greater granularity and context to Lincolnshire and its population. In developing a digital exclusion index for Lincolnshire, we felt it necessary to take a different approach in the selection of the underlying variables and their weighting in the overall composite from that used in the development of the DERI tool. Lincolnshire is a largely rural county in which many communities have poor transport links to the major population centres, which compounds the impact of poor digital infrastructure in these regions. For this reason, we included metrics related to the time required to access a medical practice using various forms of transport. Additionally, the DERI tool does not directly take account of relative differences in the levels of digital literacy, that is the skills and confidence individuals have in accessing digital services. For this reason, Experian Mosaic indicators which take these factors into account were included in our composite measure.

[2] The individual indicators in the DERI score are; the proportion of the population in the oldest age groups (over 65s and over 75s) , the proportion of over 65s on pension credit , the proportion of adults with no qualifications, the unemployment rate, the Index of Multiple Deprivation which is itself a composite indicator describing various dimensions of deprivation, (Minstry of Housing Communities and Local Government, 2019) the proportion of homes with slow broadband access (<30 and <10 MBits/s) and the average download speed.

Methods

The indicator variables representing different dimensions of digital exclusion (Table 1) were collated for each LSOA in Lincolnshire. The choice of variables was based on a review of the literature and a series of consultations with stakeholders with knowledge of the sociodemographic and other factors acting as barriers to accessing services for the local population.

Selection and derivation of Indicators

Code	Description
DER	The percentage of the LSOA's population who are considered either D or E on the NRS [3] social grade.
GPC	Recipients of Guaranteed Pension Credit [4] (Rate per 1000 of LSOA population aged 65 and over). Pension Credit gives extra money to help with living costs if for those over the state pension age and on a low income.
INT	A composite of two indicators: i) average download speed in LSOA (Mb/sec) and ii) percentage of connections receiving less than 10(Mb/sec). [5]
LAC	Percentage of population of the LSOA whose daily activity is severely limited. [6]
NQR	The percentage of residents aged over 16 in the LSOA who have no qualifications [6]
UNP	The percentage of those aged over 16 in the LSOA who are unemployed and claiming benefits[6]
TRP	A composite of three indicators for travel time to a medical practice showing the percentage of the LSOA population who are living within (i) 15 minutes by car (ii) 15 minutes by public transport and iii) 30 minutes by public transport. [7]
EXP	A composite of five Experian Mosaic indicators [8] showing the estimated level of competence in the use of email, smartphone, instant messaging, social networking or the internet amongst the LSOA population.

Table 1 – Indicators used in the derivation of the Composite indicator

[3] The NRS social grades are a system of demographic classification used in the United Kingdom. They were originally developed by the National Readership Survey (NRS) to classify readers, but have become a standard for market research. – Source Office of National Statistics (ONS)

[4] Pension Credit gives recipients aged over the state pension age and on a low income extra money to help with living costs. – Source Pension Credit: Overview - GOV.UK (www.gov.uk)

[5] Connected Nations (Summer 2022 update) - https://www.ofcom.org.uk/research-and-data/multi-sector-research/infrastructure-research/connected-nations-2022

[6] Office of National Statistics (ONS)

[7] gov.uk (https://www.nao.org.uk/wp-content/uploads/2020/10/Transport_accessibility_tool_Tech-guide.pdf)

[8] Experian Mosaic is cross channel classification system used to segment the population based on a comprehensive list of different factors including demographics, behaviours, and employment for example. LCC hold a license for Experian Mosaic.

Indicator variables were aggregated to the LSOA level allowing for small-area analysis. To ensure comparability, each variable was normalised with a mean value of 0 and a standard deviation of 1 to preserve the relative differences in values between LSOAs. Where necessary, indicator variables were multiplied by -1 so that the lowest value indicated the highest level of exclusion. For the variables comprising the internet (INT), transport (TRP) and Experian (EXP) indicators an average of the individual component variables was taken, and the resultant composite standardised with a mean value of 0 and a standard deviation of 1.

To investigate the degree of co-linearity between variables, correlation plots were derived showing the pairwise scatter plots overlaid with best fit regression lines and the values for the Spearman's rank correlation coefficient (Figure 1) (Spearman, 2010). A correlation network diagram was also developed showing which sub-groups of indicators formed mutually correlated sub-groups (Figure 2).

Factor analysis was used to generate weightings for the individual normalised indicators in the composite index (Shrestha, 2021). The principle underlying factor analysis is that the variability among correlated variables can be described by a lower number of unobserved or latent variables. For each unobserved variable or factor, a loading is derived for each original indicator. These individual indicator loadings are then combined by assigning a weight to each of them equal to the amount of the total variance in the data described by the factor to generate overall weights which can be applied to the individual indicators to create an overall composite.

All analyses were carried out using the R statistical software package. (R Core Team, 2022) The correlation plot was generated using a customised version of the chart correlation function in the Performance Analytics package (Peterson and Carl, 2020). The correlation network diagram was generated using the qgraph package (Epskamp et al., 2012). Weightings were obtained using the Compind package (Fusco et al., 2018). All maps were produced using the leaflet package (Cheng et al., 2022). All code is freely available for download from the following GitHub repository https://github.com/Paul-Mee/digex_linc .

Results

The correlation plot (Figure 1) and the correlation network diagram (Figure 2) describe the pairwise correlations between the eight indicator variables used to form the composite indicators. Three of these variables GPC (claiming of guaranteed pension credit), UNP (Unemployment), and DER (D or E socio-economic status) show a high degree of mutual correlation (correlation coefficients (CCs) GPC-UNP=0.75, GPC-DER=0.75, UNP-DER=0.82). LAC (Low levels of activity) is correlated to NQR (lack of qualifications) (CC= 0.61) and these two are weakly correlated to DER (CCs LAC-DER=0.52, NQR-DER=0.51). There is a weak correlation between TRP (transport access) and INT (internet access) (CC=0.55). These variables are not highly correlated with the other variables. EXP (composite of Experian indicators) is not correlated with any of the other indicator variables.

The map of all LSOA's (Figure 3) shows that the easternmost coastal areas of the county experience the highest degree of digital exclusion with a shift towards lower levels of exclusion towards the west. However, within this overall trend there is a high degree of local heterogeneity. For example, within the City of Lincoln (Figure 4a) or the town of Grantham (Figure 4b), neighbouring LSOAs have very different levels of digital exclusion.

Iterative analyses indicated that it was optimal to extract three factors which explained nearly 67% percent of the variance in the original indicator variables (Table 2). Adding additional factors resulted in only a small increase in the explanatory power. The communality scores (Table 3) showed that these represented a reasonable level of the variation in all but the TRP (communality = 0.370) and EXP (communality = 0.112) indicators.

An analysis of the individual factor loadings (Table 3) would suggest that the first factor is predominantly constructed from four indicators which show a high degree of mutual correlation (GPC, UNP, DER & LAC). This factor explained 31.3% of the variance in the original data (Table 2). The dominant contribution to Factor 2 came from NQR (loading = 0.849) with a lesser contribution from LAC (0.652), DER (0.342) and EXP (0.286). Factor 2 explained 17.0% of the variance of the data. The highest loadings for Factor 3 came from INT and TRP (0.996 & 0.431) respectively, this factor explained a further 15.8 % of the variance in the data.

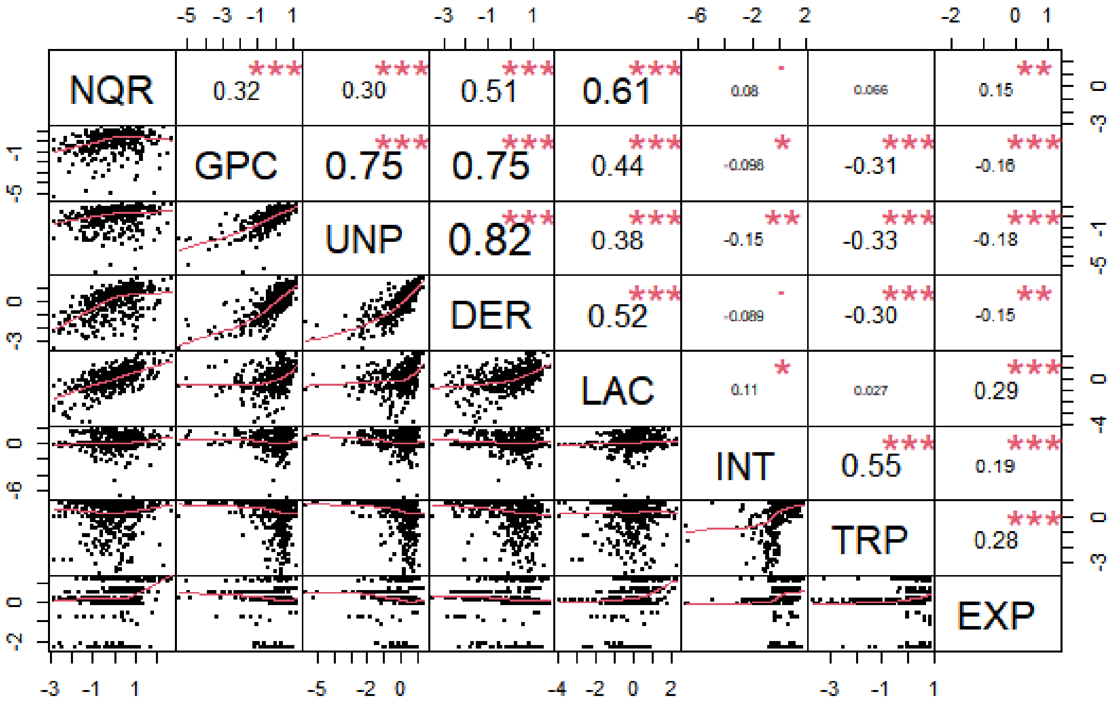


Figure 1 – Summary correlation plot for the original indicator variables. Scatter plots of pairs of indicators are shown below the diagonal and the Spearman's correlation coefficient (ρ) values are shown above the diagonal. p-values for the correlation are indicated as (* = <0.05, ** = <0.01, * = <0.001). Indicator codes are described in Table 1.**

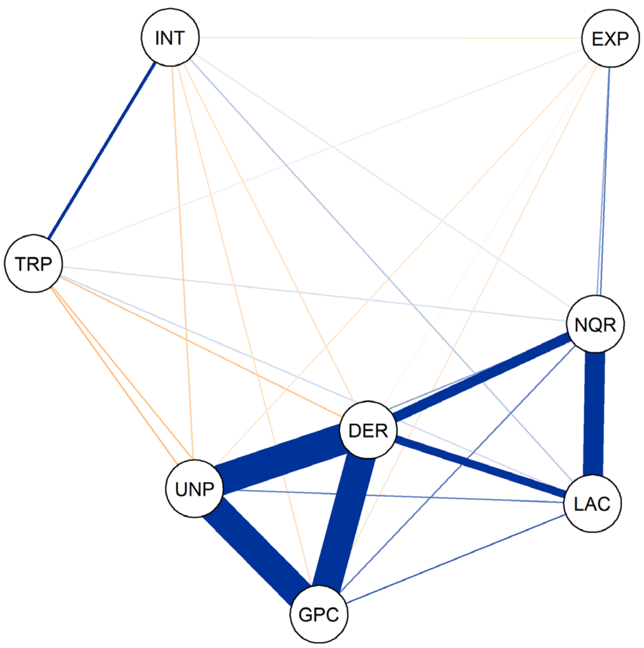


Figure 2 - Correlation network diagram for the normalised indicator variables the thickness of the lines linking pairs of nodes indicates the strength of the correlations pair of variables. Indicator codes are described in Table 1.

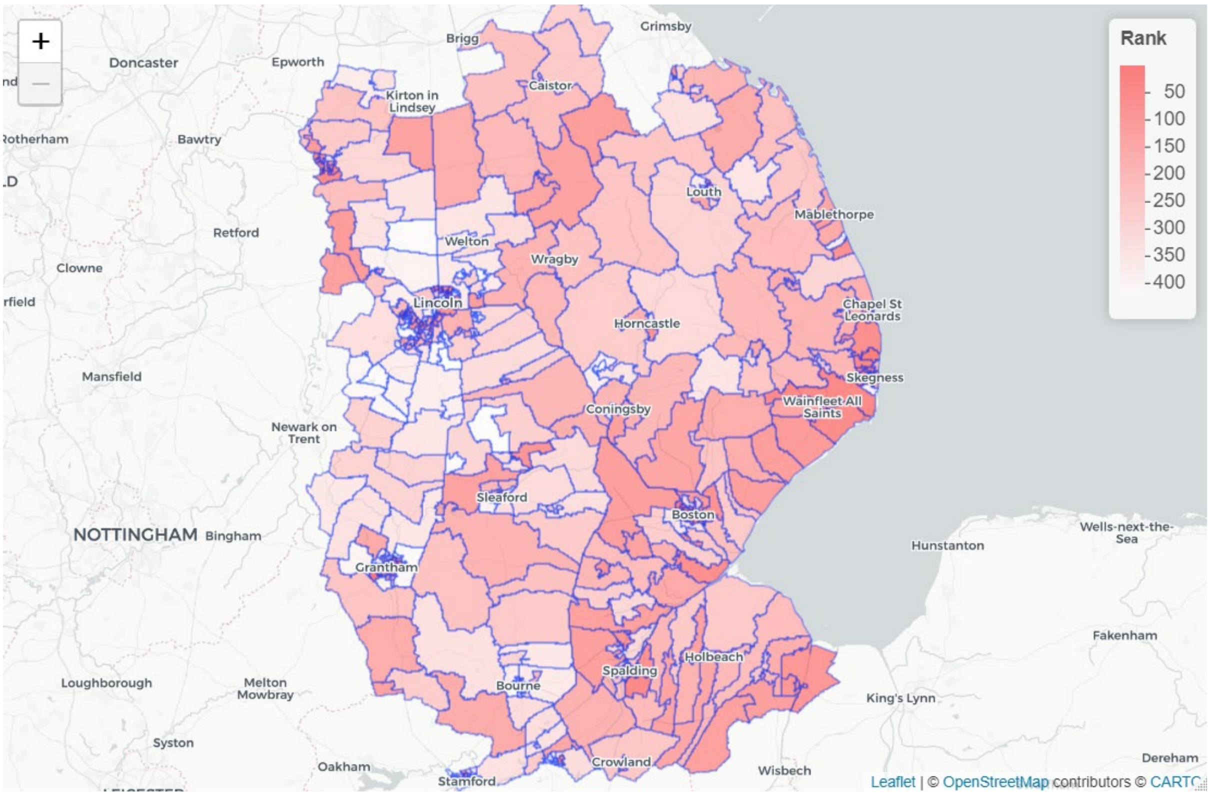


Figure 3 Map of Lincolnshire showing the relative rankings of the LSOA's using factor analysis derived composite indicator scores ranging from 1 (highest level of exclusion – dark red) to 420 (lowest exclusion – white)

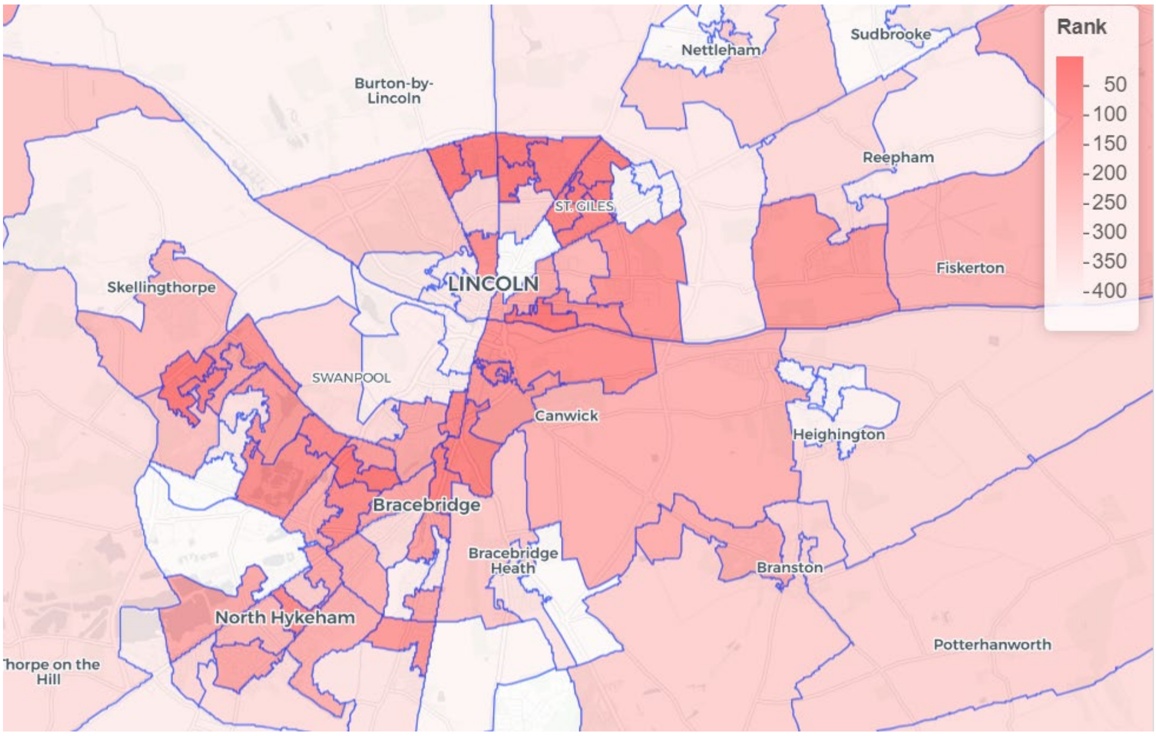


Figure 4a

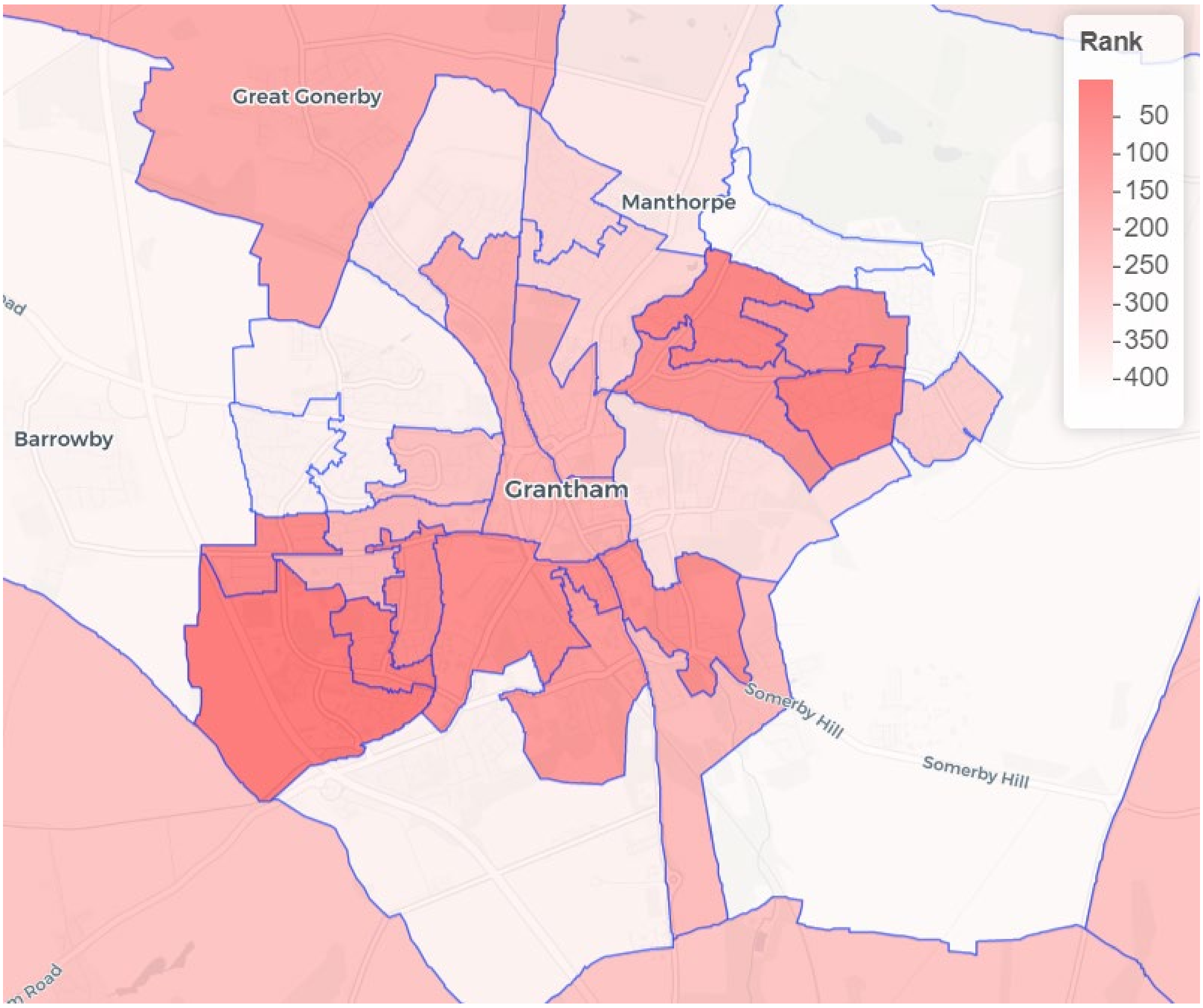


Figure 4b

Figure 4 a and b Expanded view of LSOAs in Lincoln (4a) and, Grantham (4b) showing the local variation in the extent of digital exclusion.

	Factor 1	Factor 2	Factor 3
Proportion of variance explained	0.313	0.170	0.158
Cumulative proportion of variance explained	0.313	0.483	0.641

Table 2 – Proportion of variance in the dataset explained by each factor.

Indicator	Communality[9]	Factor Loadings[10]		
		Factor 1	Factor 2	Factor 3
NQR	0.795	0.258	0.849	
GPC	0.714	0.836		-0.102
UNP	0.816	0.885		-0.181
DER	0.896	0.878	0.342	
LAC	0.555	0.329	0.652	0.146
INT	0.995			0.996
TRP	0.256	-0.248		0.431
EXP	0.102	-0.128	0.286	

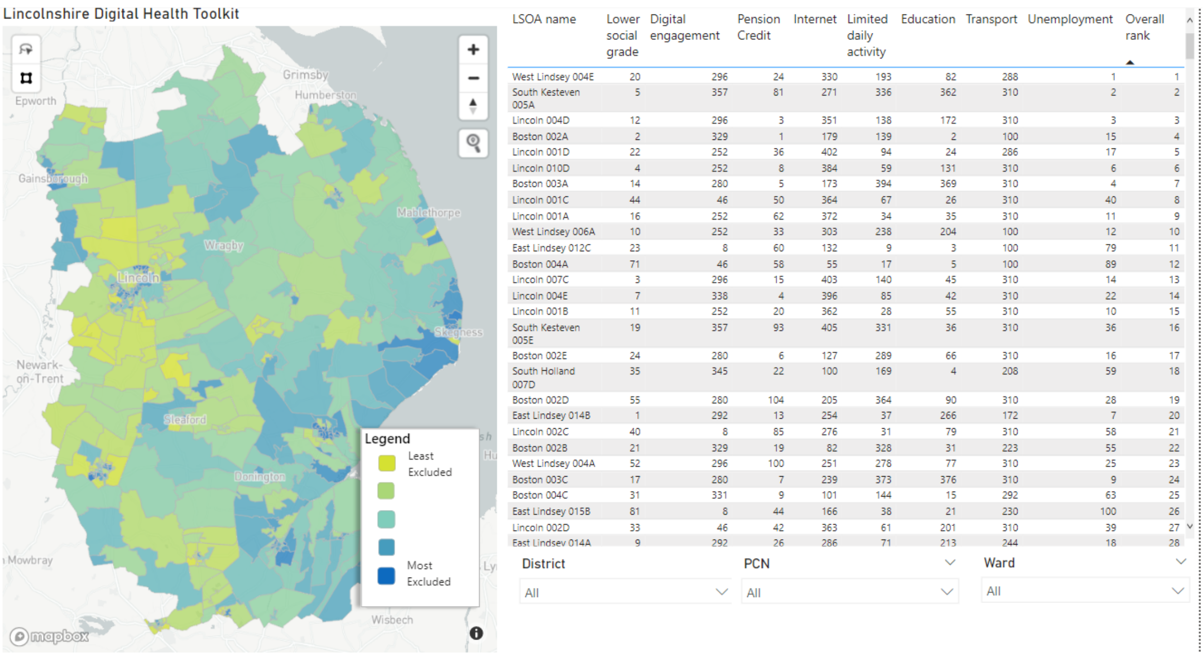
Table 3 – Factor analysis – Communality and Factor Loadings (codes are as described in Table 1).

[9] Communality indicates the overall proportion of the variance in the indicator variable explained by the factors

[10] Loadings are the contribution of each original variable to the factor

Online Dashboard

An online dashboard the 'Lincolnshire Digital Health Toolkit' (https://lhih.org.uk/lincolnshire-digital-health-toolkit/) has been developed which presents data on the individual indicators and the composite metric superimposed on an interactive map (Figure 5). This enables users to interrogate factors associated with digital exclusion at an LSOA level alongside additional contextual information. This is designed to provide an analytical platform for local decision makers informing strategic approaches in the development of targeted interventions.



LSOA name	Lower social grade	Digital engagement	Pension Credit	Internet	Limited daily activity	Education	Transport	Unemployment	Overall rank
West Lindsey 004E	20	296	24	330	193	82	288	1	1
South Kesteven 005A	5	357	81	271	336	362	310	2	2
Lincoln 004D	12	296	3	351	138	172	310	3	3
Boston 002A	2	329	1	179	139	2	100	15	4
Lincoln 001D	22	252	36	402	94	24	286	17	5
Lincoln 010D	4	252	8	384	59	131	310	6	6
Boston 003A	14	280	5	173	394	369	310	4	7
Lincoln 001C	44	46	50	364	67	26	310	40	8
Lincoln 001A	16	252	62	372	34	35	310	11	9
West Lindsey 006A	10	252	33	303	238	204	100	12	10
East Lindsey 012C	23	8	60	132	9	3	100	79	11
Boston 004A	71	46	58	55	17	5	100	89	12
Lincoln 007C	3	296	15	403	140	45	310	14	13
Lincoln 004E	7	338	4	396	85	42	310	22	14
Lincoln 001B	11	252	20	362	28	55	310	10	15
South Kesteven 005E	19	357	93	405	331	36	310	36	16
Boston 002E	24	280	6	127	289	66	310	16	17
South Holland 007D	35	345	22	100	169	4	208	59	18
Boston 002D	55	280	104	205	364	90	310	28	19
East Lindsey 014B	1	292	13	254	37	266	172	7	20
Lincoln 002C	40	8	85	276	31	79	310	58	21
Boston 002B	21	329	19	82	328	31	223	55	22
West Lindsey 004A	52	296	100	251	278	77	310	25	23
Boston 003C	17	280	7	239	373	376	310	9	24
Boston 004C	31	331	9	101	144	15	292	63	25
East Lindsey 015B	81	8	44	166	38	21	230	100	26
Lincoln 002D	33	46	42	363	61	201	310	39	27
East Lindsey 014A	9	292	26	286	71	213	244	18	28

Figure 5 - A screenshot from the Lincolnshire Digital Health Toolkit showing the LSOAs across the county categorised into 5 quintiles of digital exclusion based on their ranks in the composite indicator.

Case Studies

Targeted provision of digital devices - The Lincolnshire Digital Health Toolkit has been utilised by Lincolnshire County Council to fund a local charity in their delivery of services aimed at supporting those who are at a greater risk of digital exclusion. The index assisted with targeting the limited support and prioritising how this support is delivered. This included the provision of devices, data SIM cards, and help to access the internet to over 100 people in the community.

Provision of digital access kiosks in healthcare centres -

It has been identified that whilst many people using medical practices access websites and social media via their mobile phones, they do not make use of digital services to support their healthcare provision. Anecdotal evidence from medical practitioners indicated that many of their appointments could be managed by people having access to digital services and information which is available across the health and social care sector. Using data from the Lincolnshire Digital Health Toolkit. digital access kiosks were placed in NHS properties located in or close to the most digitally deprived LSOA's in the county.

Discussion

The rapid switch to online provision of services and interpersonal communication necessitated by the COVID-19 epidemic accelerated the level of digital exclusion experienced by some sub-groups such as those with low levels of digital literacy or access to appropriate digital devices (Litchfield et al., 2021).The impact of digital exclusion in these groups must be addressed through both digital education initiatives and the provision of access to digital devices to reduce marginalisation and isolation. Metrics to quantify relative local differences in levels of digital exclusion are a necessary pre-requisite for the targeted provision of interventions to address this. The Lincolnshire Digital Health

Toolkit provides a novel composite metric tailored to the conditions of this largely rural county and an interactive dashboard to support decisions on resource allocation.

There is a link between social deprivation and digital exclusion (Longley and Singleton, 2009), however it is clear that other factors related to poor digital access or lack of IT skills are also important over and above the background level of deprivation in a particular community. In this study methodologies for the development of indicators of intra-country economic performance and social development have been used to develop a composite index of digital exclusion which balances the different underlying constructs that drive exclusion.

We have identified three underlying constructs in the individual indicator variables that were combined to create this composite. The first and dominant factor can be described as representing socioeconomic deprivation and is composed of the highly correlated indicators describing the proportion of those in each LSOA: claiming guaranteed pension credit, unemployed, with lower socioeconomic status and inactive. The second construct relates to low levels of qualifications and lack of activity with a smaller contribution from the Experian score and low socioeconomic status. The final indicator primarily describes barriers to digital access due to poor provision of internet connectivity and the time taken to travel to medical practices.

Digital exclusion is a multi-faceted concept. Individuals may experience exclusion from certain services but not from others for a variety of reasons (Hernandez and Faith, 2023). For example, the high prevalence of smartphone ownership, at least among those in younger age groups, may mean that barriers to accessing social media and instant messaging applications are relatively low. This same group may, however, experience barriers when accessing more complex systems such as those used to apply for employment or access government and council services due to a lack of IT skills, equipment, or adequate broadband. It is important to take a nuanced approach when interpreting a composite indicator for digital exclusion and explore local variations in the individual indicator variables from which the composite has been derived.

Aggregating the component indicators at the LSOA level may lead to a loss of ability to understand individual level experiences of digital exclusion. For example, in a single multi-generational household there may be younger members who are more internet aware, so called 'digital natives' living with those of an older generation who have had to adapt to digital technology later in life. Further development of this tool should include a multi-level algorithm for individual level and aggregate inputs to develop a more nuanced individual metrics of exclusion.

The use of the Experian indicators derived from representative data aggregated up to LSOA level did not add a significant amount of power to describe the overall variation in the underlying data and hence made only a small contribution to the composite. This may be due to the lack of discrimination between LSOAs in the underlying Experian indicators with many LSOAs showing identical values for the same indicator. However, the specific nature of the information given by these indicators may be useful in exploring fine-grained aspects of exclusion.

A fundamental question remaining is whether this or other metrics adequately reflect individual's experiences of digital exclusion. In future studies we plan to carry out representative individual level surveys to validate and improve the predictive ability of the composite metric.

These indicators and the composite metric will allow those with responsibility for commissioning and planning the delivery of services, communicating and engaging with local populations, and supporting people to access services to understand the likelihood of digital exclusion in an area and the factors which underly it. Services and activities could then be designed to lower barriers for those at higher risk of digital exclusion. The tool should be used alongside other local knowledge, expertise, and intelligence to support decision making.

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