A MINIMUM DIGITAL LIVING STANDARD FOR HOUSEHOLDS WITH CHILDREN

SURVEY APPENDICES

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Minimum Digital Living Standard: For Households With Children: Survey Report Appendices

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Chapter 1

Appendix 1: Pilot survey on household skills – selecting skills for final survey

1.1 Introduction

This appendix outlines the process by which we reduced the initial list of 30 functional and critical skills to a target list of 13 for adults, 12 for secondary school children and 8 for primary school children. This was necessary for two reasons. First, undertaking all the questions for each household member was not possible within the limitations of our in-home survey. For a household with 5 people, this would be a total of 150 repetitive questions just on skills. Second, skill needs in the MDLS vary by child's age and we had to try to account for this in our more rigid split of primary and secondary-age children.

We therefore collected pilot data from an online sample of 207 households. This data covered:

- 350 Adults with parental responsibility
- 61 Further adults without parental responsibility
- 133 Secondary school children
- 159 Primary school children

We made the selection of skills to use in the full survey by exploring a Principal Components Analysis of the functional and critical skills data for all parental adults, non-parental adults, and primary school-age children. As we did not assess non-parental adults in the MDLS analysis presented in the main report we have not included that analysis here. Principal components analysis was done using FactoMiner (2.9), FactoInvestigate (1.9), and Psych (2.3.12) packages in R (4.3.2 (2023-10-31)) running under R-studio (2023.12.0+369).

From the work described below we selected the following as the skills to be assessed in the full survey.

- Adult functional
  - Save a document on a computer or laptop
  - Look for information online using Google or Bing
  - Create an email account
  - Make online payments or cashless payments (e.g. through Apple Pay or Google Pay)
  - Manage mobile phone data usage?
  - Use apps to communicate between parents and schools/ check on child's homework etc.
- Secondary school functional
  - Save a document on a computer or laptop?
  - Look for information online using Google or Bing
  - Create an email account
  - Make online payments or cashless payments (e.g. through Apple Pay or Google Pay)?
  - Manage mobile phone data usage?
- Primary school functional

- Save a document on a computer or laptop
- Look for information online using Google or Bing
- Connect a tablet or smartphone to the internet
- Fully turn off devices like laptops, mobile phones or tablets

- Adult critical and secondary school critical
  - Think about whether online friend requests are genuine (e.g. is the person who they say they are)
  - Think about what personal information should and should not be shared online
  - Identify risks online (e.g. scams, unsafe links or inappropriate/ offensive content etc.)
  - Manage online pressures when online (e.g. pressures to always be online, to respond immediately, to use social media)
  - Think about the quality of the information found online (e.g. is it true, could it be misinformation or unrealistic)
  - Know how to report inappropriate or offensive things online
  - Can understand that everything that is posted online will leave a mark or 'digital footprint'

- Primary school critical
  - Think about whether online friend requests are genuine (e.g. is the person who they say they are)
  - Identify risks online (e.g. scams, unsafe links or inappropriate/ offensive content etc.)
  - Think about the quality of the information found online (e.g. is it true, could it be misinformation or unrealistic)
  - Know how to avoid inappropriate or offensive things online

1.2 Note on distributions

The data are highly skewed with the average score for nearly all parents being close to 1 – Very confident – on most variables. However, there is a clear variation between variables for many respondents. Given the results below we find that this does not appear to have been problematic with both Kaiser-Meyer-Olkin values is Bartletts test results being very good in all cases.

1.3 Parents' functional skills

A factor analysis for functional skills produces a clear two-factor result, most items loaded on the first factor. Full details of the analysis can be found in section 1.13. The factor loadings are high, and the factor result looks robust as the Kaiser-Meyer-Olkin value is 0.95 (> 0.6) and Bartletts test is significant ($p<0.00$). The first two factors have eigenvalues above 1 and the scree plot indicates a clear 'elbow' at 2 factors. Loadings (PCA with Oblimin rotation) for the first two factors are presented in Table 1.1.

Variable	Factor1	Factor2	Description
B1c05	0.84		**B1c05**: Connect to the internet via a second device as a hotspot?
B1c11	0.82		**B1c11**: Create an email account?
B1c03	0.72		**B1c03**: Save a document on a computer or laptop?
B1c12	0.72		**B1c12**: Make online payments or cashless payments (e.g., through Apple Pay or Google Pay)?
B1c14	0.71		**B1c14**: Create files or folders on a computer or laptop?
B1c10	0.69		**B1c10**: Change settings on a mobile phone or tablet?
B1c06	0.67		**B1c06**: Use a video calling app like Zoom/ Teams or Google Classroom?
B1c16	0.66		**B1c16**: Use apps to communicate between parents and schools/ check on child's homework etc.?
B1c15	0.58		**B1c15**: Complete online forms or make online bookings?
B1c13	0.52		**B1c13**: Manage mobile phone data usage?
B1c07		0.85	**B1c07**: Look for information online using Google or Bing?
B1c01		0.79	**B1c01**: Adjust the volume on a mobile phone, tablet, or TV set?
B1c09		0.75	**B1c09**: Fully turn off devices like laptops, mobile phones, or tablets?
B1c04		0.55	**B1c04**: Connect a tablet or smartphone to the internet?
B1c08		0.46	**B1c08**: Delete unused apps to free up storage space?
B1c02		0.44	**B1c02**: Download an app onto a smartphone or tablet?

Table 1.1: Factor loadings **parents'** functional skills

Looking at these two factors they appear to differentiate between:

- Factor 1: Functional skills with apps and systems
- Factor 2: Functional skills with devices and operating systems

It is important to note that the factors are all positively loaded. As a higher score implies **LESS** confidence then were we to allocate factor scores each respondent then a high score on both would indicate very low levels of confidence.

From the factor analysis we could conclude that taking the items below (arbitrary but arguable cut off at 0.72 rotated loading), would provide a reasonably robust set of proxies for adult skills:

- Factor 1: Functional skills with apps and systems
  - **B1c05**: Connect to the internet via a second device as a hotspot?
  - **B1c11**: Create an email account?
  - **B1c03**: Save a document on a computer or laptop?
  - **B1c12**: Make online payments or cashless payments (e.g., through Apple Pay or Google Pay)?
- Factor 2: Functional skills with devices and operating systems
  - **B1c07**: Look for information online using Google or Bing?
  - **B1c01**: Adjust the volume on a mobile phone, tablet, or TV set?
  - **B1c09**: Fully turn off devices like laptops, mobile phones, or tablets?

The one parent only item:

- **B1c16**: Use apps to communicate between parents and schools/ check on child's homework etc.?

Is not on this list. There is a clear argument for retaining this item for parents.

1.4 Parents' critical skills

A factor analysis for critical skills produces a clear two-factor result, this most items loaded on the first factor. Further details fo the analysis can be found in section 1.14. The factor loadings are high, and the factor result looks robust as the Kaiser-Meyer-Olkin value is 0.99 (> 0.6) and Bartletts test is significant ($p<0.00$). The first two factors have eigenvalues above 1 and the scree plot indicates a clear 'elbow' at 2 factors. Loadings (PCA with Oblimin rotation) for the first two factors are presented in Table 1.2.

Variable	Factor1	Factor2	Description
B2c11	0.87		**B2c11**: Check any online banking activity or any in-app purchases?
B2c12	0.87		**B2c12**: Understand that everything that is posted online will leave a mark or 'digital footprint'?
B2c07	0.85		**B2c07**: Think about how much time is spent online and whether this is a good thing?
B2c03	0.79		**B2c03**: Think about whether online friend requests are genuine (e.g., is the person who they say they are)?
B2c04	0.73		**B2c04**: Think about what personal information should and should not be shared online?
B2c06	0.66		**B2c06**: Manage online pressures when online (e.g., pressures to always be online, to respond immediately, to use social media)?
B2c01	0.65		**B2c01**: Use secure passwords online?
B2c05	0.63		**B2c05**: Identify risks online (e.g., scams, unsafe links etc.)
B2c08	0.62		**B2c08**: Think about the quality of the information found online (e.g., is it true, could it be misinformation or unrealistic)?
B2c09	0.62		**B2c09**: Know how to avoid inappropriate or offensive things online?
B2c13		0.85	**B2c13**: Know how to set up parental controls on devices used to go online?
B2c10		0.76	**B2c10**: Know how to report inappropriate or offensive things online?
B2c02		0.66	**B2c02**: Use safety features on devices when away from home (e.g., 'triple tap' or 'Emergency calls')?
B2c14		0.58	**B2c14**: Know how to delete credit card details from online accounts to prevent accidental purchases?

Table 1.2: Factor loadings **parents'** critical skills

Looking at these two factors they appear to differentiate between:

- Factor 1: Critical thinking about online behaviour
- Factor 2: Safety online

It is important to note that the factors are all positively loaded. As a higher score implies **LESS** confidence then were we to allocate factor scores each respondent then a high score on both would indicate very low levels of confidence.

From the factor analysis we could conclude that taking the items below (arbitrary but arguable cut off at 0.72 rotated loading), would provide a reasonably robust set of proxies for adult skills:

- Factor 1: Critical thinking about online behaviour
  - **B2c11**: Check any online banking activity or any in-app purchases?
  - **B2c12**: Understand that everything that is posted online will leave a mark or 'digital footprint'?
  - **B2c07**: Think about how much time is spent online and whether this is a good thing?
  - **B2c03**: Think about whether online friend requests are genuine (e.g., is the person who they say they are)?
  - **B2c04**: Think about what personal information should and should not be shared online?
- Factor 2: Safety online
  - **B2c13:** Know how to set up parental controls on devices used to go online?
  - **B2c10:** Know how to report inappropriate or offensive things online?

This includes one parent item (**B2c13**) but leaves out:

- B2c14: Know how to delete credit card details from online accounts to prevent accidental purchases?

Which was only asked of parents.

1.5 Conclusions - Parents

From our results we argue that we can reduce the functional skills questions to:

- Factor 1: Functional skills with apps and systems
  - **B1c05**: Connect to the internet via a second device as a hotspot?
  - **B1c11**: Create an email account?
  - **B1c03**: Save a document on a computer or laptop?
  - **B1c12**: Make online payments or cashless payments (e.g., through Apple Pay or Google Pay)?
- Factor 2: Functional skills with devices and operating systems
  - **B1c07**: Look for information online using Google or Bing?
  - **B1c01**: Adjust the volume on a mobile phone, tablet, or TV set?
  - **B1c09**: Fully turn off devices like laptops, mobile phones, or tablets?

With:

- **B1c16:** Use apps to communicate between parents and schools/ check on child's homework etc.?

For critical skills we can reduce the questions to:

- Factor 1: Critical thinking about online behaviour
  - **B2c11**: Check any online banking activity or any in-app purchases?
  - **B2c12**: Understand that everything that is posted online will leave a mark or 'digital footprint'?
  - **B2c07**: Think about how much time is spent online and whether this is a good thing?
  - **B2c03**: Think about whether online friend requests are genuine (e.g., is the person who they say they are)?
  - **B2c04**: Think about what personal information should and should not be shared online?
- Factor 2: Safety online
  - **B2c13:** Know how to set up parental controls on devices used to go online?
  - **B2c10:** Know how to report inappropriate or offensive things online?

1.6 Secondary school children's functional skills

A factor analysis for functional skills produces a clear two factor result, this most items loaded on the first factor. More details on the analysis can be found in section 1.15. The factor loadings are high, and the factor result looks robust as the Kaiser-Meyer-Olkin value is 0.94 (> 0.6) and Bartletts test is significant ($p<0.00$). The first two factors have eigenvalues above 1 and the scree plot indicates a clear 'elbow' at 2 factors. Loadings (PCA with Oblimin rotation) for the first two factors are presented in Table 1.3.

Variable	Factor1	Factor2	Description	Mapping
B1c01	0.92		**B1c01**: Adjust the volume on a mobile phone, tablet, or TV set?	**F1 - 2**
B1c07	0.91		**B1c07**: Look for information online using Google or Bing?	**F2 - 1**
B1c02	0.79		**B1c02**: Download an app onto a smartphone or tablet?	**F2 - 6**
B1c09	0.77		**B1c09**: Fully turn off devices like laptops, mobile phones, or tablets?	**F2 - 3**
B1c06	0.62		**B1c06**: Use a video calling app like Zoom/ Teams or Google Classroom?	**F1 - 7**
B1c08	0.48		**B1c08**: Delete unused apps to free up storage space?	**F2 - 5**
B1c10	0.43	0.45	**B1c10**: Change settings on a mobile phone or tablet?	**F1 - 6**
B1c03	0.42	0.49	**B1c03**: Save a document on a computer or laptop?	**F1 - 3**
B1c11		0.83	**B1c11**: Create an email account?	**F1 -2**
B1c05		0.82	**B1c05**: Connect to the internet via a second device as a hotspot?	**F1 - 1**
B1c12		0.78	**B1c12**: Make online payments or cashless payments (e.g., through Apple Pay or Google Pay)?	**F1 - 4**
B1c13		0.76	**B1c13**: Manage mobile phone data usage?	**F1 - 8**
B1c04		0.52	**B1c04**: Connect a tablet or smartphone to the internet?	**F2 - 4**
B1c14		0.50	**B1c14**: Create files or folders on a computer or laptop?	**F1 - 5**

Table 1.3: Factor loadings for **secondary school children's** functional skills with mapping to parents' results

The two factors are similar to those of the parents but with their relative importance reversed. Though again the first factor covers most items and is the strongest predictor. I would argue that this implies the same set of core questions can work for parents and secondary school children.

1.7 Secondary school children's critical skills

A factor analysis for functional skills produces a clear two factor result, this most items loaded on the first factor. Further details can be found in section 1.16. The factor loadings are high, and the factor result looks robust as the Kaiser Meyer-Olkin value is 0.92 ($>$ 0.6) and Bartletts test is significant (p$<$0.00). The first two factors have eigenvalues above 1 and the scree plot indicates a clear 'elbow' at 2 factors. Loadings (PCA with Oblimin rotation) for the first two factors are presented in Table 1.4.

Variable	Factor1	Factor2	Description	Mapping
B2c01	0.94		**B2c01**: Use secure passwords online?	**F1 - 7**
B2c10	0.92		**B2c10**: Know how to report inappropriate or offensive things online?	**F2 - 3**
B2c08	0.83		**B2c08**: Think about the quality of the information found online (e.g., is it true, could it be misinformation or unrealistic)?	**F1 - 9**
B2c04	0.76		**B2c04**: Think about what personal information should and should not be shared online?	**F1 - 5**
B2c06	0.76		**B2c06**: Manage online pressures when online (e.g., pressures to always be online, to respond immediately, to use social media)?	**F1 - 6**
B2c12	0.73		**B2c12**: Understand that everything that is posted online will leave a mark or 'digital footprint'?	**F1 - 2**
B2c09	0.61		**B2c09**: Know how to avoid inappropriate or offensive things online?	**F1 - 10**
B2c11	0.57		**B2c11**: Check any online banking activity or any in-app purchases?	**F1 - 1**
B2c05	0.53		**B2c05**: Identify risks online (e.g., scams, unsafe links etc.)	**F1 - 8**
B2c03	0.48	0.42	**B2c03**: Think about whether online friend requests are genuine (e.g., is the person who they say they are)?	**F1 - 4**
B2c02	0.45	0.41	**B2c02**: Use safety features on devices when away from home (e.g., 'triple tap' or 'Emergency calls')?	**F2 - 4**
B2c07		0.44	**B2c07**: Think about how much time is spent online and whether this is a good thing?	**F1 - 3**

Table 1.4: Factor loadings for **secondary school children's** critical skills with mapping to parents' results

This is really one-factor result that is very similar to the main factor for the parents. We would argue that this implies the same set of core questions can work for parents and secondary school children.

1.8 Conclusions – Secondary school children's skills

From this we would argue that we can reduce the functional skills questions to two overlapping sets:

- Factor 1: Functional skills
  - **B1c01**: Adjust the volume on a mobile phone, tablet, or TV set?
  - **B1c07**: Look for information online using Google or Bing?
  - **B1c02**: Download an app onto a smartphone or tablet?
  - **B1c09**: Fully turn off devices like laptops, mobile phones, or tablets?
- Factor 2: Functional skills
  - **B1c11**: Create an email account?
  - **B1c05**: Connect to the internet via a second device as a hotspot?
  - **B1c12**: Make online payments or cashless payments (e.g., through Apple Pay or Google Pay)?
  - **B1c13**: Manage mobile phone data usage?

For critical skills we can reduce the questions to:

- Factor 1: Critical thinking about online behaviour
  - **B2c01**: Use secure passwords online?
  - **B2c10**: Know how to report inappropriate or offensive things online?
  - **B2c08**: Think about the quality of the information found online (e.g., is it true, could it be misinformation or unrealistic)?
  - **B2c04**: Think about what personal information should and should not be shared online?
  - **B2c06**: Manage online pressures when online (e.g., pressures to always be online, to respond immediately, to use social media)?
  - **B2c12**: Understand that everything that is posted online will leave a mark or 'digital footprint'?

1.9 Primary school children's functional skills

A factor analysis for functional skills produces a clear two factor result, this most items loaded on the first factor. Further details can be found in section 1.17.The factor loadings are high, and the factor result looks robust as the Kaiser-Meyer-Olkin value is 0.91 ($>$ 0.6) and Bartletts test is significant (p$<$0.00). The first two factors have eigenvalues above 1 and the scree plot indicates a clear 'elbow' at 2 factors. Loadings (PCA with Oblimin rotation) for the first two factors are presented in Table 1.5.

Variable	Factor1	Factor2	Description
B1c03	0.93		**B1c03**: Save a document on a computer or laptop?
B1c05	0.92		**B1c05**: Connect to the internet via a second device as a hotspot?
B1c04	0.80		**B1c04**: Connect a tablet or smartphone to the internet?
B1c06	0.63		**B1c06**: Use a video calling app like Zoom/ Teams or Google Classroom?
B1c07	0.63		**B1c07**: Look for information online using Google or Bing?
B1c08	0.63		**B1c08**: Delete unused apps to free up storage space?
B1c01		0.90	**B1c01**: Adjust the volume on a mobile phone, tablet, or TV set?
B1c09		0.81	**B1c09**: Fully turn off devices like laptops, mobile phones, or tablets?
B1c02		0.59	**B1c02**: Download an app onto a smartphone or tablet?

Table 1.5: Factor loadings for **primary school children's** functional skills

The two factors are the most distinct in the analysis, but both sets mainly overlap with the first factor in the parents' data. We would argue that this implies the same set of core questions can work for parents and primary school children. Notably, primary children's functional skill scores are more varied than parents and secondary school.

1.10 Primary school children's critical skills

A factor analysis for functional skills produces a clear two factor result, this most items loaded on the first factor. The factor loadings are high, and the factor result looks robust as the Kaiser-Meyer-Olkin value is 0.96 ($>$ 0.6) and Bartletts test is significant (p$<$0.00). The first two factors have eigenvalues above 1 and the scree plot indicates a clear 'elbow' at 2 factors. Loadings (PCA with Oblimin rotation) for the first two factors are presented in Table 5.

Variable	Factor1	Description
B2c03	0.89	**B2c03**: Think about whether online friend requests are genuine (e.g., is the person who they say they are)?
B2c04	0.89	**B2c04**: Think about what personal information should and should not be shared online?
B2c05	0.88	**B2c05**: Identify risks online (e.g., scams, unsafe links etc.)
B2c08	0.87	**B2c08**: Think about the quality of the information found online (e.g., is it true, could it be misinformation or unrealistic)?
B2c01	0.86	**B2c01**: Use secure passwords online?
B2c06	0.86	**B2c06**: Manage online pressures when online (e.g., pressures to always be online, to respond immediately, to use social media)?
B2c10	0.81	**B2c10**: Know how to report inappropriate or offensive things online?
B2c09	0.80	**B2c09**: Know how to avoid inappropriate or offensive things online?
B2c07	0.79	**B2c07**: Think about how much time is spent online and whether this is a good thing?
B2c02	0.78	**B2c02**: Use safety features on devices when away from home (e.g., 'triple tap' or 'Emergency calls')?

Table 1.6: Factor loadings for **primary school children's** critical skills

This is a one factor result that is very similar to the man factor for the parents. But the results indicate that confidence levels are low overall for these items for primary school children.

1.11 Conclusions – Primary school children's skills

From this we would argue that we can reduce the functional skills questions to two overlapping sets:

- Factor 1: Functional skills

- **B1c03**: Save a document on a computer or laptop?
  - **B1c05**: Connect to the internet via a second device as a hotspot?
  - **B1c04**: Connect a tablet or smartphone to the internet?
- Factor 2: Functional skills
  - **B1c01**: Adjust the volume on a mobile phone, tablet, or TV set?
  - **B1c09**: Fully turn off devices like laptops, mobile phones, or tablets?

For critical skills, all items sit on the factor loading more than 0.7.But as scores are overall low we are likely able to select say the top 4 items:

- Factor 1: Critical thinking about online behaviour
  - **B2c03**: Think about whether online friend requests are genuine (e.g., is the person who they say they are)?
  - **B2c04**: Think about what personal information should and should not be shared online?
  - **B2c05**: Identify risks online (e.g., scams, unsafe links etc.)
  - **B2c08**: Think about the quality of the information found online (e.g., is it true, could it be misinformation or unrealistic)?

1.12 Overall conclusion

1.12.1 Functional skills

The following tables indicate which variables most strongly link to the identified factors for functional skills for:

- Adult functional
  - Save a document on a computer or laptop
  - Look for information online using Google or Bing
  - Create an email account
  - Make online payments or cashless payments (e.g. through Apple Pay or Google Pay)
  - Manage mobile phone data usage?
  - Use apps to communicate between parents and schools/ check on child's homework etc.
- Secondary school functional
  - Save a document on a computer or laptop?
  - Look for information online using Google or Bing
  - Create an email account
  - Make online payments or cashless payments (e.g. through Apple Pay or Google Pay)?
  - Manage mobile phone data usage?
- Primary school functional
  - Save a document on a computer or laptop
  - Look for information online using Google or Bing
  - Connect a tablet or smartphone to the internet
  - Fully turn off devices like laptops, mobile phones or tablets
- Adult critical and secondary school critical
  - Think about whether online friend requests are genuine (e.g. is the person who they say they are)
  - Think about what personal information should and should not be shared online
  - Identify risks online (e.g. scams, unsafe links or inappropriate/ offensive content etc.)
  - Manage online pressures when online (e.g. pressures to always be online, to respond immediately, to use social media)

- Think about the quality of the information found online (e.g. is it true, could it be misinformation or unrealistic)
- Know how to report inappropriate or offensive things online
- Can understand that everything that is posted online will leave a mark or 'digital footprint'

- Primary school critical
  - Think about whether online friend requests are genuine (e.g. is the person who they say they are)
  - Identify risks online (e.g. scams, unsafe links or inappropriate/ offensive content etc.)
  - Think about the quality of the information found online (e.g. is it true, could it be misinformation or unrealistic)
  - Know how to avoid inappropriate or offensive things online

1.13 Parents' Functional Skills Principal Component Analysis

Dataset B1_parents This dataset contains 350 individuals and 16 variables.

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1. Study of the outliers

The analysis of the graphs does not detect any outlier.

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2. Inertia distribution

The first two dimensions of analyse express **59.58%** of the total dataset inertia ; that means that 59.58% of the individuals (or variables) cloud total variability is explained by the plane. This percentage is relatively high and thus the first plane well represents the data variability. This value is strongly greater than the reference value that equals **17.48%**, the variability explained by this plane is thus highly significant (the reference value is the 0.95-quantile of the inertia percentages distribution obtained by simulating 18505 data tables of equivalent size on the basis of a normal distribution).

From these observations, it should be better to also interpret the dimensions greater or equal to the third one.

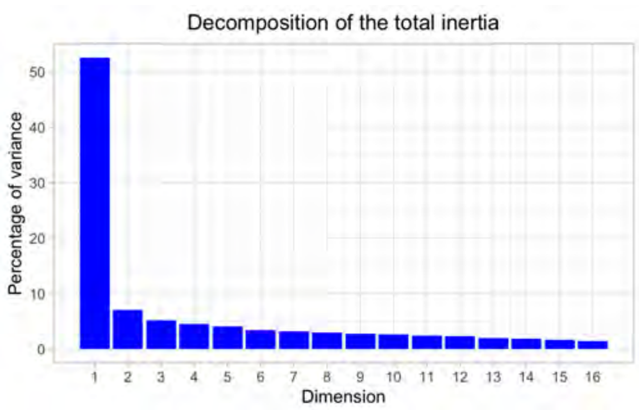

Figure 1.1

Figure 1.1 - Decomposition of the total inertia *The first factor is major: it expresses itself 52.54% of the data variability. Note that in such a case, the variability related to the other components might be meaningless, despite of a high percentage.*

An estimation of the right number of axis to interpret suggests to restrict the analysis to the description of the first 1 axis. These axis present an amount of inertia greater than those obtained by the 0.95-quantile of random distributions (52.54% against 9.15%). This observation suggests that only this axis is carrying real information. As a consequence, the description will stand to these axis.

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3. Description of the dimension 1

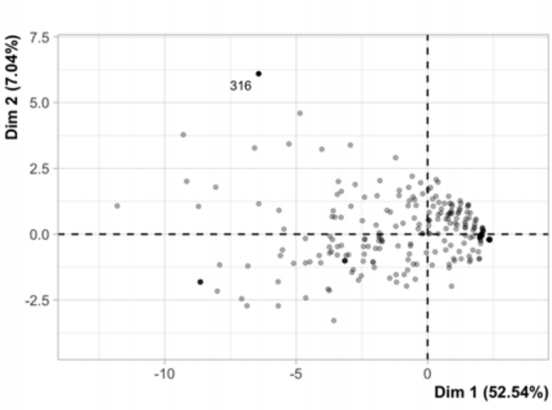

Figure 1.2: Enter Caption

Figure 1.2 - Individuals factor map (PCA) *The labeled individuals are those with the higher contribution to the plane construction.*

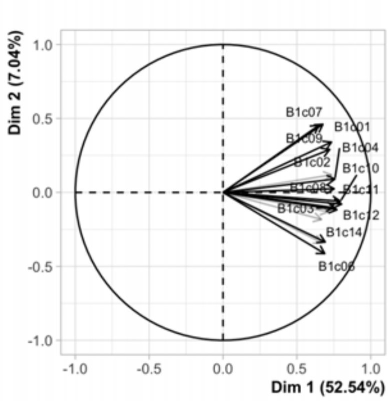

Figure 1.3: Enter Caption

Figure 1.3 - Variables factor map (PCA) *The labeled variables are those the best shown on the plane.*

The **dimension 1** opposes individuals characterized by a strongly positive coordinate on the axis (to the right of the graph) to individuals such as *316* (to the left of the graph, characterized by a strongly negative coordinate on the axis). The group 1 (characterized by a positive coordinate on the axis) is sharing :

- high values for variables like *B1c11*, *B1c13*, *B1c02*, *B1c08*, *B1c15*, *B1c12*, *B1c10*, *B1c04*, *B1c14* and *B1c16* (variables are sorted from the strongest).

The group in which the individual *316* stands (characterized by a negative coordinate on the axis) is sharing :

- low values for variables like *B1c06*, *B1c05*, *B1c12*, *B1c11*, *B1c16*, *B1c03*, *B1c14*, *B1c04*, *B1c13* and *B1c10* (variables are sorted from the weakest).

The group 3 (characterized by a negative coordinate on the axis) is sharing :

- low values for variables like *B1c07*, *B1c09*, *B1c02*, *B1c01*, *B1c15*, *B1c08*, *B1c10*, *B1c04*, *B1c11* and *B1c03* (variables are sorted from the weakest).

The group 4 (characterized by a negative coordinate on the axis) is sharing :

- low values for variables like *B1c01*, *B1c13*, *B1c08*, *B1c15*, *B1c02*, *B1c16*, *B1c09*, *B1c14*, *B1c12* and *B1c07* (variables are sorted from the weakest).

---

4. Classification

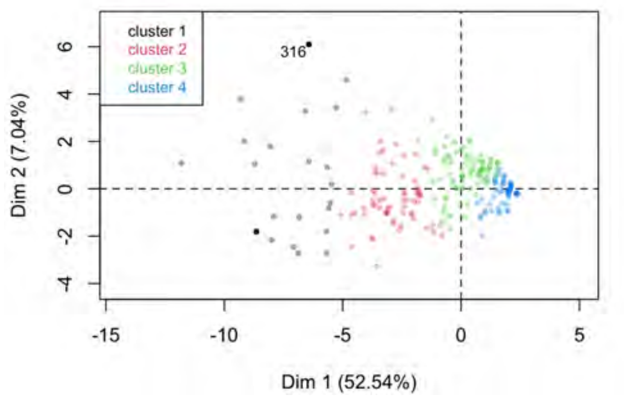

Figure 1.4: Enter Caption

Figure 1.4 - Ascending Hierarchical Classification of the individuals. *The classification made on individuals reveals 4 clusters.*

The **cluster 1** is made of individuals such as *316*. This group is characterized by :

- low values for variables like *B1c10*, *B1c11*, *B1c08*, *B1c03*, *B1c04*, *B1c02*, *B1c06*, *B1c01*, *B1c12* and *B1c13* (variables are sorted from the weakest).

The **cluster 2** is made of individuals sharing :

- low values for variables like *B1c09*, *B1c07*, *B1c12*, *B1c01*, *B1c15*, *B1c04*, *B1c11*, *B1c02*, *B1c03* and *B1c16* (variables are sorted from the weakest).

The **cluster 3** is made of individuals sharing :

- high values for the variables *B1c01*, *B1c09*, *B1c07* and *B1c04* (variables are sorted from the strongest).
- low values for the variables *B1c06*, *B1c14* and *B1c16* (variables are sorted from the weakest).

The **cluster 4** is made of individuals sharing :

- high values for variables like *B1c14*, *B1c16*, *B1c06*, *B1c13*, *B1c15*, *B1c10*, *B1c11*, *B1c12*, *B1c05* and *B1c03* (variables are sorted from the strongest).

1.14 Parents' Critical Skills Principal Component Analysis

Dataset B2_parents This dataset contains 350 individuals and 14 variables.

---

1. Study of the outliers

The analysis of the graphs does not detect any outlier.

---

2. Inertia distribution

The first two dimensions of analyse express **64.87%** of the total dataset inertia; that means that 64.87% of the individuals (or variables) cloud total variability is explained by the plane. This percentage is relatively high and thus the first plane well represents the data variability. This value is strongly greater than the reference value that equals **19.45%**, the variability explained by this plane is thus highly significant (the reference value is the 0.95-quantile of the inertia percentages distribution obtained by simulating 12630 data tables of equivalent size on the basis of a normal distribution).

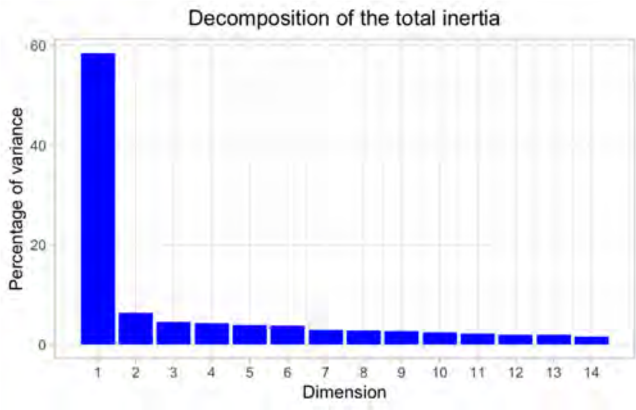

Figure 1.5

Figure 1.5 - Decomposition of the total inertia *The first factor is major: it expresses itself 58.47% of the data variability. Note that in such a case, the variability related to the other components might be meaningless, despite of a high percentage.*

An estimation of the right number of axis to interpret suggests to restrict the analysis to the description of the first 1 axis. These axis present an amount of inertia greater than those obtained by the 0.95-quantile of random distributions (58.47% against 10.19%). This observation suggests that only this axis is carrying real information. As a consequence, the description will stand to these axis.

---

3. Description of the dimension 1

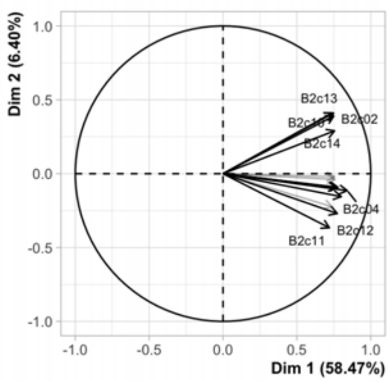

Figure 1.6: Enter Caption

Figure 1.6 - Individuals factor map (PCA) *The labeled individuals are those with the higher contribution to the plane construction.*

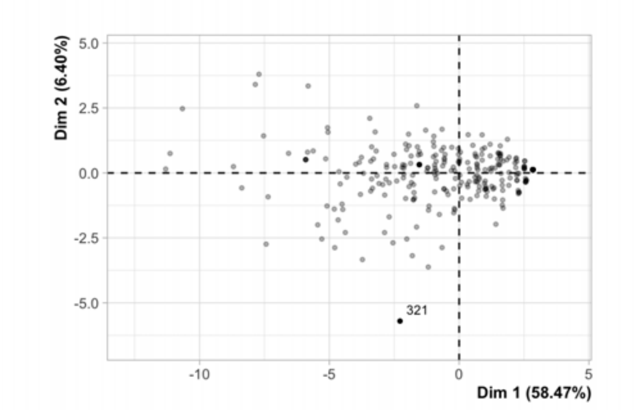

Figure 1.7: Enter Caption

Figure 1.7 - Variables factor map (PCA) *The labeled variables are those the best shown on the plane.*

The **dimension 1** opposes individuals characterized by a strongly positive coordinate on the axis (to the right of the graph) to individuals such as *321* (to the left of the graph, characterized by a strongly negative coordinate on the axis). The group 1 (characterized by a positive coordinate on the axis) is sharing :

- high values for variables like *B2c14*, *B2c03*, *B2c13*, *B2c02*, *B2c06*, *B2c04*, *B2c08*, *B2c05*, *B2c09* and *B2c10* (variables are sorted from the strongest).

The group 2 (characterized by a negative coordinate on the axis) is sharing :

- low values for variables like *B2c04*, *B2c11*, *B2c09*, *B2c06*, *B2c03*, *B2c12*, *B2c01*, *B2c07*, *B2c05* and *B2c14* (variables are sorted from the weakest).

The group in which the individual *321* stands (characterized by a negative coordinate on the axis) is sharing :

- low values for variables like *B2c02*, *B2c13*, *B2c14*, *B2c08*, *B2c10*, *B2c03*, *B2c05*, *B2c06*, *B2c12* and *B2c09* (variables are sorted from the weakest).

---

4. Classification

Figure 4 - Ascending Hierarchical Classification of the individuals. *The classification made on individuals reveals 3 clusters.*

The **cluster 1** is made of individuals sharing :

- low values for variables like *B2c04*, *B2c14*, *B2c01*, *B2c12*, *B2c06*, *B2c05*, *B2c03*, *B2c07*, *B2c10* and *B2c08* (variables are sorted from the weakest).

The **cluster 2** is made of individuals such as *321*. This group is characterized by :

- low values for variables like *B2c13*, *B2c02*, *B2c03*, *B2c09*, *B2c05*, *B2c06*, *B2c10*, *B2c08*, *B2c07* and *B2c04* (variables are sorted from the weakest).

The **cluster 3** is made of individuals sharing :

- high values for variables like *B2c04*, *B2c03*, *B2c13*, *B2c02*, *B2c05*, *B2c06*, *B2c09*, *B2c14*, *B2c01* and *B2c10* (variables are sorted from the strongest).

1.15 Secondary School Childrens' Functional Skills Principal Component Analysis

Dataset B1_secondary This dataset contains 133 individuals and 14 variables.

---

1. Study of the outliers

The analysis of the graphs does not detect any outlier.

---

2. Inertia distribution

The first two dimensions of analyse express **70.79%** of the total dataset inertia ; that means that 70.79% of the individuals (or variables) cloud total variability is explained by the plane. This percentage is high and thus the first plane represents an important part of the data variability. This value is strongly greater than the reference value that equals **22.99%**, the variability explained by this plane is thus highly significant (the reference value is the 0.95-quantile of the inertia percentages distribution obtained by simulating 18932 data tables of equivalent size on the basis of a normal distribution).

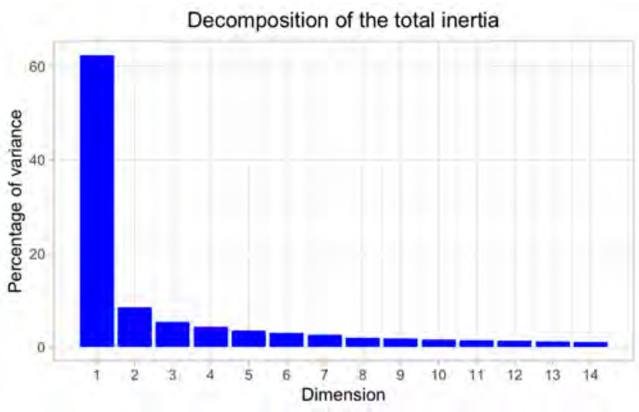

Figure 1.8

Figure 1.8 - Decomposition of the total inertia *The first factor is major: it expresses itself 62.33% of the data variability. Note that in such a case, the variability related to the other components might be meaningless, despite of a high percentage.*

An estimation of the right number of axis to interpret suggests to restrict the analysis to the description of the first 1 axis. These axis present an amount of inertia greater than those obtained by the 0.95-quantile of random distributions (62.33% against 12.34%). This observation suggests that only this axis is carrying real information. As a consequence, the description will stand to these axis.

---

3. Description of the dimension 1

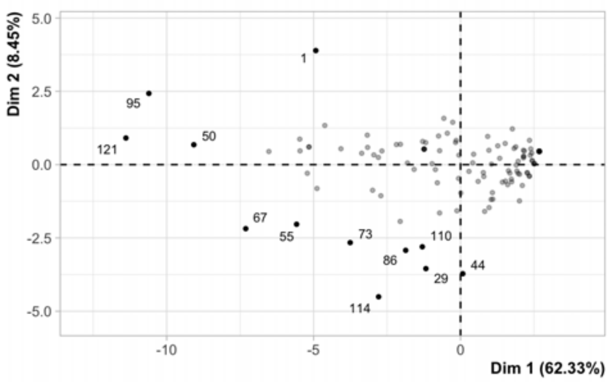

Figure 1.9: Enter Caption

Figure 1.9 - Individuals factor map (PCA) *The labeled individuals are those with the higher contribution to the plane construction.*

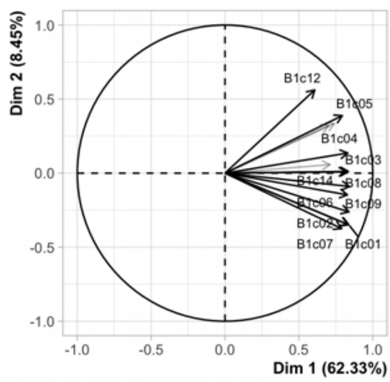

Figure 1.10: Enter Caption

Figure 1.10 - Variables factor map (PCA) *The labeled variables are those the best shown on the plane.*

The **dimension 1** opposes individuals characterized by a strongly positive coordinate on the axis (to the right of the graph) to individuals such as *50*, *95*, *121*, *67*, *114*, *73*, *1*, *55*, *110* and *86* (to the left of the graph, characterized by a strongly negative coordinate on the axis).

The group 1 (characterized by a positive coordinate on the axis) is sharing :

- high values for variables like *B1c04*, *B1c05*, *B1c03*, *B1c08*, *B1c13*, *B1c09*, *B1c11*, *B1c06*, *B1c14* and *B1c10* (variables are sorted from the strongest).

The group in which the individuals *50*, *95*, *121* and *67* stand (characterized by a negative coordinate on the axis) is sharing :

- low values for variables like *B1c03*, *B1c14*, *B1c02*, *B1c07*, *B1c06*, *B1c04*, *B1c09*, *B1c11*, *B1c08* and *B1c13* (variables are sorted from the weakest).

The group in which the individuals *114*, *73*, *1*, *55*, *110* and *86* stand (characterized by a negative coordinate on the axis) is sharing :

- low values for variables like *B1c05*, *B1c10*, *B1c04*, *B1c13*, *B1c08*, *B1c09*, *B1c12*, *B1c11*, *B1c01* and *B1c03* (variables are sorted from the weakest).

---

4. Classification

Figure 4 - Ascending Hierarchical Classification of the individuals. *The classification made on individuals reveals 3 clusters.*

The **cluster 1** is made of individuals such as *1*, *50*, *55*, *67*, *95* and *121*. This group is characterized by :

- low values for variables like *B1c07*, *B1c01*, *B1c02*, *B1c06*, *B1c08*, *B1c09*, *B1c04*, *B1c14*, *B1c03* and *B1c05* (variables are sorted from the weakest).

The **cluster 2** is made of individuals such as *29*, *44*, *73*, *86*, *110* and *114*. This group is characterized by :

- low values for variables like *B1c11*, *B1c03*, *B1c05*, *B1c09*, *B1c08*, *B1c04*, *B1c13*, *B1c14*, *B1c10* and *B1c12* (variables are sorted from the weakest).

The **cluster 3** is made of individuals sharing :

- high values for variables like *B1c09*, *B1c03*, *B1c05*, *B1c08*, *B1c11*, *B1c04*, *B1c14*, *B1c01*, *B1c02* and *B1c06* (variables are sorted from the strongest).

1.16 Secondary School Children's Critical Skills Principal Component Analysis

Dataset B2_secondary This dataset contains 133 individuals and 12 variables.

---

1. Study of the outliers

The analysis of the graphs does not detect any outlier.

---

2. Inertia distribution

The first two dimensions of analyse express **66.43%** of the total dataset inertia ; that means that 66.43% of the individuals (or variables) cloud total variability is explained by the plane. This percentage is relatively high and thus the first plane well represents the data variability. This value is strongly greater than the reference value that equals **25.69%**, the variability explained by this plane is thus highly significant (the reference value is the 0.95-quantile of the inertia percentages distribution obtained by simulating 22250 data tables of equivalent size on the basis of a normal distribution).

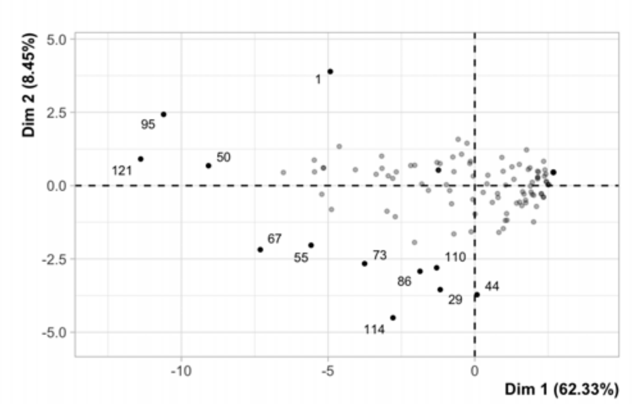

Figure 1.11

Figure 1.11 - Decomposition of the total inertia *The first factor is major: it expresses itself 59.61% of the data variability. Note that in such a case, the variability related to the other components might be meaningless, despite of a high percentage.*

An estimation of the right number of axis to interpret suggests to restrict the analysis to the description of the first 1 axis. These axis present an amount of inertia greater than those obtained by the 0.95-quantile of random distributions (59.61% against 13.82%). This observation suggests that only this axis is carrying real information. As a consequence, the description will stand to these axis.

---

3. Description of the dimension 1

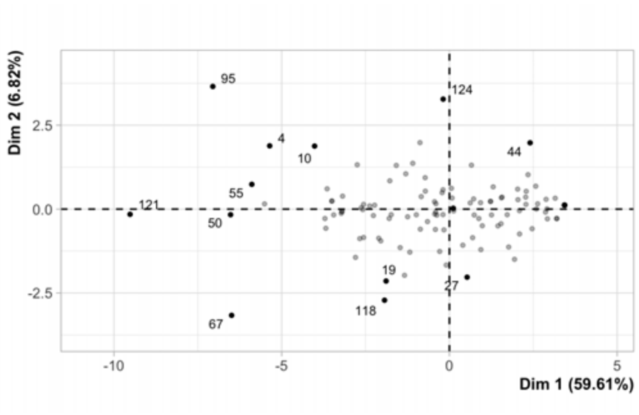

Figure 1.12: Enter Caption

Figure 1.12 - Individuals factor map (PCA) *The labeled individuals are those with the higher contribution to the plane construction.*

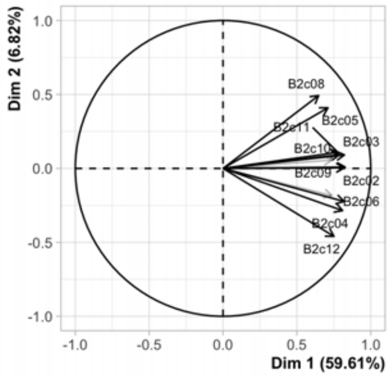

Figure 1.13: Enter Caption

Figure 1.13 - Variables factor map (PCA) *The labeled variables are those the best shown on the plane.*

The **dimension 1** opposes individuals characterized by a strongly positive coordinate on the axis (to the right of the graph) to individuals such as *50*, *121*, *67*, *95*, *55*, *19*, *4* and *118* (to the left of the graph, characterized by a strongly negative coordinate on the axis).

The group 1 (characterized by a positive coordinate on the axis) is sharing :

- high values for variables like *B2c10*, *B2c11*, *B2c02*, *B2c06*, *B2c05*, *B2c03*, *B2c09*, *B2c04*, *B2c01* and *B2c08* (variables are sorted from the strongest).

The group in which the individuals *50*, *121*, *67*, *95*, *55* and *4* stand (characterized by a negative coordinate on the axis) is sharing :

- low values for variables like *B2c09*, *B2c02*, *B2c06*, *B2c03*, *B2c04*, *B2c01*, *B2c12*, *B2c07*, *B2c10* and *B2c11* (variables are sorted from the weakest).

The group in which the individuals *19* and *118* stand (characterized by a negative coordinate on the axis) is sharing :

- low values for variables like *B2c05*, *B2c11*, *B2c10*, *B2c08*, *B2c07*, *B2c06*, *B2c02*, *B2c04*, *B2c03* and *B2c01* (variables are sorted from the weakest).

---

4. Classification

Figure 4 - Ascending Hierarchical Classification of the individuals. *The classification made on individuals reveals 3 clusters.*

The **cluster 1** is made of individuals such as *4*, *10*, *19*, *50*, *55*, *67*, *95*, *118* and *121*. This group is characterized by :

- low values for variables like *B2c02*, *B2c11*, *B2c10*, *B2c05*, *B2c03*, *B2c09*, *B2c06*, *B2c04*, *B2c12* and *B2c01* (variables are sorted from the weakest).

The **cluster 2** is made of individuals such as *27* and *124*. This group is characterized by :

- low values for the variables *B2c08* and *B2c07* (variables are sorted from the weakest).

The **cluster 3** is made of individuals such as *44*. This group is characterized by :

- high values for variables like *B2c04*, *B2c07*, *B2c10*, *B2c08*, *B2c03*, *B2c01*, *B2c09*, *B2c06*, *B2c02* and *B2c12* (variables are sorted from the strongest).

1.17 Primary School Children's Functional Skills Principal Component Analysis

Dataset B1_primary This dataset contains 159 individuals and 9 variables.

---

1. Study of the outliers

The analysis of the graphs does not detect any outlier.

---

2. Inertia distribution

The first two dimensions of analyse express **71.87%** of the total dataset inertia ; that means that 71.87% of the individuals (or variables) cloud total variability is explained by the plane. This percentage is high and thus the first plane represents an important part of the data variability. This value is strongly greater than the reference value that equals **30.93%**, the variability explained by this plane is thus highly significant (the reference value is the 0.95-quantile of the inertia percentages distribution obtained by simulating 22587 data tables of equivalent size on the basis of a normal distribution).

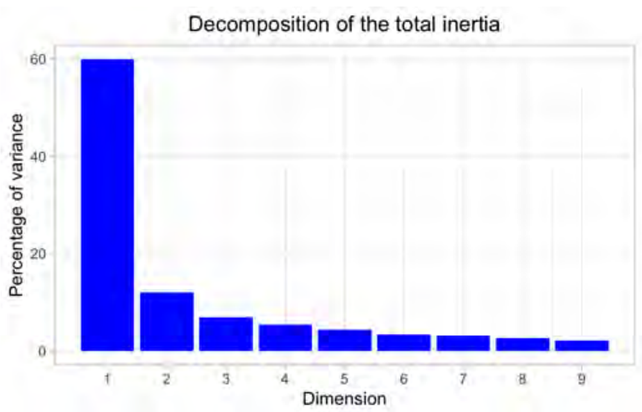

Figure 1.14

Figure 1.14 - Decomposition of the total inertia *The first factor is major: it expresses itself 59.89% of the data variability. Note that in such a case, the variability related to the other components might be meaningless, despite of a high percentage.* An estimation of the right number of axis to interpret suggests to restrict the analysis to the description of the first 1 axis. These axis present an amount of inertia greater than those obtained by the 0.95-quantile of random distributions (59.89% against 16.64%). This observation suggests that only this axis is carrying real information. As a consequence, the description will stand to these axis.

---

3. Description of the dimension 1

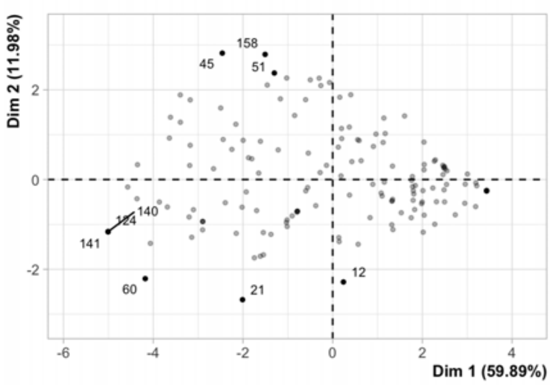

Figure 1.15: Enter Caption

Figure 1.15 - Individuals factor map (PCA) *The labeled individuals are those with the higher contribution to the plane construction.*

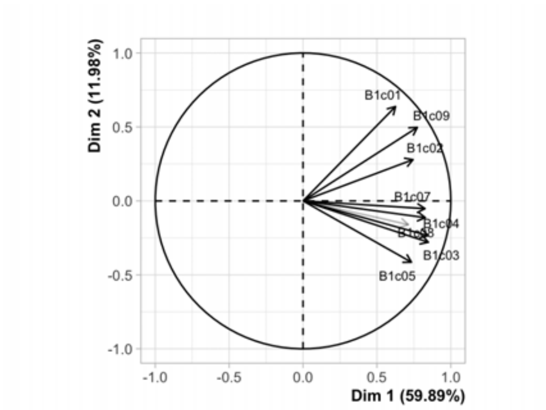

Figure 1.16: Enter Caption

Figure 1.16 - Variables factor map (PCA) *The labeled variables are those the best shown on the plane.*

The **dimension 1** opposes individuals characterized by a strongly positive coordinate on the axis (to the right of the graph) to individuals such as *124*, *140*, *141*, *45*, *60*, *21*, *51* and *158* (to the left of the graph, characterized by a strongly negative coordinate on the axis).
The group 1 (characterized by a positive coordinate on the axis) is sharing :

- high values for the variables *B1c03*, *B1c04*, *B1c06*, *B1c08*, *B1c05*, *B1c07*, *B1c02*, *B1c09* and *B1c01* (variables are sorted from the strongest).

The group in which the individuals *124*, *140*, *141*, *60* and *21* stand (characterized by a negative coordinate on the axis) is sharing :

- low values for the variables *B1c09*, *B1c01*, *B1c02*, *B1c08*, *B1c06*, *B1c07*, *B1c03*, *B1c04* and *B1c05* (variables are sorted from the weakest).

The group in which the individuals *45*, *51* and *158* stand (characterized by a negative coordinate on the axis) is sharing :

- high values for the variable *B1c01*.
- low values for the variables *B1c05*, *B1c03*, *B1c04*, *B1c06*, *B1c07* and *B1c08* (variables are sorted from the weakest).

---

4. Classification

Figure 4 - Ascending Hierarchical Classification of the individuals. *The classification made on individuals reveals 3 clusters.*
The **cluster 1** is made of individuals such as *21*, *45*, *60*, *124*, *140* and *141*. This group is characterized by :

- low values for the variables *B1c09*, *B1c07*, *B1c08*, *B1c04*, *B1c03*, *B1c02*, *B1c01*, *B1c06* and *B1c05* (variables are sorted from the weakest).

The **cluster 2** is made of individuals such as *12*, *51* and *158*. This group is characterized by :

- high values for the variable *B1c09*.
- low values for the variable *B1c05*.

The **cluster 3** is made of individuals sharing :

- high values for the variables *B1c05*, *B1c03*, *B1c04*, *B1c08*, *B1c07*, *B1c06*, *B1c09*, *B1c02* and *B1c01* (variables are sorted from the strongest).

1.18 Primary School Children's Skills Principal Component Analysis

Dataset B2_primary This dataset contains 159 individuals and 10 variables.

---

1. Study of the outliers

The analysis of the graphs does not detect any outlier.

---

2. Inertia distribution

The first two dimensions of analyse express **78.66%** of the total dataset inertia; that means that 78.66% of the individuals (or variables) cloud total variability is explained by the plane. This percentage is high and thus the first plane represents an important part of the data variability. This value is strongly greater than the reference value that equals **28.55%**, the variability explained by this plane is thus highly significant (the reference value is the 0.95-quantile of the inertia percentages distribution obtained by simulating 20157 data tables of equivalent size on the basis of a normal distribution).

From these observations, it is probably not useful to interpret the next dimensions. From these observations, it should be better to also interpret the dimensions greater or equal to the third one.

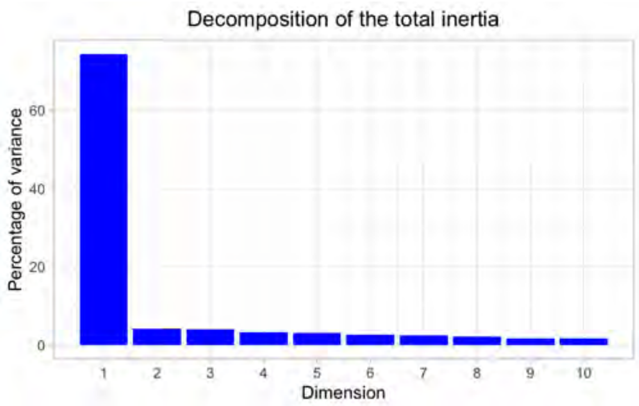

Figure 1.17

Figure 1.17 - Decomposition of the total inertia *The first factor is major: it expresses itself 74.41% of the data variability. Note that in such a case, the variability related to the other components might be meaningless, despite of a high percentage.*

An estimation of the right number of axis to interpret suggests to restrict the analysis to the description of the first 1 axis. These axis present an amount of inertia greater than those obtained by the 0.95-quantile of random distributions (74.41% against 15.31%). This observation suggests that only this axis is carrying real information. As a consequence, the description will stand to these axis.

---

3. Description of the dimension 1

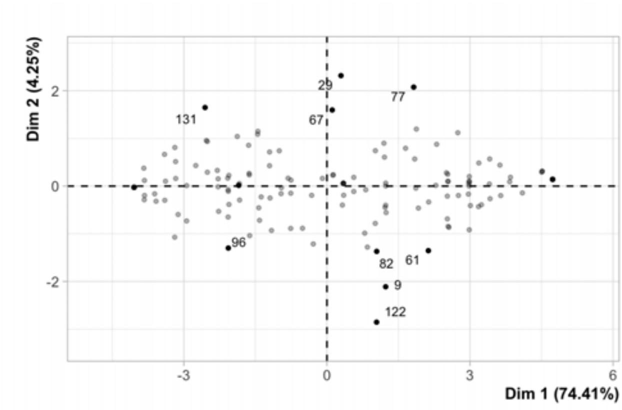

Figure 1.18: Enter Caption

Figure 1.18 - Individuals factor map (PCA) *The labeled individuals are those with the higher contribution to the plane construction.*

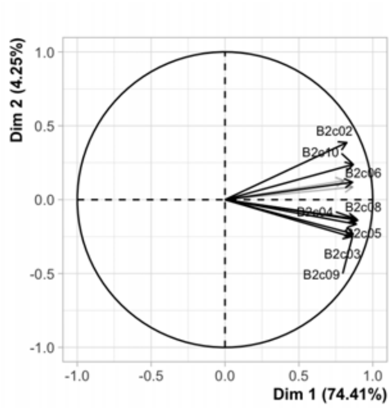

Figure 1.19: Enter Caption

Figure 1.19 - Variables factor map (PCA) *The labeled variables are those the best shown on the plane.*

The **dimension 1** opposes individuals characterized by a strongly positive coordinate on the axis (to the right of the graph) to individuals such as *96* (to the left of the graph, characterized by a strongly negative coordinate on the axis).

The group 1 (characterized by a positive coordinate on the axis) is sharing :

- high values for the variables *B2c04*, *B2c08*, *B2c05*, *B2c01*, *B2c06*, *B2c03*, *B2c02*, *B2c09*, *B2c10* and *B2c07* (variables are sorted from the strongest).

The group 2 (characterized by a negative coordinate on the axis) is sharing :

- low values for the variables *B2c01*, *B2c04*, *B2c08*, *B2c09*, *B2c10*, *B2c05*, *B2c03*, *B2c02*, *B2c06* and *B2c07* (variables are sorted from the weakest).

The group in which the individual *96* stands (characterized by a negative coordinate on the axis) is sharing :

- low values for the variables *B2c07*, *B2c06*, *B2c05*, *B2c02*, *B2c03*, *B2c08*, *B2c04*, *B2c01*, *B2c10* and *B2c09* (variables are sorted from the weakest).

---

4. Classification

Figure 4 - Ascending Hierarchical Classification of the individuals. *The classification made on individuals reveals 3 clusters.*

The **cluster 1** is made of individuals such as *96* and *131*. This group is characterized by :

- low values for the variables *B2c05*, *B2c08*, *B2c06*, *B2c04*, *B2c03*, *B2c10*, *B2c09*, *B2c01*, *B2c02* and *B2c07* (variables are sorted from the weakest).

The **cluster 2** is made of individuals such as *9*, *29*, *67*, *77*, *82* and *122*. This group is characterized by :

- high values for the variable *B2c05*.

The **cluster 3** is made of individuals such as *61*. This group is characterized by :

- high values for the variables *B2c08*, *B2c09*, *B2c04*, *B2c03*, *B2c01*, *B2c02*, *B2c06*, *B2c05*, *B2c10* and *B2c07* (variables are sorted from the strongest).

Minimum Digital Living Standard: For Households With Children: Survey Report Appendices

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March 2024

Contents

Chapter 2

Appendix 2

2.1 Devices and services

2.1.1 Large Screen Device

	Pct
Not adequate LSD	10.90
Adequate LSD	89.10

Table 2.1: Data table

2.1.2 Broadband

	Pct
Not adequate BB	8.70
Adequate BB	91.30

Table 2.2: Data table

2.1.3 Internet speed

	Pct
Not adequate BB speed	21.90
Adequate BB speed	78.10

Table 2.3: Data table

2.1.4 Data Package

	Pct
Not adequate data	9.70
Adequate data	90.30

Table 2.4: Data table

2.1.5 Games Console

	Pct
Not adequate GC	10.90
Adequate GC	89.10

Table 2.5: Data table

2.1.6 Games Service

	Pct
Not adequate GS	66.40
Adequate GS	33.60

Table 2.6: Data table

2.1.7 Smart Speaker

	Pct
Not adequate SS	45.00
Adequate sS	55.00

Table 2.7: Data table

2.1.8 Smart TV

	Pct
Not adequate STV	7.40
Adequate STV	92.60

Table 2.8: Data table

2.1.9 Smart Phone

	Pct
Not adequate SM	6.20
Adequate SM	93.80

Table 2.9: Data table

2.1.10 TV Service

	Pct
Not adequate TVS	18.30
Adequate TVS	81.70

Table 2.10: Data table

2.1.11 MDLS equipment totals

	Pct
1	0.20
2	0.90
3	1.30
4	2.30
5	4.40
6	6.90
7	14.00
8	26.40
9	28.60
10	15.00

Table 2.11: Data table

2.1.12 MDLS equipment totals (no SS or GC)

	Pct
1	0.20
2	1.00
3	1.40
4	2.90
5	5.40
6	13.00
7	25.60
8	50.40

Table 2.12: Data table

2.1.13 MDLS equipment (no smart speaker or full games service)

	Pct
Not MDLS adequate	49.60
MDLS adequate	50.40

Table 2.13: Data table

2.1.14 How we get to this figure

Those households with adequate smartphone access

	Pct
Not MDLS adequate	6.20
MDLS adequate	93.80

Table 2.14: Data table

Those households in table 2.14 with adequate smartphone data package

	Pct
Not MDLS adequate	15.60
MDLS adequate	84.40

Table 2.15: Data table

Those households in table 2.15 with broadband access

	Pct
Not MDLS adequate	22.10
MDLS adequate	77.90

Table 2.16: Data table

Those households in table 2.16 with adequate TV service

	Pct
Not MDLS adequate	33.60
MDLS adequate	66.40

Table 2.17: Data table

Those households in table 2.17 with adequate broadband speed

	Pct
Not MDLS adequate	42.40
MDLS adequate	57.60

Table 2.18: Data table

Those households in table 2.18 with adequate large screen devices

	Pct
Not MDLS adequate	46.60
MDLS adequate	53.40

Table 2.19: Data table

Those households in table 2.19 with adequate smart TV

	Pct
Not MDLS adequate	46.60
MDLS adequate	53.40

Table 2.20: Data table

Those households in table 2.20 with access to gaming

	Pct
Not MDLS adequate	49.60
MDLS adequate	50.40

Table 2.21: Data table

Those households in table 2.21 with access to gaming service

	Pct
Not MDLS adequate	80.80
MDLS adequate	19.20

Table 2.22: Data table

Those households in table 2.22 with access to smart speaker

	Pct
Not MDLS adequate	85.00
MDLS adequate	15.00

Table 2.23: Data table

2.2 Skills

2.2.1 Adults with parental responsibilites - Functional skills

	Pct
Not adequate Functional	25.10
Adequate Functional	74.90

Table 2.24: Data table

	Pct
Not adequate Functional	21.50
Adequate Functional	78.50

Table 2.25: Data table

	Pct
Not adequate Functional	17.30
Adequate Functional	82.70

Table 2.26: Data table

2.2.2 Secondary school children - Functional skills

	Pct
Not adequate Functional	20.70
Adequate Functional	79.30

Table 2.27: Data table

2.2.3 Primary school children - Functional skills

	Pct
Not adequate Functional	43.90
Adequate Functional	56.10

Table 2.28: Data table

2.2.4 Adults with parental responsibilities - Critical skills

	Pct
Not adequate Critical	37.30
Adequate Critical	62.70

Table 2.29: Data table

	Pct
Not adequate Critical	30.10
Adequate Critical	69.90

Table 2.30: Data table

	Pct
Not adequate Critical	27.20
Adequate Critical	72.80

Table 2.31: Data table

2.2.5 Secondary school children - Critical skills

	Pct
Not adequate Critical	26.00
Adequate Critical	74.00

Table 2.32: Data table

2.2.6 Primary school children - Functional skills

	Pct
Not adequate Critical	50.10
Adequate Critical	49.90

Table 2.33: Data table

2.2.7 Overall skills

	Pct
Not adequate Skills	65.30
Adequate Functional Skills	11.60
Adequate Critical Skills	3.30
Adequate Total Skills	19.80

Table 2.34: Data table

2.2.8 OVerall household skills

	Pct
Not adequate Skills	4.40
Children Have Adequate Skills	27.30
Parents Have Adequate Skills	7.20
Household Has Adequate Skills	61.10

Table 2.35: Data table

2.3 Categorising households

2.3.1 Simple (Absolute) MDLS Equipment cutoff

	Pct
Not MDLS adequate	49.60
MDLS adequate	50.40

Table 2.36: Data table

2.3.2 Grouped MDLS equipment using Latent Class Analysis

	NoClasses	ll	df	BIC	AIC	ll ratio	Chi	entValue
1	2.00	-4042.77	238.00	8210.78	8119.55	598.22	860.39	0.75
2	3.00	-3886.64	229.00	7964.81	7825.28	285.95	381.36	0.87
3	4.00	-3836.86	220.00	7931.55	7743.72	186.39	246.50	0.81
4	5.00	-3801.15	211.00	7926.43	7690.31	114.97	123.03	0.77
5	6.00	-3787.78	202.00	7965.98	7681.56	88.23	95.53	0.81
6	7.00	-3779.14	193.00	8015.00	7682.28	70.95	76.59	0.70
7	8.00	-3776.23	184.00	8075.48	7694.46	65.13	70.56	0.63

Table 2.37: Data table

MDLS LCA Graphs

MDLS LCA Proportions

	Pct
Fully MDLS	81.50
Partial MDLS – poor broadband via 4G/5G	6.00
Partial MDLS – lacks smart TV access	4.80
Partial MDLS – lacks enough devices (large screen / gaming)	4.20
Significantly below MDLS	3.50

Table 2.38: Data table

2.3.3 Combining MDLS abs Equipment and Skills

	Pct
Not MDLS adequate	64.20
MDLS adequate	35.80

Table 2.39: Data table

2.3.4 Combinging MDLS LCA Equipment and Skills

	Pct
Not MDLS adequate	46.70
MDLS adequate	53.30

Table 2.40: Data table

2.4 Analyses and comparisons

Note: in all the following χ^2 analyses effect sizes are labelled following Funder's (2019) recommendations and $p-values$ were simulated based on 2000 replicates.

2.4.1 SEGfactorbyLCA

The Pearson's Chi-squared test with simulated p-value of independence between variables suggests that the effect is statistically significant and small ($chi^2 = 112.98, p < .001; Adjusted Cramer'sv = 0.15, 95\% CI[0.11, 1.00]$). The following tables 2.42, 2.41, and 2.43 provide detals of the observations, column and row percentages. Figures 2.1 and 2.2 present plots of residuals and contributions. Figure 2.3 presents the data in stacked proprtions.

	Fully MDLS	Part MDLS: poor BB	Part MDLS: No STV	Part MDLS: Low Dev	Sig below MDLS
AB (col.)	22.60	9.50	14.50	11.90	3.60
C1 (col.)	32.70	18.90	27.60	19.40	12.70
C2 (col.)	23.00	25.30	26.30	20.90	14.50
DE (col.)	21.60	46.30	31.60	47.80	69.10

Table 2.41: SEG factor by LCA (Column Percentages) (χ^2(NA, 1582) = 112.976, p = 0, Cramer's V = 0.154)

	Fully MDLS	Part MDLS: poor BB	Part MDLS: No STV	Part MDLS: Low Dev	Sig below MDLS
AB (row)	90.70	2.80	3.40	2.50	0.60
C1 (row)	87.70	3.70	4.40	2.70	1.50
C2 (row)	81.80	6.60	5.50	3.90	2.20
DE (row)	66.90	10.60	5.80	7.70	9.10

Table 2.42: SEG factor by LCA (Row Percentages) (χ^2(NA, 1582) = 112.976, p = 0, Cramer's V = 0.154)

	Fully MDLS	Part MDLS: poor BB	Part MDLS: No STV	Part MDLS: Low Dev	Sig below MDLS
AB (obs.)	291.00	9.00	11.00	8.00	2.00
AB (row)	90.70	2.80	3.40	2.50	0.60
AB (col.)	22.60	9.50	14.50	11.90	3.60
C1 (obs.)	422.00	18.00	21.00	13.00	7.00
C1 (row)	87.70	3.70	4.40	2.70	1.50
C1 (col.)	32.70	18.90	27.60	19.40	12.70
C2 (obs.)	297.00	24.00	20.00	14.00	8.00
C2 (row)	81.80	6.60	5.50	3.90	2.20
C2 (col.)	23.00	25.30	26.30	20.90	14.50
DE (obs.)	279.00	44.00	24.00	32.00	38.00
DE (row)	66.90	10.60	5.80	7.70	9.10
DE (col.)	21.60	46.30	31.60	47.80	69.10

Table 2.43: SEG factor by LCA (χ^2(NA, 1582) = 112.976, p = 0, Cramer's V = 0.154)

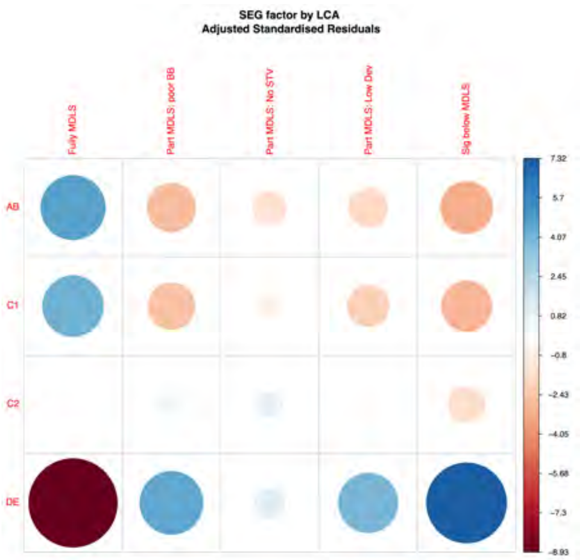

Figure 2.1: Res. Cont. plots-1

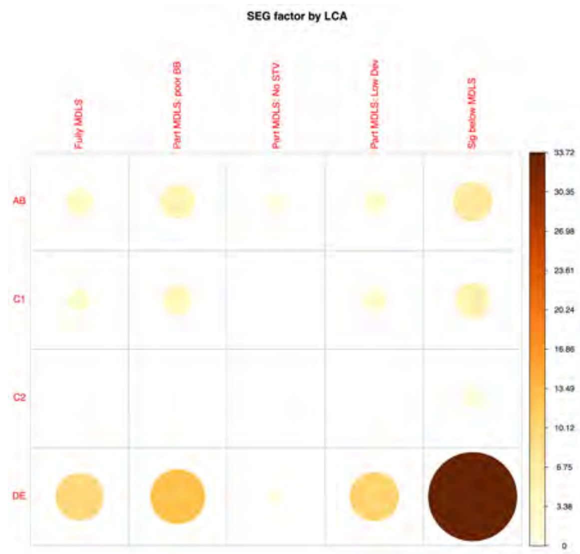

Figure 2.2: Res. Cont. plots-2

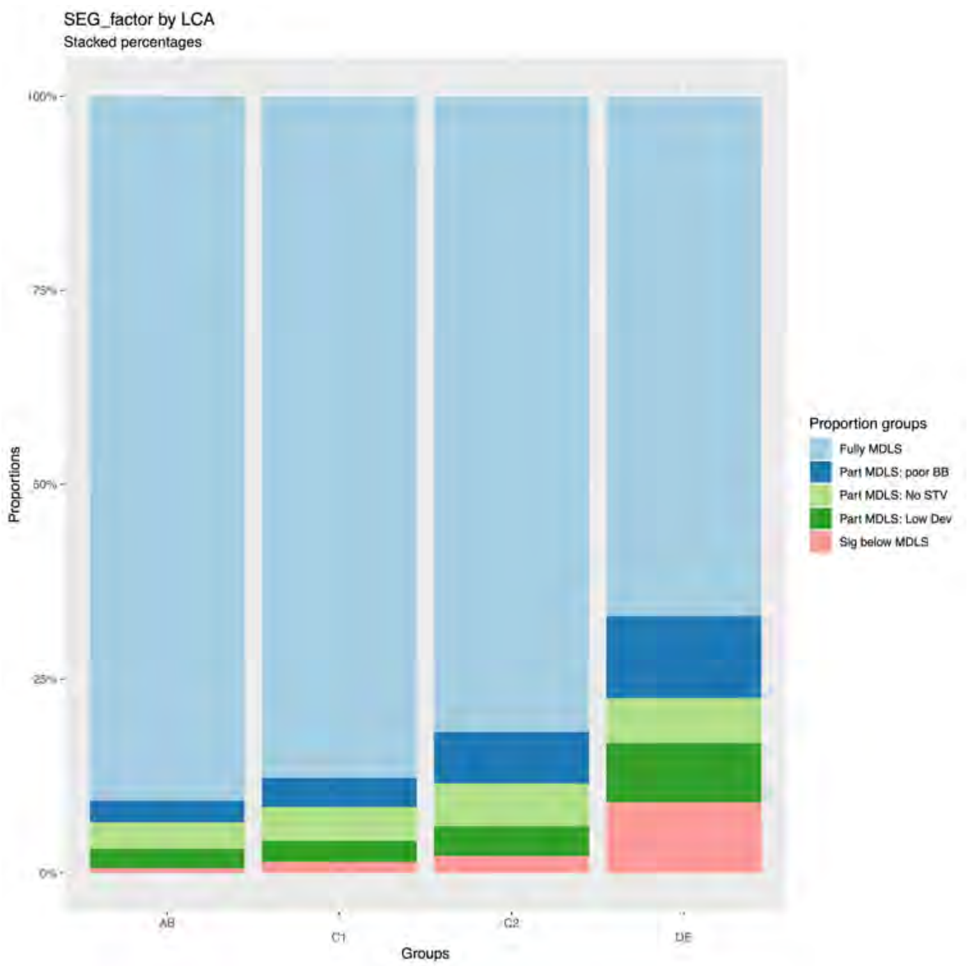

Figure 2.3: Proportions plot-1

2.4.2 HTYPEfactorbyLCA

The Pearson's Chi-squared test with simulated p-value of independence between variables suggests that the effect is statistically significant and small ($chi^2 = 128.17, p < .001; AdjustedCramer'sv = 0.12, 95\%CI[0.07, 1.00]$). The following tables 2.45, 2.44, and 2.46 provide detals of the observations, column and row percentages. Figures 2.4 and 2.5 present plots of residuals and contributions. Figure 2.6 presents the data in stacked proprtions.

	Fully MDLS	Part MDLS: poor BB	Part MDLS: No STV	Part MDLS: Low Dev	Sig below MDLS
1 adult and 1 child (col.)	13.20	27.40	21.10	10.40	40.00
1 adult and 2 children (col.)	7.20	14.70	11.80	13.40	20.00
1 adult and more than 2 children (col.)	3.20	4.20	3.90	14.90	3.60
2 adults and 1 child (col.)	28.60	22.10	22.40	9.00	20.00
2 adults and 2 children (col.)	29.50	22.10	19.70	23.90	10.90
2 adults and more than 2 children (col.)	8.90	3.20	13.20	20.90	5.50
More than 2 adults in HH and 1 child (col.)	4.70	4.20	5.30	3.00	0.00
More than 2 adults in HH and 2 children (col.)	3.60	2.10	2.60	1.50	0.00
More than 2 adults in HH and 2+ children (col.)	1.20	0.00	0.00	3.00	0.00

Table 2.44: HTYPE factor by LCA (Column Percentages) (χ^2(NA, 1582) = 128.166, p = 0, Cramer's V = 0.142)

	Fully MDLS	Part MDLS: poor BB	Part MDLS: No STV	Part MDLS: Low Dev	Sig below MDLS
1 adult and 1 child (row)	70.50	10.80	6.60	2.90	9.10
1 adult and 2 children (row)	68.40	10.30	6.60	6.60	8.10
1 adult and more than 2 children (row)	68.30	6.70	5.00	16.70	3.30
2 adults and 1 child (row)	87.00	5.00	4.00	1.40	2.60
2 adults and 2 children (row)	86.80	4.80	3.40	3.70	1.40
2 adults and more than 2 children (row)	79.30	2.10	6.90	9.70	2.10
More than 2 adults in HH and 1 child (row)	85.70	5.70	5.70	2.90	0.00
More than 2 adults in HH and 2 children (row)	90.20	3.90	3.90	2.00	0.00
More than 2 adults in HH and 2+ children (row)	88.20	0.00	0.00	11.80	0.00

Table 2.45: HTYPE factor by LCA (Row Percentages) (χ^2(NA, 1582) = 128.166, p = 0, Cramer's V = 0.142)

	Fully MDLS	Part MDLS: poor BB	Part MDLS: No STV	Part MDLS: Low Dev	Sig below MDLS
1 adult and 1 child (obs.)	170.00	26.00	16.00	7.00	22.00
1 adult and 1 child (row)	70.50	10.80	6.60	2.90	9.10
1 adult and 1 child (col.)	13.20	27.40	21.10	10.40	40.00
1 adult and 2 children (obs.)	93.00	14.00	9.00	9.00	11.00
1 adult and 2 children (row)	68.40	10.30	6.60	6.60	8.10
1 adult and 2 children (col.)	7.20	14.70	11.80	13.40	20.00
1 adult and more than 2 children (obs.)	41.00	4.00	3.00	10.00	2.00
1 adult and more than 2 children (row)	68.30	6.70	5.00	16.70	3.30
1 adult and more than 2 children (col.)	3.20	4.20	3.90	14.90	3.60
2 adults and 1 child (obs.)	369.00	21.00	17.00	6.00	11.00
2 adults and 1 child (row)	87.00	5.00	4.00	1.40	2.60
2 adults and 1 child (col.)	28.60	22.10	22.40	9.00	20.00
2 adults and 2 children (obs.)	380.00	21.00	15.00	16.00	6.00
2 adults and 2 children (row)	86.80	4.80	3.40	3.70	1.40
2 adults and 2 children (col.)	29.50	22.10	19.70	23.90	10.90
2 adults and more than 2 children (obs.)	115.00	3.00	10.00	14.00	3.00
2 adults and more than 2 children (row)	79.30	2.10	6.90	9.70	2.10
2 adults and more than 2 children (col.)	8.90	3.20	13.20	20.90	5.50
More than 2 adults in HH and 1 child (obs.)	60.00	4.00	4.00	2.00	0.00
More than 2 adults in HH and 1 child (row)	85.70	5.70	5.70	2.90	0.00
More than 2 adults in HH and 1 child (col.)	4.70	4.20	5.30	3.00	0.00
More than 2 adults in HH and 2 children (obs.)	46.00	2.00	2.00	1.00	0.00
More than 2 adults in HH and 2 children (row)	90.20	3.90	3.90	2.00	0.00
More than 2 adults in HH and 2 children (col.)	3.60	2.10	2.60	1.50	0.00
More than 2 adults in HH and 2+ children (obs.)	15.00	0.00	0.00	2.00	0.00
More than 2 adults in HH and 2+ children (row)	88.20	0.00	0.00	11.80	0.00
More than 2 adults in HH and 2+ children (col.)	1.20	0.00	0.00	3.00	0.00

Table 2.46: HTYPE factor by LCA (χ^2(NA, 1582) = 128.166, p = 0, Cramer's V = 0.142)

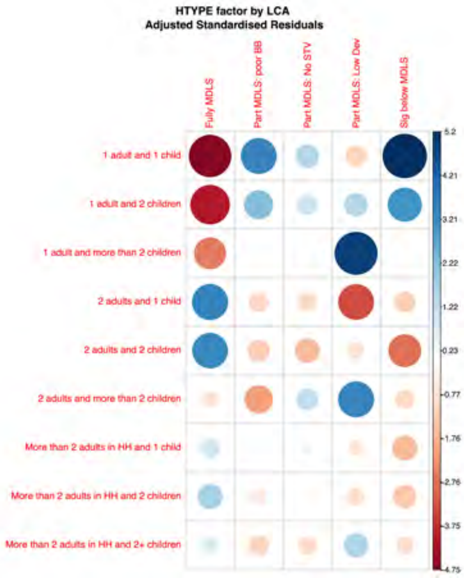

Figure 2.4: Res. Cont. plots-3

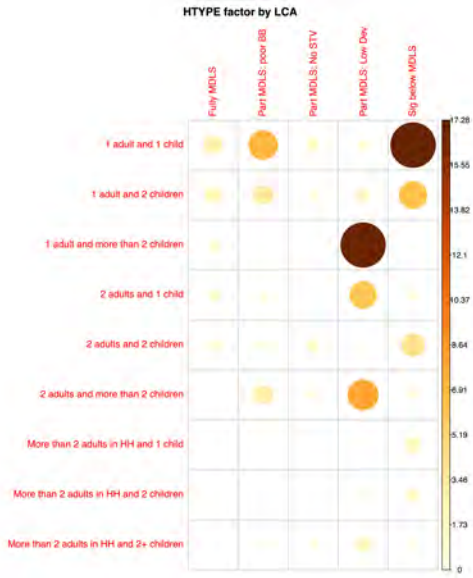

Figure 2.5: Res. Cont. plots-4

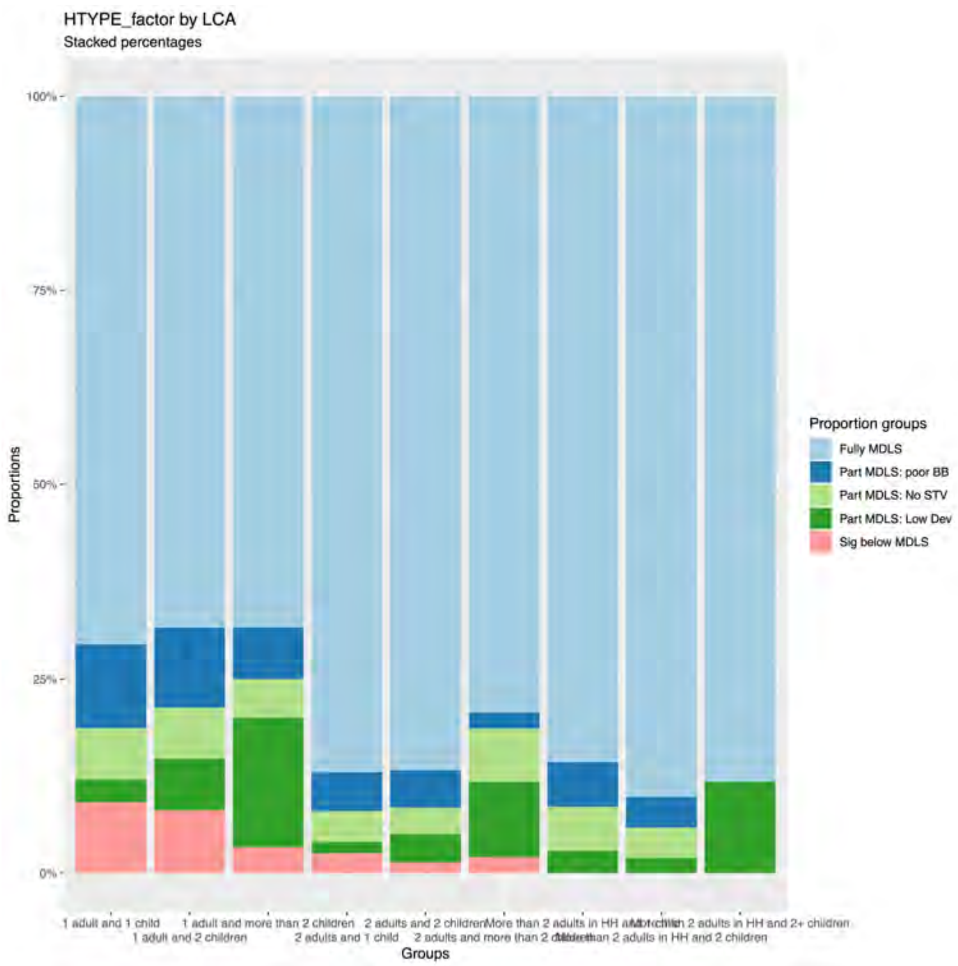

Figure 2.6: Proportions plot-2

2.4.3 REGIONfactorbyLCA

The Pearson's Chi-squared test with simulated p-value of independence between variables suggests that the effect is statistically significant and small ($chi^2 = 145.79, p < .001; Adjusted Cramer'sv = 0.13, 95\% CI [0.06, 1.00]$).. The following tables 2.48, 2.47, and 2.49 provide detals of the observations, column and row percentages. Figures 2.7 and 2.8 present plots of residuals and contributions. Figure 2.9 presents the data in stacked proprtions.

	Fully MDLS	Part MDLS: poor BB	Part MDLS: No STV	Part MDLS: Low Dev	Sig below MDLS
North East (col.)	3.10	10.50	2.60	1.50	9.10
North West (col.)	9.20	13.70	6.60	16.40	16.40
Yorkshire and The Humber (col.)	7.90	5.30	7.90	11.90	20.00
East Midlands (col.)	6.60	5.30	2.60	11.90	3.60
West Midlands (col.)	9.90	8.40	2.60	7.50	5.50
East of England (col.)	8.80	6.30	13.20	10.40	0.00
London (col.)	13.50	6.30	43.40	11.90	12.70
South East (col.)	14.70	9.50	9.20	10.40	5.50
South West (col.)	7.90	9.50	2.60	4.50	7.30
Wales (col.)	5.10	2.10	1.30	4.50	14.50
Northern Ireland (col.)	4.30	8.40	2.60	6.00	0.00
Scotland (col.)	9.10	14.70	5.30	3.00	5.50

Table 2.47: REGION factor by LCA (Column Percentages) (χ^2(NA, 1582) = 145.787, p = 0, Cramer's V = 0.152)

	Fully MDLS	Part MDLS: poor BB	Part MDLS: No STV	Part MDLS: Low Dev	Sig below MDLS
North East (row)	69.00	17.20	3.40	1.70	8.60
North West (row)	75.60	8.30	3.20	7.10	5.80
Yorkshire and The Humber (row)	77.30	3.80	4.50	6.10	8.30
East Midlands (row)	83.30	4.90	2.00	7.80	2.00
West Midlands (row)	87.60	5.50	1.40	3.40	2.10
East of England (row)	83.10	4.40	7.40	5.10	0.00
London (row)	76.30	2.60	14.50	3.50	3.10
South East (row)	87.90	4.20	3.30	3.30	1.40
South West (row)	85.00	7.50	1.70	2.50	3.30
Wales (row)	82.50	2.50	1.20	3.80	10.00
Northern Ireland (row)	80.00	11.40	2.90	5.70	0.00
Scotland (row)	83.60	10.00	2.90	1.40	2.10

Table 2.48: REGION factor by LCA (Row Percentages) (χ^2(NA, 1582) = 145.787, p = 0, Cramer's V = 0.152)

	Fully MDLS	Part MDLS: poor BB	Part MDLS: No STV	Part MDLS: Low Dev	Sig below MDLS
North East (obs.)	40.00	10.00	2.00	1.00	5.00
North East (row)	69.00	17.20	3.40	1.70	8.60
North East (col.)	3.10	10.50	2.60	1.50	9.10
North West (obs.)	118.00	13.00	5.00	11.00	9.00
North West (row)	75.60	8.30	3.20	7.10	5.80
North West (col.)	9.20	13.70	6.60	16.40	16.40
Yorkshire and The Humber (obs.)	102.00	5.00	6.00	8.00	11.00
Yorkshire and The Humber (row)	77.30	3.80	4.50	6.10	8.30
Yorkshire and The Humber (col.)	7.90	5.30	7.90	11.90	20.00
East Midlands (obs.)	85.00	5.00	2.00	8.00	2.00
East Midlands (row)	83.30	4.90	2.00	7.80	2.00
East Midlands (col.)	6.60	5.30	2.60	11.90	3.60
West Midlands (obs.)	127.00	8.00	2.00	5.00	3.00
West Midlands (row)	87.60	5.50	1.40	3.40	2.10
West Midlands (col.)	9.90	8.40	2.60	7.50	5.50
East of England (obs.)	113.00	6.00	10.00	7.00	0.00
East of England (row)	83.10	4.40	7.40	5.10	0.00
East of England (col.)	8.80	6.30	13.20	10.40	0.00
London (obs.)	174.00	6.00	33.00	8.00	7.00
London (row)	76.30	2.60	14.50	3.50	3.10
London (col.)	13.50	6.30	43.40	11.90	12.70
South East (obs.)	189.00	9.00	7.00	7.00	3.00
South East (row)	87.90	4.20	3.30	3.30	1.40
South East (col.)	14.70	9.50	9.20	10.40	5.50
South West (obs.)	102.00	9.00	2.00	3.00	4.00
South West (row)	85.00	7.50	1.70	2.50	3.30
South West (col.)	7.90	9.50	2.60	4.50	7.30
Wales (obs.)	66.00	2.00	1.00	3.00	8.00
Wales (row)	82.50	2.50	1.20	3.80	10.00
Wales (col.)	5.10	2.10	1.30	4.50	14.50
Northern Ireland (obs.)	56.00	8.00	2.00	4.00	0.00
Northern Ireland (row)	80.00	11.40	2.90	5.70	0.00
Northern Ireland (col.)	4.30	8.40	2.60	6.00	0.00
Scotland (obs.)	117.00	14.00	4.00	2.00	3.00
Scotland (row)	83.60	10.00	2.90	1.40	2.10
Scotland (col.)	9.10	14.70	5.30	3.00	5.50

Table 2.49: REGION factor by LCA (χ^2(NA, 1582) = 145.787, p = 0, Cramer's V = 0.152)

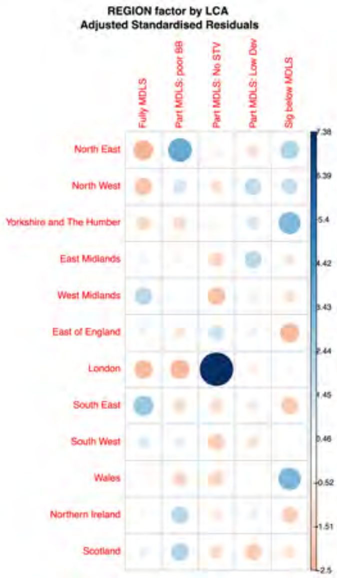

Figure 2.7: Res. Cont. plots-5

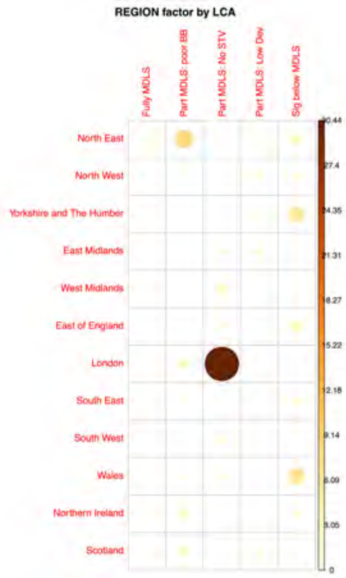

Figure 2.8: Res. Cont. plots-6

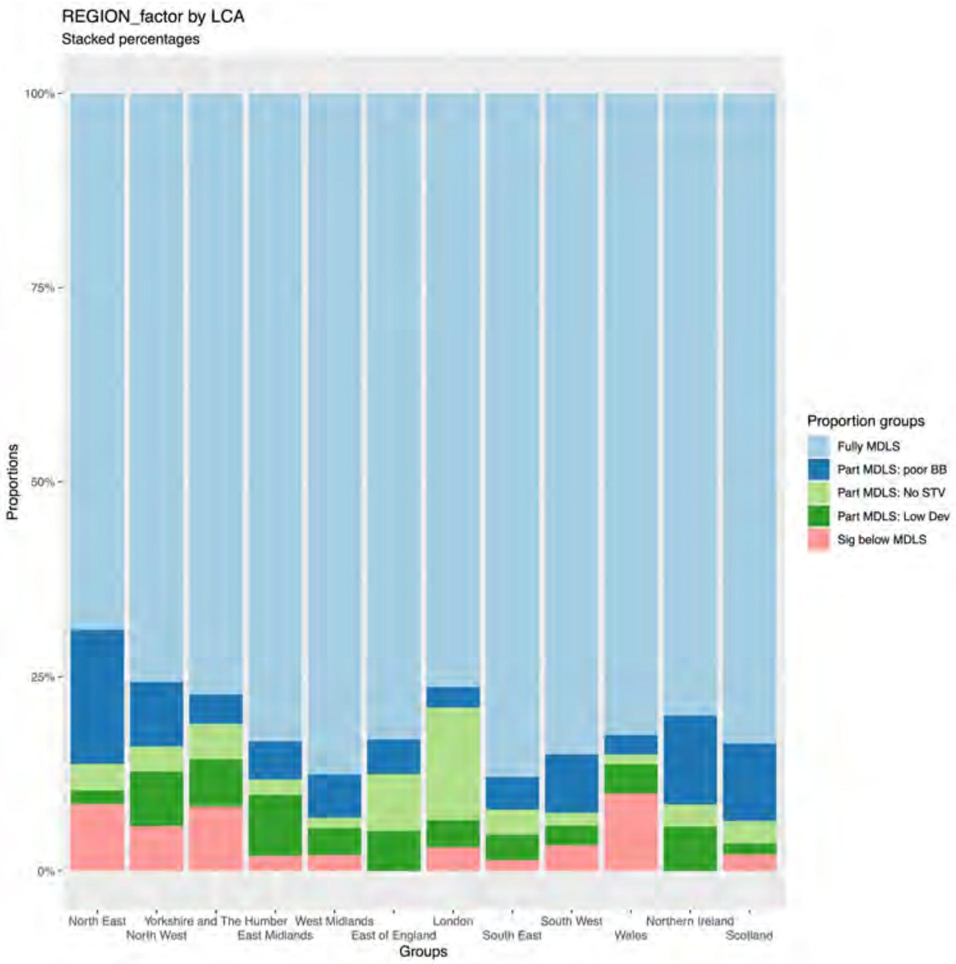

Figure 2.9: Proportions plot-3

2.4.4 OverallhouseholdskillsfactorbyLCA

The Pearson's Chi-squared test with simulated p-value of independence between variables suggests that the effect is statistically significant and small ($chi^2 = 106.35, p < .001; AdjustedCramer'sv = 0.14, 95\%CI[0.11, 1.00]$). The following tables 2.51, 2.50, and 2.52 provide detals of the observations, column and row percentages. Figures 2.10 and 2.11 present plots of residuals and contributions. Figure 2.12 presents the data in stacked proprtions.

	Fully MDLS	Part MDLS: poor BB	Part MDLS: No STV	Part MDLS: Low Dev	Sig below MDLS
Not adequate Skills (col.)	4.00	4.20	5.30	10.40	5.50
Children Have Adequate Skills (col.)	22.80	48.40	43.40	31.30	69.10
Parents Have Adequate Skills (col.)	7.80	3.20	3.90	10.40	1.80
Household Has Adequate Skills (col.)	65.40	44.20	47.40	47.80	23.60

Table 2.50: Overall household skills factor by LCA (Column Percentages) (χ^2(NA, 1582) = 106.352, p = 0, Cramer's V = 0.15)

	Fully MDLS	Part MDLS: poor BB	Part MDLS: No STV	Part MDLS: Low Dev	Sig below MDLS
Not adequate Skills (row)	74.30	5.70	5.70	10.00	4.30
Children Have Adequate Skills (row)	68.10	10.60	7.60	4.90	8.80
Parents Have Adequate Skills (row)	87.70	2.60	2.60	6.10	0.90
Household Has Adequate Skills (row)	87.30	4.30	3.70	3.30	1.30

Table 2.51: Overall household skills factor by LCA (Row Percentages) (χ^2(NA, 1582) = 106.352, p = 0, Cramer's V = 0.15)

	Fully MDLS	Part MDLS: poor BB	Part MDLS: No STV	Part MDLS: Low Dev	Sig below MDLS
Not adequate Skills (obs.)	52.00	4.00	4.00	7.00	3.00
Not adequate Skills (row)	74.30	5.70	5.70	10.00	4.30
Not adequate Skills (col.)	4.00	4.20	5.30	10.40	5.50
Children Have Adequate Skills (obs.)	294.00	46.00	33.00	21.00	38.00
Children Have Adequate Skills (row)	68.10	10.60	7.60	4.90	8.80
Children Have Adequate Skills (col.)	22.80	48.40	43.40	31.30	69.10
Parents Have Adequate Skills (obs.)	100.00	3.00	3.00	7.00	1.00
Parents Have Adequate Skills (row)	87.70	2.60	2.60	6.10	0.90
Parents Have Adequate Skills (col.)	7.80	3.20	3.90	10.40	1.80
Household Has Adequate Skills (obs.)	843.00	42.00	36.00	32.00	13.00
Household Has Adequate Skills (row)	87.30	4.30	3.70	3.30	1.30
Household Has Adequate Skills (col.)	65.40	44.20	47.40	47.80	23.60

Table 2.52: Overall household skills factor by LCA (χ^2(NA, 1582) = 106.352, p = 0, Cramer's V = 0.15)

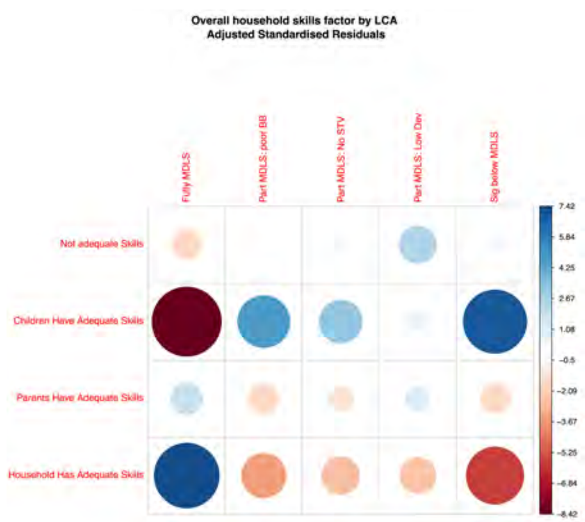

Figure 2.10: Res. Cont. plots-7

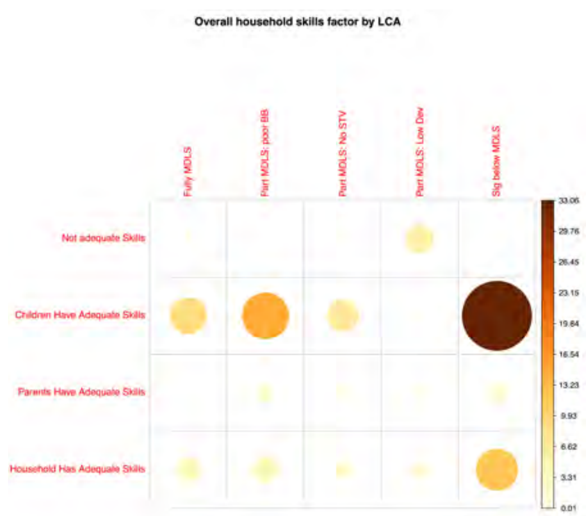

Figure 2.11: Res. Cont. plots-8

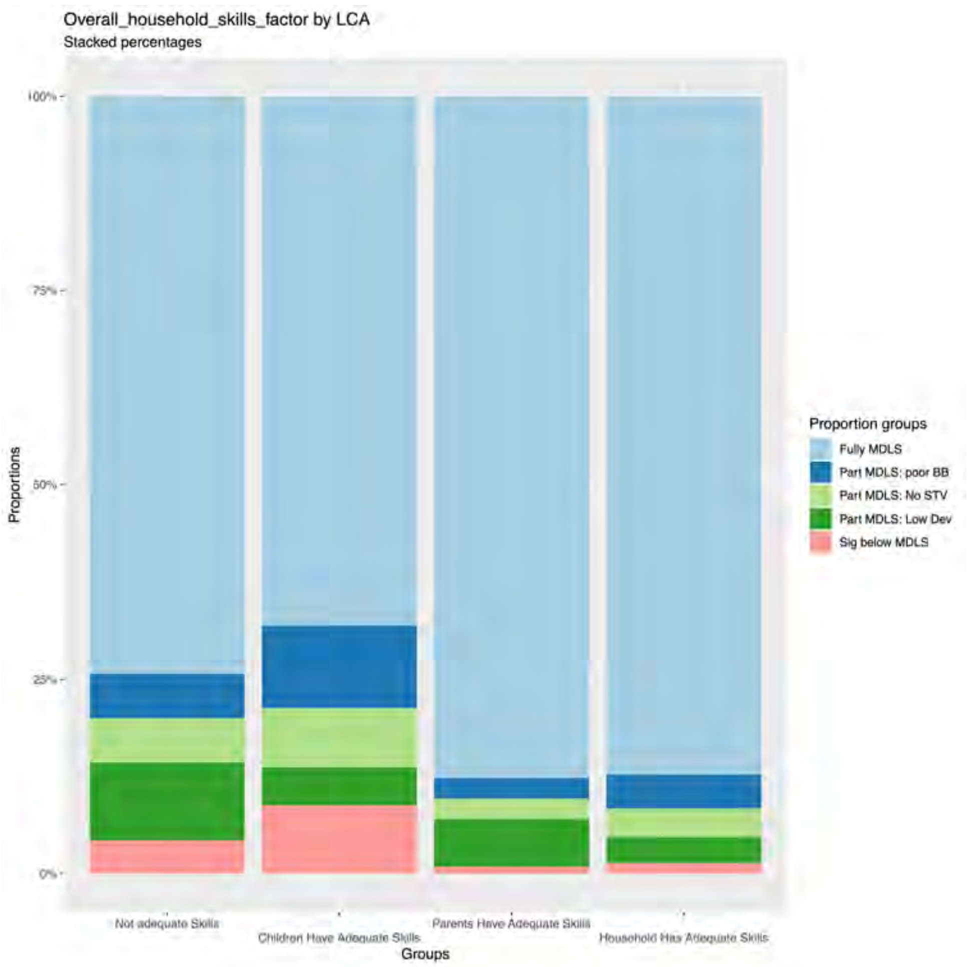

Figure 2.12: Proportions plot-4

2.4.5 BroadbandfactorbyLCA

The Pearson's Chi-squared test with simulated p-value of independence between variables suggests that the effect is statistically not significant and tiny ($chi^2 = 2.95, p = 0.563; AdjustedCramer'sv = 0.00, 95\% CI[0.00, 1.00]$). The following tables 2.54, 2.53, and 2.55 provide detals of the observations, column and row percentages. Figures 2.13 and 2.14 present plots of residuals and contributions. Figure 2.15 presents the data in stacked proprtions.

	Fully MDLS	Part MDLS: poor BB	Part MDLS: No STV	Part MDLS: Low Dev	Sig below MDLS
Below average broadband speed (col.)	42.20	50.50	42.10	38.80	43.60
Above average broadband speed (col.)	57.80	49.50	57.90	61.20	56.40

Table 2.53: Broadband factor by LCA (Column Percentages) (χ^2(NA, 1582) = 2.95, p = 0.563, Cramer's V = 0.043)

	Fully MDLS	Part MDLS: poor BB	Part MDLS: No STV	Part MDLS: Low Dev	Sig below MDLS
Below average broadband speed (row)	80.70	7.10	4.70	3.90	3.60
Above average broadband speed (row)	82.00	5.20	4.80	4.50	3.40

Table 2.54: Broadband factor by LCA (Row Percentages) (χ^2(NA, 1582) = 2.95, p = 0.563, Cramer's V = 0.043)

	Fully MDLS	Part MDLS: poor BB	Part MDLS: No STV	Part MDLS: Low Dev	Sig below MDLS
Below average broadband speed (obs.)	544.00	48.00	32.00	26.00	24.00
Below average broadband speed (row)	80.70	7.10	4.70	3.90	3.60
Below average broadband speed (col.)	42.20	50.50	42.10	38.80	43.60
Above average broadband speed (obs.)	745.00	47.00	44.00	41.00	31.00
Above average broadband speed (row)	82.00	5.20	4.80	4.50	3.40
Above average broadband speed (col.)	57.80	49.50	57.90	61.20	56.40

Table 2.55: Broadband factor by LCA (χ^2(NA, 1582) = 2.95, p = 0.563, Cramer's V = 0.043)

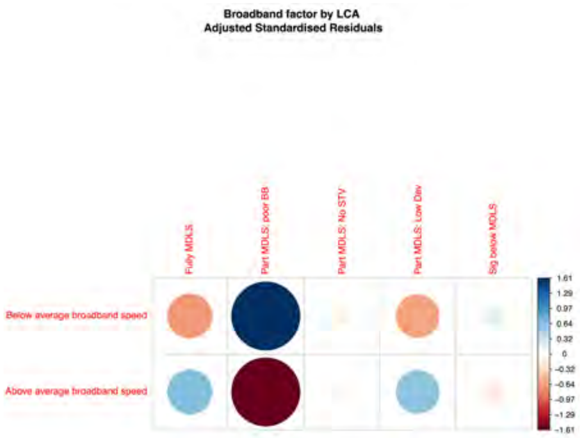

Figure 2.13: Res. Cont. plots-9

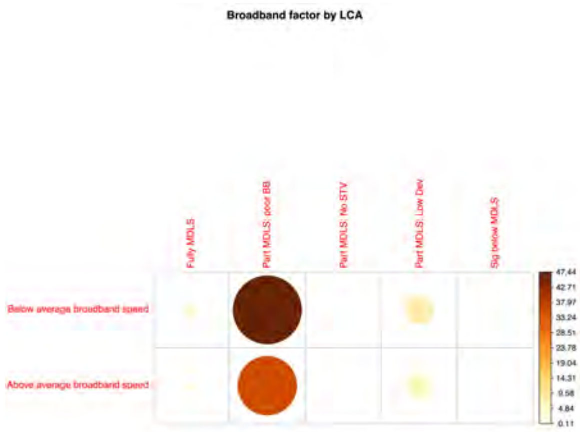

Figure 2.14: Res. Cont. plots-10

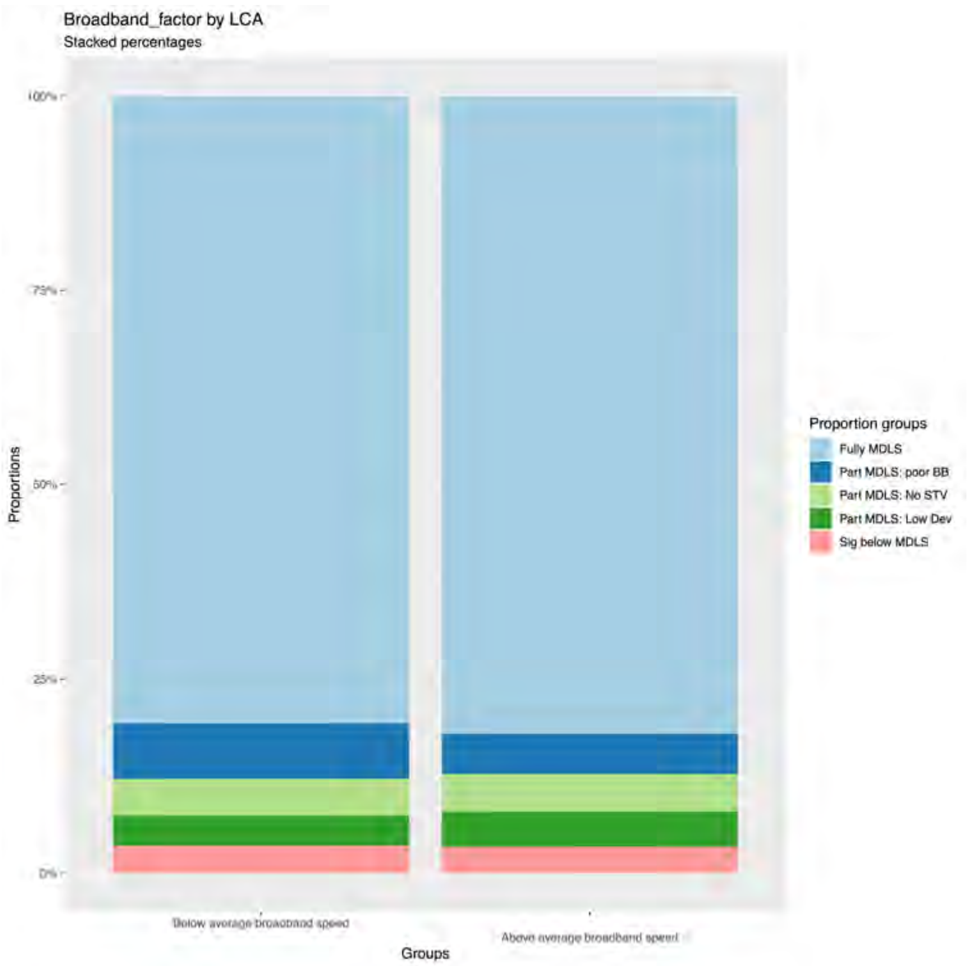

Figure 2.15: Proportions plot-5

2.4.6 URBANfactorbyLCA

The Pearson's Chi-squared test with simulated p-value of independence between variables suggests that the effect is statistically significant and very small ($chi^2 = 76.31, p < .001; Adjusted Cramer'sv = 0.10, 95\% CI[0.06, 1.00]$). The following tables 2.57, 2.56, and 2.58 provide detals of the observations, column and row percentages. Figures 2.16 and 2.17 present plots of residuals and contributions. Figure 2.18 presents the data in stacked proprtions.

	Fully MDLS	Part MDLS: poor BB	Part MDLS: No STV	Part MDLS: Low Dev	Sig below MDLS
Large city (col.)	15.30	9.50	44.70	14.90	16.40
Smaller city or large town (col.)	15.80	15.80	13.20	22.40	38.20
Medium town (col.)	36.60	34.70	19.70	29.90	29.10
Small town (col.)	20.00	22.10	17.10	19.40	10.90
Rural area (col.)	12.30	17.90	5.30	13.40	5.50

Table 2.56: URBAN factor by LCA (Column Percentages) (χ^2(NA, 1582) = 76.308, p = 0, Cramer's V = 0.11)

	Fully MDLS	Part MDLS: poor BB	Part MDLS: No STV	Part MDLS: Low Dev	Sig below MDLS
Large city (row)	76.10	3.50	13.10	3.90	3.50
Smaller city or large town (row)	77.00	5.70	3.80	5.70	7.90
Medium town (row)	84.90	5.90	2.70	3.60	2.90
Small town (row)	83.00	6.80	4.20	4.20	1.90
Rural area (row)	82.70	8.90	2.10	4.70	1.60

Table 2.57: URBAN factor by LCA (Row Percentages) (χ^2(NA, 1582) = 76.308, p = 0, Cramer's V = 0.11)

	Fully MDLS	Part MDLS: poor BB	Part MDLS: No STV	Part MDLS: Low Dev	Sig below MDLS
Large city (obs.)	197.00	9.00	34.00	10.00	9.00
Large city (row)	76.10	3.50	13.10	3.90	3.50
Large city (col.)	15.30	9.50	44.70	14.90	16.40
Smaller city or large town (obs.)	204.00	15.00	10.00	15.00	21.00
Smaller city or large town (row)	77.00	5.70	3.80	5.70	7.90
Smaller city or large town (col.)	15.80	15.80	13.20	22.40	38.20
Medium town (obs.)	472.00	33.00	15.00	20.00	16.00
Medium town (row)	84.90	5.90	2.70	3.60	2.90
Medium town (col.)	36.60	34.70	19.70	29.90	29.10
Small town (obs.)	258.00	21.00	13.00	13.00	6.00
Small town (row)	83.00	6.80	4.20	4.20	1.90
Small town (col.)	20.00	22.10	17.10	19.40	10.90
Rural area (obs.)	158.00	17.00	4.00	9.00	3.00
Rural area (row)	82.70	8.90	2.10	4.70	1.60
Rural area (col.)	12.30	17.90	5.30	13.40	5.50

Table 2.58: URBAN factor by LCA (χ^2(NA, 1582) = 76.308, p = 0, Cramer's V = 0.11)

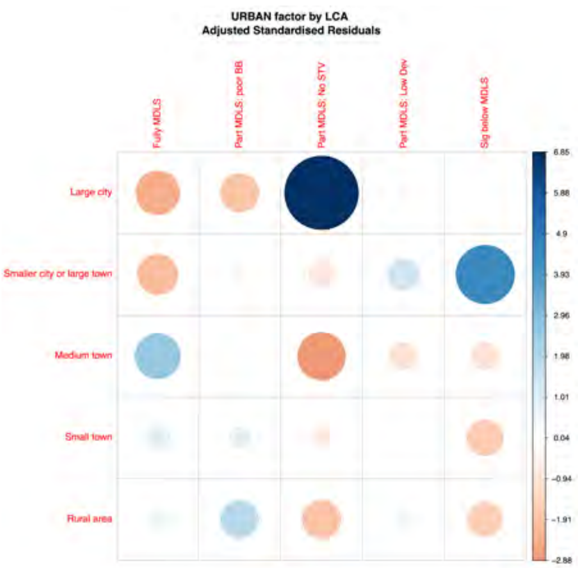

Figure 2.16: Res. Cont. plots-11

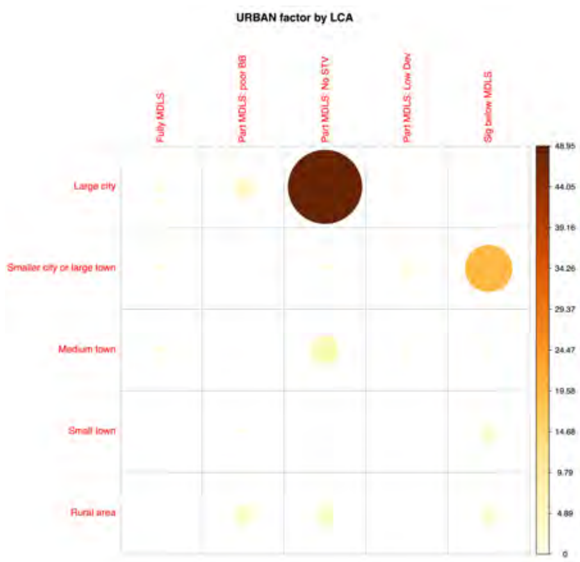

Figure 2.17: Res. Cont. plots-12

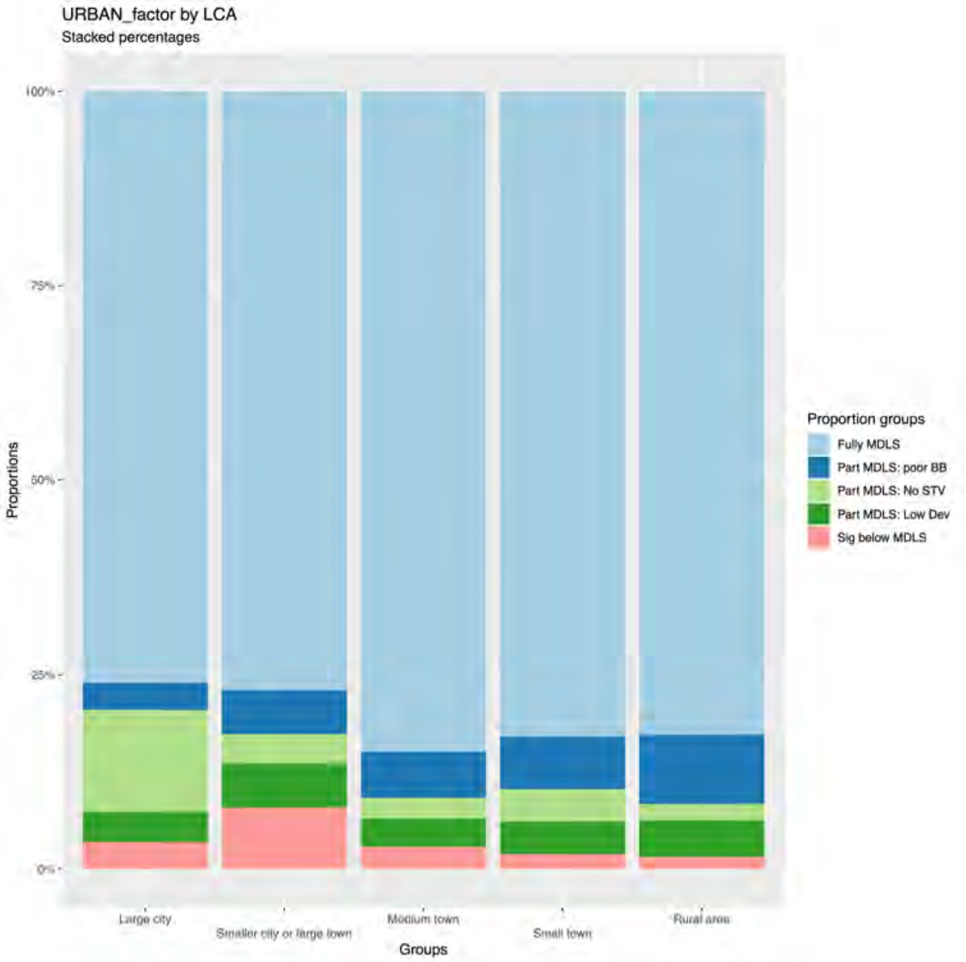

Figure 2.18: Proportions plot-6

2.4.7 URBAN2factorbyLCA

The Pearson's Chi-squared test with simulated p-value of independence between variables suggests that the effect is statistically not significant and very small ($chi^2 = 8.78, p = 0.068; AdjustedCramer'sv = 0.05, 95\%CI[0.00, 1.00]$). The following tables 2.60, 2.59, and 2.61 provide details of the observations, column and row percentages. Figures 2.19 and 2.20 present plots of residuals and contributions. Figure 2.21 presents the data in stacked proportions.

	Fully MDLS	Part MDLS: poor BB	Part MDLS: No STV	Part MDLS: Low Dev	Sig below MDLS
Urban (col.)	87.70	82.10	94.70	86.60	94.50
Rural (col.)	12.30	17.90	5.30	13.40	5.50

Table 2.59: URBAN2 factor by LCA (Column Percentages) (χ^2(NA, 1582) = 8.781, p = 0.068, Cramer's V = 0.074)

	Fully MDLS	Part MDLS: poor BB	Part MDLS: No STV	Part MDLS: Low Dev	Sig below MDLS
Urban (row)	81.30	5.60	5.20	4.20	3.70
Rural (row)	82.70	8.90	2.10	4.70	1.60

Table 2.60: URBAN2 factor by LCA (Row Percentages) (χ^2(NA, 1582) = 8.781, p = 0.068, Cramer's V = 0.074)

	Fully MDLS	Part MDLS: poor BB	Part MDLS: No STV	Part MDLS: Low Dev	Sig below MDLS
Urban (obs.)	1131.00	78.00	72.00	58.00	52.00
Urban (row)	81.30	5.60	5.20	4.20	3.70
Urban (col.)	87.70	82.10	94.70	86.60	94.50
Rural (obs.)	158.00	17.00	4.00	9.00	3.00
Rural (row)	82.70	8.90	2.10	4.70	1.60
Rural (col.)	12.30	17.90	5.30	13.40	5.50

Table 2.61: URBAN2 factor by LCA (χ^2(NA, 1582) = 8.781, p = 0.068, Cramer's V = 0.074)

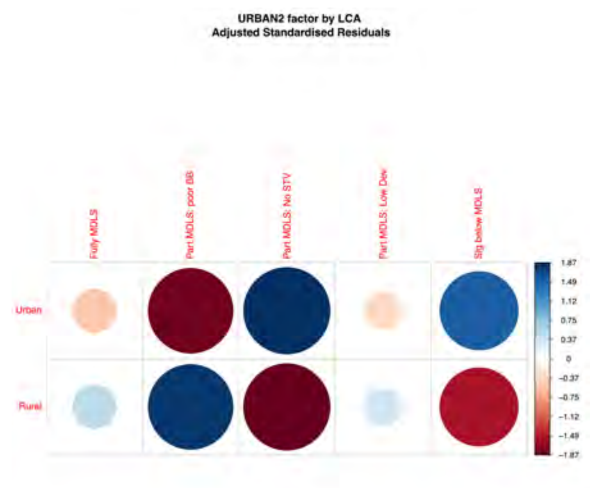

Figure 2.19: Res. Cont. plots-13

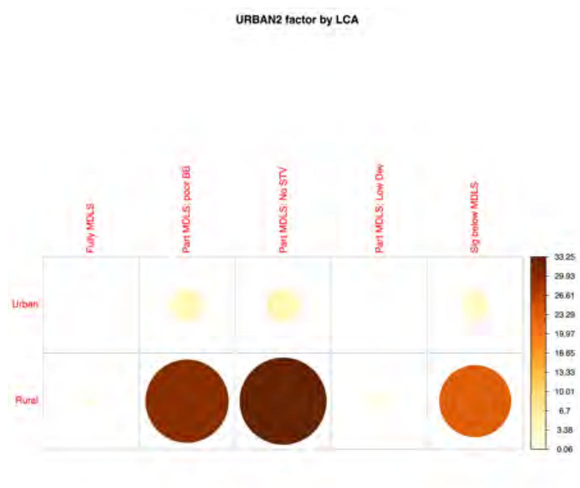

Figure 2.20: Res. Cont. plots-14

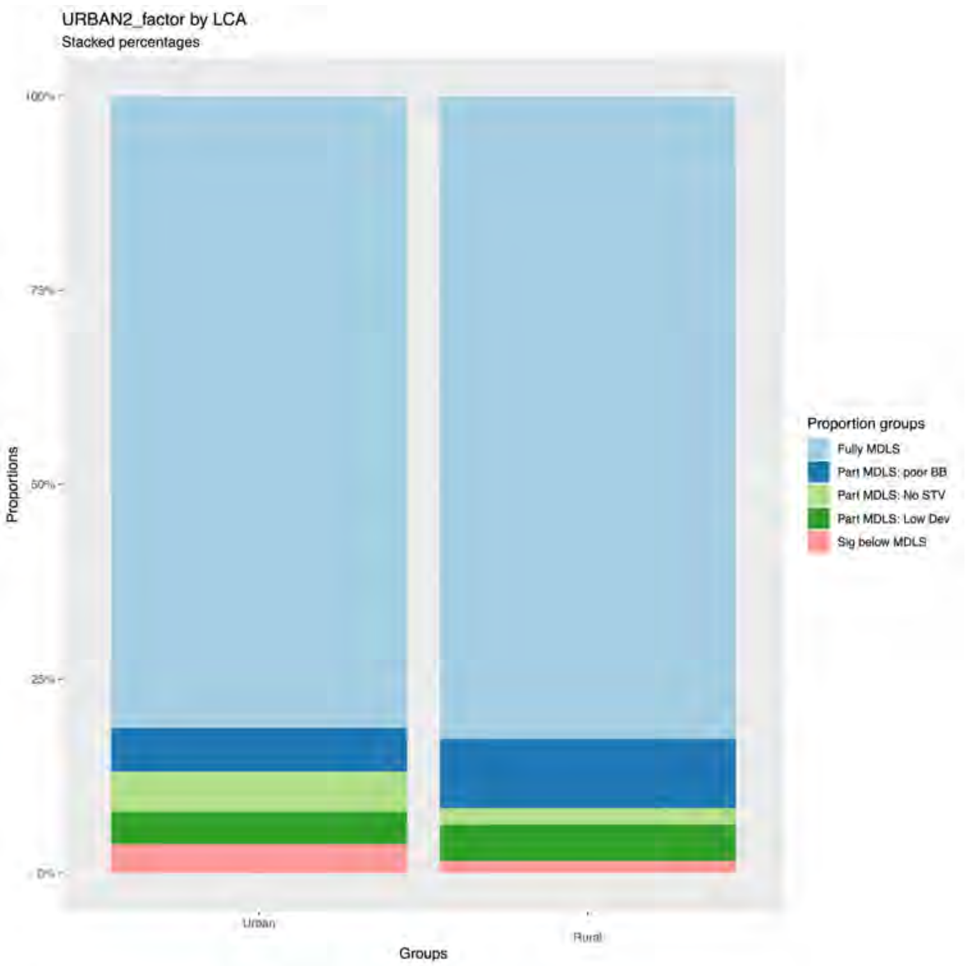

Figure 2.21: Proportions plot-7

2.4.8 iucGRPLBLrfactorbyLCA

The Pearson's Chi-squared test with simulated p-value of independence between variables suggests that the effect is statistically not significant and tiny ($chi^2 = 47.84, p = 0.096; Adjusted Cramer'sv = 0.04, 95\% CI[0.00, 1.00]$). The following tables 2.63, 2.62, and 2.64 provide details of the observations, column and row percentages. Figures 2.22 and 2.23 present plots of residuals and contributions. Figure 2.24 presents the data in stacked proportions.

	Fully MDLS	Part MDLS: poor BB	Part MDLS: No STV	Part MDLS: Low Dev	Sig below MDLS
Digital Seniors (col.)	10.10	10.60	5.50	3.20	9.30
e-Cultural Creators (col.)	0.20	0.00	0.00	0.00	0.00
e-Mainstream (col.)	14.40	16.50	11.00	19.00	11.10
e-Professionals (col.)	3.50	1.20	5.50	3.20	5.60
e-Rational Utilitarians (col.)	7.70	9.40	4.10	6.30	1.90
e-Veterans (col.)	14.00	4.70	11.00	11.10	5.60
e-Withdrawn (col.)	11.10	20.00	16.40	17.50	25.90
Passive and Uncommitted Users (col.)	26.60	30.60	28.80	30.20	29.60
Settled Offline Communities (col.)	6.10	4.70	5.50	1.60	3.70
Youthful Urban Fringe (col.)	6.20	2.40	12.30	7.90	7.40

Table 2.62: iuc GRP LBLr factor by LCA (Column Percentages) (χ^2(NA, 1491) = 47.842, p = 0.096, Cramer's V = 0.09)

	Fully MDLS	Part MDLS: poor BB	Part MDLS: No STV	Part MDLS: Low Dev	Sig below MDLS
Digital Seniors (row)	86.00	6.30	2.80	1.40	3.50
e-Cultural Creators (row)	100.00	0.00	0.00	0.00	0.00
e-Mainstream (row)	81.40	6.50	3.70	5.60	2.80
e-Professionals (row)	81.10	1.90	7.50	3.80	5.70
e-Rational Utilitarians (row)	85.50	7.30	2.70	3.60	0.90
e-Veterans (row)	88.50	2.10	4.20	3.60	1.60
e-Withdrawn (row)	71.40	9.00	6.30	5.80	7.40
Passive and Uncommitted Users (row)	79.80	6.40	5.20	4.70	4.00
Settled Offline Communities (row)	87.10	4.70	4.70	1.20	2.40
Youthful Urban Fringe (row)	79.20	2.10	9.40	5.20	4.20

Table 2.63: iuc GRP LBLr factor by LCA (Row Percentages) (χ^2(NA, 1491) = 47.842, p = 0.096, Cramer's V = 0.09)

	Fully MDLS	Part MDLS: poor BB	Part MDLS: No STV	Part MDLS: Low Dev	Sig below MDLS
Digital Seniors (obs.)	123.00	9.00	4.00	2.00	5.00
Digital Seniors (row)	86.00	6.30	2.80	1.40	3.50
Digital Seniors (col.)	10.10	10.60	5.50	3.20	9.30
e-Cultural Creators (obs.)	3.00	0.00	0.00	0.00	0.00
e-Cultural Creators (row)	100.00	0.00	0.00	0.00	0.00
e-Cultural Creators (col.)	0.20	0.00	0.00	0.00	0.00
e-Mainstream (obs.)	175.00	14.00	8.00	12.00	6.00
e-Mainstream (row)	81.40	6.50	3.70	5.60	2.80
e-Mainstream (col.)	14.40	16.50	11.00	19.00	11.10
e-Professionals (obs.)	43.00	1.00	4.00	2.00	3.00
e-Professionals (row)	81.10	1.90	7.50	3.80	5.70
e-Professionals (col.)	3.50	1.20	5.50	3.20	5.60
e-Rational Utilitarians (obs.)	94.00	8.00	3.00	4.00	1.00
e-Rational Utilitarians (row)	85.50	7.30	2.70	3.60	0.90
e-Rational Utilitarians (col.)	7.70	9.40	4.10	6.30	1.90
e-Veterans (obs.)	170.00	4.00	8.00	7.00	3.00
e-Veterans (row)	88.50	2.10	4.20	3.60	1.60
e-Veterans (col.)	14.00	4.70	11.00	11.10	5.60
e-Withdrawn (obs.)	135.00	17.00	12.00	11.00	14.00
e-Withdrawn (row)	71.40	9.00	6.30	5.80	7.40
e-Withdrawn (col.)	11.10	20.00	16.40	17.50	25.90
Passive and Uncommitted Users (obs.)	323.00	26.00	21.00	19.00	16.00
Passive and Uncommitted Users (row)	79.80	6.40	5.20	4.70	4.00
Passive and Uncommitted Users (col.)	26.60	30.60	28.80	30.20	29.60
Settled Offline Communities (obs.)	74.00	4.00	4.00	1.00	2.00
Settled Offline Communities (row)	87.10	4.70	4.70	1.20	2.40
Settled Offline Communities (col.)	6.10	4.70	5.50	1.60	3.70
Youthful Urban Fringe (obs.)	76.00	2.00	9.00	5.00	4.00
Youthful Urban Fringe (row)	79.20	2.10	9.40	5.20	4.20
Youthful Urban Fringe (col.)	6.20	2.40	12.30	7.90	7.40

Table 2.64: iuc GRP LBLr factor by LCA (χ^2(NA, 1491) = 47.842, p = 0.096, Cramer's V = 0.09)

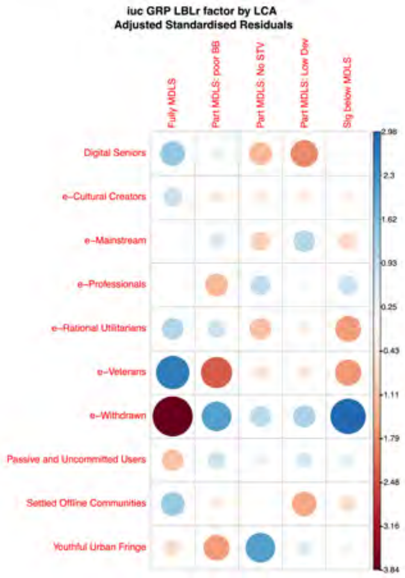

Figure 2.22: Res. Cont. plots-15

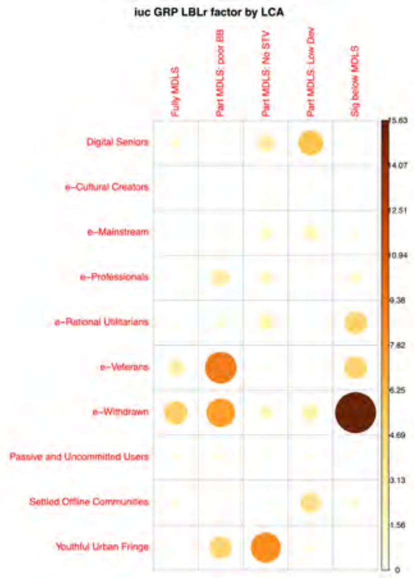

Figure 2.23: Res. Cont. plots-16

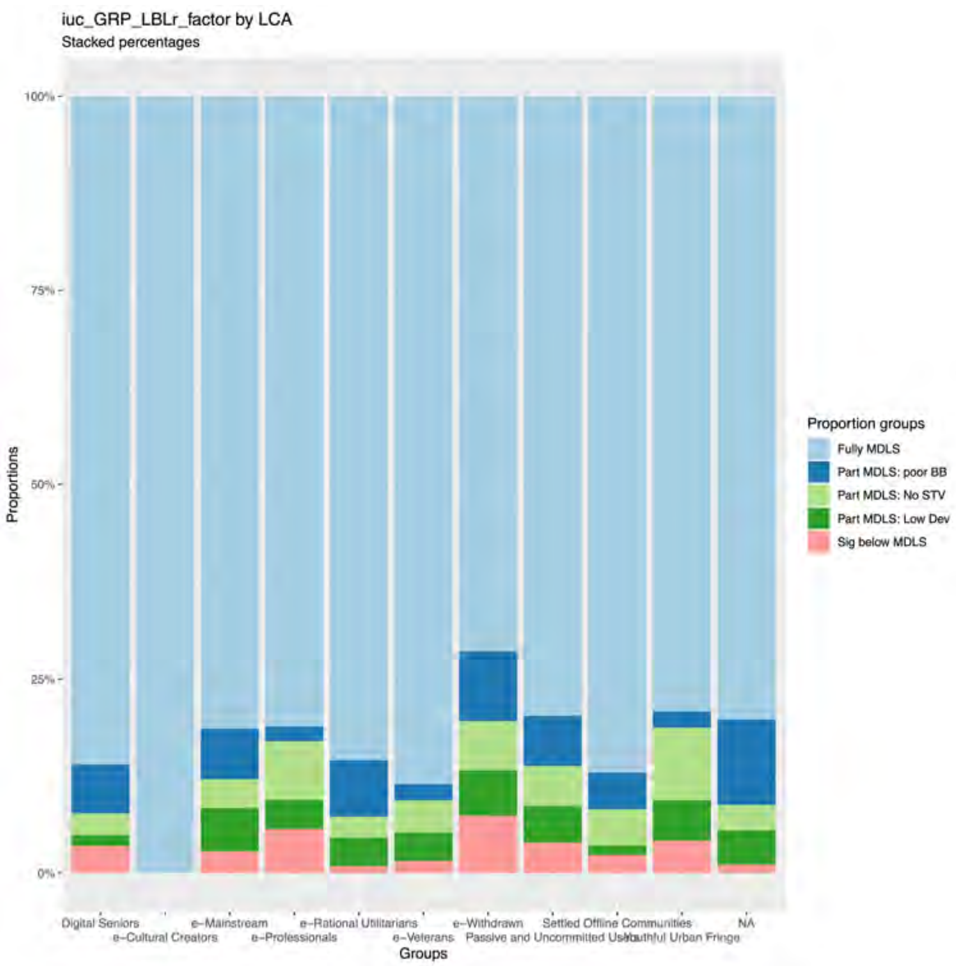

Figure 2.24: Proportions plot-8

2.4.9 oac21SGfactorbyLCA

The Pearson's Chi-squared test with simulated p-value of independence between variables suggests that the effect is statistically significant and small ($chi^2 = 94.27, p < .001; Adjusted Cramer'sv = 0.11, 95\% CI[0.05, 1.00]$). The following tables 2.66, 2.65, and 2.67 provide detals of the observations, column and row percentages. Figures 2.25 and 2.26 present plots of residuals and contributions. Figure 2.27 presents the data in stacked proprtions.

	Fully MDLS	Part MDLS: poor BB	Part MDLS: No STV	Part MDLS: Low Dev	Sig below MDLS
Retired Professionals (col.)	7.90	8.30	2.90	0.00	2.00
Suburbanites and Peri-Urbanities (col.)	19.30	15.30	4.30	13.10	3.90
Multicultural and Educated Urbanites (col.)	5.70	2.80	13.00	3.30	3.90
Low-Skilled Migrant and Student Communities (col.)	15.70	12.50	37.70	27.90	27.50
Ethnically Diverse Suburban Professionals (col.)	9.90	4.20	4.30	9.80	2.00
Baseline UK (col.)	20.90	29.20	26.10	23.00	27.50
Semi-and Un-Skilled Workforce (col.)	18.80	22.20	11.60	16.40	23.50
Legacy Communities (col.)	1.80	5.60	0.00	6.60	9.80

Table 2.65: oac21SG factor by LCA (Column Percentages) (χ^2(NA, 1357) = 94.271, p = 0, Cramer's V = 0.132)

	Fully MDLS	Part MDLS: poor BB	Part MDLS: No STV	Part MDLS: Low Dev	Sig below MDLS
Retired Professionals (row)	90.60	6.20	2.10	0.00	1.00
Suburbanites and Peri-Urbanities (row)	89.90	4.60	1.30	3.40	0.80
Multicultural and Educated Urbanites (row)	80.80	2.60	11.50	2.60	2.60
Low-Skilled Migrant and Student Communities (row)	72.40	3.80	10.90	7.10	5.90
Ethnically Diverse Suburban Professionals (row)	89.30	2.50	2.50	4.90	0.80
Baseline UK (row)	77.50	7.00	6.00	4.70	4.70
Semi-and Un-Skilled Workforce (row)	81.90	6.30	3.10	3.90	4.70
Legacy Communities (row)	60.60	12.10	0.00	12.10	15.20

Table 2.66: oac21SG factor by LCA (Row Percentages) (χ^2(NA, 1357) = 94.271, p = 0, Cramer's V = 0.132)

	Fully MDLS	Part MDLS: poor BB	Part MDLS: No STV	Part MDLS: Low Dev	Sig below MDLS
Retired Professionals (obs.)	87.00	6.00	2.00	0.00	1.00
Retired Professionals (row)	90.60	6.20	2.10	0.00	1.00
Retired Professionals (col.)	7.90	8.30	2.90	0.00	2.00
Suburbanites and Peri-Urbanities (obs.)	213.00	11.00	3.00	8.00	2.00
Suburbanites and Peri-Urbanities (row)	89.90	4.60	1.30	3.40	0.80
Suburbanites and Peri-Urbanities (col.)	19.30	15.30	4.30	13.10	3.90
Multicultural and Educated Urbanites (obs.)	63.00	2.00	9.00	2.00	2.00
Multicultural and Educated Urbanites (row)	80.80	2.60	11.50	2.60	2.60
Multicultural and Educated Urbanites (col.)	5.70	2.80	13.00	3.30	3.90
Low-Skilled Migrant and Student Communities (obs.)	173.00	9.00	26.00	17.00	14.00
Low-Skilled Migrant and Student Communities (row)	72.40	3.80	10.90	7.10	5.90
Low-Skilled Migrant and Student Communities (col.)	15.70	12.50	37.70	27.90	27.50
Ethnically Diverse Suburban Professionals (obs.)	109.00	3.00	3.00	6.00	1.00
Ethnically Diverse Suburban Professionals (row)	89.30	2.50	2.50	4.90	0.80
Ethnically Diverse Suburban Professionals (col.)	9.90	4.20	4.30	9.80	2.00
Baseline UK (obs.)	231.00	21.00	18.00	14.00	14.00
Baseline UK (row)	77.50	7.00	6.00	4.70	4.70
Baseline UK (col.)	20.90	29.20	26.10	23.00	27.50
Semi-and Un-Skilled Workforce (obs.)	208.00	16.00	8.00	10.00	12.00
Semi-and Un-Skilled Workforce (row)	81.90	6.30	3.10	3.90	4.70
Semi-and Un-Skilled Workforce (col.)	18.80	22.20	11.60	16.40	23.50
Legacy Communities (obs.)	20.00	4.00	0.00	4.00	5.00
Legacy Communities (row)	60.60	12.10	0.00	12.10	15.20
Legacy Communities (col.)	1.80	5.60	0.00	6.60	9.80

Table 2.67: oac21SG factor by LCA (χ^2(NA, 1357) = 94.271, p = 0, Cramer's V = 0.132)

Figure 2.25: Res. Cont. plots-17

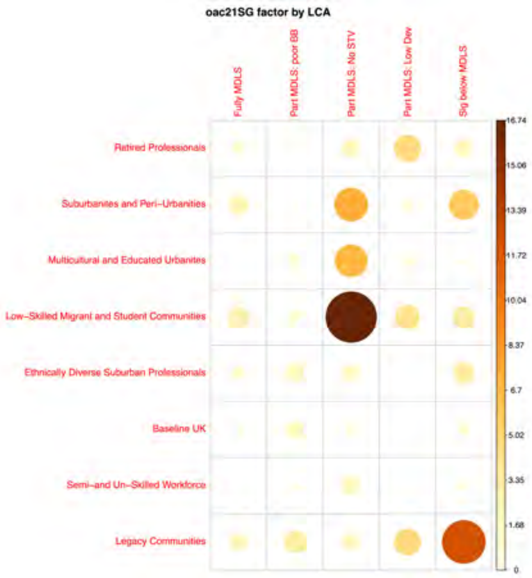

Figure 2.26: Res. Cont. plots-18

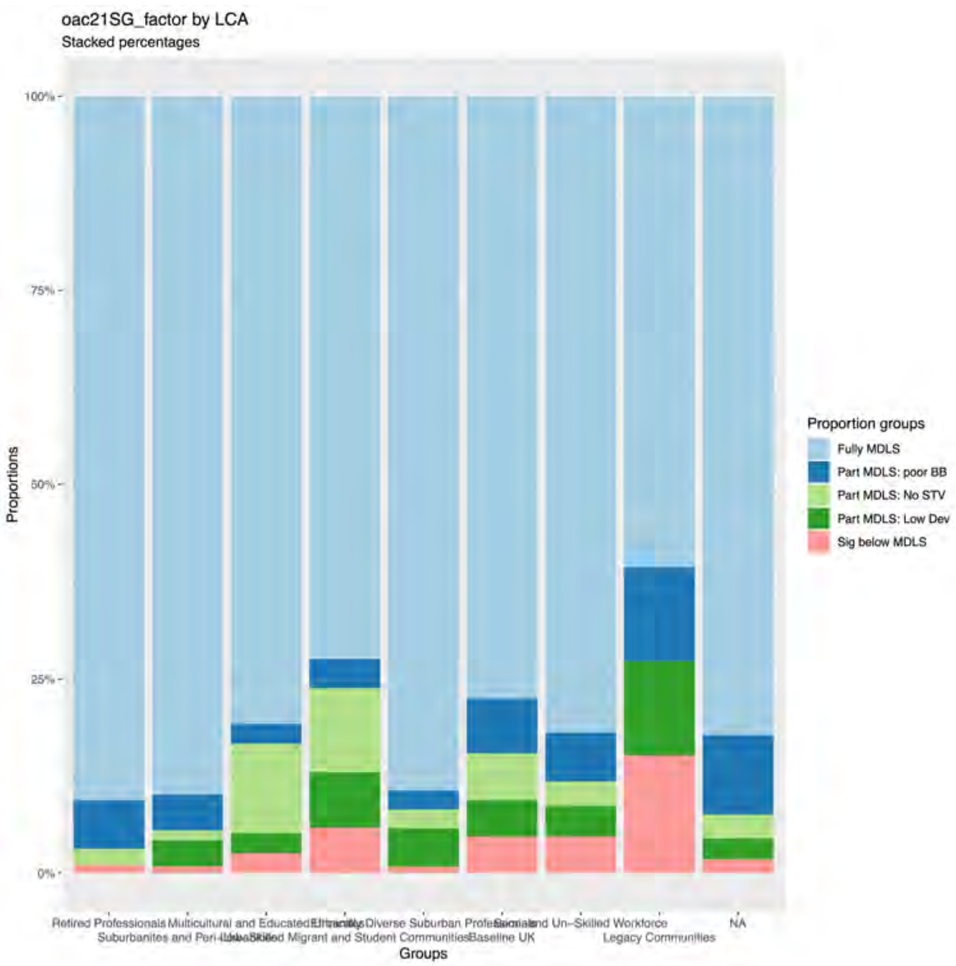

Figure 2.27: Proportions plot-9

2.4.10 aipcsupergroupnamerfactorbyLCA

The Pearson's Chi-squared test with simulated p-value of independence between variables suggests that the effect is statistically significant and small ($chi^2 = 87.57, p < .001; AdjustedCramer'sv = 0.12, 95\%CI[0.08, 1.00]$). The following tables 2.69, 2.68, and 2.70 provide detals of the observations, column and row percentages. Figures 2.28 and 2.29 present plots of residuals and contributions. Figure 2.30 presents the data in stacked proprtions.

	Fully MDLS	Part MDLS: poor BB	Part MDLS: No STV	Part MDLS: Low Dev	Sig below MDLS
1 Struggling, More Vulnerable Urbanites (col.)	28.00	38.60	19.10	44.80	39.50
2 Multicultural Central Urban Living (col.)	13.70	4.30	44.10	13.80	16.30
3 Rurban Comfortable Ageing (col.)	18.80	11.40	5.90	8.60	2.30
4 Retired Fringe and Residential Stability (col.)	22.60	37.10	11.80	22.40	25.60
5 Cosmopolitan and Coastal Ageing (col.)	16.90	8.60	19.10	10.30	16.30

Table 2.68: aipc supergroup namer factor by LCA (Column Percentages) (χ^2(NA, 1278) = 87.573, p = 0, Cramer's V = 0.131)

	Fully MDLS	Part MDLS: poor BB	Part MDLS: No STV	Part MDLS: Low Dev	Sig below MDLS
1 Struggling, More Vulnerable Urbanites (row)	77.80	7.20	3.50	7.00	4.50
2 Multicultural Central Urban Living (row)	74.70	1.60	15.80	4.20	3.70
3 Rurban Comfortable Ageing (row)	91.50	3.80	1.90	2.30	0.50
4 Retired Fringe and Residential Stability (row)	80.20	8.90	2.70	4.40	3.80
5 Cosmopolitan and Coastal Ageing (row)	84.60	2.90	6.20	2.90	3.40

Table 2.69: aipc supergroup namer factor by LCA (Row Percentages) (χ^2(NA, 1278) = 87.573, p = 0, Cramer's V = 0.131)

	Fully MDLS	Part MDLS: poor BB	Part MDLS: No STV	Part MDLS: Low Dev	Sig below MDLS
1 Struggling, More Vulnerable Urbanites (obs.)	291.00	27.00	13.00	26.00	17.00
1 Struggling, More Vulnerable Urbanites (row)	77.80	7.20	3.50	7.00	4.50
1 Struggling, More Vulnerable Urbanites (col.)	28.00	38.60	19.10	44.80	39.50
2 Multicultural Central Urban Living (obs.)	142.00	3.00	30.00	8.00	7.00
2 Multicultural Central Urban Living (row)	74.70	1.60	15.80	4.20	3.70
2 Multicultural Central Urban Living (col.)	13.70	4.30	44.10	13.80	16.30
3 Rurban Comfortable Ageing (obs.)	195.00	8.00	4.00	5.00	1.00
3 Rurban Comfortable Ageing (row)	91.50	3.80	1.90	2.30	0.50
3 Rurban Comfortable Ageing (col.)	18.80	11.40	5.90	8.60	2.30
4 Retired Fringe and Residential Stability (obs.)	235.00	26.00	8.00	13.00	11.00
4 Retired Fringe and Residential Stability (row)	80.20	8.90	2.70	4.40	3.80
4 Retired Fringe and Residential Stability (col.)	22.60	37.10	11.80	22.40	25.60
5 Cosmopolitan and Coastal Ageing (obs.)	176.00	6.00	13.00	6.00	7.00
5 Cosmopolitan and Coastal Ageing (row)	84.60	2.90	6.20	2.90	3.40
5 Cosmopolitan and Coastal Ageing (col.)	16.90	8.60	19.10	10.30	16.30

Table 2.70: aipc supergroup namer factor by LCA (χ^2(NA, 1278) = 87.573, p = 0, Cramer's V = 0.131)

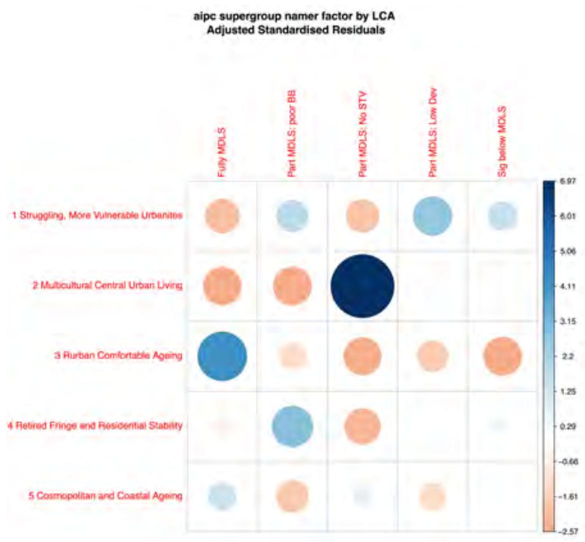

Figure 2.28: Res. Cont. plots-19

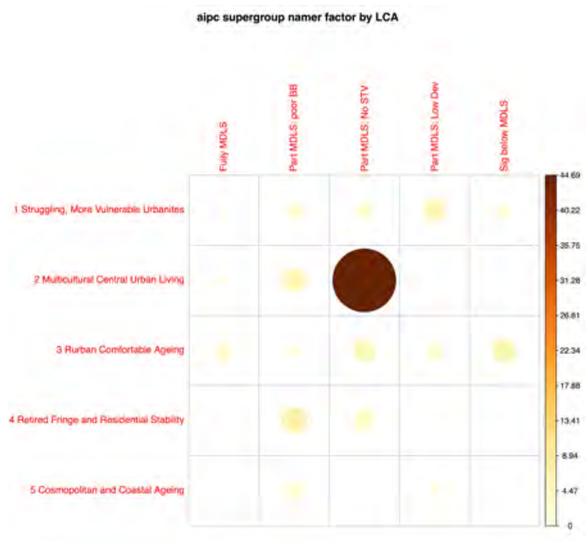

Figure 2.29: Res. Cont. plots-20

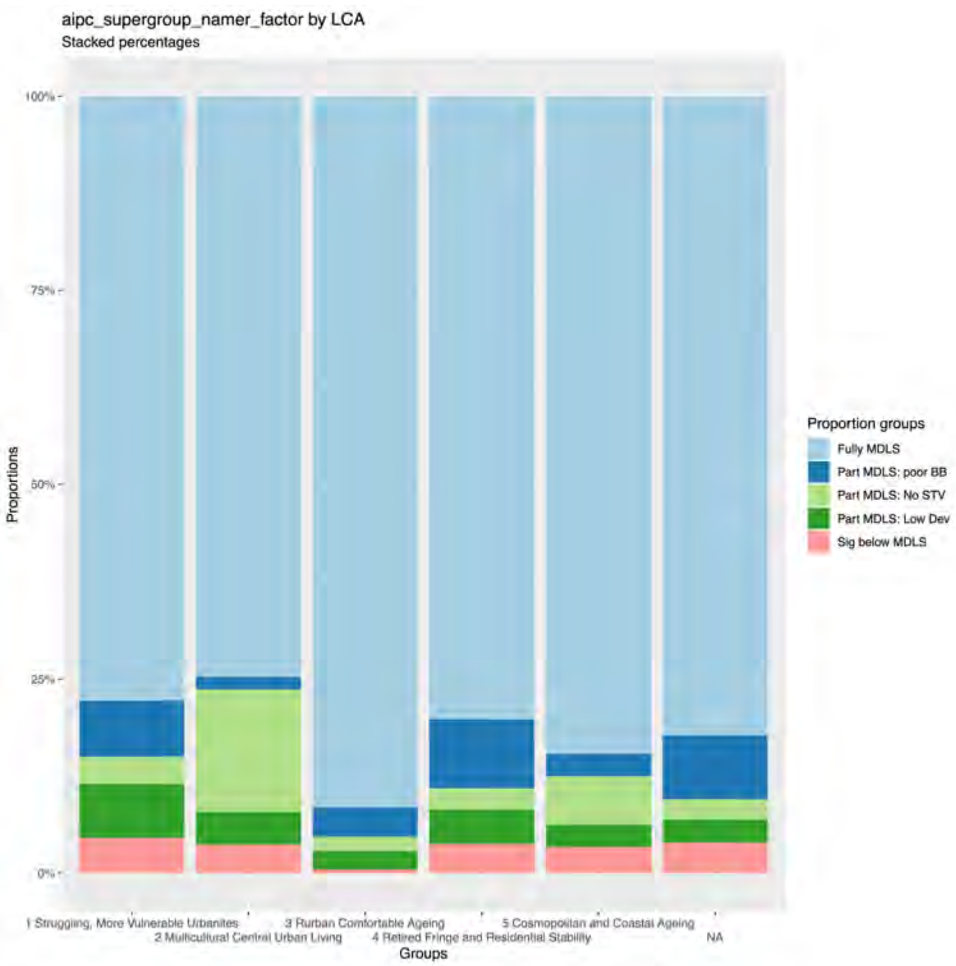

Figure 2.30: Proportions plot-10

2.4.11 BenefitsfactorbyLCA

The Pearson's Chi-squared test with simulated p-value of independence between variables suggests that the effect is statistically significant and medium ($chi^2 = 96.36, p < .001; AdjustedCramer'sv = 0.24, 95\%CI[0.19, 1.00]$). The following tables 2.72, 2.71, and 2.73 provide detals of the observations, column and row percentages. Figures 2.31 and 2.32 present plots of residuals and contributions. Figure 2.33 presents the data in stacked proprtions.

	Fully MDLS	Part MDLS: poor BB	Part MDLS: No STV	Part MDLS: Low Dev	Sig below MDLS
Not on any benefits (col.)	71.40	51.60	60.50	41.80	20.00
Receives at least one state benefit (col.)	28.60	48.40	39.50	58.20	80.00

Table 2.71: Benefits factor by LCA (Column Percentages) (χ^2(NA, 1582) = 96.364, p = 0, Cramer's V = 0.247)

	Fully MDLS	Part MDLS: poor BB	Part MDLS: No STV	Part MDLS: Low Dev	Sig below MDLS
Not on any benefits (row)	87.30	4.60	4.40	2.70	1.00
Receives at least one state benefit (row)	69.90	8.70	5.70	7.40	8.30

Table 2.72: Benefits factor by LCA (Row Percentages) (χ^2(NA, 1582) = 96.364, p = 0, Cramer's V = 0.247)

	Fully MDLS	Part MDLS: poor BB	Part MDLS: No STV	Part MDLS: Low Dev	Sig below MDLS
Not on any benefits (obs.)	920.00	49.00	46.00	28.00	11.00
Not on any benefits (row)	87.30	4.60	4.40	2.70	1.00
Not on any benefits (col.)	71.40	51.60	60.50	41.80	20.00
Receives at least one state benefit (obs.)	369.00	46.00	30.00	39.00	44.00
Receives at least one state benefit (row)	69.90	8.70	5.70	7.40	8.30
Receives at least one state benefit (col.)	28.60	48.40	39.50	58.20	80.00

Table 2.73: Benefits factor by LCA (χ^2(NA, 1582) = 96.364, p = 0, Cramer's V = 0.247)

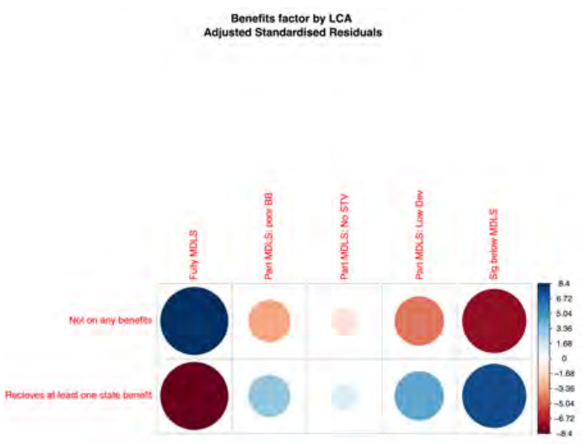

Figure 2.31: Res. Cont. plots-21

Figure 2.32: Res. Cont. plots-22

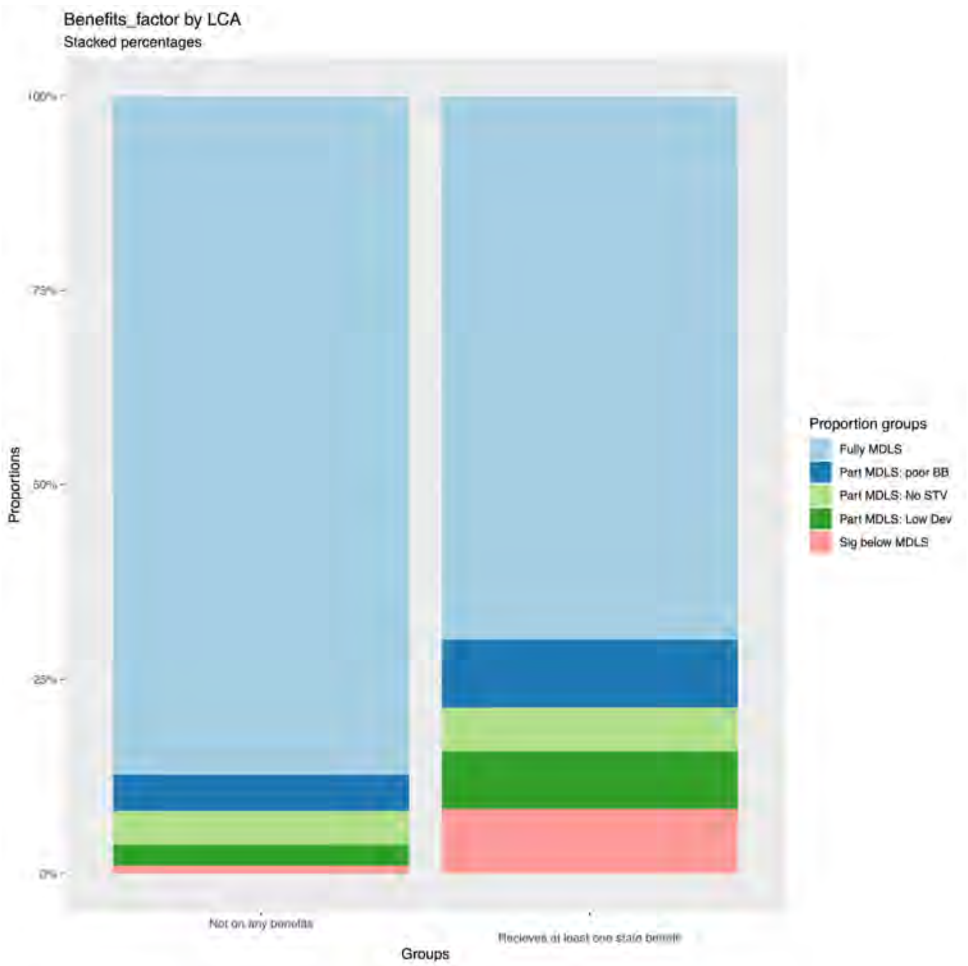

Figure 2.33: Proportions plot-11

2.4.12 WorkingfactorbyLCA

The Pearson's Chi-squared test with simulated p-value of independence between variables suggests that the effect is statistically significant and medium ($chi^2 = 123.59, p < .001; AdjustedCramer'sv = 0.28, 95\%CI[0.23, 1.00]$). The following tables 2.75, 2.74, and 2.76 provide detals of the observations, column and row percentages. Figures 2.34 and 2.35 present plots of residuals and contributions. Figure 2.36 presents the data in stacked proprtions.

	Fully MDLS	Part MDLS: poor BB	Part MDLS: No STV	Part MDLS: Low Dev	Sig below MDLS
Chief income earner not working (col.)	15.10	32.60	30.30	43.30	63.60
Chief income earner working (col.)	84.90	67.40	69.70	56.70	36.40

Table 2.74: Working factor by LCA (Column Percentages) (χ^2(NA, 1582) = 123.588, p = 0, Cramer's V = 0.28)

	Fully MDLS	Part MDLS: poor BB	Part MDLS: No STV	Part MDLS: Low Dev	Sig below MDLS
Chief income earner not working (row)	62.20	9.90	7.40	9.30	11.20
Chief income earner working (row)	86.20	5.00	4.20	3.00	1.60

Table 2.75: Working factor by LCA (Row Percentages) (χ^2(NA, 1582) = 123.588, p = 0, Cramer's V = 0.28)

	Fully MDLS	Part MDLS: poor BB	Part MDLS: No STV	Part MDLS: Low Dev	Sig below MDLS
Chief income earner not working (obs.)	194.00	31.00	23.00	29.00	35.00
Chief income earner not working (row)	62.20	9.90	7.40	9.30	11.20
Chief income earner not working (col.)	15.10	32.60	30.30	43.30	63.60
Chief income earner working (obs.)	1095.00	64.00	53.00	38.00	20.00
Chief income earner working (row)	86.20	5.00	4.20	3.00	1.60
Chief income earner working (col.)	84.90	67.40	69.70	56.70	36.40

Table 2.76: Working factor by LCA (χ^2(NA, 1582) = 123.588, p = 0, Cramer's V = 0.28)

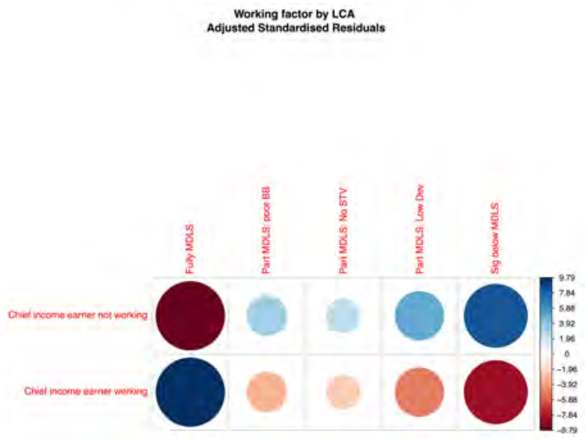

Figure 2.34: Res. Cont. plots-23

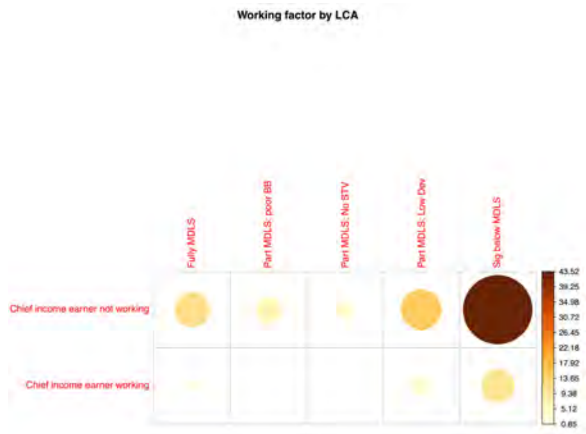

Figure 2.35: Res. Cont. plots-24

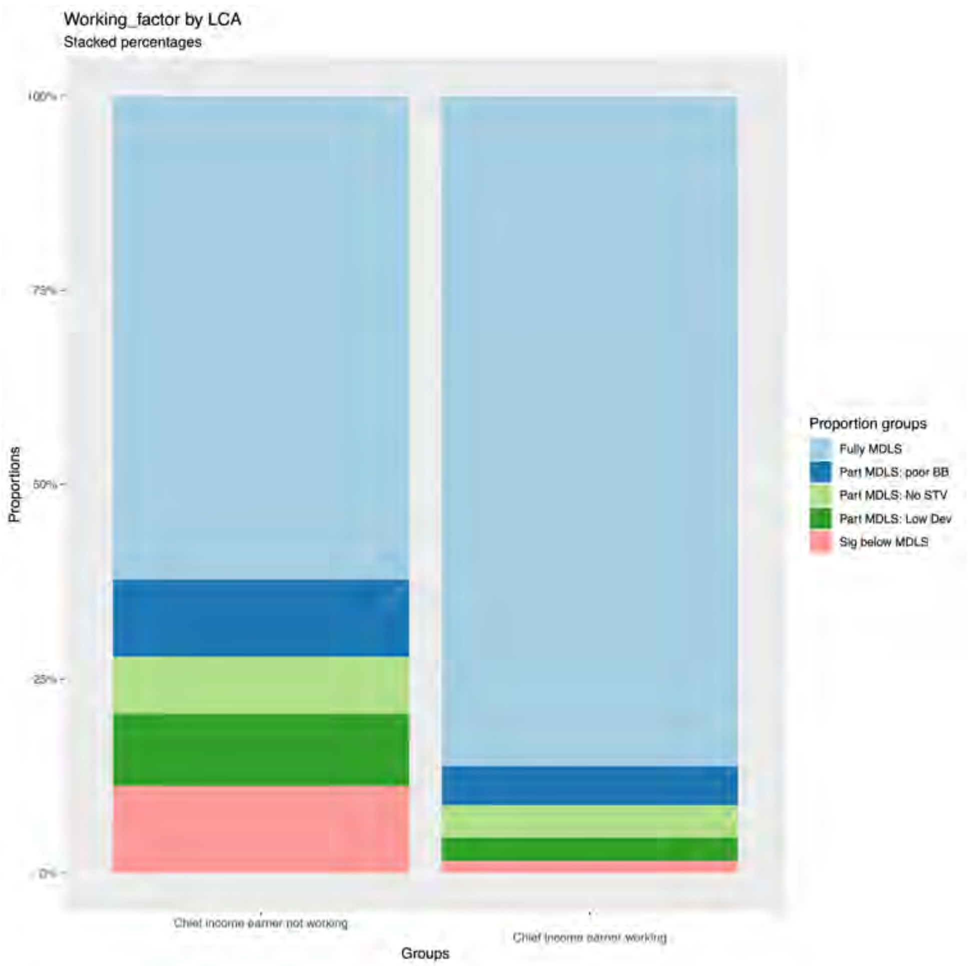

Figure 2.36: Proportions plot-12

2.4.13 HealthlimitationfactorbyLCA

The Pearson's Chi-squared test with simulated p-value of independence between variables suggests that the effect is statistically significant and very small ($chi^2 = 18.08, p = 0.003; AdjustedCramer'sv = 0.09, 95\% CI[0.02, 1.00]$). The following tables 2.78, 2.77, and 2.79 provide detals of the observations, column and row percentages. Figures 2.37 and 2.38 present plots of residuals and contributions. Figure 2.39 presents the data in stacked proprtions.

	Fully MDLS	Part MDLS: poor BB	Part MDLS: No STV	Part MDLS: Low Dev	Sig below MDLS
Respondent has **no** health issue (col.)	86.20	76.80	82.90	80.60	69.10
Respondent **has** a health issue (col.)	13.80	23.20	17.10	19.40	30.90

Table 2.77: Health limitation factor by LCA (Column Percentages) (χ^2(NA, 1582) = 18.077, p = 0.003, Cramer's V = 0.107)

	Fully MDLS	Part MDLS: poor BB	Part MDLS: No STV	Part MDLS: Low Dev	Sig below MDLS
Respondent has no health issue(row)	83.00	5.50	4.70	4.00	2.80
Respondent **has** a health issue (row)	73.30	9.10	5.30	5.30	7.00

Table 2.78: Health limitation factor by LCA (Row Percentages) (χ^2(NA, 1582) = 18.077, p = 0.003, Cramer's V = 0.107)

	Fully MDLS	Part MDLS: poor BB	Part MDLS: No STV	Part MDLS: Low Dev	Sig below MDLS
Respondent has no health issue(obs.)	1111.00	73.00	63.00	54.00	38.00
Respondent has **no** health issue (row)	83.00	5.50	4.70	4.00	2.80
Respondent has **no** health issue (col.)	86.20	76.80	82.90	80.60	69.10
Respondent **has** a health issue (obs.)	178.00	22.00	13.00	13.00	17.00
Respondent **has** a health issue (row)	73.30	9.10	5.30	5.30	7.00
Respondent **has** a health issue (col.)	13.80	23.20	17.10	19.40	30.90

Table 2.79: Health limitation factor by LCA (χ^2(NA, 1582) = 18.077, p = 0.003, Cramer's V = 0.107)

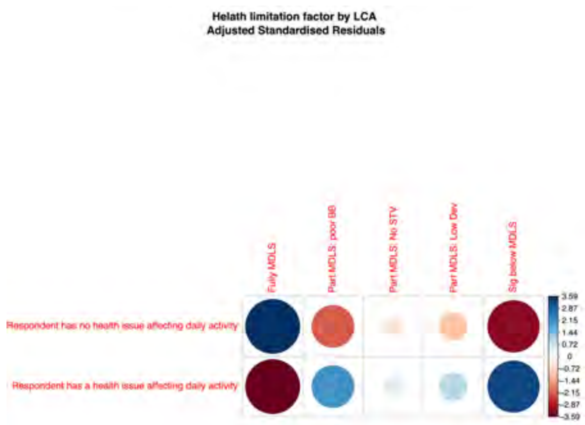

Figure 2.37: Res. Cont. plots-25

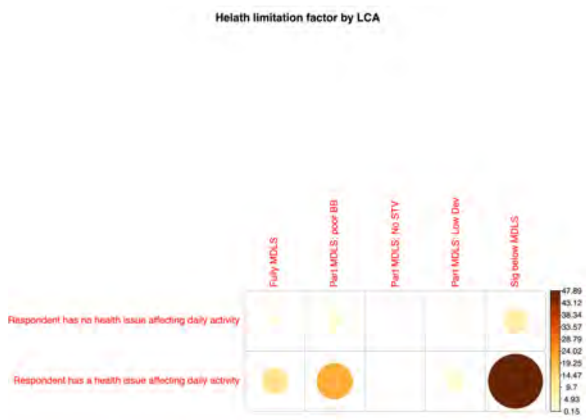

Figure 2.38: Res. Cont. plots-26

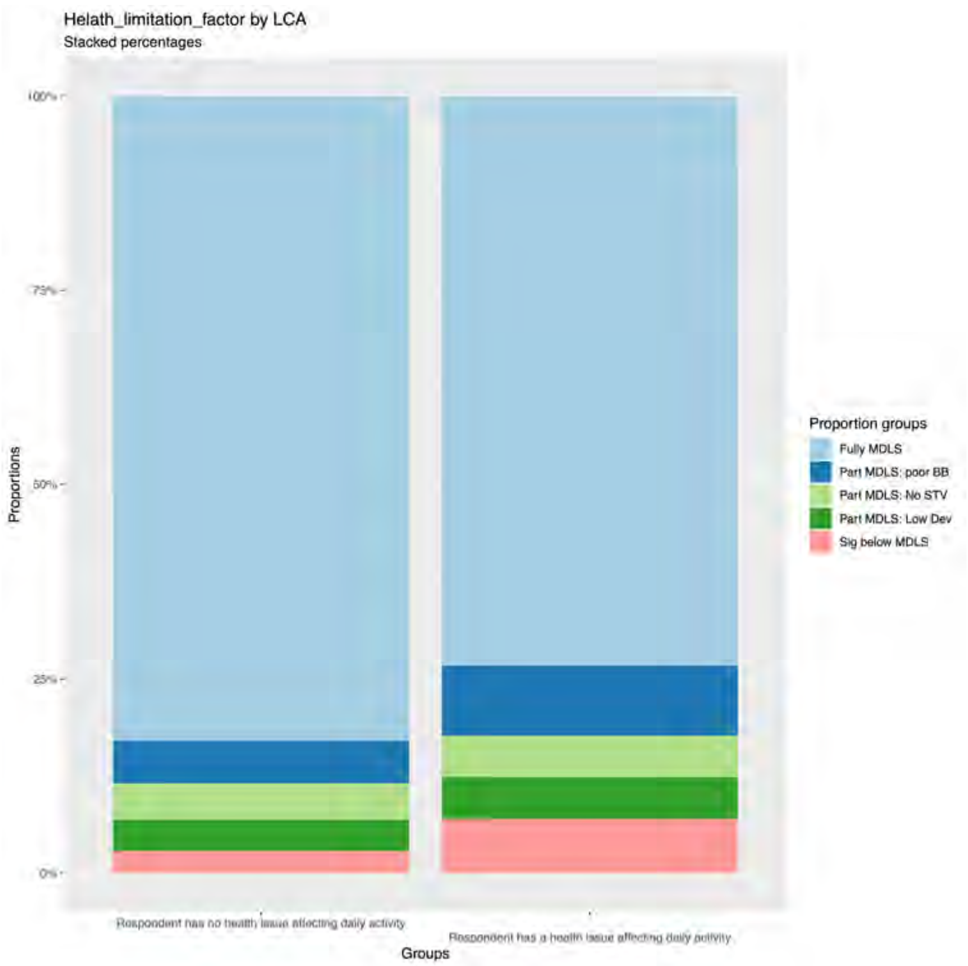

Figure 2.39: Proportions plot-13

2.4.14 EthnicityfactorbyLCA

The Pearson's Chi-squared test with simulated p-value of independence between variables suggests that the effect is statistically significant and medium ($chi^2 = 71.78, p < .001; Adjusted Cramer's v = 0.21, 95\% CI [0.16, 1.00]$). The following tables 2.81, 2.80, and 2.82 provide detals of the observations, column and row percentages. Figures 2.40 and 2.41 present plots of residuals and contributions. Figure 2.42 presents the data in stacked proprtions.

	Fully MDLS	Part MDLS: poor BB	Part MDLS: No STV	Part MDLS: Low Dev	Sig below MDLS
Respondent identifies as ethnically white(col.)	79.50	86.30	46.10	64.20	54.50
Respondent identifies as ethnically non-white (col.)	20.50	13.70	53.90	35.80	45.50

Table 2.80: Ethnicity factor by LCA (Column Percentages) (χ^2(NA, 1582) = 71.783, p = 0, Cramer's V = 0.213)

	Fully MDLS	Part MDLS: poor BB	Part MDLS: No STV	Part MDLS: Low Dev	Sig below MDLS
Respondent identifies as ethnically white(row)	84.40	6.70	2.90	3.50	2.50
Respondent identifies as ethnically non-white (row)	71.90	3.50	11.20	6.50	6.80

Table 2.81: Ethnicity factor by LCA (Row Percentages) (χ^2(NA, 1582) = 71.783, p = 0, Cramer's V = 0.213)

	Fully MDLS	Part MDLS: poor BB	Part MDLS: No STV	Part MDLS: Low Dev	Sig below MDLS
Respondent identifies as ethnically white(obs.)	1025.00	82.00	35.00	43.00	30.00
Respondent identifies as ethnically white(row)	84.40	6.70	2.90	3.50	2.50
Respondent identifies as ethnically white(col.)	79.50	86.30	46.10	64.20	54.50
Respondent identifies as ethnically non-white (obs.)	264.00	13.00	41.00	24.00	25.00
Respondent identifies as ethnically non-white (row)	71.90	3.50	11.20	6.50	6.80
Respondent identifies as ethnically non-white (col.)	20.50	13.70	53.90	35.80	45.50

Table 2.82: Ethnicity factor by LCA (χ^2(NA, 1582) = 71.783, p = 0, Cramer's V = 0.213)

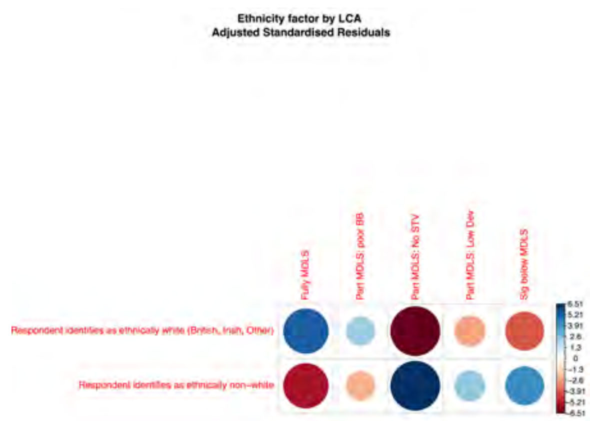

Figure 2.40: Res. Cont. plots-27

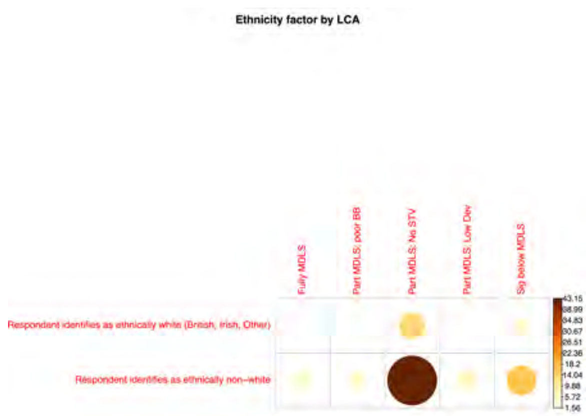

Figure 2.41: Res. Cont. plots-28

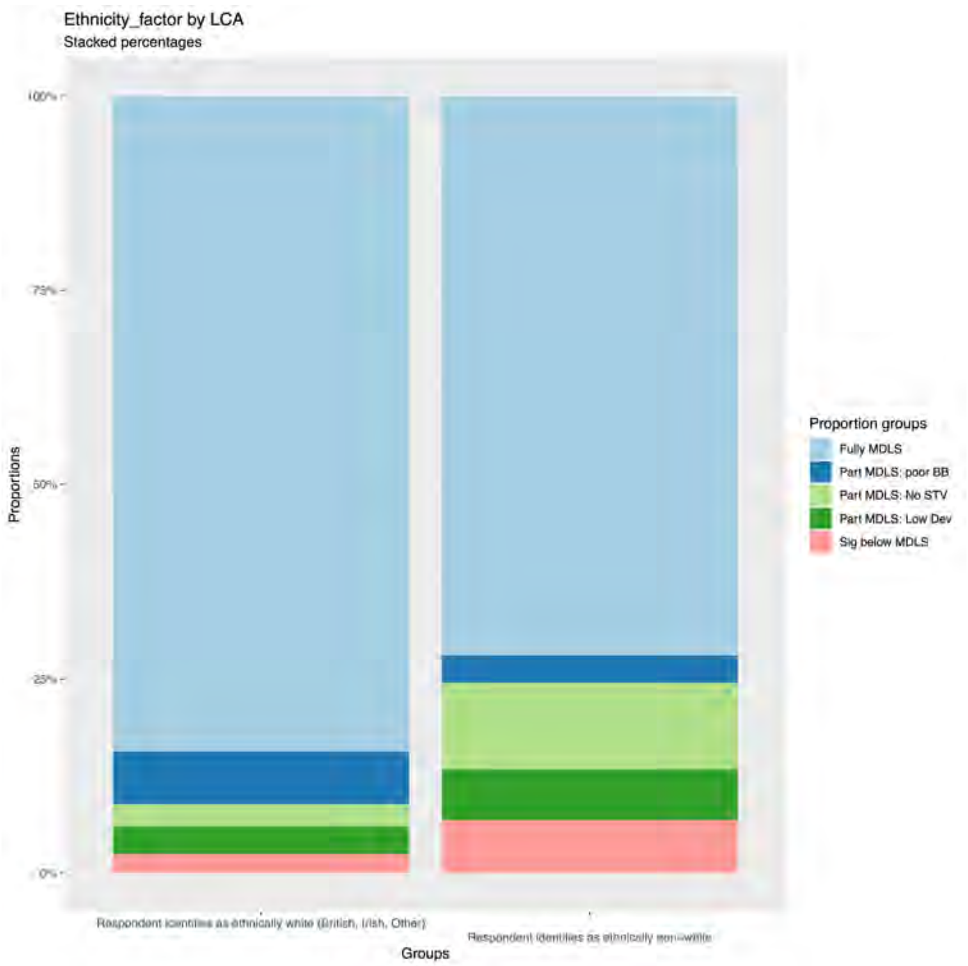

Figure 2.42: Proportions plot-14

2.4.15 SEGfactorbyEquipment(Abs.)

The Pearson's Chi-squared test with simulated p-value of independence between variables suggests that the effect is statistically significant and small ($chi^2 = 54.89, p < .001; AdjustedCramer'sv = 0.18, 95\%CI[0.13, 1.00]$). The following tables 2.84, 2.83, and 2.85 provide detals of the observations, column and row percentages. Figures 2.43 and 2.44 present plots of residuals and contributions. Figure 2.45 presents the data in stacked proprtions.

	Not MDLS adequate	MDLS adequate
AB (col.)	16.50	24.10
C1 (col.)	25.90	34.80
C2 (col.)	23.90	22.10
DE (col.)	33.80	19.00

Table 2.83: SEG factor by Equipment (Abs.) (Column Percentages) (χ^2(NA, 1582) = 54.894, p = 0, Cramer's V = 0.186)

	Not MDLS adequate	MDLS adequate
AB (row)	40.20	59.80
C1 (row)	42.20	57.80
C2 (row)	51.50	48.50
DE (row)	63.50	36.50

Table 2.84: SEG factor by Equipment (Abs.) (Row Percentages) (χ^2(NA, 1582) = 54.894, p = 0, Cramer's V = 0.186)

	Not MDLS adequate	MDLS adequate
AB (obs.)	129.00	192.00
AB (row)	40.20	59.80
AB (col.)	16.50	24.10
C1 (obs.)	203.00	278.00
C1 (row)	42.20	57.80
C1 (col.)	25.90	34.80
C2 (obs.)	187.00	176.00
C2 (row)	51.50	48.50
C2 (col.)	23.90	22.10
DE (obs.)	265.00	152.00
DE (row)	63.50	36.50
DE (col.)	33.80	19.00

Table 2.85: SEG factor by Equipment (Abs.) (χ^2(NA, 1582) = 54.894, p = 0, Cramer's V = 0.186)

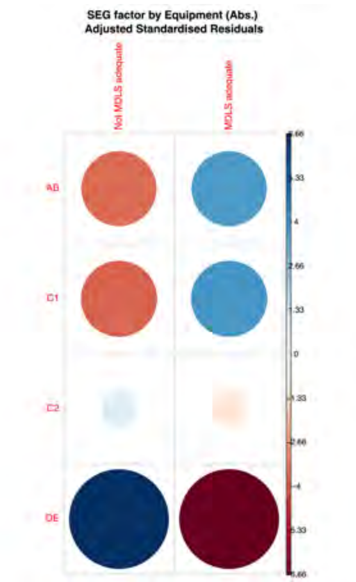

Figure 2.43: Res. Cont. plots-29

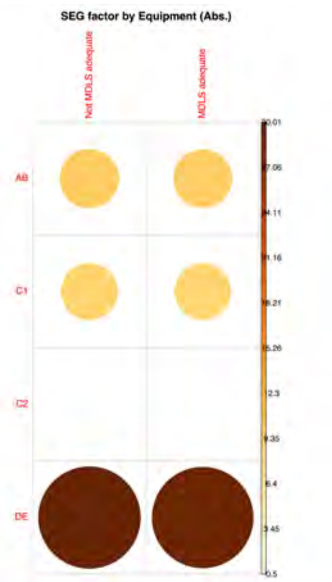

Figure 2.44: Res. Cont. plots-30

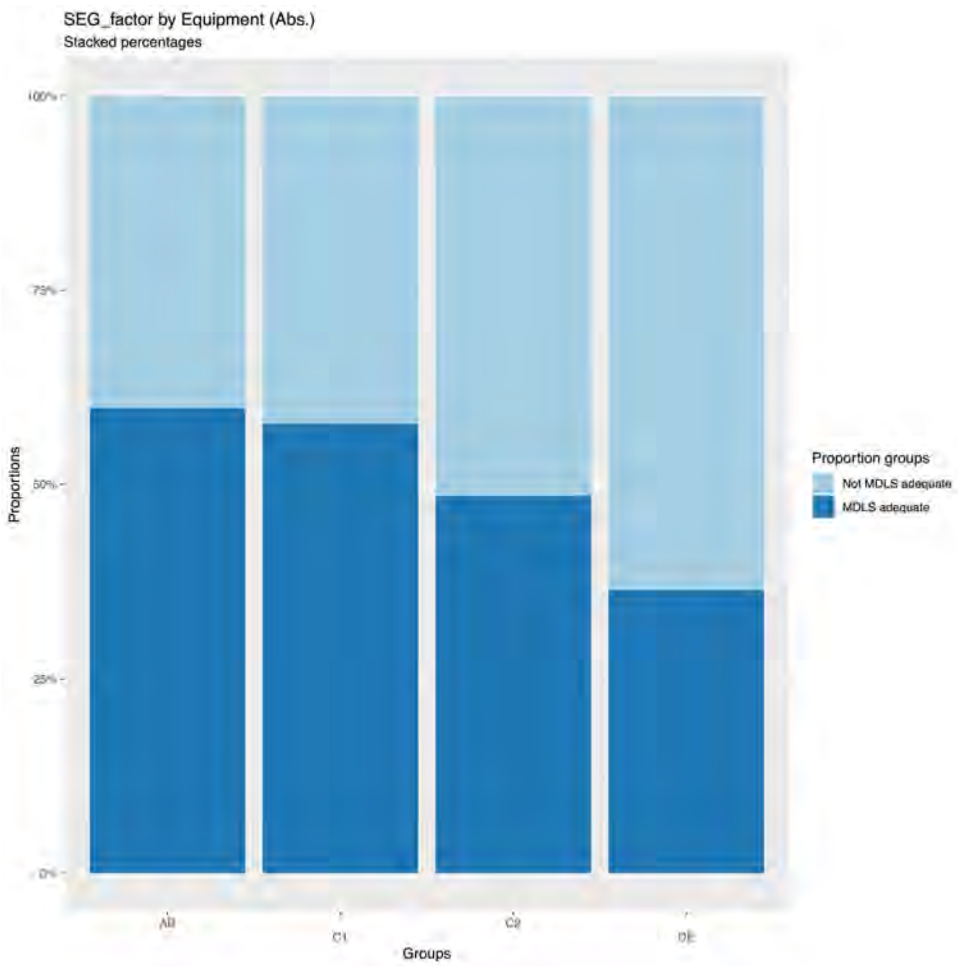

Figure 2.45: Proportions plot-15

2.4.16 HTYPEfactorbyEquipment(Abs.)

The Pearson's Chi-squared test with simulated p-value of independence between variables suggests that the effect is statistically significant and medium ($chi^2 = 84.25, p < .001; AdjustedCramer'sv = 0.22, 95\%CI[0.16, 1.00]$). The following tables 2.87, 2.86, and 2.88 provide detals of the observations, column and row percentages. Figures 2.46 and 2.47 present plots of residuals and contributions. Figure 2.48 presents the data in stacked proprtions.

	Not MDLS adequate	MDLS adequate
1 adult and 1 child (col.)	17.20	13.30
1 adult and 2 children (col.)	11.90	5.40
1 adult and more than 2 children (col.)	6.10	1.50
2 adults and 1 child (col.)	20.50	33.00
2 adults and 2 children (col.)	24.50	30.80
2 adults and more than 2 children (col.)	11.10	7.30
More than 2 adults in HH and 1 child (col.)	4.30	4.50
More than 2 adults in HH and 2 children (col.)	2.80	3.60
More than 2 adults in HH and 2+ children (col.)	1.50	0.60

Table 2.86: HTYPE factor by Equipment (Abs.) (Column Percentages) (χ^2(NA, 1582) = 84.25, p = 0, Cramer's V = 0.231)

	Not MDLS adequate	MDLS adequate
1 adult and 1 child (row)	56.00	44.00
1 adult and 2 children (row)	68.40	31.60
1 adult and more than 2 children (row)	80.00	20.00
2 adults and 1 child (row)	38.00	62.00
2 adults and 2 children (row)	43.80	56.20
2 adults and more than 2 children (row)	60.00	40.00
More than 2 adults in HH and 1 child (row)	48.60	51.40
More than 2 adults in HH and 2 children (row)	43.10	56.90
More than 2 adults in HH and 2+ children (row)	70.60	29.40

Table 2.87: HTYPE factor by Equipment (Abs.) (Row Percentages) (χ^2(NA, 1582) = 84.25, p = 0, Cramer's V = 0.231)

	Not MDLS adequate	MDLS adequate
1 adult and 1 child (obs.)	135.00	106.00
1 adult and 1 child (row)	56.00	44.00
1 adult and 1 child (col.)	17.20	13.30
1 adult and 2 children (obs.)	93.00	43.00
1 adult and 2 children (row)	68.40	31.60
1 adult and 2 children (col.)	11.90	5.40
1 adult and more than 2 children (obs.)	48.00	12.00
1 adult and more than 2 children (row)	80.00	20.00
1 adult and more than 2 children (col.)	6.10	1.50
2 adults and 1 child (obs.)	161.00	263.00
2 adults and 1 child (row)	38.00	62.00
2 adults and 1 child (col.)	20.50	33.00
2 adults and 2 children (obs.)	192.00	246.00
2 adults and 2 children (row)	43.80	56.20
2 adults and 2 children (col.)	24.50	30.80
2 adults and more than 2 children (obs.)	87.00	58.00
2 adults and more than 2 children (row)	60.00	40.00
2 adults and more than 2 children (col.)	11.10	7.30
More than 2 adults in HH and 1 child (obs.)	34.00	36.00
More than 2 adults in HH and 1 child (row)	48.60	51.40
More than 2 adults in HH and 1 child (col.)	4.30	4.50
More than 2 adults in HH and 2 children (obs.)	22.00	29.00
More than 2 adults in HH and 2 children (row)	43.10	56.90
More than 2 adults in HH and 2 children (col.)	2.80	3.60
More than 2 adults in HH and 2+ children (obs.)	12.00	5.00
More than 2 adults in HH and 2+ children (row)	70.60	29.40
More than 2 adults in HH and 2+ children (col.)	1.50	0.60

Table 2.88: HTYPE factor by Equipment (Abs.) (χ^2(NA, 1582) = 84.25, p = 0, Cramer's V = 0.231)

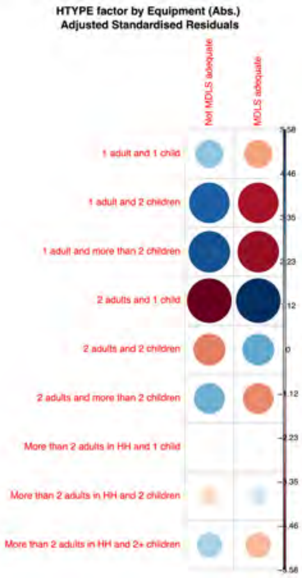

Figure 2.46: Res. Cont. plots-31

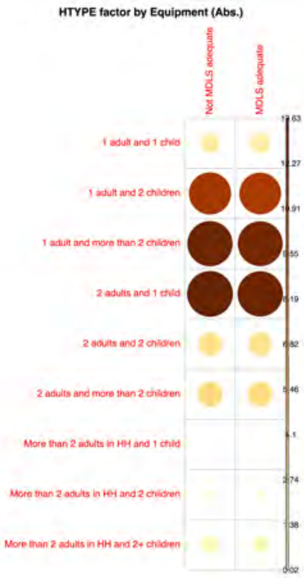

Figure 2.47: Res. Cont. plots-32

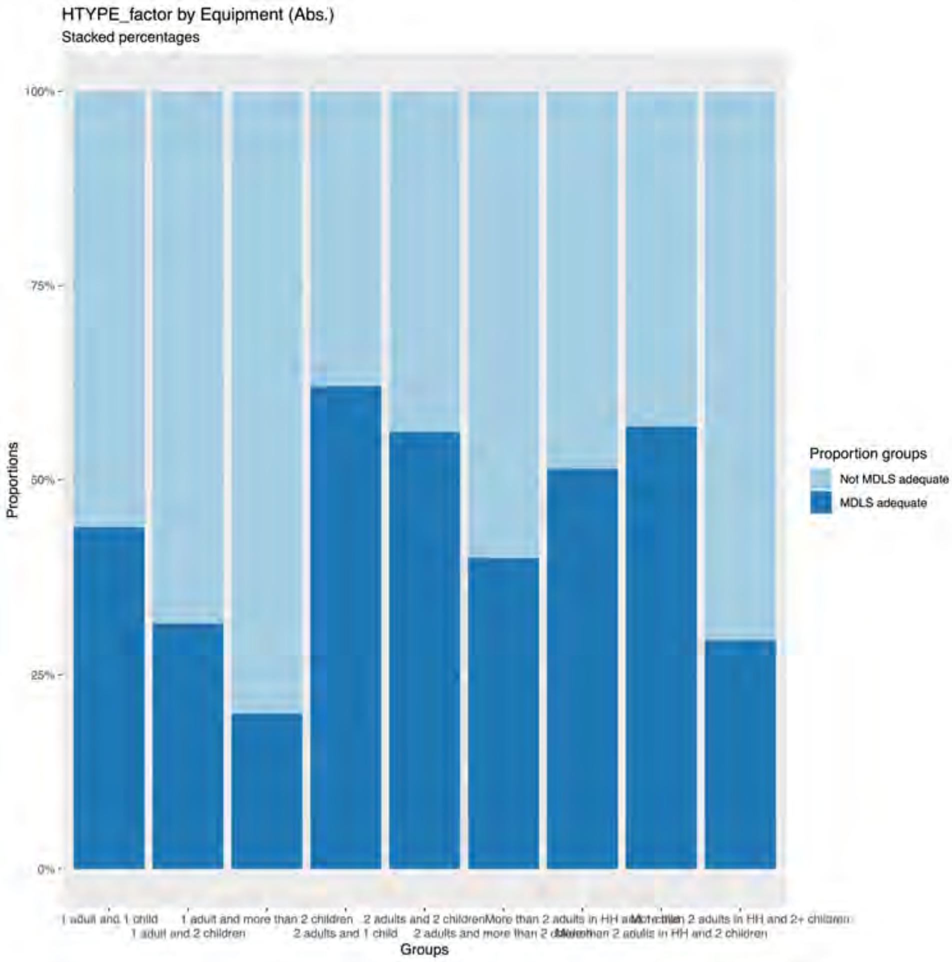

Figure 2.48: Proportions plot-16

2.4.17 REGIONfactorbyEquipment(Abs.)

The Pearson's Chi-squared test with simulated p-value of independence between variables suggests that the effect is statistically significant and small ($chi^2 = 33.68, p < .001; AdjustedCramer'sv = 0.12, 95\%CI[0.00, 1.00]$). The following tables 2.90, 2.89, and 2.91 provide detals of the observations, column and row percentages. Figures 2.49 and 2.50 present plots of residuals and contributions. Figure 2.51 presents the data in stacked proprtions.

	Not MDLS adequate	MDLS adequate
North East (col.)	4.10	3.30
North West (col.)	11.60	8.10
Yorkshire and The Humber (col.)	8.70	8.00
East Midlands (col.)	6.00	6.90
West Midlands (col.)	7.80	10.50
East of England (col.)	8.40	8.80
London (col.)	17.50	11.40
South East (col.)	12.00	15.20
South West (col.)	6.10	9.00
Wales (col.)	4.30	5.80
Northern Ireland (col.)	5.50	3.40
Scotland (col.)	8.00	9.60

Table 2.89: REGION factor by Equipment (Abs.) (Column Percentages) (χ^2(NA, 1582) = 33.676, p = 0.001, Cramer's V = 0.146)

	Not MDLS adequate	MDLS adequate
North East (row)	55.20	44.80
North West (row)	58.30	41.70
Yorkshire and The Humber (row)	51.50	48.50
East Midlands (row)	46.10	53.90
West Midlands (row)	42.10	57.90
East of England (row)	48.50	51.50
London (row)	60.10	39.90
South East (row)	43.70	56.30
South West (row)	40.00	60.00
Wales (row)	42.50	57.50
Northern Ireland (row)	61.40	38.60
Scotland (row)	45.00	55.00

Table 2.90: REGION factor by Equipment (Abs.) (Row Percentages) (χ^2(NA, 1582) = 33.676, p = 0.001, Cramer's V = 0.146)

	Not MDLS adequate	MDLS adequate
North East (obs.)	32.00	26.00
North East (row)	55.20	44.80
North East (col.)	4.10	3.30
North West (obs.)	91.00	65.00
North West (row)	58.30	41.70
North West (col.)	11.60	8.10
Yorkshire and The Humber (obs.)	68.00	64.00
Yorkshire and The Humber (row)	51.50	48.50
Yorkshire and The Humber (col.)	8.70	8.00
East Midlands (obs.)	47.00	55.00
East Midlands (row)	46.10	53.90
East Midlands (col.)	6.00	6.90
West Midlands (obs.)	61.00	84.00
West Midlands (row)	42.10	57.90
West Midlands (col.)	7.80	10.50
East of England (obs.)	66.00	70.00
East of England (row)	48.50	51.50
East of England (col.)	8.40	8.80
London (obs.)	137.00	91.00
London (row)	60.10	39.90
London (col.)	17.50	11.40
South East (obs.)	94.00	121.00
South East (row)	43.70	56.30
South East (col.)	12.00	15.20
South West (obs.)	48.00	72.00
South West (row)	40.00	60.00
South West (col.)	6.10	9.00
Wales (obs.)	34.00	46.00
Wales (row)	42.50	57.50
Wales (col.)	4.30	5.80
Northern Ireland (obs.)	43.00	27.00
Northern Ireland (row)	61.40	38.60
Northern Ireland (col.)	5.50	3.40
Scotland (obs.)	63.00	77.00
Scotland (row)	45.00	55.00
Scotland (col.)	8.00	9.60

Table 2.91: REGION factor by Equipment (Abs.) (χ^2(NA, 1582) = 33.676, p = 0.001, Cramer's V = 0.146)

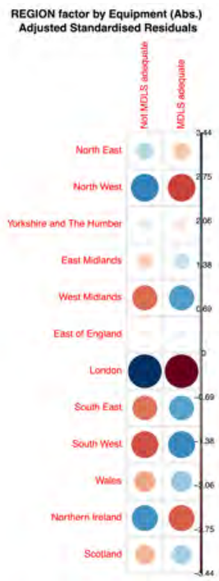

Figure 2.49: Res. Cont. plots-33

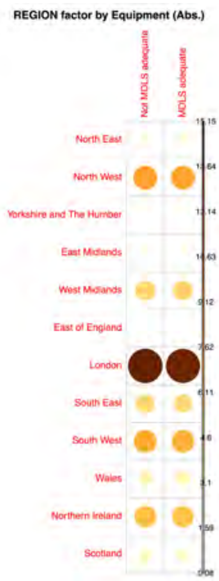

Figure 2.50: Res. Cont. plots-34

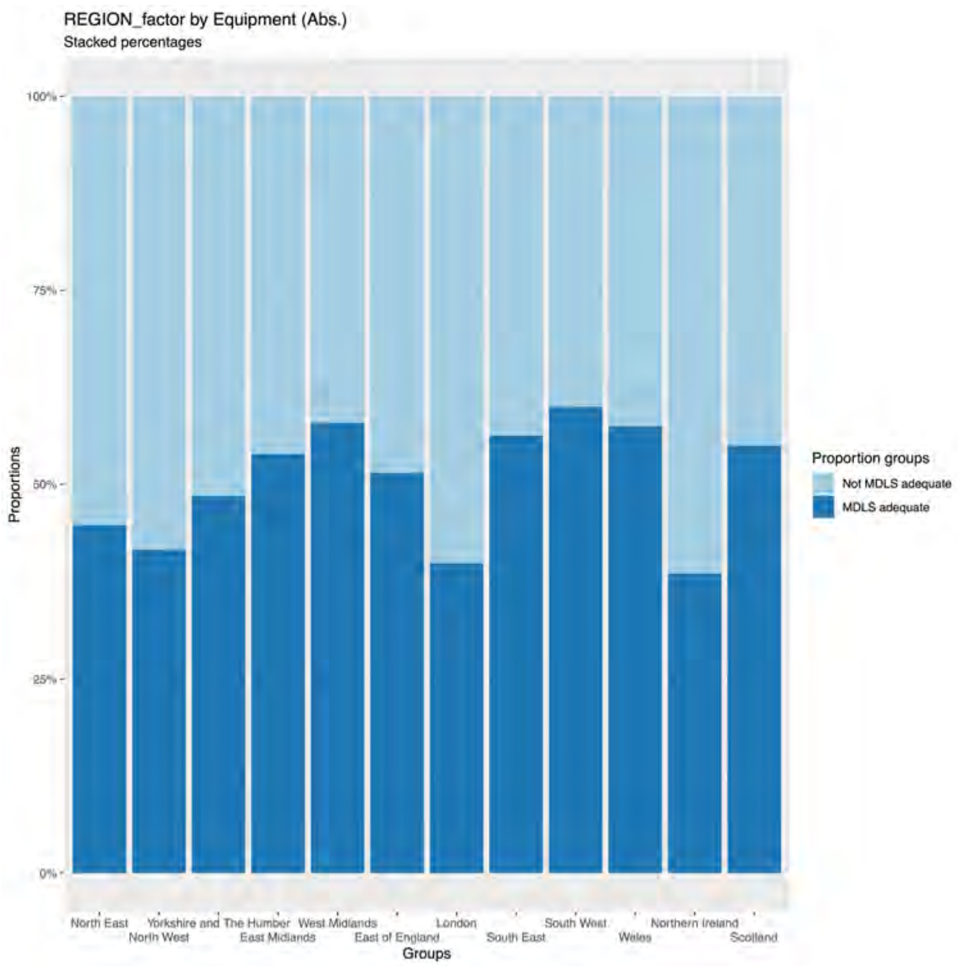

Figure 2.51: Proportions plot-17

2.4.18 OverallhouseholdskillsfactorbyEquipment(Abs.)

The Pearson's Chi-squared test with simulated p-value of independence between variables suggests that the effect is statistically significant and medium ($chi^2 = 72.32, p < .001; AdjustedCramer'sv = 0.21, 95\% CI[0.16, 1.00]$). The following tables 2.93, 2.92, and 2.94 provide detals of the observations, column and row percentages. Figures 2.52 and 2.53 present plots of residuals and contributions. Figure 2.54 presents the data in stacked proprtions.

	Not MDLS adequate	MDLS adequate
Not adequate Skills (col.)	6.80	2.10
Children Have Adequate Skills (col.)	33.90	20.80
Parents Have Adequate Skills (col.)	8.30	6.10
Household Has Adequate Skills (col.)	51.00	70.90

Table 2.92: Overall household skills factor by Equipment (Abs.) (Column Percentages) (χ^2(NA, 1582) = 72.316, p = 0, Cramer's V = 0.214)

	Not MDLS adequate	MDLS adequate
Not adequate Skills (row)	75.70	24.30
Children Have Adequate Skills (row)	61.60	38.40
Parents Have Adequate Skills (row)	57.00	43.00
Household Has Adequate Skills (row)	41.40	58.60

Table 2.93: Overall household skills factor by Equipment (Abs.) (Row Percentages) (χ^2(NA, 1582) = 72.316, p = 0, Cramer's V = 0.214)

	Not MDLS adequate	MDLS adequate
Not adequate Skills (obs.)	53.00	17.00
Not adequate Skills (row)	75.70	24.30
Not adequate Skills (col.)	6.80	2.10
Children Have Adequate Skills (obs.)	266.00	166.00
Children Have Adequate Skills (row)	61.60	38.40
Children Have Adequate Skills (col.)	33.90	20.80
Parents Have Adequate Skills (obs.)	65.00	49.00
Parents Have Adequate Skills (row)	57.00	43.00
Parents Have Adequate Skills (col.)	8.30	6.10
Household Has Adequate Skills (obs.)	400.00	566.00
Household Has Adequate Skills (row)	41.40	58.60
Household Has Adequate Skills (col.)	51.00	70.90

Table 2.94: Overall household skills factor by Equipment (Abs.) (χ^2(NA, 1582) = 72.316, p = 0, Cramer's V = 0.214)

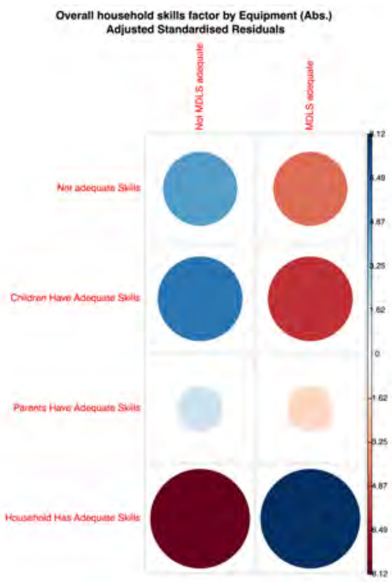

Figure 2.52: Res. Cont. plots-35

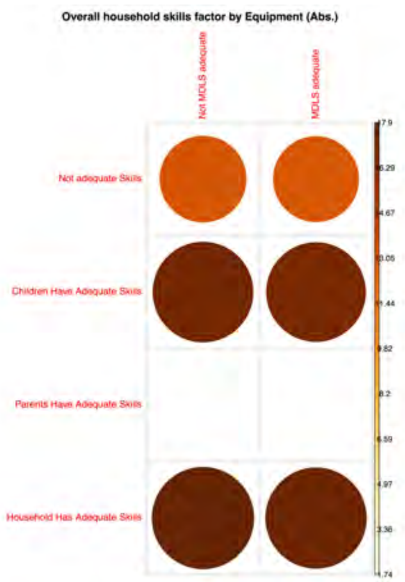

Figure 2.53: Res. Cont. plots-36

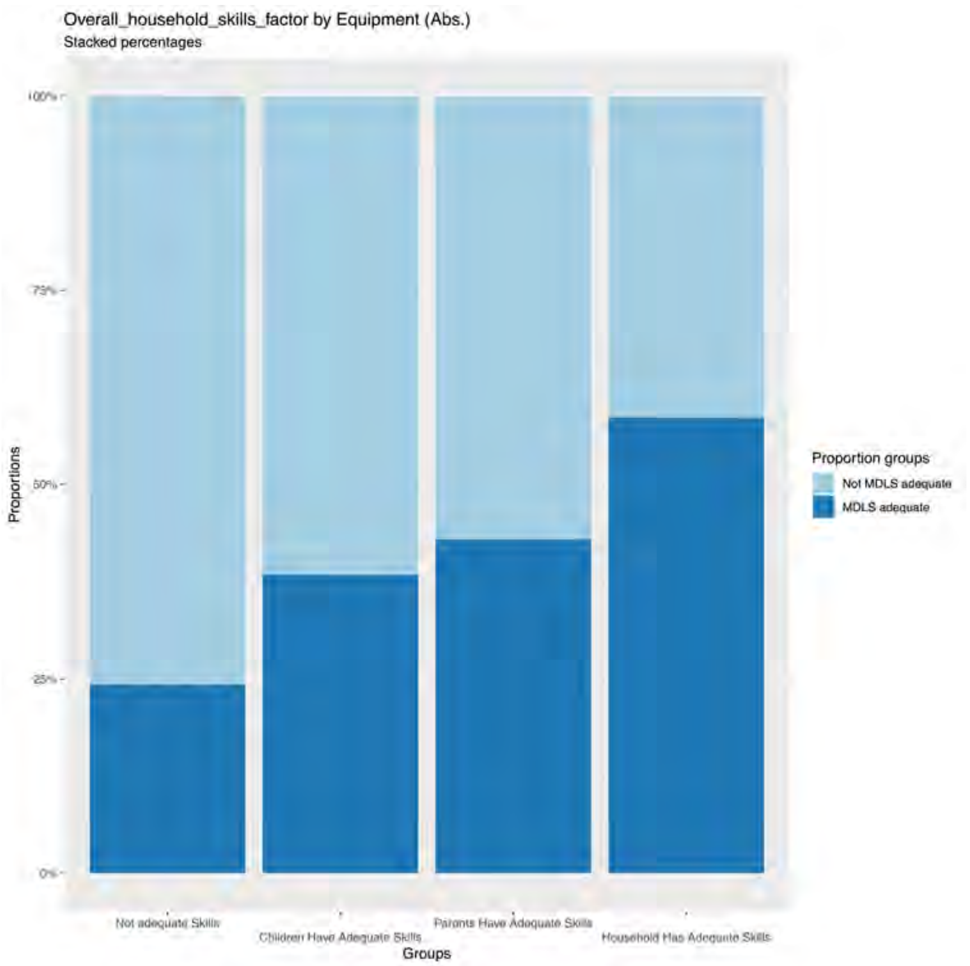

Figure 2.54: Proportions plot-18

2.4.19 BroadbandfactorbyEquipment(Abs.)

The Pearson's Chi-squared test with simulated p-value of independence between variables suggests that the effect is statistically not significant and tiny ($chi^2 = 0.09, p = 0.787; AdjustedCramer'sv = 0.00, 95\%CI[0.00, 1.00]$). The following tables 2.96, 2.95, and 2.97 provide detals of the observations, column and row percentages. Figures 2.55 and 2.56 present plots of residuals and contributions. Figure 2.57 presents the data in stacked proprtions.

	Not MDLS adequate	MDLS adequate
Below average broadband speed (col.)	43.00	42.20
Above average broadband speed (col.)	57.00	57.80

Table 2.95: Broadband factor by Equipment (Abs.) (Column Percentages) (χ^2(NA, 1582) = 0.092, p = 0.787, Cramer's V = 0.008)

	Not MDLS adequate	MDLS adequate
Below average broadband speed (row)	50.00	50.00
Above average broadband speed (row)	49.20	50.80

Table 2.96: Broadband factor by Equipment (Abs.) (Row Percentages) (χ^2(NA, 1582) = 0.092, p = 0.787, Cramer's V = 0.008)

	Not MDLS adequate	MDLS adequate
Below average broadband speed (obs.)	337.00	337.00
Below average broadband speed (row)	50.00	50.00
Below average broadband speed (col.)	43.00	42.20
Above average broadband speed (obs.)	447.00	461.00
Above average broadband speed (row)	49.20	50.80
Above average broadband speed (col.)	57.00	57.80

Table 2.97: Broadband factor by Equipment (Abs.) (χ^2(NA, 1582) = 0.092, p = 0.787, Cramer's V = 0.008)

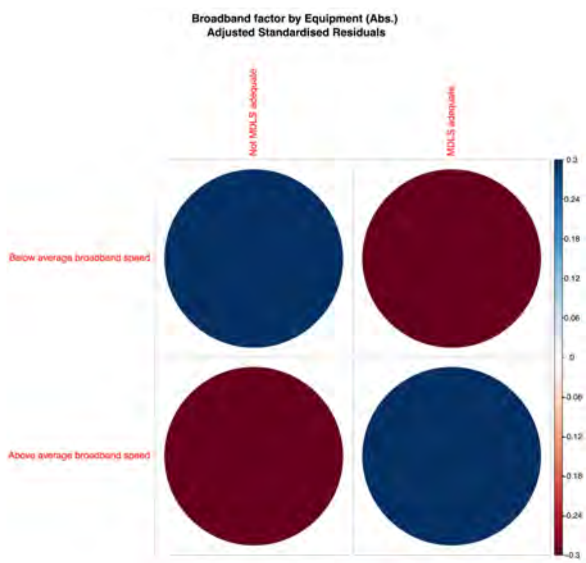

Figure 2.55: Res. Cont. plots-37

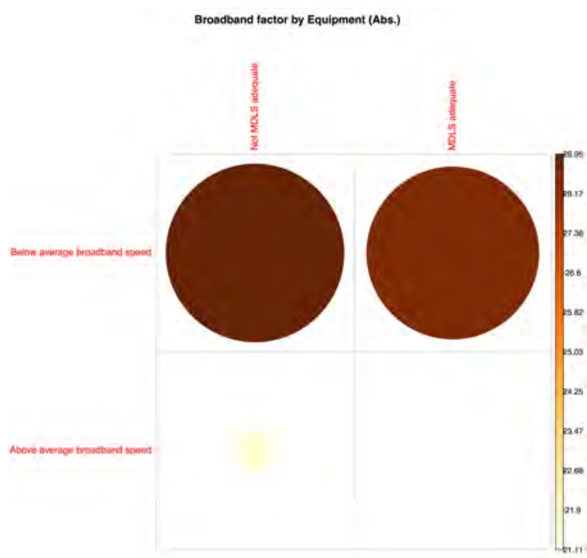

Figure 2.56: Res. Cont. plots-38

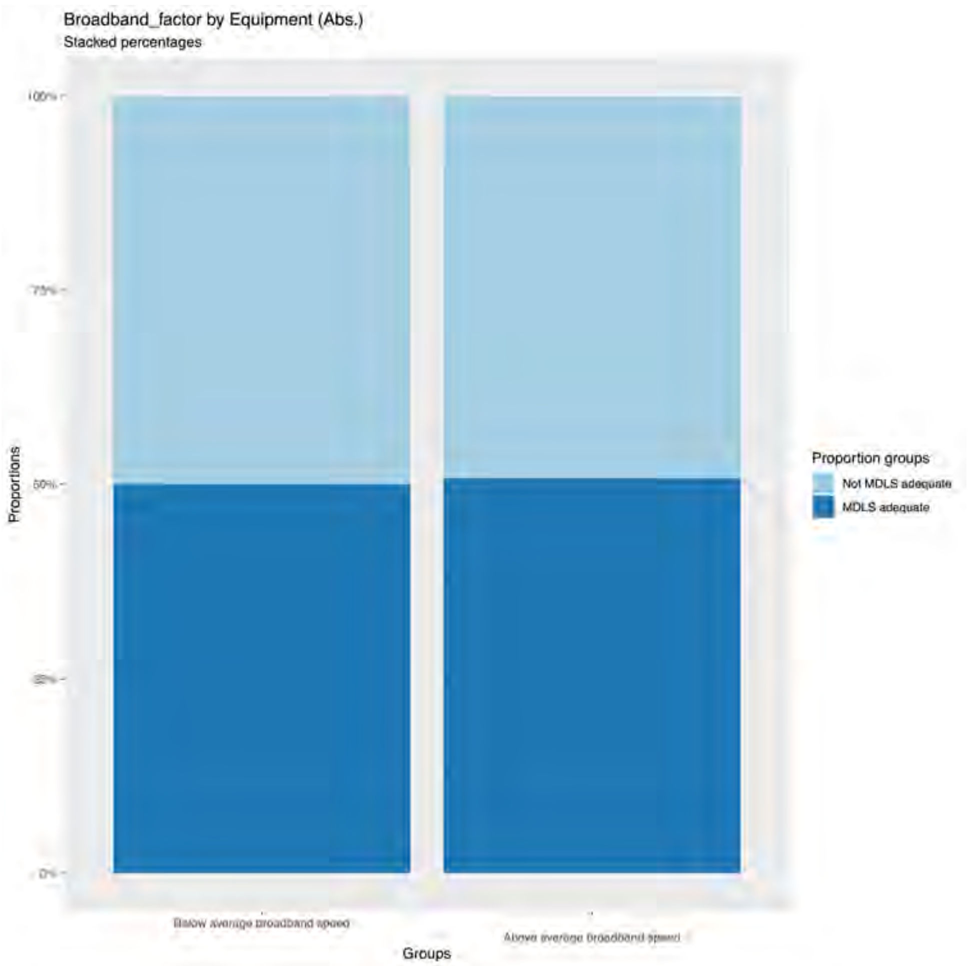

Figure 2.57: Proportions plot-19

2.4.20 URBANfactorbyEquipment(Abs.)

The Pearson's Chi-squared test with simulated p-value of independence between variables suggests that the effect is statistically significant and very small ($chi^2 = 17.05, p = 0.001; AdjustedCramer'sv = 0.09, 95\%CI[0.00, 1.00]$). The following tables 2.99, 2.98, and 2.100 provide detals of the observations, column and row percentages. Figures 2.58 and 2.59 present plots of residuals and contributions. Figure 2.60 presents the data in stacked proprtions.

	Not MDLS adequate	MDLS adequate
Large city (col.)	19.50	13.30
Smaller city or large town (col.)	17.10	16.40
Medium town (col.)	34.90	35.30
Small town (col.)	16.60	22.70
Rural area (col.)	11.90	12.30

Table 2.98: URBAN factor by Equipment (Abs.) (Column Percentages) (χ^2(NA, 1582) = 17.05, p = 0.001, Cramer's V = 0.104)

	Not MDLS adequate	MDLS adequate
Large city (row)	59.10	40.90
Smaller city or large town (row)	50.60	49.40
Medium town (row)	49.30	50.70
Small town (row)	41.80	58.20
Rural area (row)	48.70	51.30

Table 2.99: URBAN factor by Equipment (Abs.) (Row Percentages) (χ^2(NA, 1582) = 17.05, p = 0.001, Cramer's V = 0.104)

	Not MDLS adequate	MDLS adequate
Large city (obs.)	153.00	106.00
Large city (row)	59.10	40.90
Large city (col.)	19.50	13.30
Smaller city or large town (obs.)	134.00	131.00
Smaller city or large town (row)	50.60	49.40
Smaller city or large town (col.)	17.10	16.40
Medium town (obs.)	274.00	282.00
Medium town (row)	49.30	50.70
Medium town (col.)	34.90	35.30
Small town (obs.)	130.00	181.00
Small town (row)	41.80	58.20
Small town (col.)	16.60	22.70
Rural area (obs.)	93.00	98.00
Rural area (row)	48.70	51.30
Rural area (col.)	11.90	12.30

Table 2.100: URBAN factor by Equipment (Abs.) (χ^2(NA, 1582) = 17.05, p = 0.001, Cramer's V = 0.104)

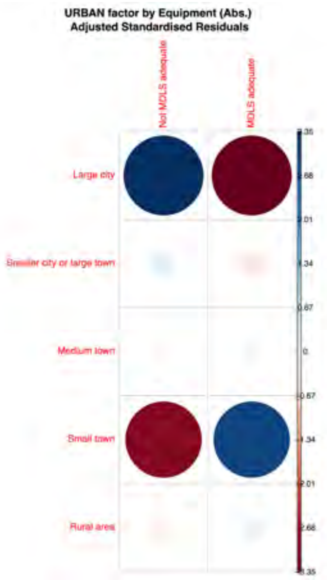

Figure 2.58: Res. Cont. plots-39

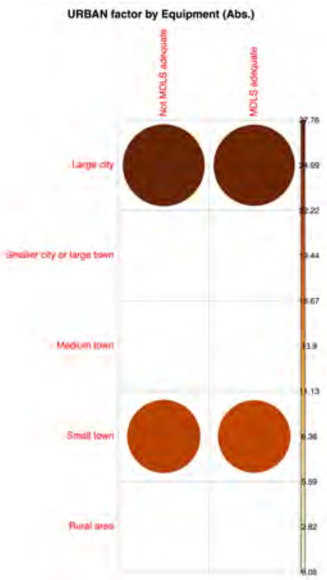

Figure 2.59: Res. Cont. plots-40

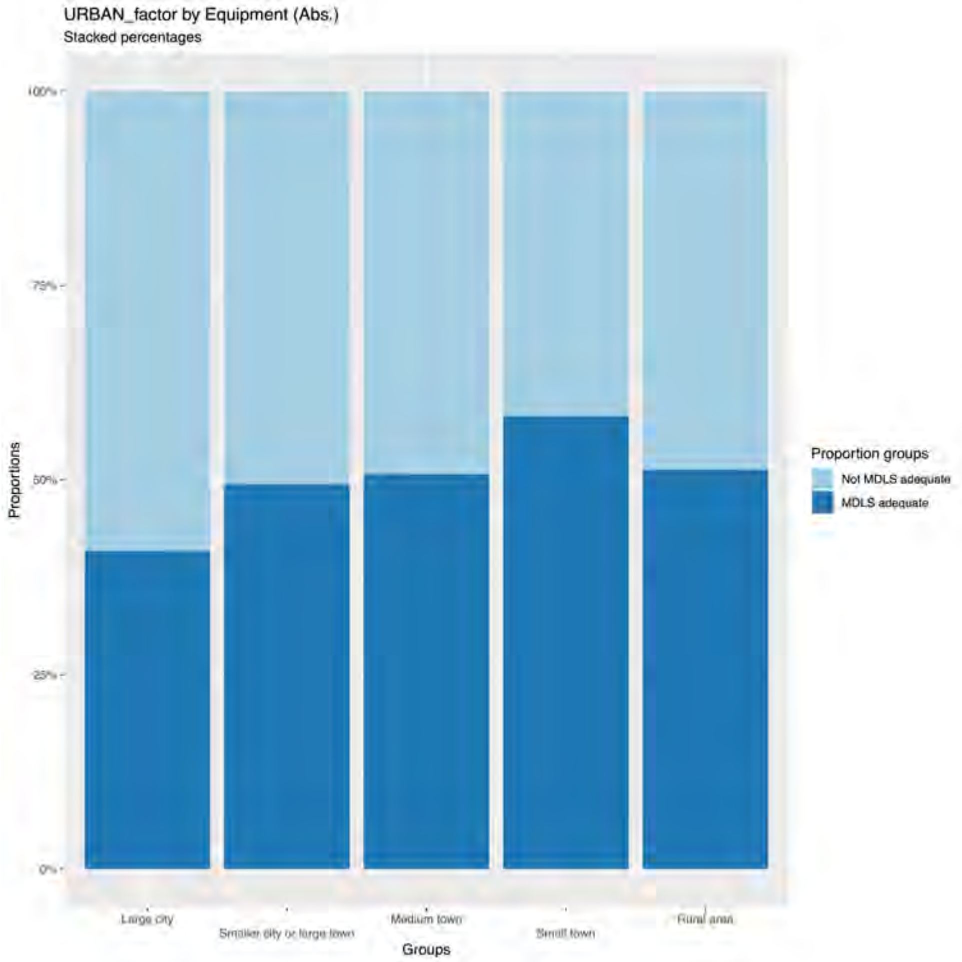

Figure 2.60: Proportions plot-20

2.4.21 URBAN2factorbyEquipment(Abs.)

The Pearson's Chi-squared test with simulated p-value of independence between variables suggests that the effect is statistically not significant and tiny ($chi^2 = 0.07, p = 0.813; AdjustedCramer'sv = 0.00, 95\% CI[0.00, 1.00]$). The following tables 2.102, 2.101, and 2.103 provide detals of the observations, column and row percentages. Figures 2.61 and 2.62 present plots of residuals and contributions. Figure 2.63 presents the data in stacked proprtions.

	Not MDLS adequate	MDLS adequate
Urban (col.)	88.10	87.70
Rural (col.)	11.90	12.30

Table 2.101: URBAN2 factor by Equipment (Abs.) (Column Percentages) (χ^2(NA, 1582) = 0.065, p = 0.813, Cramer's V = 0.006)

	Not MDLS adequate	MDLS adequate
Urban (row)	49.70	50.30
Rural (row)	48.70	51.30

Table 2.102: URBAN2 factor by Equipment (Abs.) (Row Percentages) (χ^2(NA, 1582) = 0.065, p = 0.813, Cramer's V = 0.006)

	Not MDLS adequate	MDLS adequate
Urban (obs.)	691.00	700.00
Urban (row)	49.70	50.30
Urban (col.)	88.10	87.70
Rural (obs.)	93.00	98.00
Rural (row)	48.70	51.30
Rural (col.)	11.90	12.30

Table 2.103: URBAN2 factor by Equipment (Abs.) (χ^2(NA, 1582) = 0.065, p = 0.813, Cramer's V = 0.006)

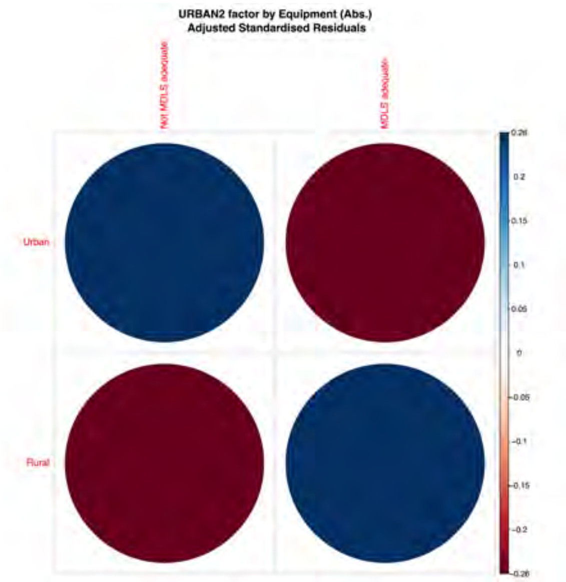

Figure 2.61: Res. Cont. plots-41

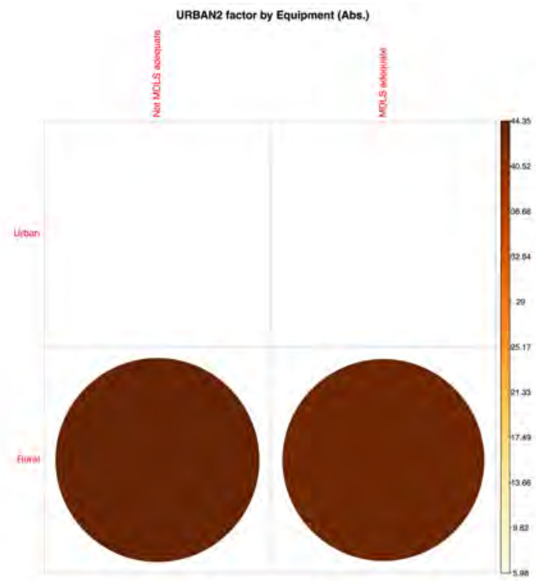

Figure 2.62: Res. Cont. plots-42

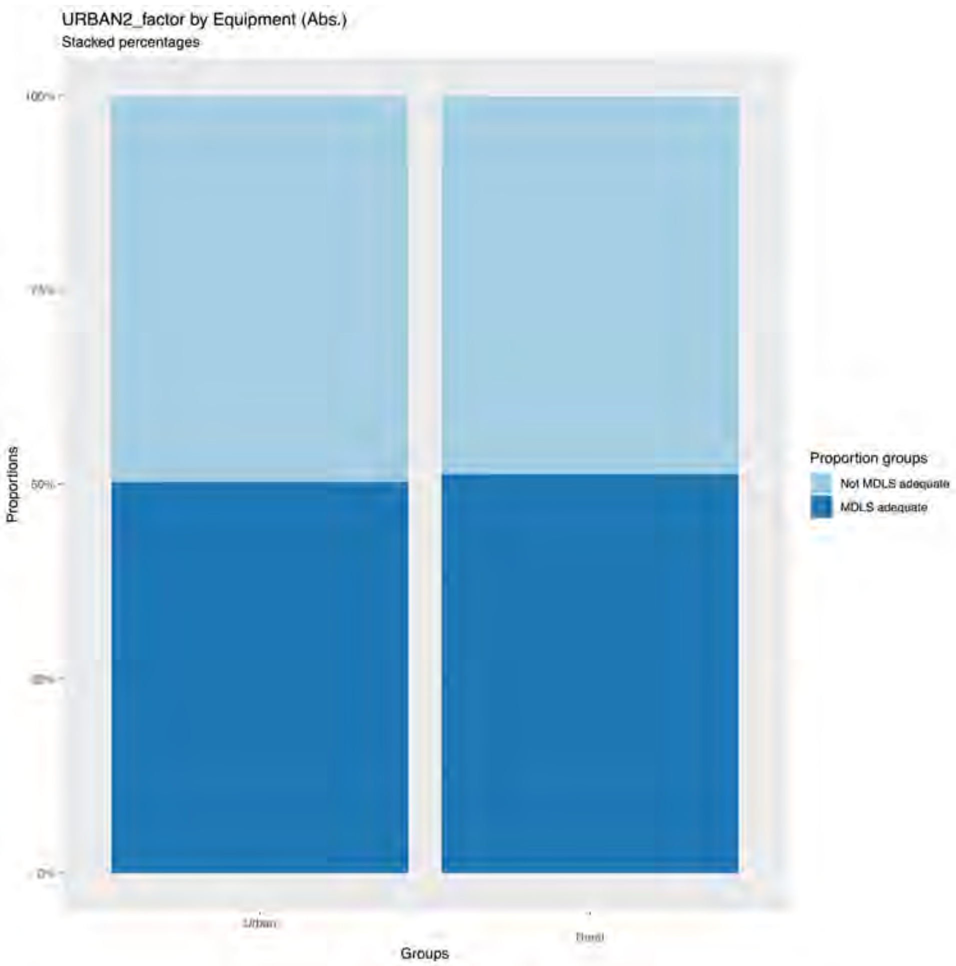

Figure 2.63: Proportions plot-21

2.4.22 iucGRPLBLrfactorbyEquipment(Abs.)

The Pearson's Chi-squared test with simulated p-value of independence between variables suggests that the effect is statistically significant and small ($chi^2 = 53.43, p < .001; AdjustedCramer'sv = 0.17, 95\%CI[0.10, 1.00]$). The following tables 2.105, 2.104, and 2.106 provide detals of the observations, column and row percentages. Figures 2.64 and 2.65 present plots of residuals and contributions. Figure 2.66 presents the data in stacked proprtions.

	Not MDLS adequate	MDLS adequate
Digital Seniors (col.)	8.30	10.80
e-Cultural Creators (col.)	0.10	0.30
e-Mainstream (col.)	13.70	15.20
e-Professionals (col.)	3.40	3.70
e-Rational Utilitarians (col.)	5.90	8.80
e-Veterans (col.)	10.00	15.70
e-Withdrawn (col.)	17.10	8.40
Passive and Uncommitted Users (col.)	29.50	24.90
Settled Offline Communities (col.)	4.10	7.20
Youthful Urban Fringe (col.)	7.90	5.00

Table 2.104: iuc GRP LBLr factor by Equipment (Abs.) (Column Percentages) (χ^2(NA, 1491) = 53.427, p = 0, Cramer's V = 0.189)

	Not MDLS adequate	MDLS adequate
Digital Seniors (row)	42.70	57.30
e-Cultural Creators (row)	33.30	66.70
e-Mainstream (row)	46.50	53.50
e-Professionals (row)	47.20	52.80
e-Rational Utilitarians (row)	39.10	60.90
e-Veterans (row)	38.00	62.00
e-Withdrawn (row)	66.10	33.90
Passive and Uncommitted Users (row)	53.30	46.70
Settled Offline Communities (row)	35.30	64.70
Youthful Urban Fringe (row)	60.40	39.60

Table 2.105: iuc GRP LBLr factor by Equipment (Abs.) (Row Percentages) (χ^2(NA, 1491) = 53.427, p = 0, Cramer's V = 0.189)

	Not MDLS adequate	MDLS adequate
Digital Seniors (obs.)	61.00	82.00
Digital Seniors (row)	42.70	57.30
Digital Seniors (col.)	8.30	10.80
e-Cultural Creators (obs.)	1.00	2.00
e-Cultural Creators (row)	33.30	66.70
e-Cultural Creators (col.)	0.10	0.30
e-Mainstream (obs.)	100.00	115.00
e-Mainstream (row)	46.50	53.50
e-Mainstream (col.)	13.70	15.20
e-Professionals (obs.)	25.00	28.00
e-Professionals (row)	47.20	52.80
e-Professionals (col.)	3.40	3.70
e-Rational Utilitarians (obs.)	43.00	67.00
e-Rational Utilitarians (row)	39.10	60.90
e-Rational Utilitarians (col.)	5.90	8.80
e-Veterans (obs.)	73.00	119.00
e-Veterans (row)	38.00	62.00
e-Veterans (col.)	10.00	15.70
e-Withdrawn (obs.)	125.00	64.00
e-Withdrawn (row)	66.10	33.90
e-Withdrawn (col.)	17.10	8.40
Passive and Uncommitted Users (obs.)	216.00	189.00
Passive and Uncommitted Users (row)	53.30	46.70
Passive and Uncommitted Users (col.)	29.50	24.90
Settled Offline Communities (obs.)	30.00	55.00
Settled Offline Communities (row)	35.30	64.70
Settled Offline Communities (col.)	4.10	7.20
Youthful Urban Fringe (obs.)	58.00	38.00
Youthful Urban Fringe (row)	60.40	39.60
Youthful Urban Fringe (col.)	7.90	5.00

Table 2.106: iuc GRP LBLr factor by Equipment (Abs.) (χ^2(NA, 1491) = 53.427, p = 0, Cramer's V = 0.189)

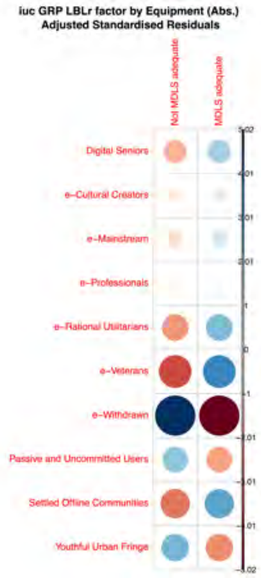

Figure 2.64: Res. Cont. plots-43

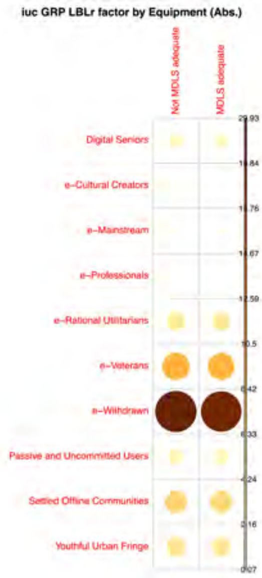

Figure 2.65: Res. Cont. plots-44

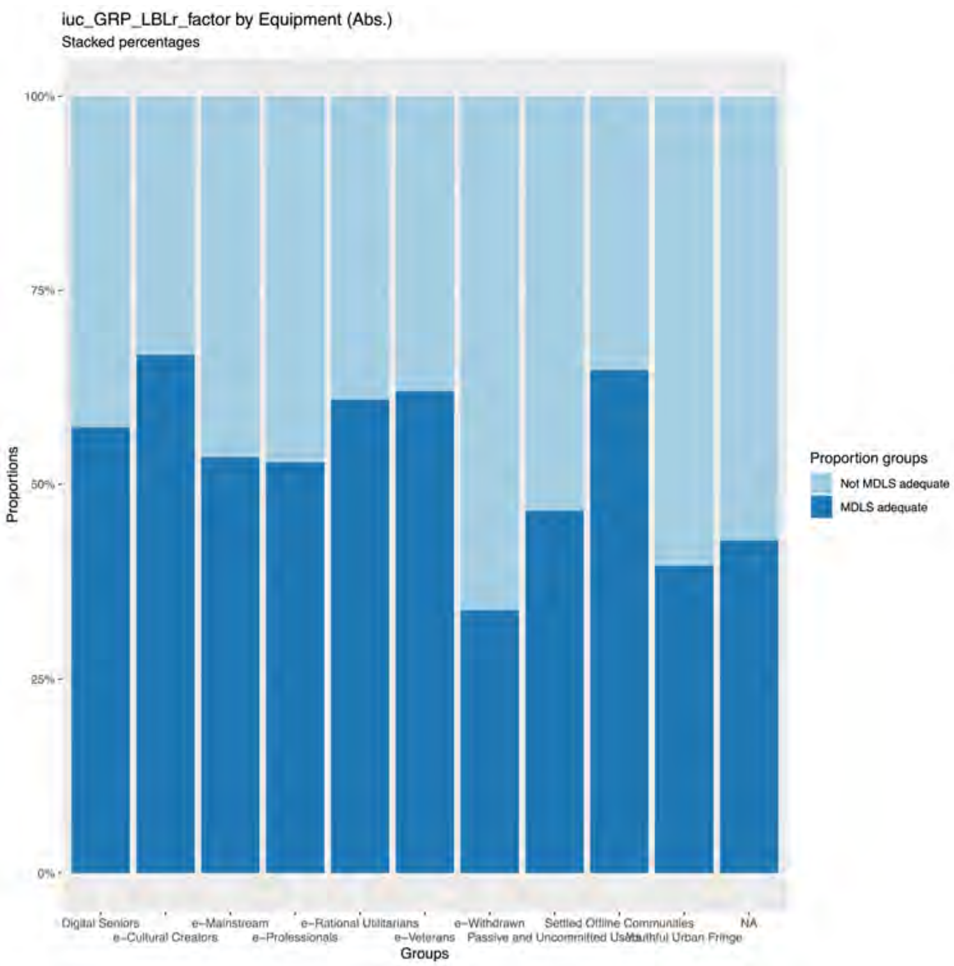

Figure 2.66: Proportions plot-22

2.4.23 oac21SGfactorbyEquipment(Abs.)

The Pearson's Chi-squared test with simulated p-value of independence between variables suggests that the effect is statistically significant and small ($chi^2 = 44.61, p < .001; AdjustedCramer'sv = 0.17, 95\%CI[0.10, 1.00]$). The following tables 2.108, 2.107, and 2.109 provide detals of the observations, column and row percentages. Figures 2.67 and 2.68 present plots of residuals and contributions. Figure 2.69 presents the data in stacked proprtions.

	Not MDLS adequate	MDLS adequate
Retired Professionals (col.)	5.80	8.30
Suburbanites and Peri-Urbanities (col.)	13.70	21.20
Multicultural and Educated Urbanites (col.)	7.10	4.40
Low-Skilled Migrant and Student Communities (col.)	21.90	13.40
Ethnically Diverse Suburban Professionals (col.)	6.40	11.50
Baseline UK (col.)	22.30	21.60
Semi-and Un-Skilled Workforce (col.)	19.80	17.70
Legacy Communities (col.)	3.00	1.90

Table 2.107: oac21SG factor by Equipment (Abs.) (Column Percentages) (χ^2(NA, 1357) = 44.606, p = 0, Cramer's V = 0.181)

	Not MDLS adequate	MDLS adequate
Retired Professionals (row)	40.60	59.40
Suburbanites and Peri-Urbanities (row)	38.80	61.20
Multicultural and Educated Urbanites (row)	61.50	38.50
Low-Skilled Migrant and Student Communities (row)	61.50	38.50
Ethnically Diverse Suburban Professionals (row)	35.20	64.80
Baseline UK (row)	50.30	49.70
Semi-and Un-Skilled Workforce (row)	52.40	47.60
Legacy Communities (row)	60.60	39.40

Table 2.108: oac21SG factor by Equipment (Abs.) (Row Percentages) (χ^2(NA, 1357) = 44.606, p = 0, Cramer's V = 0.181)

	Not MDLS adequate	MDLS adequate
Retired Professionals (obs.)	39.00	57.00
Retired Professionals (row)	40.60	59.40
Retired Professionals (col.)	5.80	8.30
Suburbanites and Peri-Urbanities (obs.)	92.00	145.00
Suburbanites and Peri-Urbanities (row)	38.80	61.20
Suburbanites and Peri-Urbanities (col.)	13.70	21.20
Multicultural and Educated Urbanites (obs.)	48.00	30.00
Multicultural and Educated Urbanites (row)	61.50	38.50
Multicultural and Educated Urbanites (col.)	7.10	4.40
Low-Skilled Migrant and Student Communities (obs.)	147.00	92.00
Low-Skilled Migrant and Student Communities (row)	61.50	38.50
Low-Skilled Migrant and Student Communities (col.)	21.90	13.40
Ethnically Diverse Suburban Professionals (obs.)	43.00	79.00
Ethnically Diverse Suburban Professionals (row)	35.20	64.80
Ethnically Diverse Suburban Professionals (col.)	6.40	11.50
Baseline UK (obs.)	150.00	148.00
Baseline UK (row)	50.30	49.70
Baseline UK (col.)	22.30	21.60
Semi-and Un-Skilled Workforce (obs.)	133.00	121.00
Semi-and Un-Skilled Workforce (row)	52.40	47.60
Semi-and Un-Skilled Workforce (col.)	19.80	17.70
Legacy Communities (obs.)	20.00	13.00
Legacy Communities (row)	60.60	39.40
Legacy Communities (col.)	3.00	1.90

Table 2.109: oac21SG factor by Equipment (Abs.) (χ^2(NA, 1357) = 44.606, p = 0, Cramer's V = 0.181)

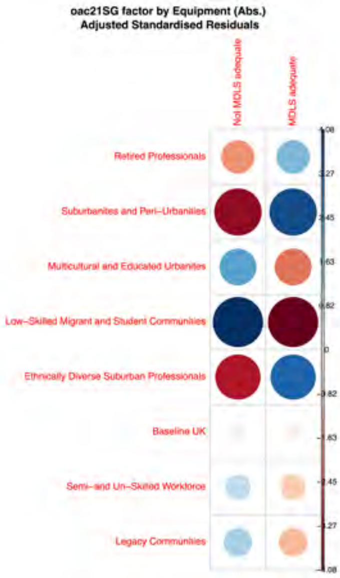

Figure 2.67: Res. Cont. plots-45

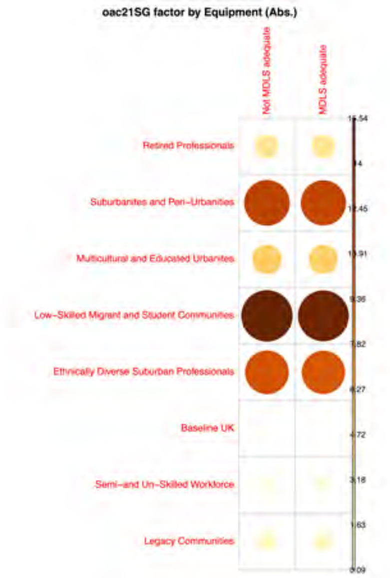

Figure 2.68: Res. Cont. plots-46

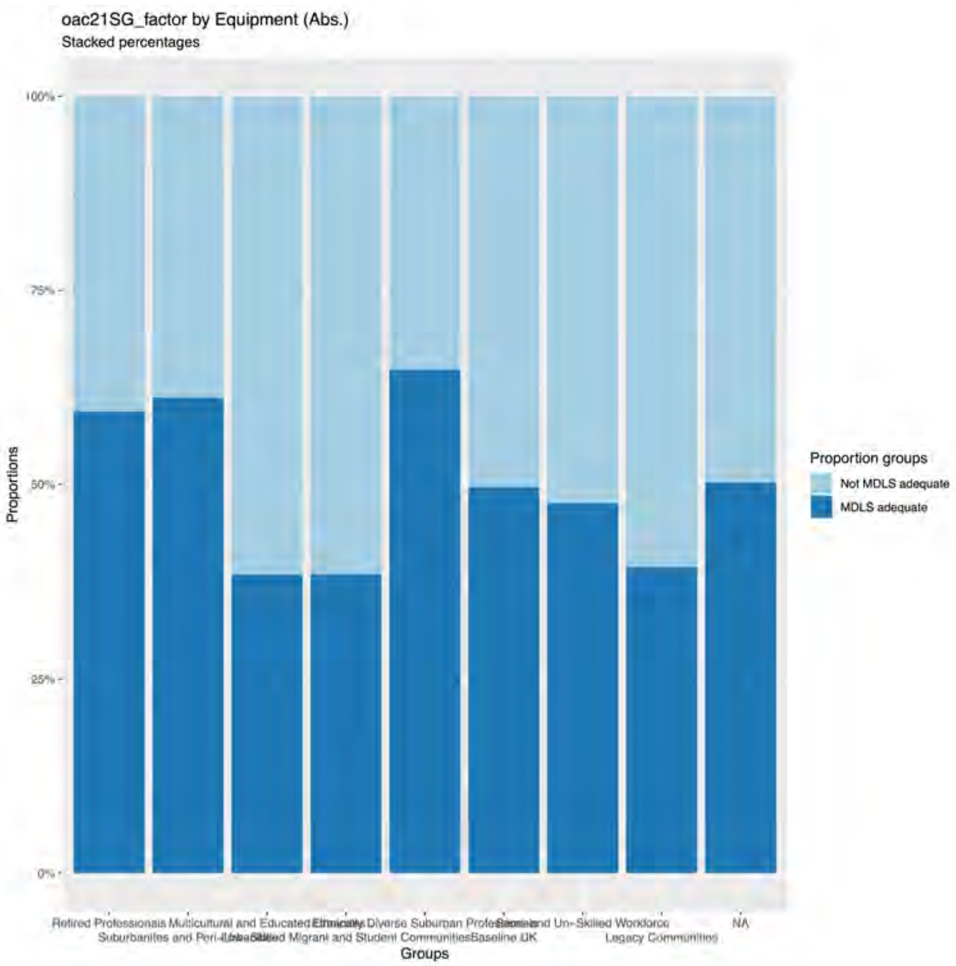

Figure 2.69: Proportions plot-23

2.4.24 aipcsupergroupnamerfactorbyEquipment(Abs.)

The Pearson's Chi-squared test with simulated p-value of independence between variables suggests that the effect is statistically significant and small ($chi^2 = 42.41, p < .001; AdjustedCramer'sv = 0.17, 95\% CI[0.12, 1.00]$). The following tables 2.111, 2.110, and 2.112 provide detals of the observations, column and row percentages. Figures 2.70 and 2.71 present plots of residuals and contributions. Figure 2.72 presents the data in stacked proprtions.

	Not MDLS adequate	MDLS adequate
1 Struggling, More Vulnerable Urbanites (col.)	32.90	25.60
2 Multicultural Central Urban Living (col.)	19.30	10.50
3 Rurban Comfortable Ageing (col.)	12.20	21.10
4 Retired Fringe and Residential Stability (col.)	21.50	24.40
5 Cosmopolitan and Coastal Ageing (col.)	14.10	18.40

Table 2.110: aipc supergroup namer factor by Equipment (Abs.) (Column Percentages) (χ^2(NA, 1278) = 42.415, p = 0, Cramer's V = 0.182)

	Not MDLS adequate	MDLS adequate
1 Struggling, More Vulnerable Urbanites (row)	56.10	43.90
2 Multicultural Central Urban Living (row)	64.70	35.30
3 Rurban Comfortable Ageing (row)	36.60	63.40
4 Retired Fringe and Residential Stability (row)	46.80	53.20
5 Cosmopolitan and Coastal Ageing (row)	43.30	56.70

Table 2.111: aipc supergroup namer factor by Equipment (Abs.) (Row Percentages) (χ^2(NA, 1278) = 42.415, p = 0, Cramer's V = 0.182)

	Not MDLS adequate	MDLS adequate
1 Struggling, More Vulnerable Urbanites (obs.)	210.00	164.00
1 Struggling, More Vulnerable Urbanites (row)	56.10	43.90
1 Struggling, More Vulnerable Urbanites (col.)	32.90	25.60
2 Multicultural Central Urban Living (obs.)	123.00	67.00
2 Multicultural Central Urban Living (row)	64.70	35.30
2 Multicultural Central Urban Living (col.)	19.30	10.50
3 Rurban Comfortable Ageing (obs.)	78.00	135.00
3 Rurban Comfortable Ageing (row)	36.60	63.40
3 Rurban Comfortable Ageing (col.)	12.20	21.10
4 Retired Fringe and Residential Stability (obs.)	137.00	156.00
4 Retired Fringe and Residential Stability (row)	46.80	53.20
4 Retired Fringe and Residential Stability (col.)	21.50	24.40
5 Cosmopolitan and Coastal Ageing (obs.)	90.00	118.00
5 Cosmopolitan and Coastal Ageing (row)	43.30	56.70
5 Cosmopolitan and Coastal Ageing (col.)	14.10	18.40

Table 2.112: aipc supergroup namer factor by Equipment (Abs.) (χ^2(NA, 1278) = 42.415, p = 0, Cramer's V = 0.182)

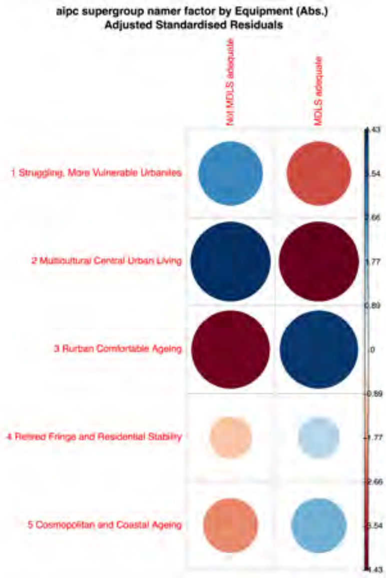

Figure 2.70: Res. Cont. plots-47

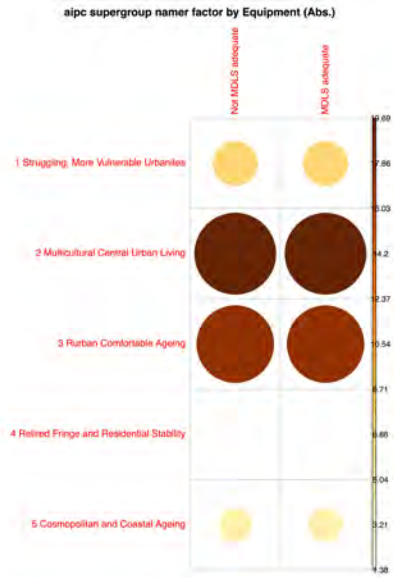

Figure 2.71: Res. Cont. plots-48

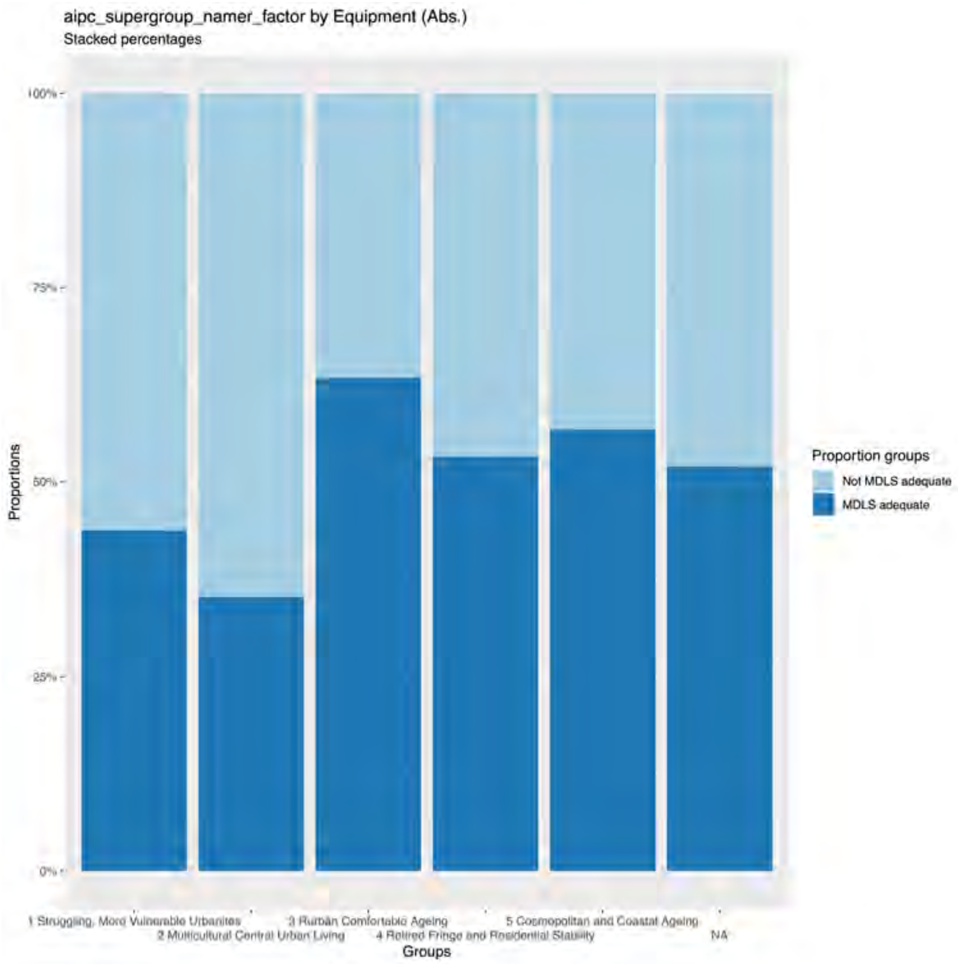

Figure 2.72: Proportions plot-24

2.4.25 BenefitsfactorbyEquipment(Abs.)

The Pearson's Chi-squared test with simulated p-value of independence between variables suggests that the effect is statistically significant and medium ($chi^2 = 64.54, p < .001; AdjustedCramer'sv = 0.20, 95\%CI[0.16, 1.00]$). The following tables 2.114, 2.113, and 2.115 provide detals of the observations, column and row percentages. Figures 2.73 and 2.74 present plots of residuals and contributions. Figure 2.75 presents the data in stacked proprtions.

	Not MDLS adequate	MDLS adequate
Not on any benefits (col.)	57.00	76.10
Receives at least one state benefit (col.)	43.00	23.90

Table 2.113: Benefits factor by Equipment (Abs.) (Column Percentages) (χ^2(NA, 1582) = 64.541, p = 0, Cramer's V = 0.202)

	Not MDLS adequate	MDLS adequate
Not on any benefits (row)	42.40	57.60
Receives at least one state benefit (row)	63.80	36.20

Table 2.114: Benefits factor by Equipment (Abs.) (Row Percentages) (χ^2(NA, 1582) = 64.541, p = 0, Cramer's V = 0.202)

	Not MDLS adequate	MDLS adequate
Not on any benefits (obs.)	447.00	607.00
Not on any benefits (row)	42.40	57.60
Not on any benefits (col.)	57.00	76.10
Receives at least one state benefit (obs.)	337.00	191.00
Receives at least one state benefit (row)	63.80	36.20
Receives at least one state benefit (col.)	43.00	23.90

Table 2.115: Benefits factor by Equipment (Abs.) (χ^2(NA, 1582) = 64.541, p = 0, Cramer's V = 0.202)

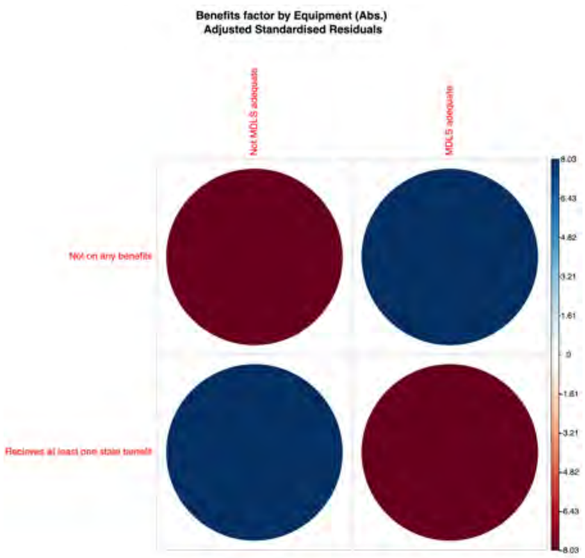

Figure 2.73: Res. Cont. plots-49

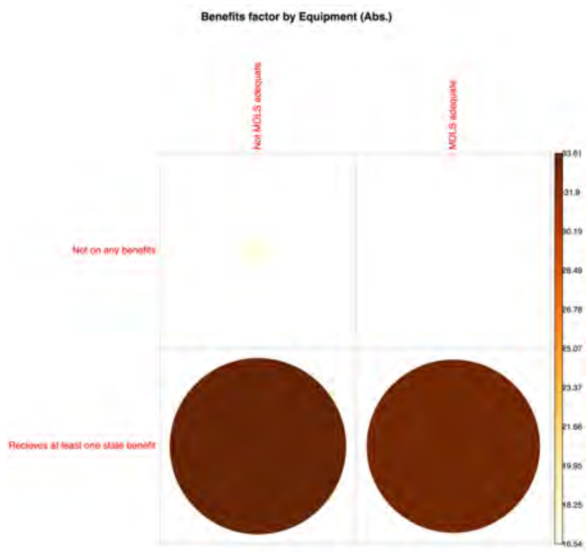

Figure 2.74: Res. Cont. plots-50

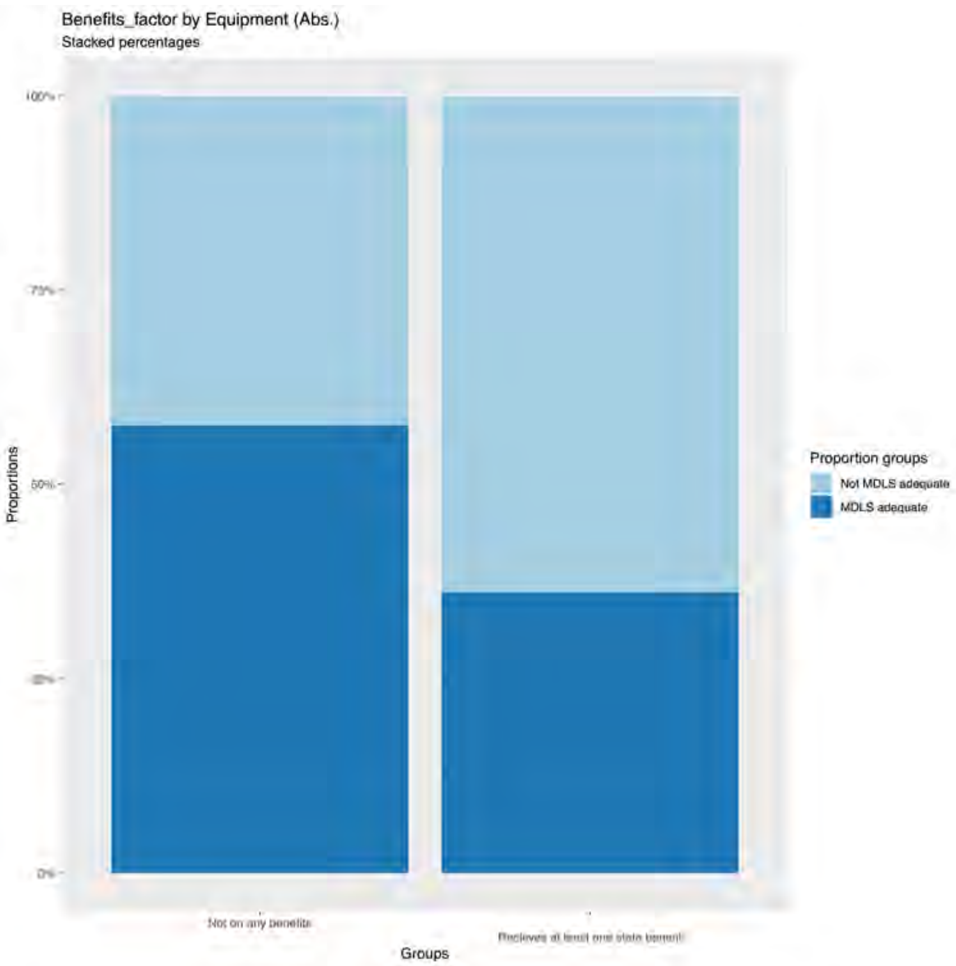

Figure 2.75: Proportions plot-25

2.4.26 WorkingfactorbyEquipment(Abs.)

The Pearson's Chi-squared test with simulated p-value of independence between variables suggests that the effect is statistically significant and small ($chi^2 = 64.16, p < .001; AdjustedCramer'sv = 0.20, 95\% CI[0.16, 1.00]$). The following tables 2.117, 2.116, and 2.118 provide detals of the observations, column and row percentages. Figures 2.76 and 2.77 present plots of residuals and contributions. Figure 2.78 presents the data in stacked proprtions.

	Not MDLS adequate	MDLS adequate
Chief income earner not working (col.)	27.80	11.80
Chief income earner working (col.)	72.20	88.20

Table 2.116: Working factor by Equipment (Abs.) (Column Percentages) (χ^2(NA, 1582) = 64.158, p = 0, Cramer's V = 0.201)

	Not MDLS adequate	MDLS adequate
Chief income earner not working (row)	69.90	30.10
Chief income earner working (row)	44.60	55.40

Table 2.117: Working factor by Equipment (Abs.) (Row Percentages) (χ^2(NA, 1582) = 64.158, p = 0, Cramer's V = 0.201)

	Not MDLS adequate	MDLS adequate
Chief income earner not working (obs.)	218.00	94.00
Chief income earner not working (row)	69.90	30.10
Chief income earner not working (col.)	27.80	11.80
Chief income earner working (obs.)	566.00	704.00
Chief income earner working (row)	44.60	55.40
Chief income earner working (col.)	72.20	88.20

Table 2.118: Working factor by Equipment (Abs.) (χ^2(NA, 1582) = 64.158, p = 0, Cramer's V = 0.201)

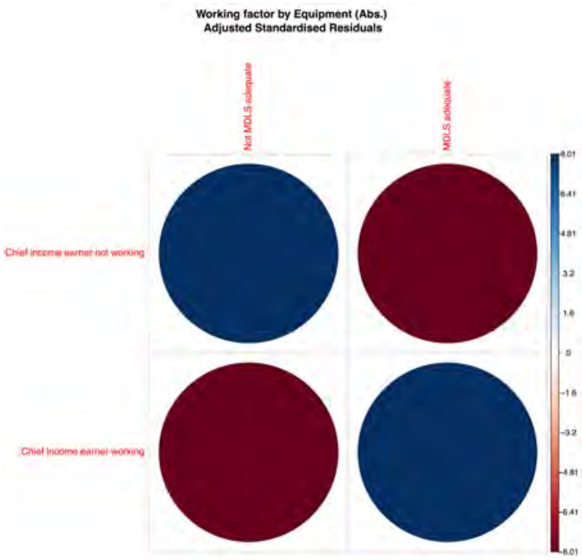

Figure 2.76: Res. Cont. plots-51

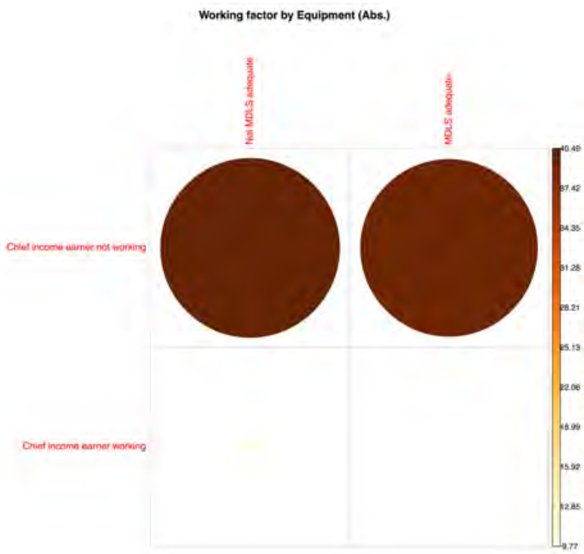

Figure 2.77: Res. Cont. plots-52

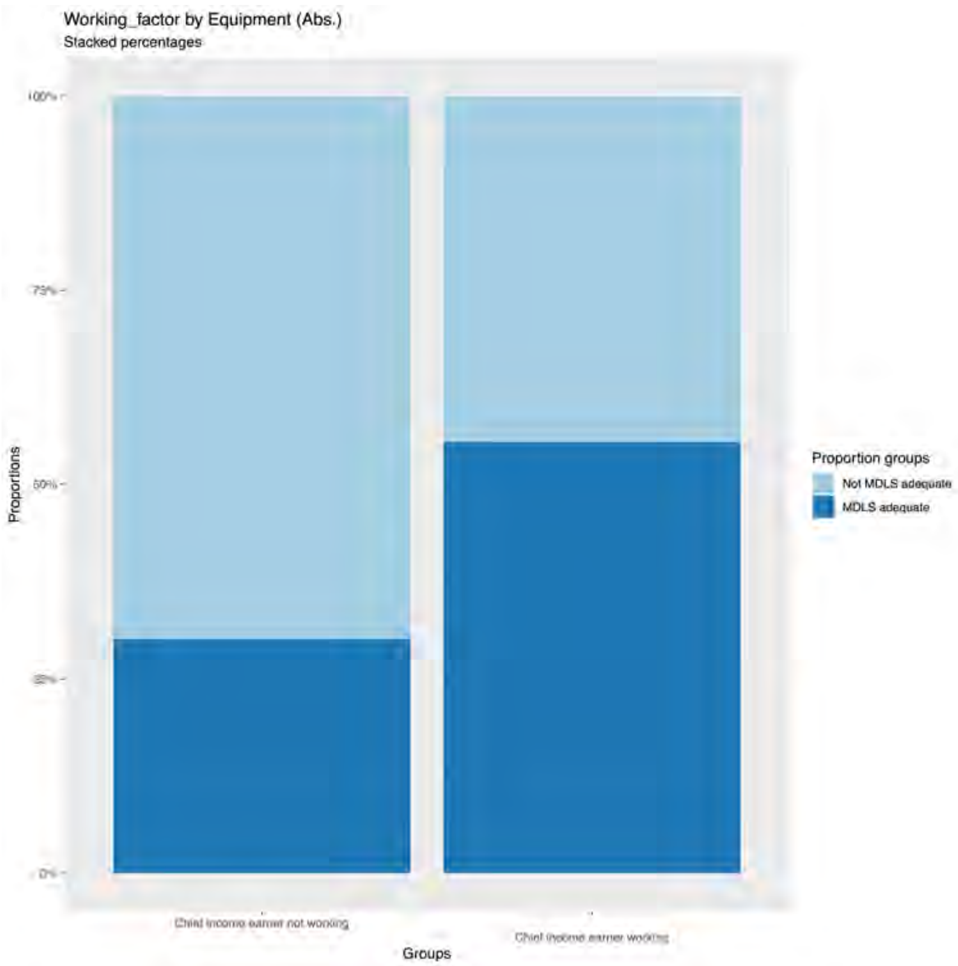

Figure 2.78: Proportions plot-26

2.4.27 HealthlimitationfactorbyEquipment(Abs.)

The Pearson's Chi-squared test with simulated p-value of independence between variables suggests that the effect is statistically significant and small ($chi^2 = 19.39, p < .001; AdjustedCramer'sv = 0.11, 95\% CI[0.06, 1.00]$). The following tables 2.120, 2.119, and 2.121 provide detals of the observations, column and row percentages. Figures 2.79 and 2.80 present plots of residuals and contributions. Figure 2.81 presents the data in stacked proprtions.

	Not MDLS adequate	MDLS adequate
Respondent has **no** health issue (col.)	80.60	88.60
Respondent **has** a health issue (col.)	19.40	11.40

Table 2.119: Health limitation factor by Equipment (Abs.) (Column Percentages) (χ^2(NA, 1582) = 19.391, p = 0, Cramer's V = 0.111)

	Not MDLS adequate	MDLS adequate
Respondent has no health issue(row)	47.20	52.80
Respondent **has** a health issue (row)	62.60	37.40

Table 2.120: Health limitation factor by Equipment (Abs.) (Row Percentages) (χ^2(NA, 1582) = 19.391, p = 0, Cramer's V = 0.111)

	Not MDLS adequate	MDLS adequate
Respondent has no health issue(obs.)	632.00	707.00
Respondent has **no** health issue (row)	47.20	52.80
Respondent has **no** health issue (col.)	80.60	88.60
Respondent **has** a health issue (obs.)	152.00	91.00
Respondent **has** a health issue (row)	62.60	37.40
Respondent **has** a health issue (col.)	19.40	11.40

Table 2.121: Health limitation factor by Equipment (Abs.) (χ^2(NA, 1582) = 19.391, p = 0, Cramer's V = 0.111)

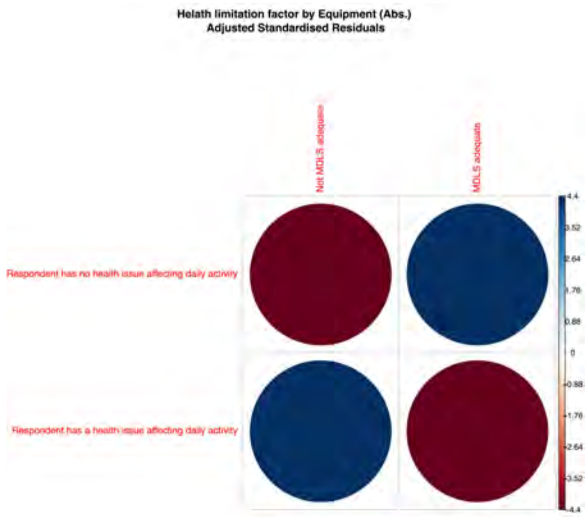

Figure 2.79: Res. Cont. plots-53

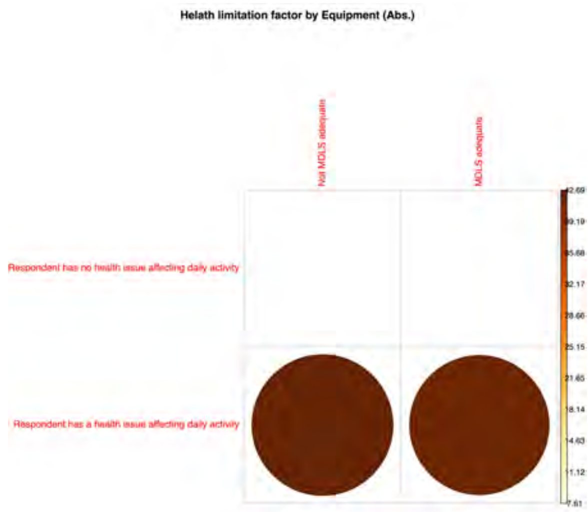

Figure 2.80: Res. Cont. plots-54

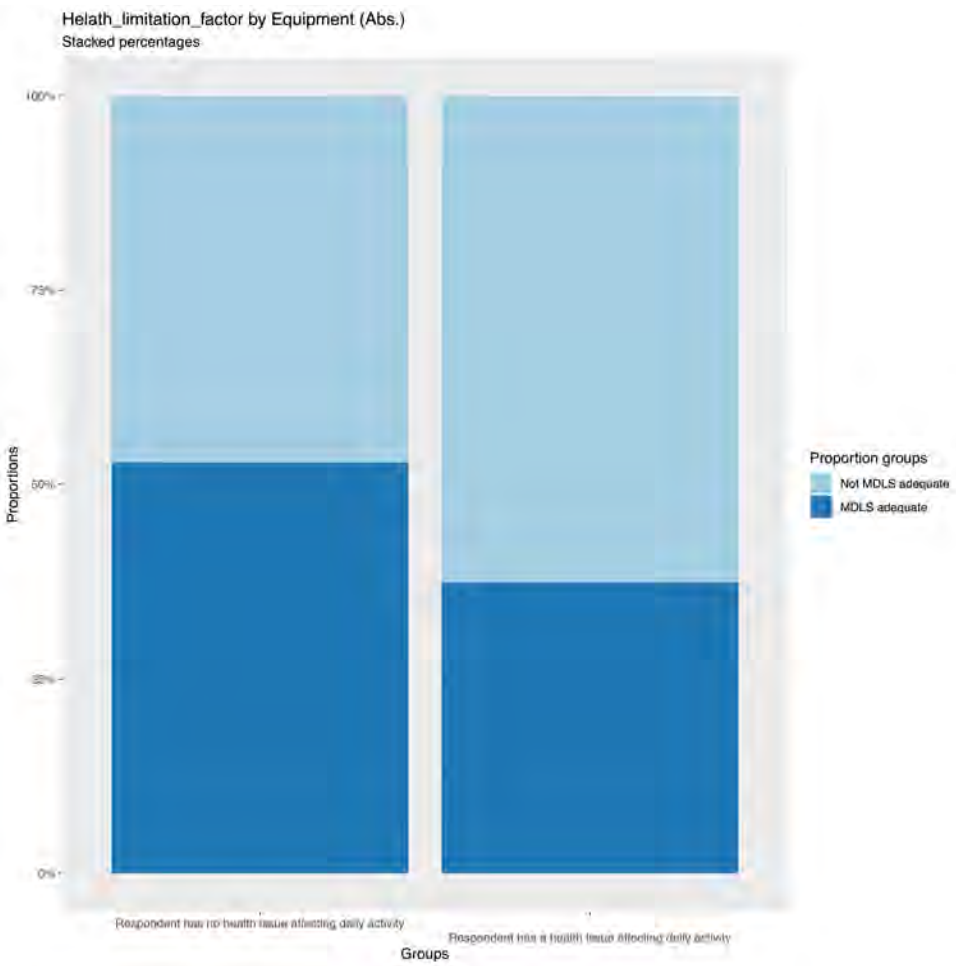

Figure 2.81: Proportions plot-27

2.4.28 EthnicityfactorbyEquipment(Abs.)

The Pearson's Chi-squared test with simulated p-value of independence between variables suggests that the effect is statistically significant and small ($chi^2 = 18.52, p < .001; AdjustedCramer'sv = 0.11, 95\%CI[0.06, 1.00]$). The following tables 2.123, 2.122, and 2.124 provide detals of the observations, column and row percentages. Figures 2.82 and 2.83 present plots of residuals and contributions. Figure 2.84 presents the data in stacked proprtions.

	Not MDLS adequate	MDLS adequate
Respondent identifies as ethnically white(col.)	72.20	81.30
Respondent identifies as ethnically non-white (col.)	27.80	18.70

Table 2.122: Ethnicity factor by Equipment (Abs.) (Column Percentages) (χ^2(NA, 1582) = 18.52, p = 0, Cramer's V = 0.108)

	Not MDLS adequate	MDLS adequate
Respondent identifies as ethnically white(row)	46.60	53.40
Respondent identifies as ethnically non-white (row)	59.40	40.60

Table 2.123: Ethnicity factor by Equipment (Abs.) (Row Percentages) (χ^2(NA, 1582) = 18.52, p = 0, Cramer's V = 0.108)

	Not MDLS adequate	MDLS adequate
Respondent identifies as ethnically white(obs.)	566.00	649.00
Respondent identifies as ethnically white(row)	46.60	53.40
Respondent identifies as ethnically white(col.)	72.20	81.30
Respondent identifies as ethnically non-white (obs.)	218.00	149.00
Respondent identifies as ethnically non-white (row)	59.40	40.60
Respondent identifies as ethnically non-white (col.)	27.80	18.70

Table 2.124: Ethnicity factor by Equipment (Abs.) (χ^2(NA, 1582) = 18.52, p = 0, Cramer's V = 0.108)

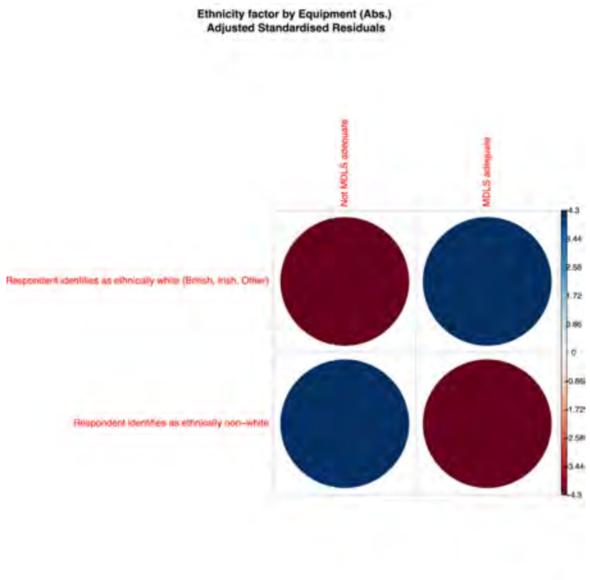

Figure 2.82: Res. Cont. plots-55

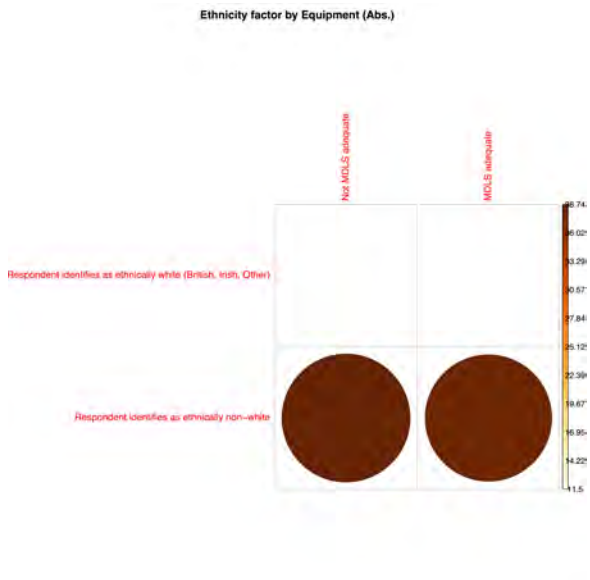

Figure 2.83: Res. Cont. plots-56

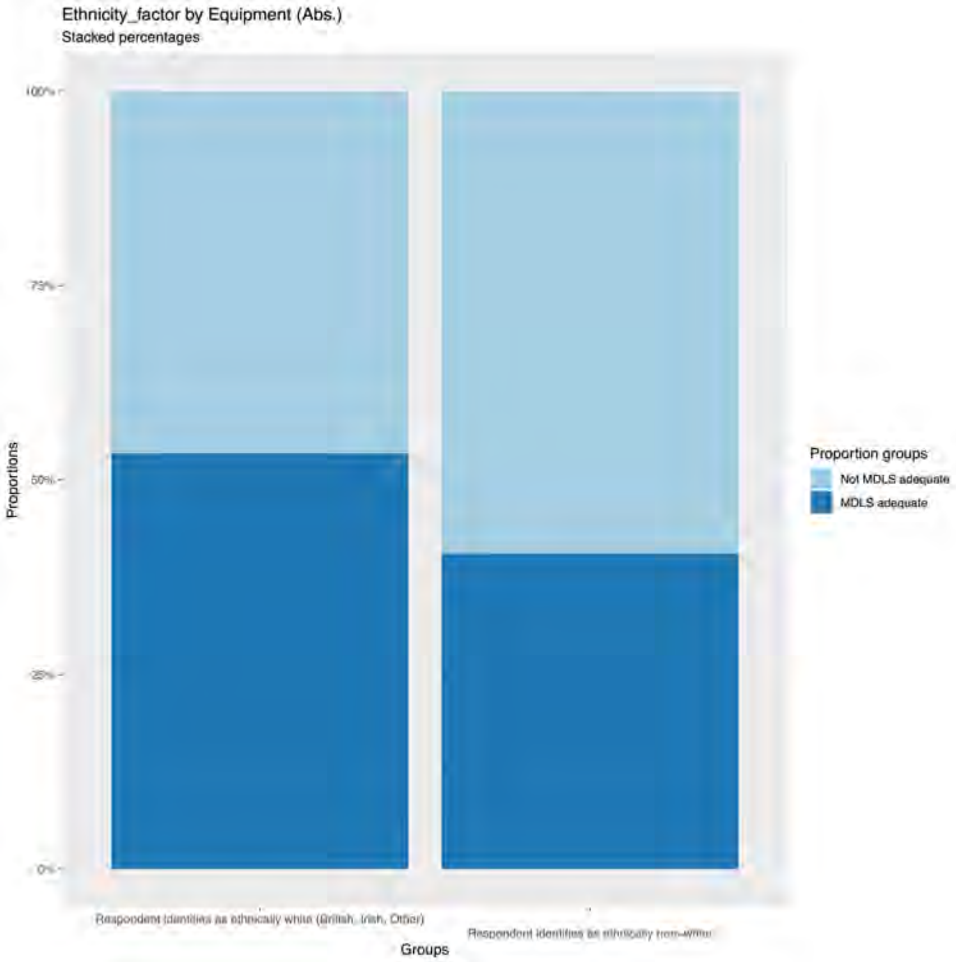

Figure 2.84: Proportions plot-28

2.4.29 SEGfactorbyhousholdskills

The Pearson's Chi-squared test with simulated p-value of independence between variables suggests that the effect is statistically significant and small ($chi^2 = 131.22, p < .001; Adjusted Cramer'sv = 0.16, 95\% CI[0.13, 1.00]$). The following tables 2.126, 2.125, and 2.127 provide detals of the observations, column and row percentages. Figures 2.85 and 2.86 present plots of residuals and contributions. Figure 2.87 presents the data in stacked proprtions.

	Not adequate Skills	Children Have Adequate Skills	Parents Have Adequate Skills	Household Has Adequate Skills
AB (col.)	10.00	10.90	24.60	24.70
C1 (col.)	31.40	23.80	28.10	33.50
C2 (col.)	22.90	20.40	29.80	23.30
DE (col.)	35.70	44.90	17.50	18.40

Table 2.125: SEG factor by houshold skills (Column Percentages) (χ^2(NA, 1582) = 131.216, p = 0, Cramer's V = 0.166)

	Not adequate Skills	Children Have Adequate Skills	Parents Have Adequate Skills	Household Has Adequate Skills
AB (row)	2.20	14.60	8.70	74.50
C1 (row)	4.60	21.40	6.70	67.40
C2 (row)	4.40	24.20	9.40	62.00
DE (row)	6.00	46.50	4.80	42.70

Table 2.126: SEG factor by houshold skills (Row Percentages) (χ^2(NA, 1582) = 131.216, p = 0, Cramer's V = 0.166)

	Not adequate Skills	Children Have Adequate Skills	Parents Have Adequate Skills	Household Has Adequate Skills
AB (obs.)	7.00	47.00	28.00	239.00
AB (row)	2.20	14.60	8.70	74.50
AB (col.)	10.00	10.90	24.60	24.70
C1 (obs.)	22.00	103.00	32.00	324.00
C1 (row)	4.60	21.40	6.70	67.40
C1 (col.)	31.40	23.80	28.10	33.50
C2 (obs.)	16.00	88.00	34.00	225.00
C2 (row)	4.40	24.20	9.40	62.00
C2 (col.)	22.90	20.40	29.80	23.30
DE (obs.)	25.00	194.00	20.00	178.00
DE (row)	6.00	46.50	4.80	42.70
DE (col.)	35.70	44.90	17.50	18.40

Table 2.127: SEG factor by houshold skills (χ^2(NA, 1582) = 131.216, p = 0, Cramer's V = 0.166)

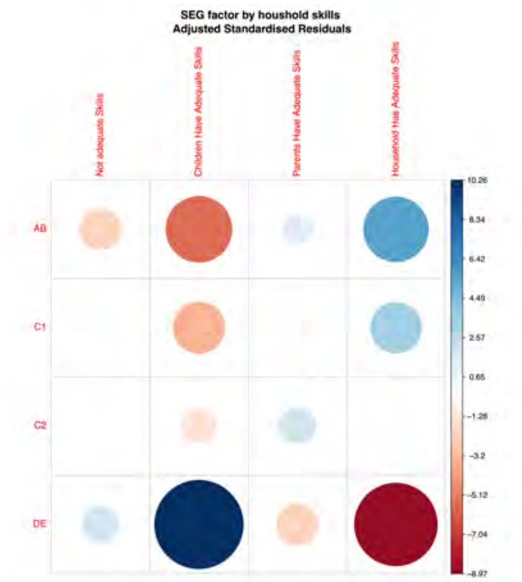

Figure 2.85: Res. Cont. plots-57

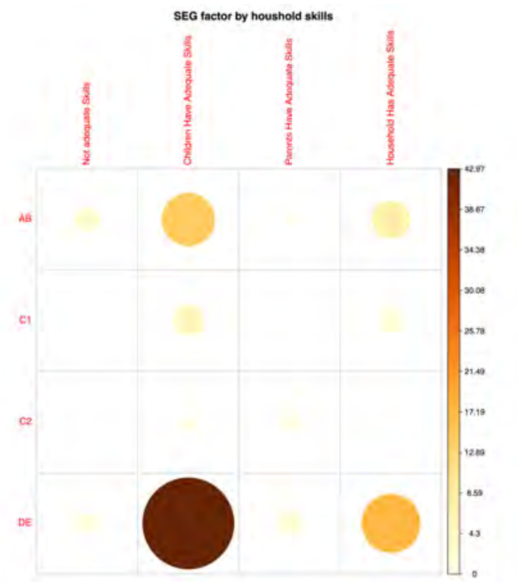

Figure 2.86: Res. Cont. plots-58

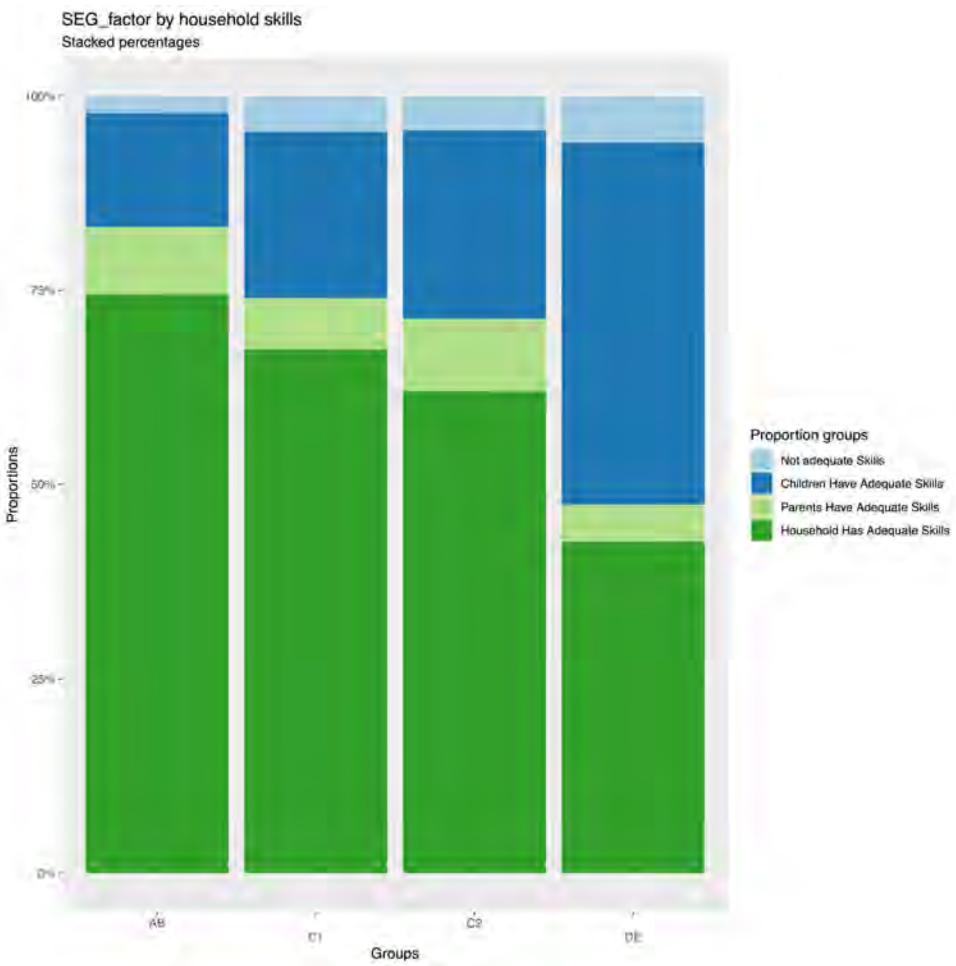

Figure 2.87: Proportions plot-29

2.4.30 HTYPEfactorbyhousholdskills

The Pearson's Chi-squared test with simulated p-value of independence between variables suggests that the effect is statistically significant and medium ($chi^2 = 430.39, p < .001; AdjustedCramer'sv = 0.29, 95\%CI[0.26, 1.00]$). The following tables 2.129, 2.128, and 2.130 provide detals of the observations, column and row percentages. Figures 2.88 and 2.89 present plots of residuals and contributions. Figure 2.90 presents the data in stacked proprtions.

	Not adequate Skills	Children Have Adequate Skills	Parents Have Adequate Skills	Household Has Adequate Skills
1 adult and 1 child (col.)	0.00	27.10	0.00	12.80
1 adult and 2 children (col.)	17.10	12.30	3.50	6.90
1 adult and more than 2 children (col.)	15.70	2.80	6.10	3.10
2 adults and 1 child (col.)	0.00	27.50	0.00	31.60
2 adults and 2 children (col.)	38.60	15.30	42.10	30.70
2 adults and more than 2 children (col.)	22.90	3.90	36.00	7.30
More than 2 adults in HH and 1 child (col.)	0.00	7.90	0.00	3.70
More than 2 adults in HH and 2 children (col.)	2.90	2.80	3.50	3.40
More than 2 adults in HH and 2+ children (col.)	2.90	0.50	8.80	0.30

Table 2.128: HTYPE factor by houshold skills (Column Percentages) (χ^2(NA, 1582) = 430.391, p = 0, Cramer's V = 0.301)

	Not adequate Skills	Children Have Adequate Skills	Parents Have Adequate Skills	Household Has Adequate Skills
1 adult and 1 child (row)	0.00	48.50	0.00	51.50
1 adult and 2 children (row)	8.80	39.00	2.90	49.30
1 adult and more than 2 children (row)	18.30	20.00	11.70	50.00
2 adults and 1 child (row)	0.00	28.10	0.00	71.90
2 adults and 2 children (row)	6.20	15.10	11.00	67.80
2 adults and more than 2 children (row)	11.00	11.70	28.30	49.00
More than 2 adults in HH and 1 child (row)	0.00	48.60	0.00	51.40
More than 2 adults in HH and 2 children (row)	3.90	23.50	7.80	64.70
More than 2 adults in HH and 2+ children (row)	11.80	11.80	58.80	17.60

Table 2.129: HTYPE factor by houshold skills (Row Percentages) (χ^2(NA, 1582) = 430.391, p = 0, Cramer's V = 0.301)

	Not adequate Skills	Children Have Adequate Skills	Parents Have Adequate Skills	Household Has Adequate Skills
1 adult and 1 child (obs.)	0.00	117.00	0.00	124.00
1 adult and 1 child (row)	0.00	48.50	0.00	51.50
1 adult and 1 child (col.)	0.00	27.10	0.00	12.80
1 adult and 2 children (obs.)	12.00	53.00	4.00	67.00
1 adult and 2 children (row)	8.80	39.00	2.90	49.30
1 adult and 2 children (col.)	17.10	12.30	3.50	6.90
1 adult and more than 2 children (obs.)	11.00	12.00	7.00	30.00
1 adult and more than 2 children (row)	18.30	20.00	11.70	50.00
1 adult and more than 2 children (col.)	15.70	2.80	6.10	3.10
2 adults and 1 child (obs.)	0.00	119.00	0.00	305.00
2 adults and 1 child (row)	0.00	28.10	0.00	71.90
2 adults and 1 child (col.)	0.00	27.50	0.00	31.60
2 adults and 2 children (obs.)	27.00	66.00	48.00	297.00
2 adults and 2 children (row)	6.20	15.10	11.00	67.80
2 adults and 2 children (col.)	38.60	15.30	42.10	30.70
2 adults and more than 2 children (obs.)	16.00	17.00	41.00	71.00
2 adults and more than 2 children (row)	11.00	11.70	28.30	49.00
2 adults and more than 2 children (col.)	22.90	3.90	36.00	7.30
More than 2 adults in HH and 1 child (obs.)	0.00	34.00	0.00	36.00
More than 2 adults in HH and 1 child (row)	0.00	48.60	0.00	51.40
More than 2 adults in HH and 1 child (col.)	0.00	7.90	0.00	3.70
More than 2 adults in HH and 2 children (obs.)	2.00	12.00	4.00	33.00
More than 2 adults in HH and 2 children (row)	3.90	23.50	7.80	64.70
More than 2 adults in HH and 2 children (col.)	2.90	2.80	3.50	3.40
More than 2 adults in HH and 2+ children (obs.)	2.00	2.00	10.00	3.00
More than 2 adults in HH and 2+ children (row)	11.80	11.80	58.80	17.60
More than 2 adults in HH and 2+ children (col.)	2.90	0.50	8.80	0.30

Table 2.130: HTYPE factor by houshold skills (χ^2(NA, 1582) = 430.391, p = 0, Cramer's V = 0.301)

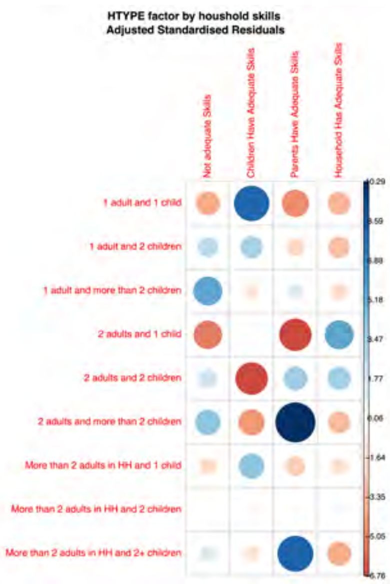

Figure 2.88: Res. Cont. plots-59

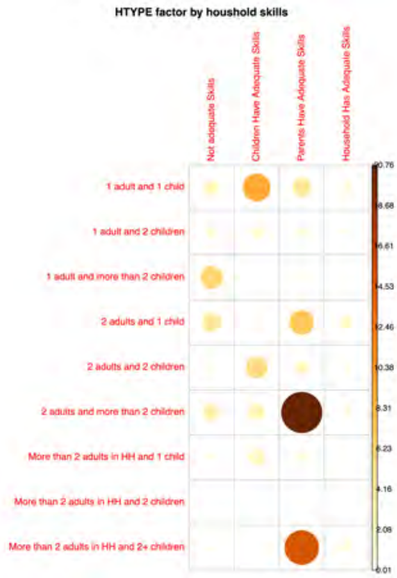

Figure 2.89: Res. Cont. plots-60

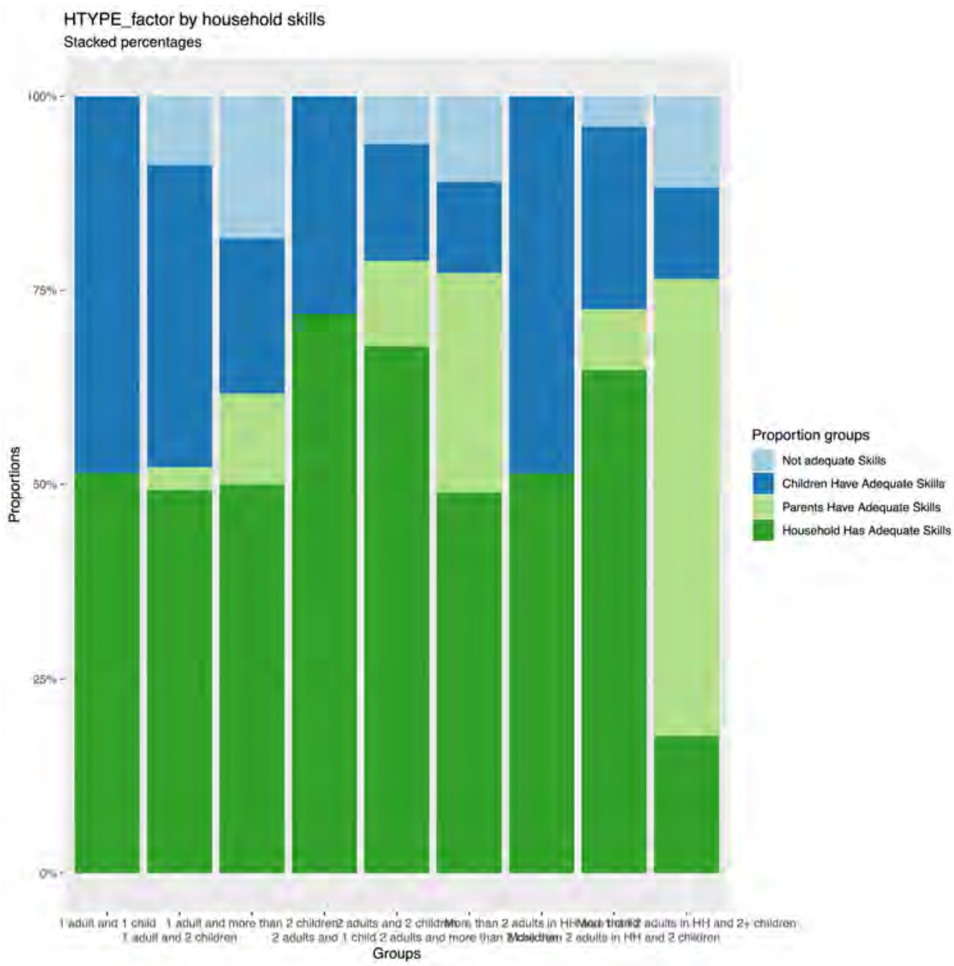

Figure 2.90: Proportions plot-30

2.4.31 REGIONfactorbyhousholdskills

The Pearson's Chi-squared test with simulated p-value of independence between variables suggests that the effect is statistically significant and small ($chi^2 = 118.69, p < .001; AdjustedCramer'sv = 0.13, 95\%CI[0.07, 1.00]$). The following tables 2.132, 2.131, and 2.133 provide detals of the observations, column and row percentages. Figures 2.91 and 2.92 present plots of residuals and contributions. Figure 2.93 presents the data in stacked proprtions.

	Not adequate Skills	Children Have Adequate Skills	Parents Have Adequate Skills	Household Has Adequate Skills
North East (col.)	2.90	5.10	3.50	3.10
North West (col.)	10.00	13.00	11.40	8.30
Yorkshire and The Humber (col.)	7.10	9.30	8.80	8.00
East Midlands (col.)	8.60	4.60	10.50	6.60
West Midlands (col.)	5.70	8.10	7.00	10.10
East of England (col.)	7.10	4.20	3.50	11.30
London (col.)	22.90	14.10	9.60	14.50
South East (col.)	10.00	9.00	17.50	15.40
South West (col.)	10.00	4.40	15.80	7.90
Wales (col.)	0.00	6.50	3.50	5.00
Northern Ireland (col.)	7.10	6.00	1.80	3.80
Scotland (col.)	8.60	15.70	7.00	6.00

Table 2.131: REGION factor by houshold skills (Column Percentages) (χ^2(NA, 1582) = 118.691, p = 0, Cramer's V = 0.158)

	Not adequate Skills	Children Have Adequate Skills	Parents Have Adequate Skills	Household Has Adequate Skills
North East (row)	3.40	37.90	6.90	51.70
North West (row)	4.50	35.90	8.30	51.30
Yorkshire and The Humber (row)	3.80	30.30	7.60	58.30
East Midlands (row)	5.90	19.60	11.80	62.70
West Midlands (row)	2.80	24.10	5.50	67.60
East of England (row)	3.70	13.20	2.90	80.10
London (row)	7.00	26.80	4.80	61.40
South East (row)	3.30	18.10	9.30	69.30
South West (row)	5.80	15.80	15.00	63.30
Wales (row)	0.00	35.00	5.00	60.00
Northern Ireland (row)	7.10	37.10	2.90	52.90
Scotland (row)	4.30	48.60	5.70	41.40

Table 2.132: REGION factor by houshold skills (Row Percentages) (χ^2(NA, 1582) = 118.691, p = 0, Cramer's V = 0.158)

	Not adequate Skills	Children Have Adequate Skills	Parents Have Adequate Skills	Household Has Adequate Skills
North East (obs.)	2.00	22.00	4.00	30.00
North East (row)	3.40	37.90	6.90	51.70
North East (col.)	2.90	5.10	3.50	3.10
North West (obs.)	7.00	56.00	13.00	80.00
North West (row)	4.50	35.90	8.30	51.30
North West (col.)	10.00	13.00	11.40	8.30
Yorkshire and The Humber (obs.)	5.00	40.00	10.00	77.00
Yorkshire and The Humber (row)	3.80	30.30	7.60	58.30
Yorkshire and The Humber (col.)	7.10	9.30	8.80	8.00
East Midlands (obs.)	6.00	20.00	12.00	64.00
East Midlands (row)	5.90	19.60	11.80	62.70
East Midlands (col.)	8.60	4.60	10.50	6.60
West Midlands (obs.)	4.00	35.00	8.00	98.00
West Midlands (row)	2.80	24.10	5.50	67.60
West Midlands (col.)	5.70	8.10	7.00	10.10
East of England (obs.)	5.00	18.00	4.00	109.00
East of England (row)	3.70	13.20	2.90	80.10
East of England (col.)	7.10	4.20	3.50	11.30
London (obs.)	16.00	61.00	11.00	140.00
London (row)	7.00	26.80	4.80	61.40
London (col.)	22.90	14.10	9.60	14.50
South East (obs.)	7.00	39.00	20.00	149.00
South East (row)	3.30	18.10	9.30	69.30
South East (col.)	10.00	9.00	17.50	15.40
South West (obs.)	7.00	19.00	18.00	76.00
South West (row)	5.80	15.80	15.00	63.30
South West (col.)	10.00	4.40	15.80	7.90
Wales (obs.)	0.00	28.00	4.00	48.00
Wales (row)	0.00	35.00	5.00	60.00
Wales (col.)	0.00	6.50	3.50	5.00
Northern Ireland (obs.)	5.00	26.00	2.00	37.00
Northern Ireland (row)	7.10	37.10	2.90	52.90
Northern Ireland (col.)	7.10	6.00	1.80	3.80
Scotland (obs.)	6.00	68.00	8.00	58.00
Scotland (row)	4.30	48.60	5.70	41.40
Scotland (col.)	8.60	15.70	7.00	6.00

Table 2.133: REGION factor by houshold skills (χ^2(NA, 1582) = 118.691, p = 0, Cramer's V = 0.158)

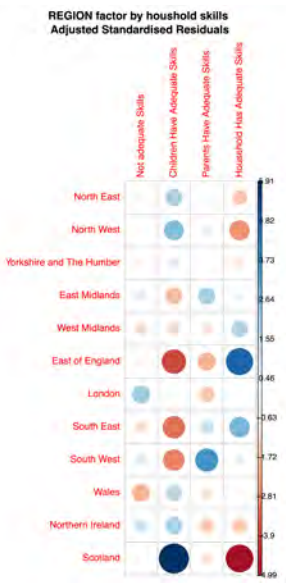

Figure 2.91: Res. Cont. plots-61

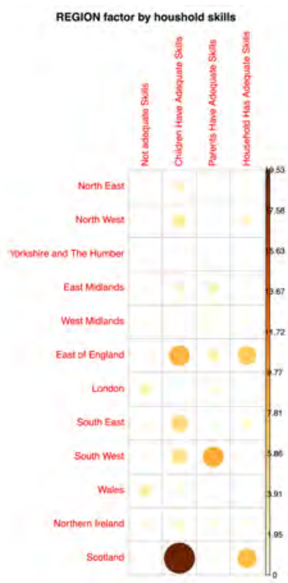

Figure 2.92: Res. Cont. plots-62

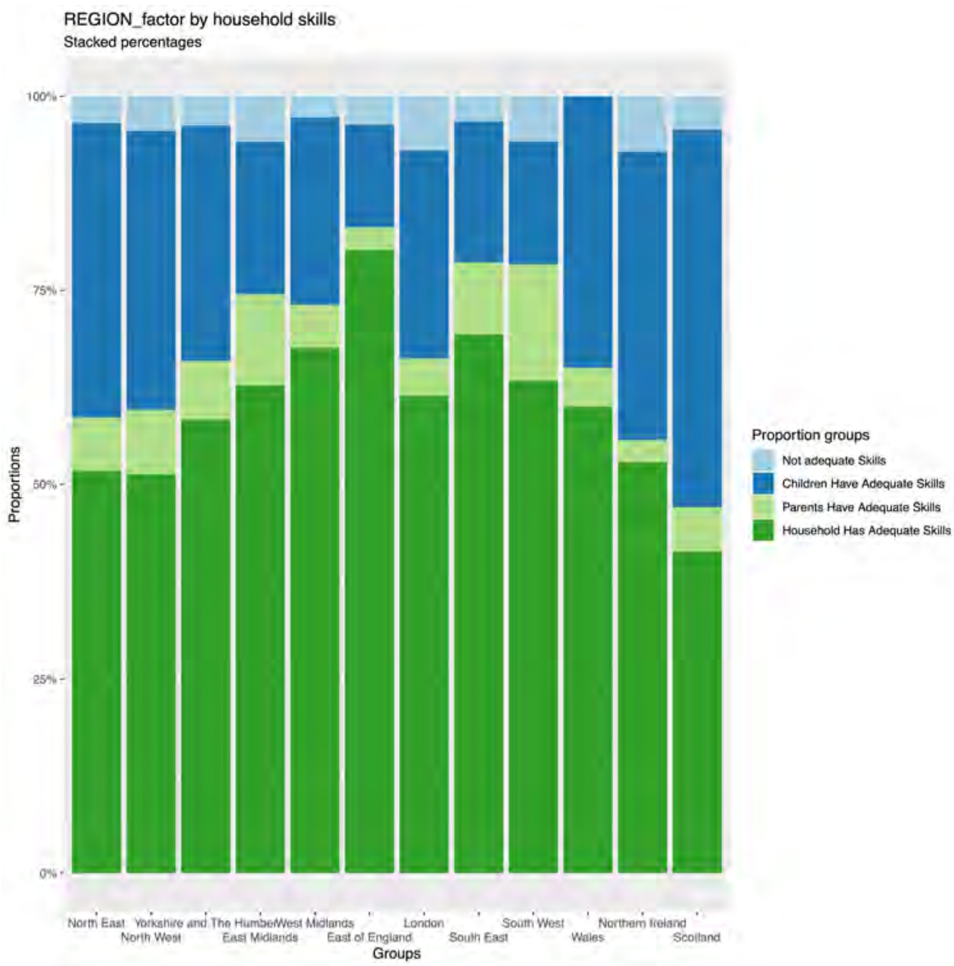

Figure 2.93: Proportions plot-31

2.4.32 Overallhouseholdskillsfactorbyhousholdskills

The Pearson's Chi-squared test with simulated p-value of independence between variables suggests that the effect is statistically significant and very large ($chi^2 = 4746.00, p < .001; Adjusted Cramer'sv = 1.00, 95\% CI[0.98, 1.00]$). The following tables 2.135, 2.134, and 2.136 provide detals of the observations, column and row percentages. Figures 2.94 and 2.95 present plots of residuals and contributions. Figure 2.96 presents the data in stacked proprtions.

	Not adequate Skills	Children Have Adequate Skills	Parents Have Adequate Skills	Household Has Adequate Skills
Not adequate Skills (col.)	100.00	0.00	0.00	0.00
Children Have Adequate Skills (col.)	0.00	100.00	0.00	0.00
Parents Have Adequate Skills (col.)	0.00	0.00	100.00	0.00
Household Has Adequate Skills (col.)	0.00	0.00	0.00	100.00

Table 2.134: Overall household skills factor by houshold skills (Column Percentages) (χ^2(NA, 1582) = 4746, p = 0, Cramer's V = 1)

	Not adequate Skills	Children Have Adequate Skills	Parents Have Adequate Skills	Household Has Adequate Skills
Not adequate Skills (row)	100.00	0.00	0.00	0.00
Children Have Adequate Skills (row)	0.00	100.00	0.00	0.00
Parents Have Adequate Skills (row)	0.00	0.00	100.00	0.00
Household Has Adequate Skills (row)	0.00	0.00	0.00	100.00

Table 2.135: Overall household skills factor by houshold skills (Row Percentages) (χ^2(NA, 1582) = 4746, p = 0, Cramer's V = 1)

	Not adequate Skills	Children Have Adequate Skills	Parents Have Adequate Skills	Household Has Adequate Skills
Not adequate Skills (obs.)	70.00	0.00	0.00	0.00
Not adequate Skills (row)	100.00	0.00	0.00	0.00
Not adequate Skills (col.)	100.00	0.00	0.00	0.00
Children Have Adequate Skills (obs.)	0.00	432.00	0.00	0.00
Children Have Adequate Skills (row)	0.00	100.00	0.00	0.00
Children Have Adequate Skills (col.)	0.00	100.00	0.00	0.00
Parents Have Adequate Skills (obs.)	0.00	0.00	114.00	0.00
Parents Have Adequate Skills (row)	0.00	0.00	100.00	0.00
Parents Have Adequate Skills (col.)	0.00	0.00	100.00	0.00
Household Has Adequate Skills (obs.)	0.00	0.00	0.00	966.00
Household Has Adequate Skills (row)	0.00	0.00	0.00	100.00
Household Has Adequate Skills (col.)	0.00	0.00	0.00	100.00

Table 2.136: Overall household skills factor by houshold skills (χ^2(NA, 1582) = 4746, p = 0, Cramer's V = 1)

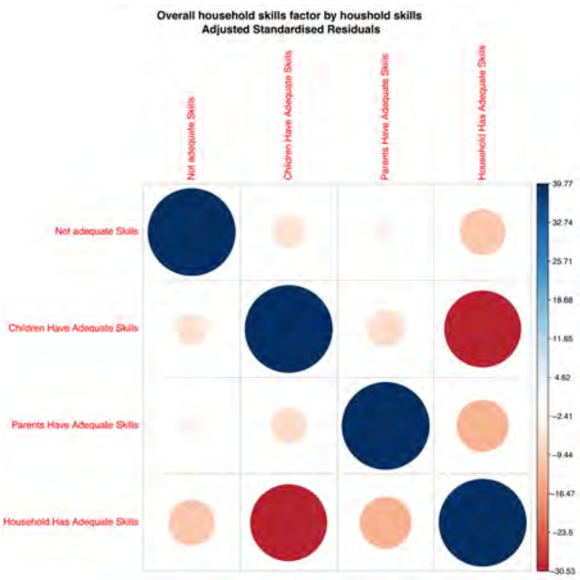

Figure 2.94: Res. Cont. plots-63

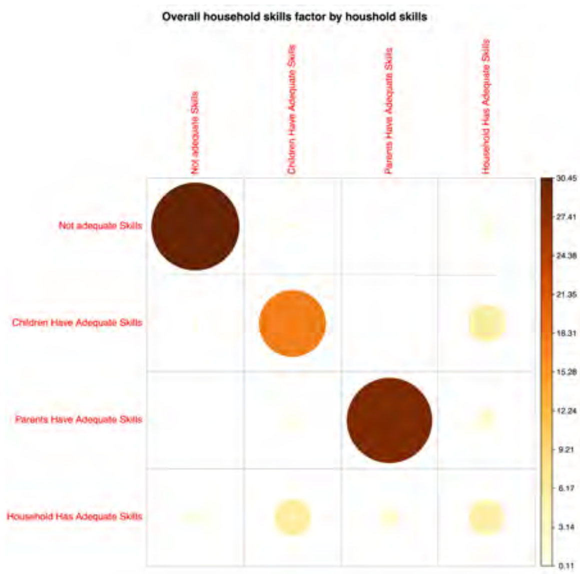

Figure 2.95: Res. Cont. plots-64

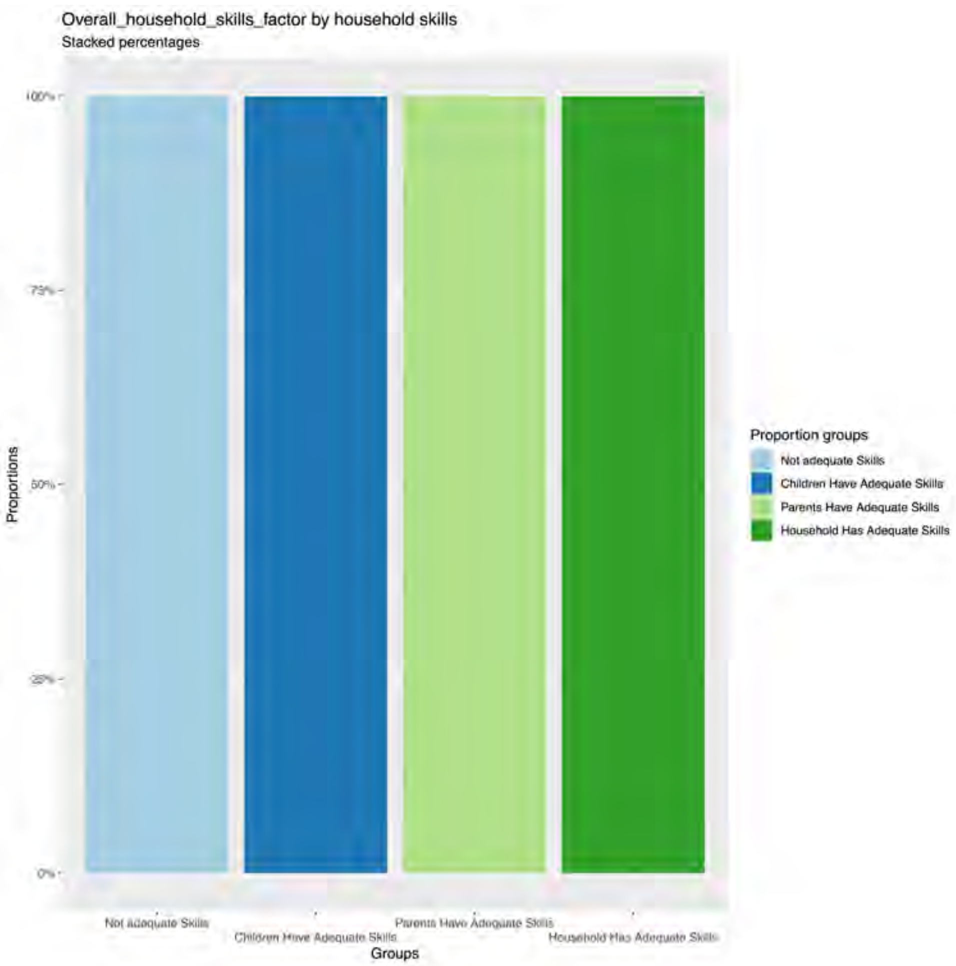

Figure 2.96: Proportions plot-32

2.4.33 Broadbandfactorbyhousholdskills

The Pearson's Chi-squared test with simulated p-value of independence between variables suggests that the effect is statistically not significant and tiny ($chi^2 = 1.46, p = 0.675; AdjustedCramer'sv = 0.00, 95\%CI[0.00, 1.00]$). The following tables 2.138, 2.137, and 2.139 provide detals of the observations, column and row percentages. Figures 2.97 and 2.98 present plots of residuals and contributions. Figure 2.99 presents the data in stacked proprtions.

	Not adequate Skills	Children Have Adequate Skills	Parents Have Adequate Skills	Household Has Adequate Skills
Below average broadband speed (col.)	41.40	40.30	43.00	43.70
Above average broadband speed (col.)	58.60	59.70	57.00	56.30

Table 2.137: Broadband factor by houshold skills (Column Percentages) (χ^2(NA, 1582) = 1.464, p = 0.675, Cramer's V = 0.03)

	Not adequate Skills	Children Have Adequate Skills	Parents Have Adequate Skills	Household Has Adequate Skills
Below average broadband speed (row)	4.30	25.80	7.30	62.60
Above average broadband speed (row)	4.50	28.40	7.20	59.90

Table 2.138: Broadband factor by houshold skills (Row Percentages) (χ^2(NA, 1582) = 1.464, p = 0.675, Cramer's V = 0.03)

	Not adequate Skills	Children Have Adequate Skills	Parents Have Adequate Skills	Household Has Adequate Skills
Below average broadband speed (obs.)	29.00	174.00	49.00	422.00
Below average broadband speed (row)	4.30	25.80	7.30	62.60
Below average broadband speed (col.)	41.40	40.30	43.00	43.70
Above average broadband speed (obs.)	41.00	258.00	65.00	544.00
Above average broadband speed (row)	4.50	28.40	7.20	59.90
Above average broadband speed (col.)	58.60	59.70	57.00	56.30

Table 2.139: Broadband factor by houshold skills (χ^2(NA, 1582) = 1.464, p = 0.675, Cramer's V = 0.03)

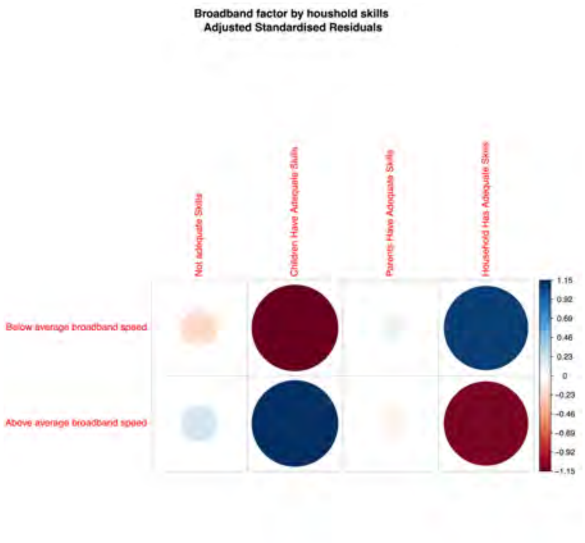

Figure 2.97: Res. Cont. plots-65

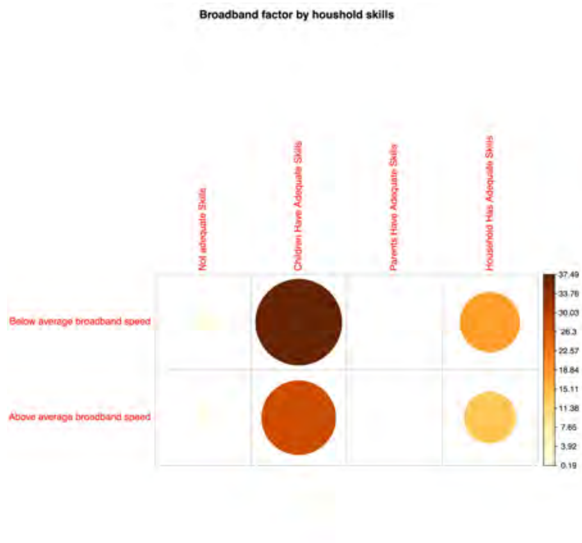

Figure 2.98: Res. Cont. plots-66

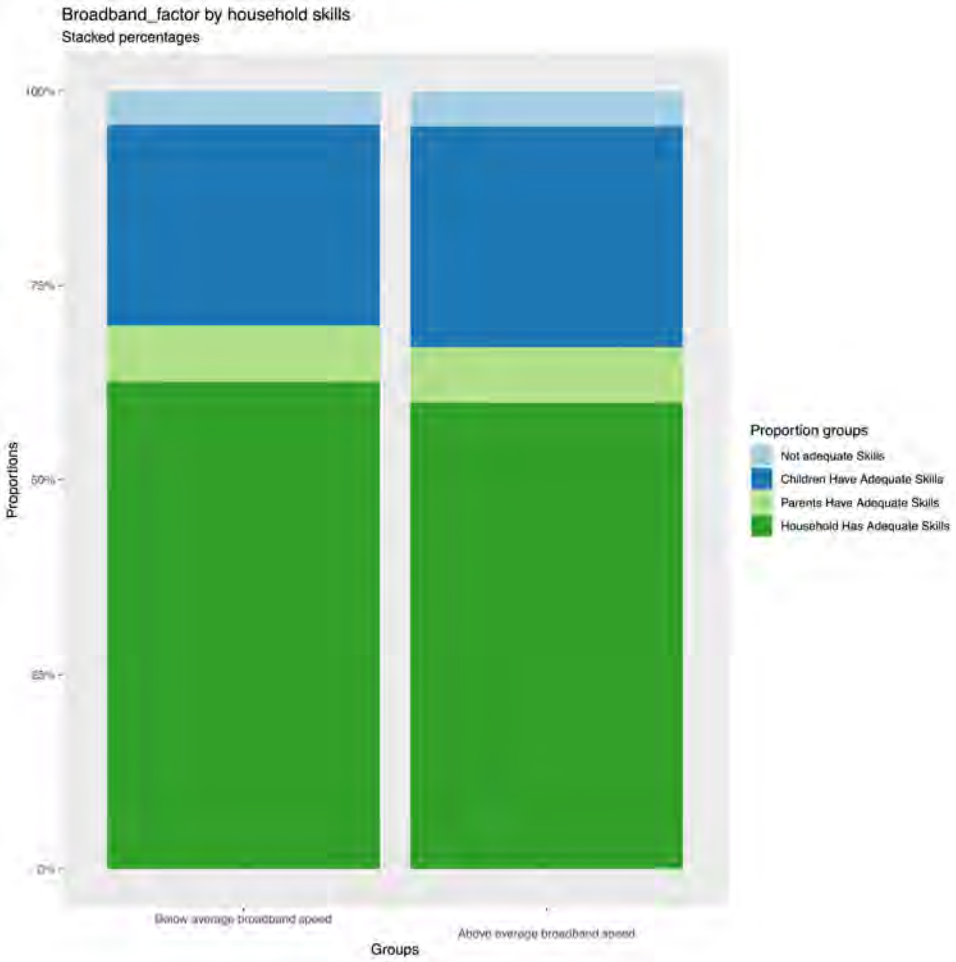

Figure 2.99: Proportions plot-33

2.4.34 URBANfactorbyhousholdskills

The Pearson's Chi-squared test with simulated p-value of independence between variables suggests that the effect is statistically significant and very small ($chi^2 = 41.85, p < .001; AdjustedCramer'sv = 0.08, 95\%CI[0.02, 1.00]$). The following tables 2.141, 2.140, and 2.142 provide detals of the observations, column and row percentages. Figures 2.100 and 2.101 present plots of residuals and contributions. Figure 2.102 presents the data in stacked proprtions.

	Not adequate Skills	Children Have Adequate Skills	Parents Have Adequate Skills	Household Has Adequate Skills
Large city (col.)	24.30	19.70	10.50	15.00
Smaller city or large town (col.)	12.90	22.90	21.10	13.80
Medium town (col.)	28.60	32.90	39.50	36.10
Small town (col.)	21.40	16.90	15.80	21.20
Rural area (col.)	12.90	7.60	13.20	13.90

Table 2.140: URBAN factor by houshold skills (Column Percentages) (χ^2(NA, 1582) = 41.855, p = 0, Cramer's V = 0.094)

	Not adequate Skills	Children Have Adequate Skills	Parents Have Adequate Skills	Household Has Adequate Skills
Large city (row)	6.60	32.80	4.60	56.00
Smaller city or large town (row)	3.40	37.40	9.10	50.20
Medium town (row)	3.60	25.50	8.10	62.80
Small town (row)	4.80	23.50	5.80	65.90
Rural area (row)	4.70	17.30	7.90	70.20

Table 2.141: URBAN factor by houshold skills (Row Percentages) (χ^2(NA, 1582) = 41.855, p = 0, Cramer's V = 0.094)

	Not adequate Skills	Children Have Adequate Skills	Parents Have Adequate Skills	Household Has Adequate Skills
Large city (obs.)	17.00	85.00	12.00	145.00
Large city (row)	6.60	32.80	4.60	56.00
Large city (col.)	24.30	19.70	10.50	15.00
Smaller city or large town (obs.)	9.00	99.00	24.00	133.00
Smaller city or large town (row)	3.40	37.40	9.10	50.20
Smaller city or large town (col.)	12.90	22.90	21.10	13.80
Medium town (obs.)	20.00	142.00	45.00	349.00
Medium town (row)	3.60	25.50	8.10	62.80
Medium town (col.)	28.60	32.90	39.50	36.10
Small town (obs.)	15.00	73.00	18.00	205.00
Small town (row)	4.80	23.50	5.80	65.90
Small town (col.)	21.40	16.90	15.80	21.20
Rural area (obs.)	9.00	33.00	15.00	134.00
Rural area (row)	4.70	17.30	7.90	70.20
Rural area (col.)	12.90	7.60	13.20	13.90

Table 2.142: URBAN factor by houshold skills (χ^2(NA, 1582) = 41.855, p = 0, Cramer's V = 0.094)

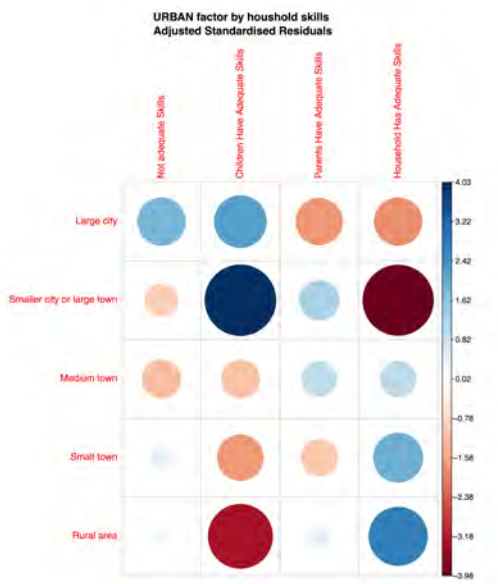

Figure 2.100: Res. Cont. plots-67

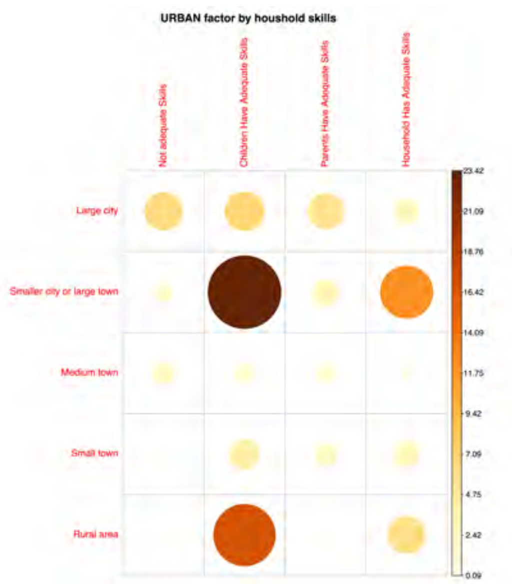

Figure 2.101: Res. Cont. plots-68

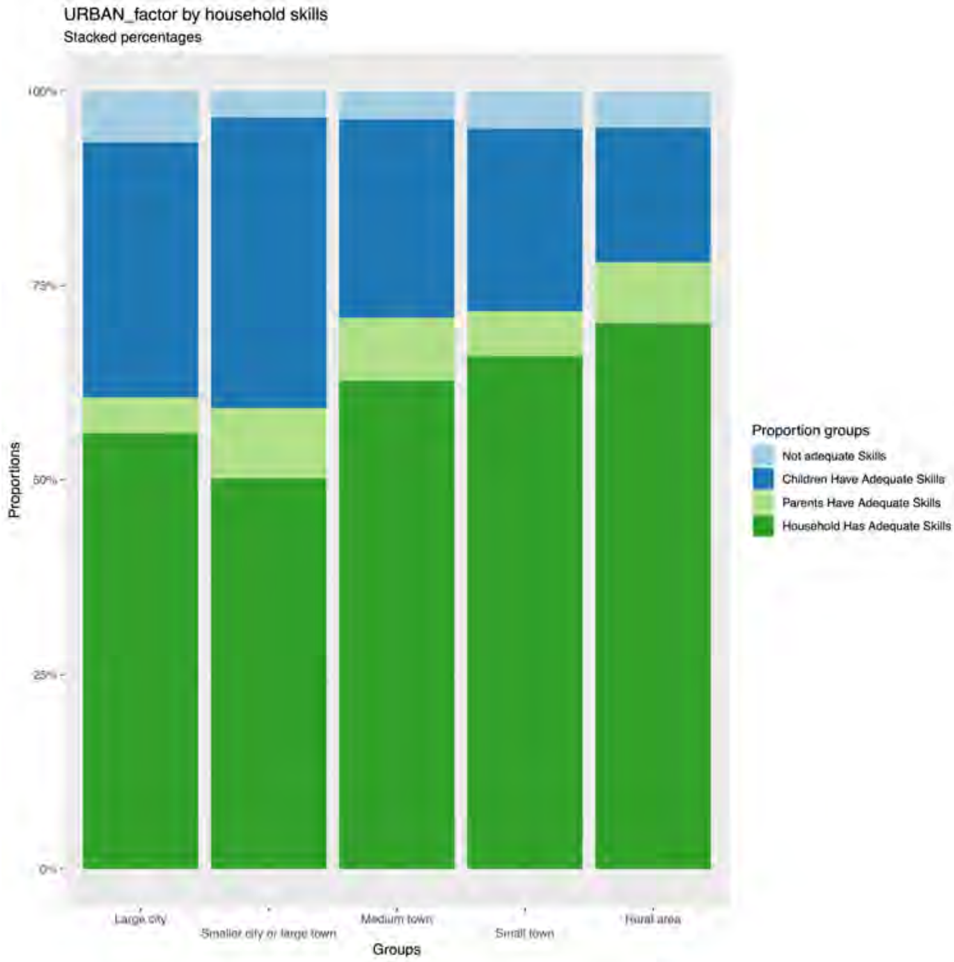

Figure 2.102: Proportions plot-34

2.4.35 URBAN2factorbyhousholdskills

The Pearson's Chi-squared test with simulated p-value of independence between variables suggests that the effect is statistically significant and very small ($chi^2 = 11.11, p = 0.012; AdjustedCramer'sv = 0.07, 95\%CI[0.00, 1.00]$). The following tables 2.144, 2.143, and 2.145 provide detals of the observations, column and row percentages. Figures 2.103 and 2.104 present plots of residuals and contributions. Figure 2.105 presents the data in stacked proprtions.

	Not adequate Skills	Children Have Adequate Skills	Parents Have Adequate Skills	Household Has Adequate Skills
Urban (col.)	87.10	92.40	86.80	86.10
Rural (col.)	12.90	7.60	13.20	13.90

Table 2.143: URBAN2 factor by houshold skills (Column Percentages) (χ^2(NA, 1582) = 11.112, p = 0.012, Cramer's V = 0.084)

	Not adequate Skills	Children Have Adequate Skills	Parents Have Adequate Skills	Household Has Adequate Skills
Urban (row)	4.40	28.70	7.10	59.80
Rural (row)	4.70	17.30	7.90	70.20

Table 2.144: URBAN2 factor by houshold skills (Row Percentages) (χ^2(NA, 1582) = 11.112, p = 0.012, Cramer's V = 0.084)

	Not adequate Skills	Children Have Adequate Skills	Parents Have Adequate Skills	Household Has Adequate Skills
Urban (obs.)	61.00	399.00	99.00	832.00
Urban (row)	4.40	28.70	7.10	59.80
Urban (col.)	87.10	92.40	86.80	86.10
Rural (obs.)	9.00	33.00	15.00	134.00
Rural (row)	4.70	17.30	7.90	70.20
Rural (col.)	12.90	7.60	13.20	13.90

Table 2.145: URBAN2 factor by houshold skills (χ^2(NA, 1582) = 11.112, p = 0.012, Cramer's V = 0.084)

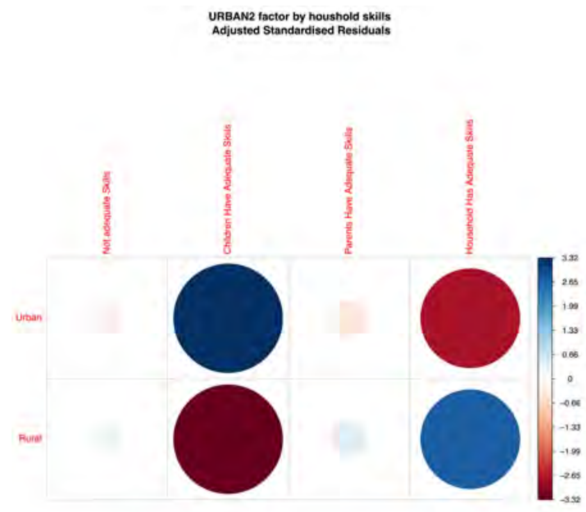

Figure 2.103: Res. Cont. plots-69

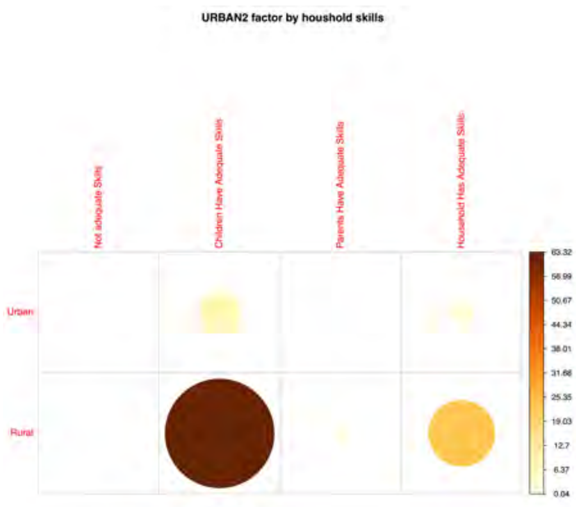

Figure 2.104: Res. Cont. plots-70

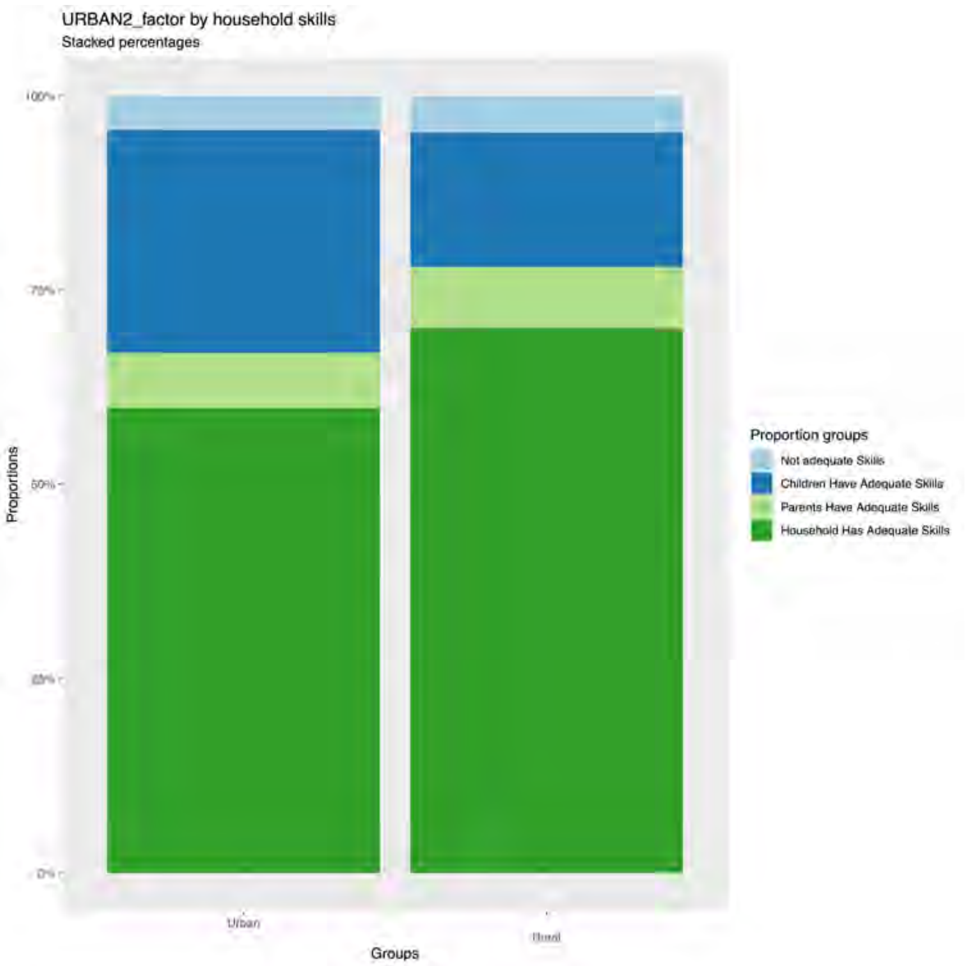

Figure 2.105: Proportions plot-35

2.4.36 iucGRPLBLrfactorbyhousholdskills

The Pearson's Chi-squared test with simulated p-value of independence between variables suggests that the effect is statistically significant and small ($chi^2 = 96.10, p < .001; AdjustedCramer'sv = 0.12, 95\% CI[0.06, 1.00]$). The following tables 2.147, 2.146, and 2.148 provide detals of the observations, column and row percentages. Figures 2.106 and 2.107 present plots of residuals and contributions. Figure 2.108 presents the data in stacked proprtions.

	Not adequate Skills	Children Have Adequate Skills	Parents Have Adequate Skills	Household Has Adequate Skills
Digital Seniors (col.)	13.80	8.20	13.60	9.40
e-Cultural Creators (col.)	0.00	0.20	1.80	0.00
e-Mainstream (col.)	13.80	12.00	13.60	15.60
e-Professionals (col.)	9.20	2.80	3.60	3.50
e-Rational Utilitarians (col.)	4.60	4.20	7.30	9.00
e-Veterans (col.)	3.10	10.00	11.80	15.00
e-Withdrawn (col.)	7.70	18.80	13.60	10.30
Passive and Uncommitted Users (col.)	40.00	32.20	17.30	25.20
Settled Offline Communities (col.)	1.50	3.20	6.40	7.00
Youthful Urban Fringe (col.)	6.20	8.20	10.90	5.10

Table 2.146: iuc GRP LBLr factor by houshold skills (Column Percentages) (χ^2(NA, 1491) = 96.096, p = 0, Cramer's V = 0.147)

	Not adequate Skills	Children Have Adequate Skills	Parents Have Adequate Skills	Household Has Adequate Skills
Digital Seniors (row)	6.30	23.10	10.50	60.10
e-Cultural Creators (row)	0.00	33.30	66.70	0.00
e-Mainstream (row)	4.20	22.30	7.00	66.50
e-Professionals (row)	11.30	20.80	7.50	60.40
e-Rational Utilitarians (row)	2.70	15.50	7.30	74.50
e-Veterans (row)	1.00	20.80	6.80	71.40
e-Withdrawn (row)	2.60	39.70	7.90	49.70
Passive and Uncommitted Users (row)	6.40	31.90	4.70	57.00
Settled Offline Communities (row)	1.20	15.30	8.20	75.30
Youthful Urban Fringe (row)	4.20	34.40	12.50	49.00

Table 2.147: iuc GRP LBLr factor by houshold skills (Row Percentages) (χ^2(NA, 1491) = 96.096, p = 0, Cramer's V = 0.147)

	Not adequate Skills	Children Have Adequate Skills	Parents Have Adequate Skills	Household Has Adequate Skills
Digital Seniors (obs.)	9.00	33.00	15.00	86.00
Digital Seniors (row)	6.30	23.10	10.50	60.10
Digital Seniors (col.)	13.80	8.20	13.60	9.40
e-Cultural Creators (obs.)	0.00	1.00	2.00	0.00
e-Cultural Creators (row)	0.00	33.30	66.70	0.00
e-Cultural Creators (col.)	0.00	0.20	1.80	0.00
e-Mainstream (obs.)	9.00	48.00	15.00	143.00
e-Mainstream (row)	4.20	22.30	7.00	66.50
e-Mainstream (col.)	13.80	12.00	13.60	15.60
e-Professionals (obs.)	6.00	11.00	4.00	32.00
e-Professionals (row)	11.30	20.80	7.50	60.40
e-Professionals (col.)	9.20	2.80	3.60	3.50
e-Rational Utilitarians (obs.)	3.00	17.00	8.00	82.00
e-Rational Utilitarians (row)	2.70	15.50	7.30	74.50
e-Rational Utilitarians (col.)	4.60	4.20	7.30	9.00
e-Veterans (obs.)	2.00	40.00	13.00	137.00
e-Veterans (row)	1.00	20.80	6.80	71.40
e-Veterans (col.)	3.10	10.00	11.80	15.00
e-Withdrawn (obs.)	5.00	75.00	15.00	94.00
e-Withdrawn (row)	2.60	39.70	7.90	49.70
e-Withdrawn (col.)	7.70	18.80	13.60	10.30
Passive and Uncommitted Users (obs.)	26.00	129.00	19.00	231.00
Passive and Uncommitted Users (row)	6.40	31.90	4.70	57.00
Passive and Uncommitted Users (col.)	40.00	32.20	17.30	25.20
Settled Offline Communities (obs.)	1.00	13.00	7.00	64.00
Settled Offline Communities (row)	1.20	15.30	8.20	75.30
Settled Offline Communities (col.)	1.50	3.20	6.40	7.00
Youthful Urban Fringe (obs.)	4.00	33.00	12.00	47.00
Youthful Urban Fringe (row)	4.20	34.40	12.50	49.00
Youthful Urban Fringe (col.)	6.20	8.20	10.90	5.10

Table 2.148: iuc GRP LBLr factor by houshold skills (χ^2(NA, 1491) = 96.096, p = 0, Cramer's V = 0.147)

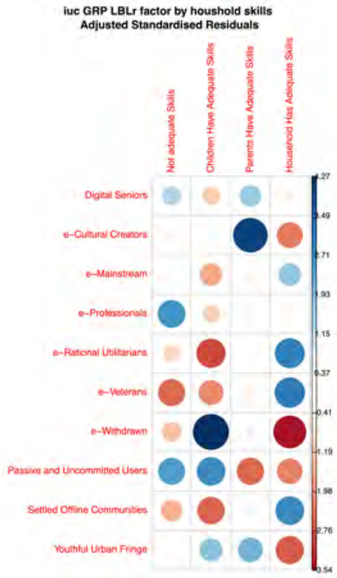

Figure 2.106: Res. Cont. plots-71

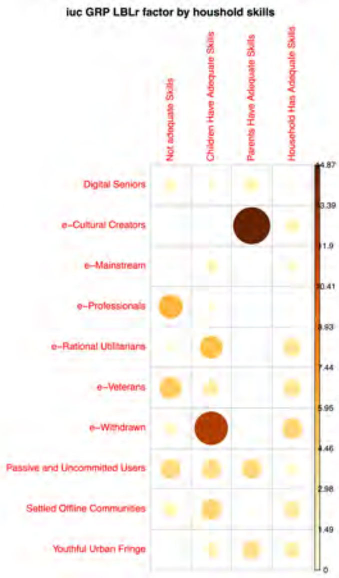

Figure 2.107: Res. Cont. plots-72

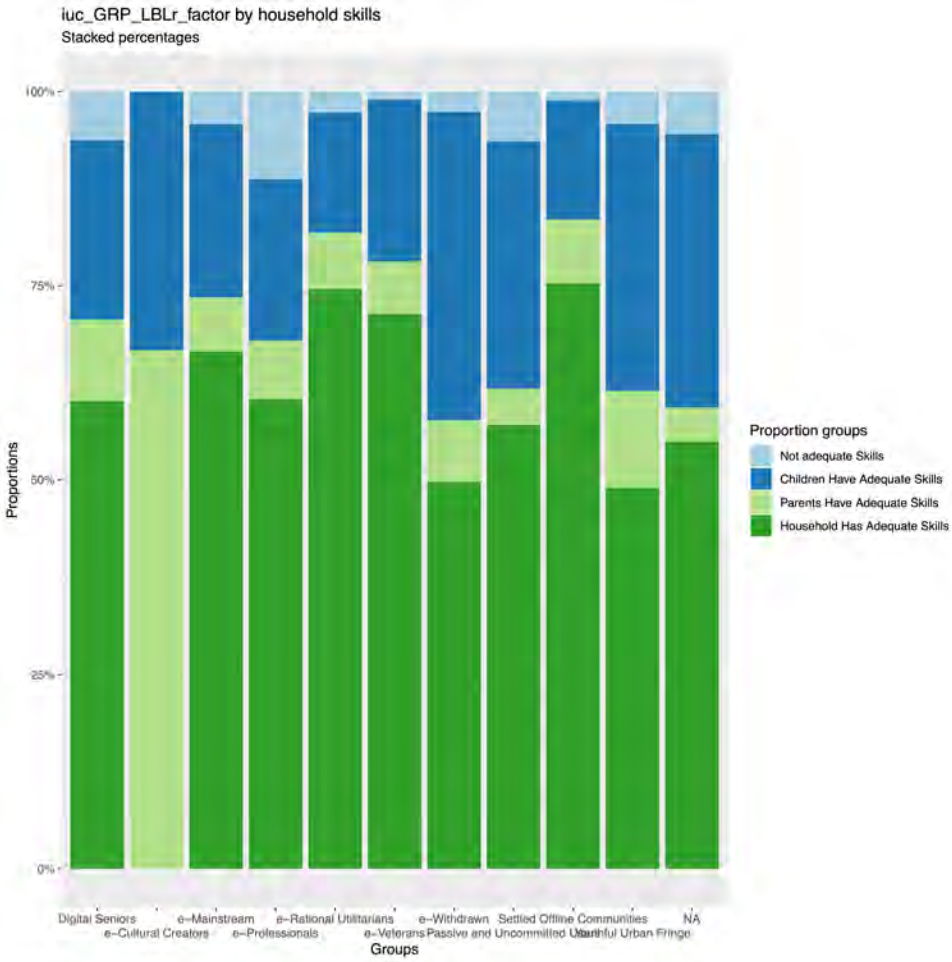

Figure 2.108: Proportions plot-36

2.4.37 oac21SGfactorbyhousholdskills

The Pearson's Chi-squared test with simulated p-value of independence between variables suggests that the effect is statistically significant and small ($chi^2 = 67.46, p < .001; AdjustedCramer'sv = 0.11, 95\% CI[0.03, 1.00]$). The following tables 2.150, 2.149, and 2.151 provide detals of the observations, column and row percentages. Figures 2.109 and 2.110 present plots of residuals and contributions. Figure 2.111 presents the data in stacked proprtions.

	Not adequate Skills	Children Have Adequate Skills	Parents Have Adequate Skills	Household Has Adequate Skills
Retired Professionals (col.)	6.80	4.80	5.80	8.10
Suburbanites and Peri-Urbanities (col.)	13.60	12.50	21.20	19.20
Multicultural and Educated Urbanites (col.)	15.30	5.40	2.90	5.60
Low-Skilled Migrant and Student Communities (col.)	15.30	24.50	15.40	15.40
Ethnically Diverse Suburban Professionals (col.)	10.20	3.00	11.50	10.90
Baseline UK (col.)	13.60	25.10	21.20	21.40
Semi-and Un-Skilled Workforce (col.)	20.30	20.30	20.20	17.80
Legacy Communities (col.)	5.10	4.50	1.90	1.50

Table 2.149: oac21SG factor by houshold skills (Column Percentages) (χ^2(NA, 1357) = 67.457, p = 0, Cramer's V = 0.129)

	Not adequate Skills	Children Have Adequate Skills	Parents Have Adequate Skills	Household Has Adequate Skills
Retired Professionals (row)	4.20	16.70	6.20	72.90
Suburbanites and Peri-Urbanities (row)	3.40	17.70	9.30	69.60
Multicultural and Educated Urbanites (row)	11.50	23.10	3.80	61.50
Low-Skilled Migrant and Student Communities (row)	3.80	34.30	6.70	55.20
Ethnically Diverse Suburban Professionals (row)	4.90	8.20	9.80	77.00
Baseline UK (row)	2.70	28.20	7.40	61.70
Semi-and Un-Skilled Workforce (row)	4.70	26.80	8.30	60.20
Legacy Communities (row)	9.10	45.50	6.10	39.40

Table 2.150: oac21SG factor by houshold skills (Row Percentages) (χ^2(NA, 1357) = 67.457, p = 0, Cramer's V = 0.129)

	Not adequate Skills	Children Have Adequate Skills	Parents Have Adequate Skills	Household Has Adequate Skills
Retired Professionals (obs.)	4.00	16.00	6.00	70.00
Retired Professionals (row)	4.20	16.70	6.20	72.90
Retired Professionals (col.)	6.80	4.80	5.80	8.10
Suburbanites and Peri-Urbanities (obs.)	8.00	42.00	22.00	165.00
Suburbanites and Peri-Urbanities (row)	3.40	17.70	9.30	69.60
Suburbanites and Peri-Urbanities (col.)	13.60	12.50	21.20	19.20
Multicultural and Educated Urbanites (obs.)	9.00	18.00	3.00	48.00
Multicultural and Educated Urbanites (row)	11.50	23.10	3.80	61.50
Multicultural and Educated Urbanites (col.)	15.30	5.40	2.90	5.60
Low-Skilled Migrant and Student Communities (obs.)	9.00	82.00	16.00	132.00
Low-Skilled Migrant and Student Communities (row)	3.80	34.30	6.70	55.20
Low-Skilled Migrant and Student Communities (col.)	15.30	24.50	15.40	15.40
Ethnically Diverse Suburban Professionals (obs.)	6.00	10.00	12.00	94.00
Ethnically Diverse Suburban Professionals (row)	4.90	8.20	9.80	77.00
Ethnically Diverse Suburban Professionals (col.)	10.20	3.00	11.50	10.90
Baseline UK (obs.)	8.00	84.00	22.00	184.00
Baseline UK (row)	2.70	28.20	7.40	61.70
Baseline UK (col.)	13.60	25.10	21.20	21.40
Semi-and Un-Skilled Workforce (obs.)	12.00	68.00	21.00	153.00
Semi-and Un-Skilled Workforce (row)	4.70	26.80	8.30	60.20
Semi-and Un-Skilled Workforce (col.)	20.30	20.30	20.20	17.80
Legacy Communities (obs.)	3.00	15.00	2.00	13.00
Legacy Communities (row)	9.10	45.50	6.10	39.40
Legacy Communities (col.)	5.10	4.50	1.90	1.50

Table 2.151: oac21SG factor by houshold skills (χ^2(NA, 1357) = 67.457, p = 0, Cramer's V = 0.129)

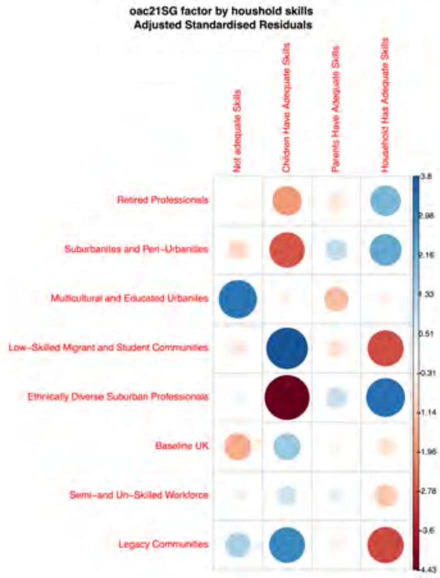

Figure 2.109: Res. Cont. plots-73

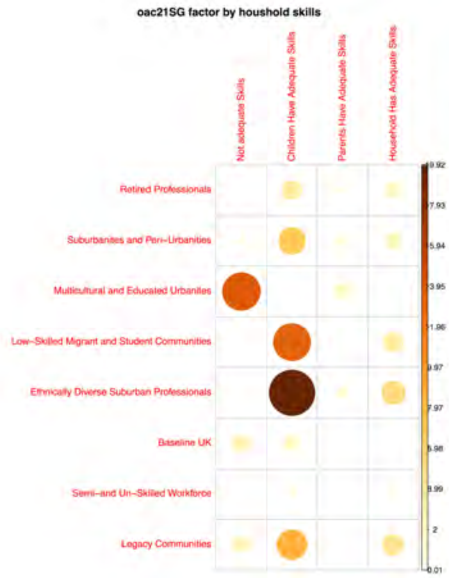

Figure 2.110: Res. Cont. plots-74

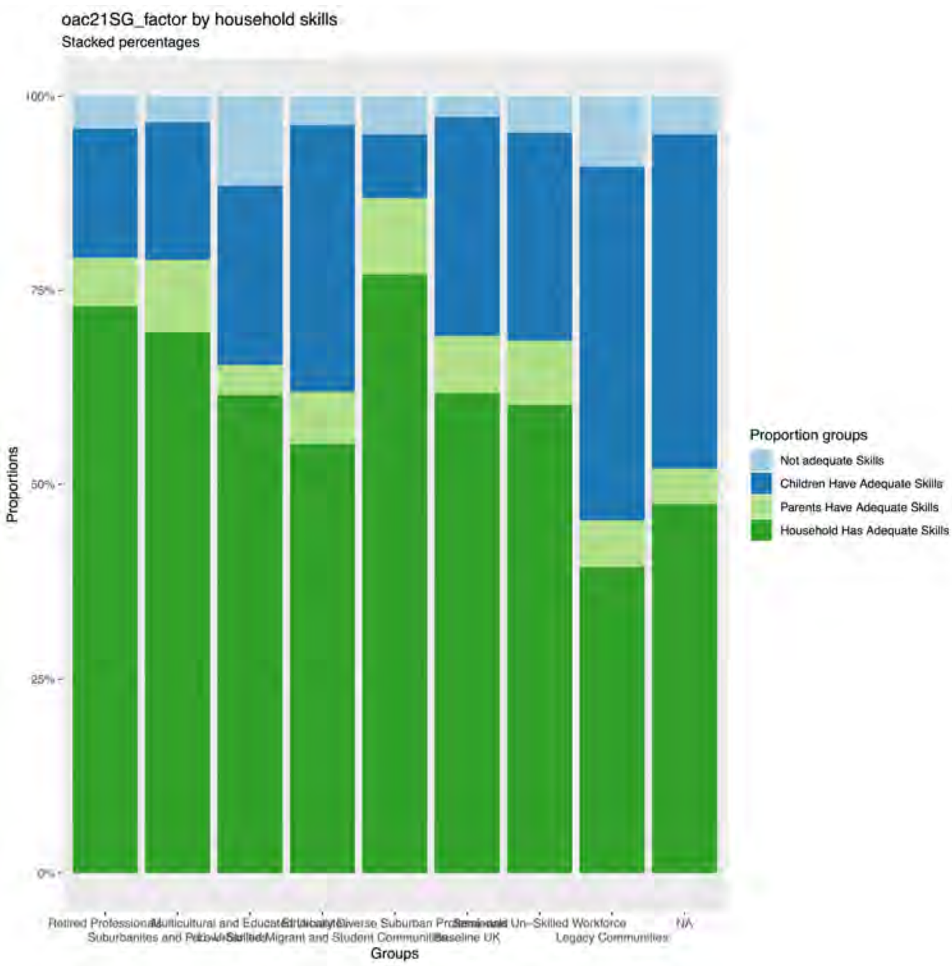

Figure 2.111: Proportions plot-37

2.4.38 aipcsupergroupnamerfactorbyhousholdskills

The Pearson's Chi-squared test with simulated p-value of independence between variables suggests that the effect is statistically significant and small ($chi^2 = 55.94, p < .001; Adjusted Cramer's v = 0.11, 95\% CI [0.06, 1.00]$). The following tables 2.153, 2.152, and 2.154 provide detals of the observations, column and row percentages. Figures 2.112 and 2.113 present plots of residuals and contributions. Figure 2.114 presents the data in stacked proprtions.

	Not adequate Skills	Children Have Adequate Skills	Parents Have Adequate Skills	Household Has Adequate Skills
1 Struggling, More Vulnerable Urbanites (col.)	30.50	39.70	34.00	24.60
2 Multicultural Central Urban Living (col.)	20.30	18.90	10.00	13.50
3 Rurban Comfortable Ageing (col.)	5.10	8.50	21.00	20.10
4 Retired Fringe and Residential Stability (col.)	28.80	18.90	23.00	24.00
5 Cosmopolitan and Coastal Ageing (col.)	15.30	14.00	12.00	17.70

Table 2.152: aipc supergroup namer factor by houshold skills (Column Percentages) (χ^2(NA, 1278) = 55.94, p = 0, Cramer's V = 0.121)

	Not adequate Skills	Children Have Adequate Skills	Parents Have Adequate Skills	Household Has Adequate Skills
1 Struggling, More Vulnerable Urbanites (row)	4.80	32.60	9.10	53.50
2 Multicultural Central Urban Living (row)	6.30	30.50	5.30	57.90
3 Rurban Comfortable Ageing (row)	1.40	12.20	9.90	76.50
4 Retired Fringe and Residential Stability (row)	5.80	19.80	7.80	66.60
5 Cosmopolitan and Coastal Ageing (row)	4.30	20.70	5.80	69.20

Table 2.153: aipc supergroup namer factor by houshold skills (Row Percentages) (χ^2(NA, 1278) = 55.94, p = 0, Cramer's V = 0.121)

	Not adequate Skills	Children Have Adequate Skills	Parents Have Adequate Skills	Household Has Adequate Skills
1 Struggling, More Vulnerable Urbanites (obs.)	18.00	122.00	34.00	200.00
1 Struggling, More Vulnerable Urbanites (row)	4.80	32.60	9.10	53.50
1 Struggling, More Vulnerable Urbanites (col.)	30.50	39.70	34.00	24.60
2 Multicultural Central Urban Living (obs.)	12.00	58.00	10.00	110.00
2 Multicultural Central Urban Living (row)	6.30	30.50	5.30	57.90
2 Multicultural Central Urban Living (col.)	20.30	18.90	10.00	13.50
3 Rurban Comfortable Ageing (obs.)	3.00	26.00	21.00	163.00
3 Rurban Comfortable Ageing (row)	1.40	12.20	9.90	76.50
3 Rurban Comfortable Ageing (col.)	5.10	8.50	21.00	20.10
4 Retired Fringe and Residential Stability (obs.)	17.00	58.00	23.00	195.00
4 Retired Fringe and Residential Stability (row)	5.80	19.80	7.80	66.60
4 Retired Fringe and Residential Stability (col.)	28.80	18.90	23.00	24.00
5 Cosmopolitan and Coastal Ageing (obs.)	9.00	43.00	12.00	144.00
5 Cosmopolitan and Coastal Ageing (row)	4.30	20.70	5.80	69.20
5 Cosmopolitan and Coastal Ageing (col.)	15.30	14.00	12.00	17.70

Table 2.154: aipc supergroup namer factor by houshold skills (χ^2(NA, 1278) = 55.94, p = 0, Cramer's V = 0.121)

Figure 2.112: Res. Cont. plots-75

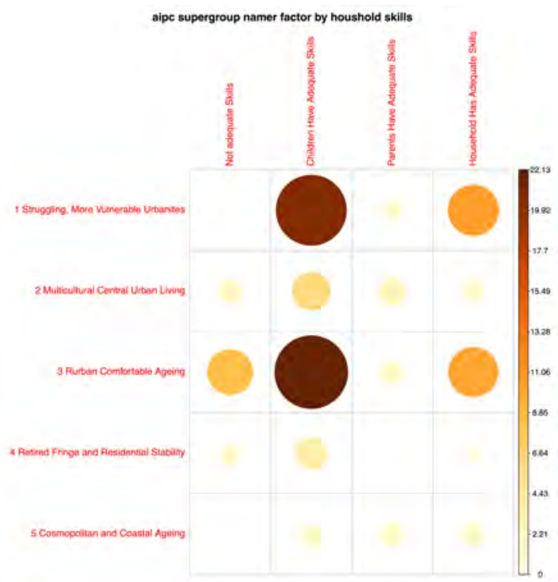

Figure 2.113: Res. Cont. plots-76

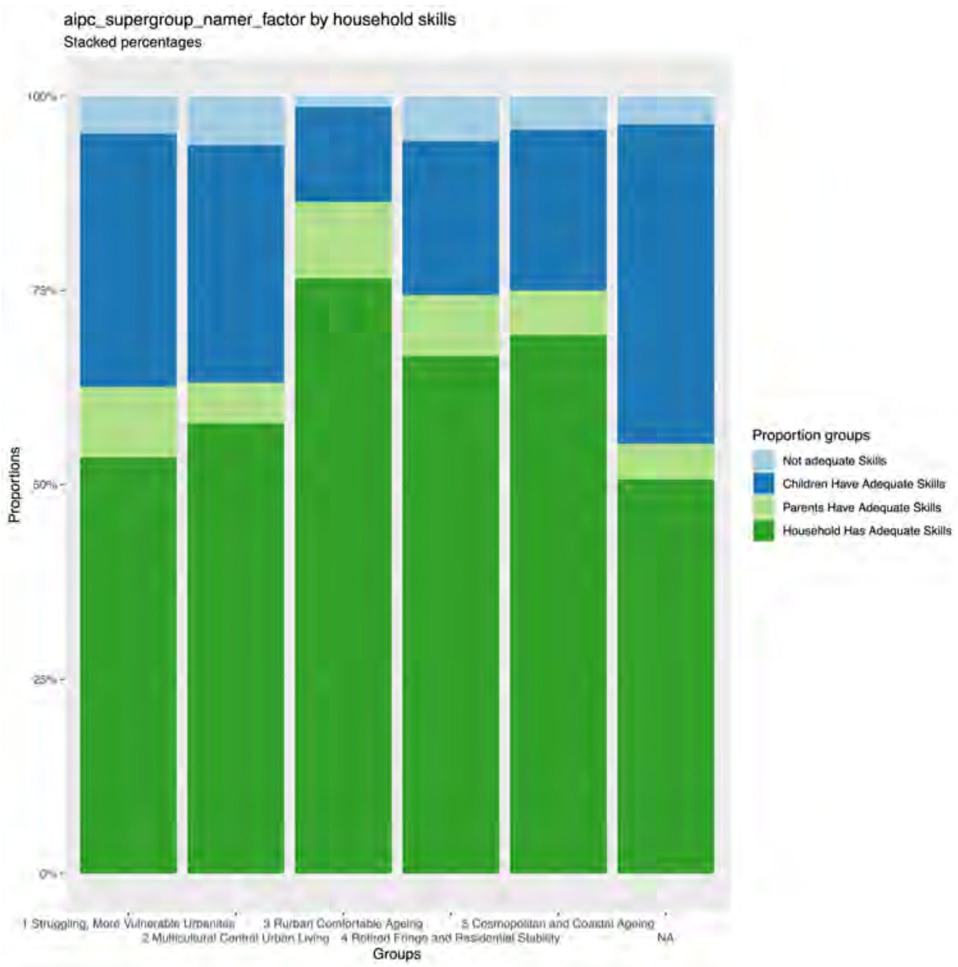

Figure 2.114: Proportions plot-38

2.4.39 Benefitsfactorbyhousholdskills

The Pearson's Chi-squared test with simulated p-value of independence between variables suggests that the effect is statistically significant and medium ($chi^2 = 86.43, p < .001; AdjustedCramer'sv = 0.23, 95\%CI[0.18, 1.00]$). The following tables 2.156, 2.155, and 2.157 provide detals of the observations, column and row percentages. Figures 2.115 and 2.116 present plots of residuals and contributions. Figure 2.117 presents the data in stacked proprtions.

	Not adequate Skills	Children Have Adequate Skills	Parents Have Adequate Skills	Household Has Adequate Skills
Not on any benefits (col.)	41.40	52.50	67.50	74.60
Receives at least one state benefit (col.)	58.60	47.50	32.50	25.40

Table 2.155: Benefits factor by houshold skills (Column Percentages) (χ^2(NA, 1582) = 86.428, p = 0, Cramer's V = 0.234)

	Not adequate Skills	Children Have Adequate Skills	Parents Have Adequate Skills	Household Has Adequate Skills
Not on any benefits (row)	2.80	21.50	7.30	68.40
Receives at least one state benefit (row)	7.80	38.80	7.00	46.40

Table 2.156: Benefits factor by houshold skills (Row Percentages) (χ^2(NA, 1582) = 86.428, p = 0, Cramer's V = 0.234)

	Not adequate Skills	Children Have Adequate Skills	Parents Have Adequate Skills	Household Has Adequate Skills
Not on any benefits (obs.)	29.00	227.00	77.00	721.00
Not on any benefits (row)	2.80	21.50	7.30	68.40
Not on any benefits (col.)	41.40	52.50	67.50	74.60
Receives at least one state benefit (obs.)	41.00	205.00	37.00	245.00
Receives at least one state benefit (row)	7.80	38.80	7.00	46.40
Receives at least one state benefit (col.)	58.60	47.50	32.50	25.40

Table 2.157: Benefits factor by houshold skills (χ^2(NA, 1582) = 86.428, p = 0, Cramer's V = 0.234)

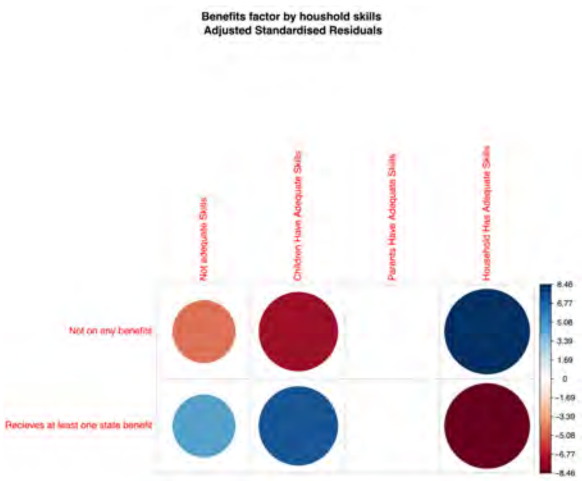

Figure 2.115: Res. Cont. plots-77

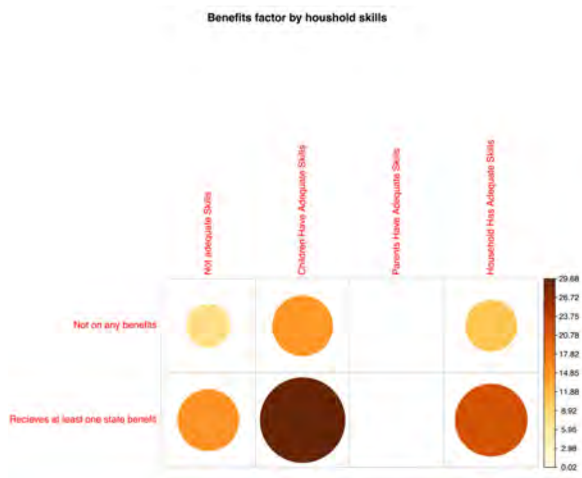

Figure 2.116: Res. Cont. plots-78

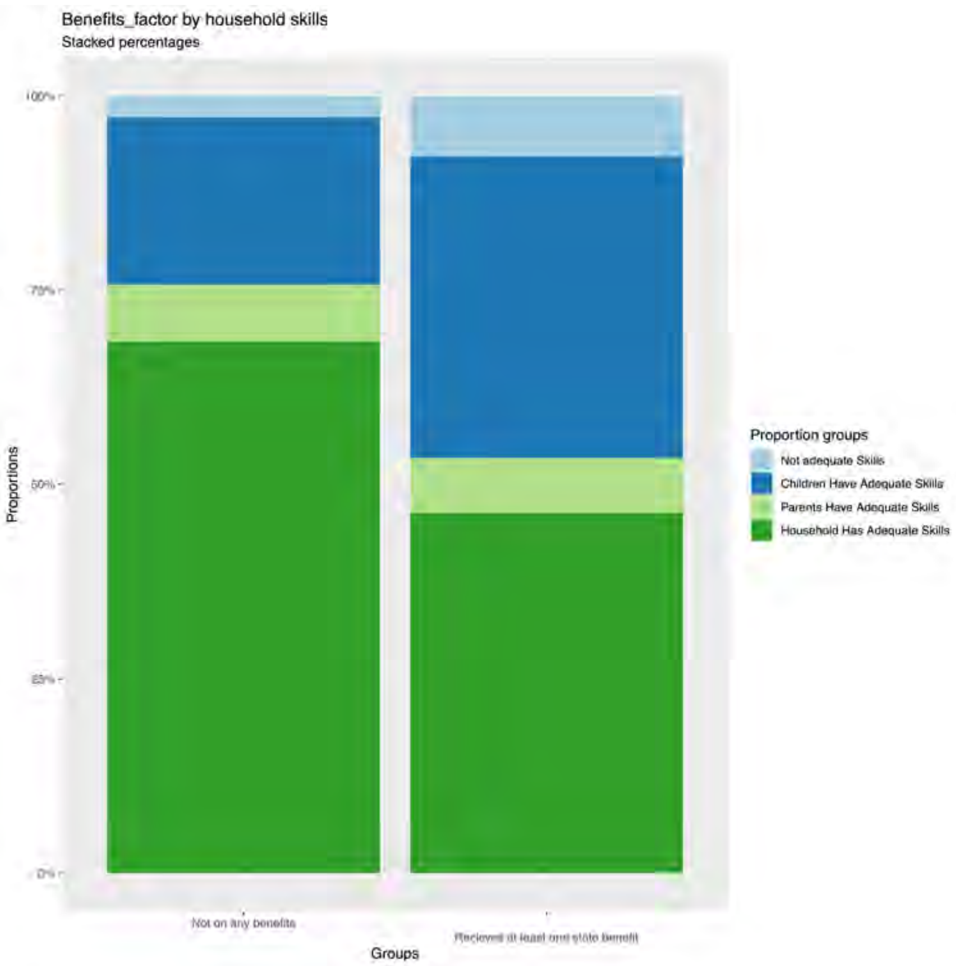

Figure 2.117: Proportions plot-39

2.4.40 Workingfactorbyhousholdskills

The Pearson's Chi-squared test with simulated p-value of independence between variables suggests that the effect is statistically significant and medium ($chi^2 = 95.28, p < .001; Adjusted Cramer's v = 0.24, 95\% CI [0.20, 1.00]$). The following tables 2.159, 2.158, and 2.160 provide detals of the observations, column and row percentages. Figures 2.118 and 2.119 present plots of residuals and contributions. Figure 2.120 presents the data in stacked proprtions.

	Not adequate Skills	Children Have Adequate Skills	Parents Have Adequate Skills	Household Has Adequate Skills
Chief income earner not working (col.)	27.10	35.00	14.00	13.00
Chief income earner working (col.)	72.90	65.00	86.00	87.00

Table 2.158: Working factor by houshold skills (Column Percentages) (χ^2(NA, 1582) = 95.282, p = 0, Cramer's V = 0.245)

	Not adequate Skills	Children Have Adequate Skills	Parents Have Adequate Skills	Household Has Adequate Skills
Chief income earner not working (row)	6.10	48.40	5.10	40.40
Chief income earner working (row)	4.00	22.10	7.70	66.10

Table 2.159: Working factor by houshold skills (Row Percentages) (χ^2(NA, 1582) = 95.282, p = 0, Cramer's V = 0.245)

	Not adequate Skills	Children Have Adequate Skills	Parents Have Adequate Skills	Household Has Adequate Skills
Chief income earner not working (obs.)	19.00	151.00	16.00	126.00
Chief income earner not working (row)	6.10	48.40	5.10	40.40
Chief income earner not working (col.)	27.10	35.00	14.00	13.00
Chief income earner working (obs.)	51.00	281.00	98.00	840.00
Chief income earner working (row)	4.00	22.10	7.70	66.10
Chief income earner working (col.)	72.90	65.00	86.00	87.00

Table 2.160: Working factor by houshold skills (χ^2(NA, 1582) = 95.282, p = 0, Cramer's V = 0.245)

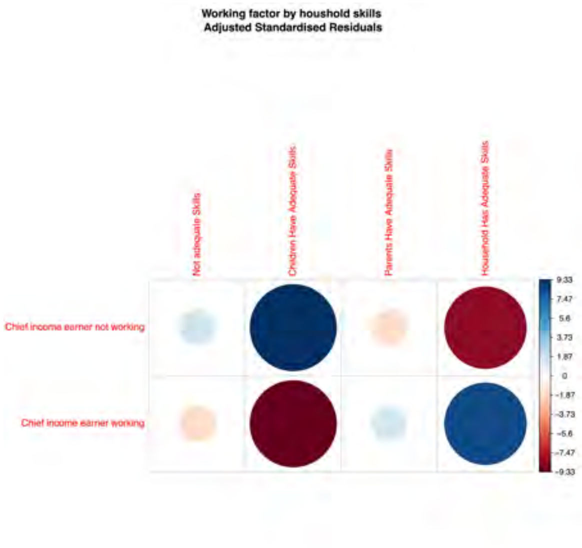

Figure 2.118: Res. Cont. plots-79

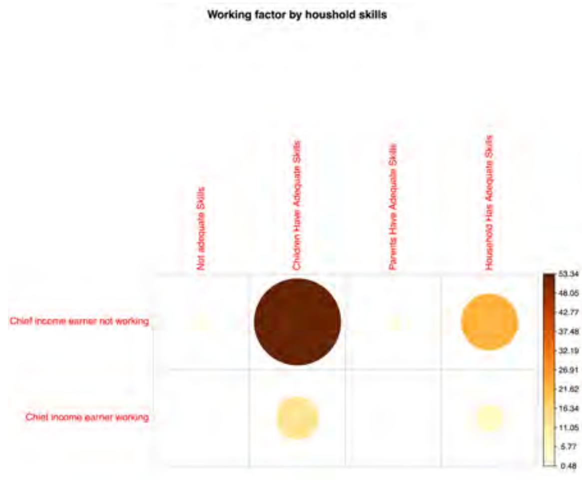

Figure 2.119: Res. Cont. plots-80

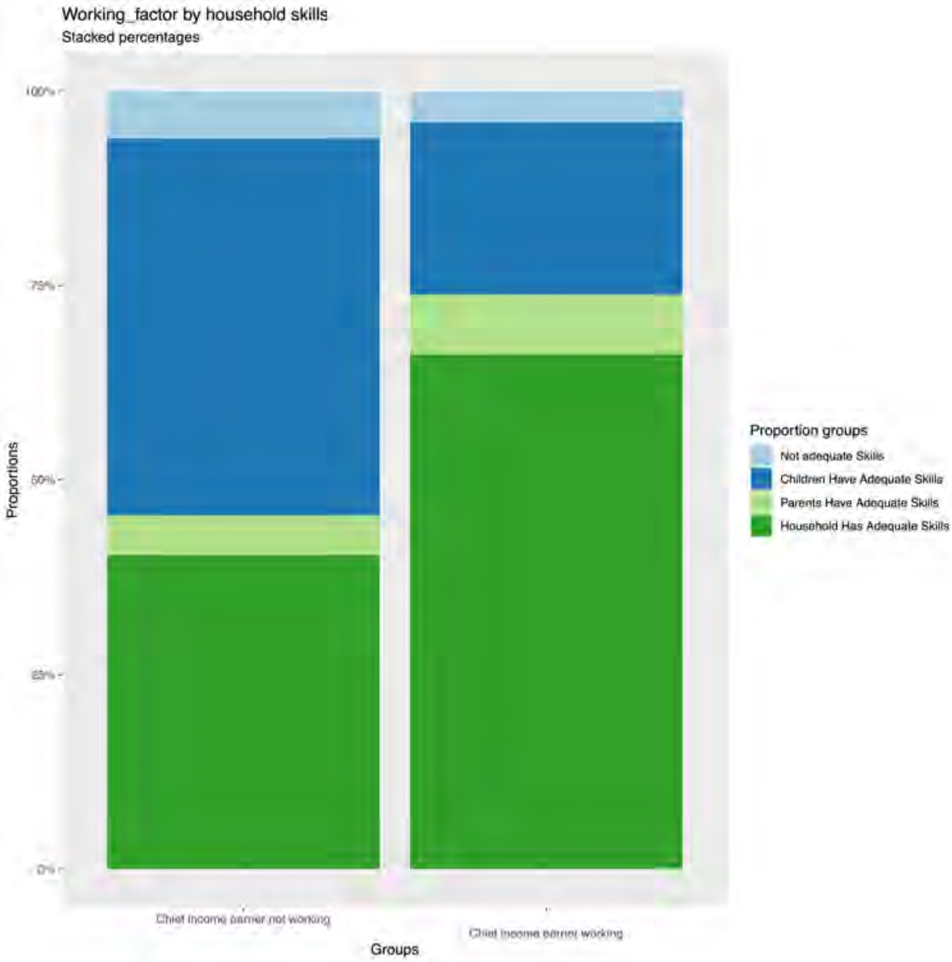

Figure 2.120: Proportions plot-40

2.4.41 Healthlimitationfactorbyhousholdskills

The Pearson's Chi-squared test with simulated p-value of independence between variables suggests that the effect is statistically significant and small ($chi^2 = 50.31, p < .001; AdjustedCramer'sv = 0.17, 95\% CI[0.13, 1.00]$). The following tables 2.162, 2.161, and 2.163 provide detals of the observations, column and row percentages. Figures 2.121 and 2.122 present plots of residuals and contributions. Figure 2.123 presents the data in stacked proprtions.

	Not adequate Skills	Children Have Adequate Skills	Parents Have Adequate Skills	Household Has Adequate Skills
Respondent has **no** health issue (col.)	74.30	75.50	86.00	89.30
Respondent **has** a health issue (col.)	25.70	24.50	14.00	10.70

Table 2.161: Health limitation factor by houshold skills (Column Percentages) (χ^2(NA, 1582) = 50.307, p = 0, Cramer's V = 0.178)

	Not adequate Skills	Children Have Adequate Skills	Parents Have Adequate Skills	Household Has Adequate Skills
Respondent has no health issue(row)	3.90	24.30	7.30	64.50
Respondent **has** a health issue (row)	7.40	43.60	6.60	42.40

Table 2.162: Health limitation factor by houshold skills (Row Percentages) (χ^2(NA, 1582) = 50.307, p = 0, Cramer's V = 0.178)

	Not adequate Skills	Children Have Adequate Skills	Parents Have Adequate Skills	Household Has Adequate Skills
Respondent has no health issue(obs.)	52.00	326.00	98.00	863.00
Respondent has **no** health issue (row)	3.90	24.30	7.30	64.50
Respondent has **no** health issue (col.)	74.30	75.50	86.00	89.30
Respondent **has** a health issue (obs.)	18.00	106.00	16.00	103.00
Respondent **has** a health issue (row)	7.40	43.60	6.60	42.40
Respondent **has** a health issue (col.)	25.70	24.50	14.00	10.70

Table 2.163: Health limitation factor by houshold skills (χ^2(NA, 1582) = 50.307, p = 0, Cramer's V = 0.178)

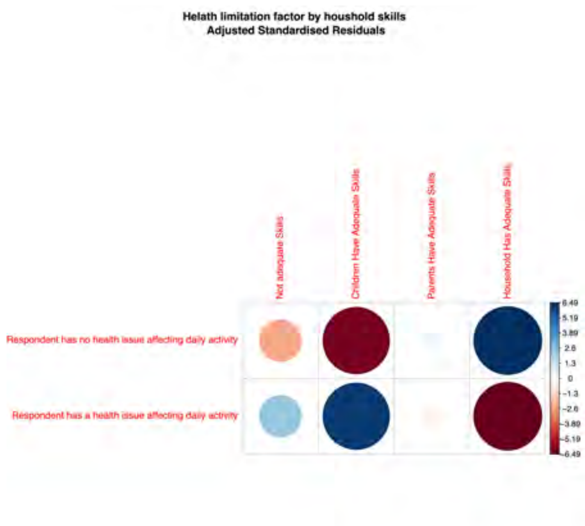

Figure 2.121: Res. Cont. plots-81

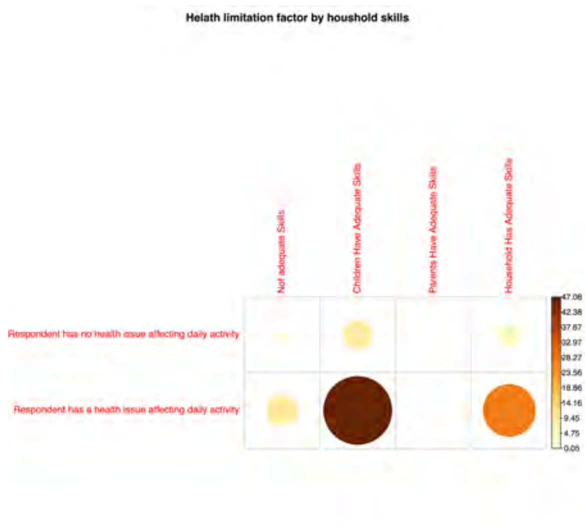

Figure 2.122: Res. Cont. plots-82

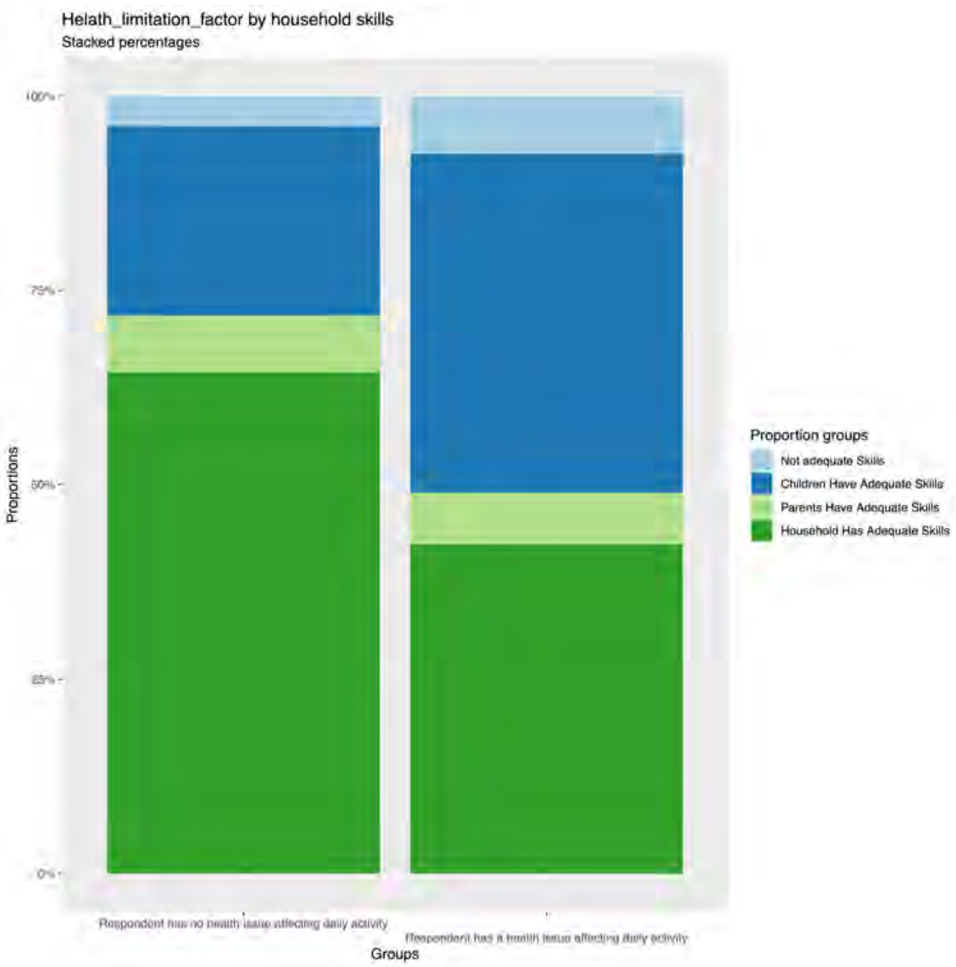

Figure 2.123: Proportions plot-41

2.4.42 Ethnicityfactorbyhousholdskills

The Pearson's Chi-squared test with simulated p-value of independence between variables suggests that the effect is statistically significant and very small ($chi^2 = 9.10, p = 0.029; AdjustedCramer'sv = 0.06, 95\% CI[0.00, 1.00]$). The following tables 2.165, 2.164, and 2.166 provide detals of the observations, column and row percentages. Figures 2.124 and 2.125 present plots of residuals and contributions. Figure 2.126 presents the data in stacked proprtions.

	Not adequate Skills	Children Have Adequate Skills	Parents Have Adequate Skills	Household Has Adequate Skills
Respondent identifies as ethnically white(col.)	67.10	73.40	77.20	79.00
Respondent identifies as ethnically non-white (col.)	32.90	26.60	22.80	21.00

Table 2.164: Ethnicity factor by houshold skills (Column Percentages) (χ^2(NA, 1582) = 9.1, p = 0.029, Cramer's V = 0.076)

	Not adequate Skills	Children Have Adequate Skills	Parents Have Adequate Skills	Household Has Adequate Skills
Respondent identifies as ethnically white(row)	3.90	26.10	7.20	62.80
Respondent identifies as ethnically non-white (row)	6.30	31.30	7.10	55.30

Table 2.165: Ethnicity factor by houshold skills (Row Percentages) (χ^2(NA, 1582) = 9.1, p = 0.029, Cramer's V = 0.076)

	Not adequate Skills	Children Have Adequate Skills	Parents Have Adequate Skills	Household Has Adequate Skills
Respondent identifies as ethnically white(obs.)	47.00	317.00	88.00	763.00
Respondent identifies as ethnically white(row)	3.90	26.10	7.20	62.80
Respondent identifies as ethnically white(col.)	67.10	73.40	77.20	79.00
Respondent identifies as ethnically non-white (obs.)	23.00	115.00	26.00	203.00
Respondent identifies as ethnically non-white (row)	6.30	31.30	7.10	55.30
Respondent identifies as ethnically non-white (col.)	32.90	26.60	22.80	21.00

Table 2.166: Ethnicity factor by houshold skills (χ^2(NA, 1582) = 9.1, p = 0.029, Cramer's V = 0.076)

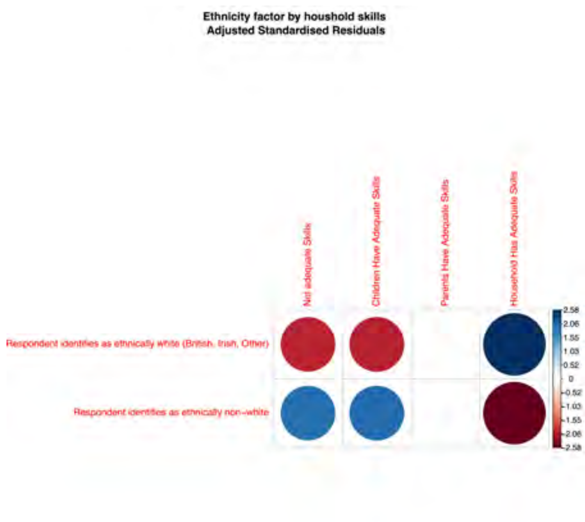

Figure 2.124: Res. Cont. plots-83

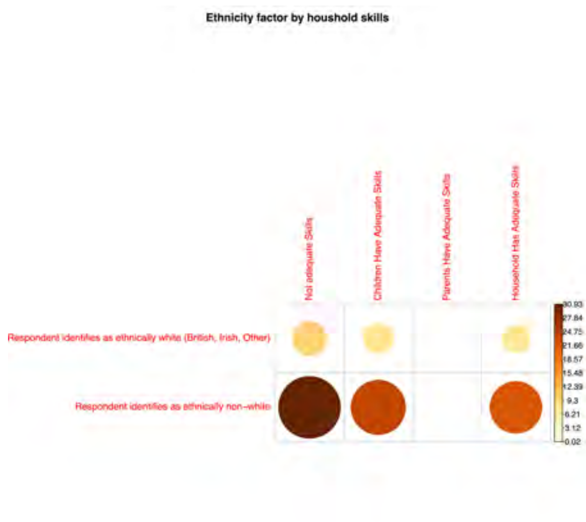

Figure 2.125: Res. Cont. plots-84

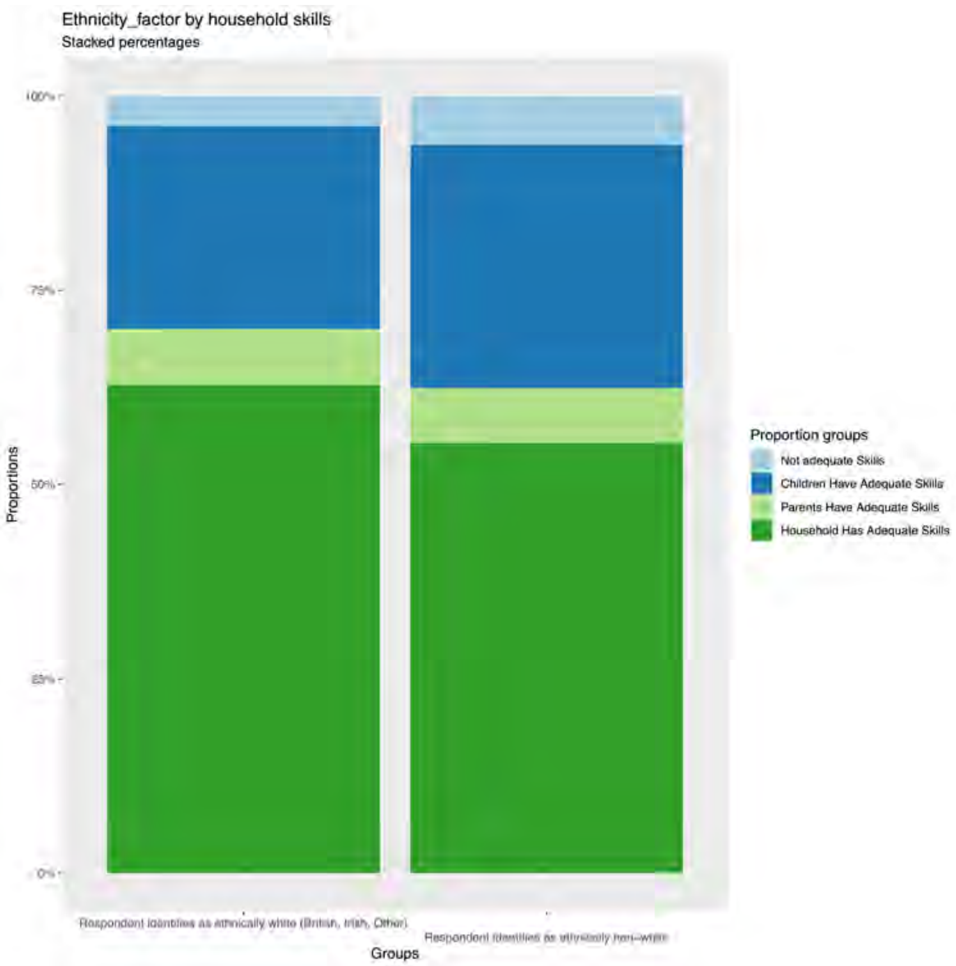

Figure 2.126: Proportions plot-42

2.4.43 SEGfactorbyMDLS(Abs.)

The Pearson's Chi-squared test with simulated p-value of independence between variables suggests that the effect is statistically significant and medium ($chi^2 = 74.52, p < .001; AdjustedCramer'sv = 0.21, 95\%CI[0.17, 1.00]$). The following tables 2.168, 2.167, and 2.169 provide detals of the observations, column and row percentages. Figures 2.127 and 2.128 present plots of residuals and contributions. Figure 2.129 presents the data in stacked proprtions.

	Not MDLS adequate	MDLS adequate
AB (col.)	16.80	26.50
C1 (col.)	27.30	36.00
C2 (col.)	22.80	23.10
DE (col.)	33.10	14.30

Table 2.167: SEG factor by MDLS (Abs.) (Column Percentages) (χ^2(NA, 1582) = 74.517, p = 0, Cramer's V = 0.217)

	Not MDLS adequate	MDLS adequate
AB (row)	53.30	46.70
C1 (row)	57.60	42.40
C2 (row)	63.90	36.10
DE (row)	80.60	19.40

Table 2.168: SEG factor by MDLS (Abs.) (Row Percentages) (χ^2(NA, 1582) = 74.517, p = 0, Cramer's V = 0.217)

	Not MDLS adequate	MDLS adequate
AB (obs.)	171.00	150.00
AB (row)	53.30	46.70
AB (col.)	16.80	26.50
C1 (obs.)	277.00	204.00
C1 (row)	57.60	42.40
C1 (col.)	27.30	36.00
C2 (obs.)	232.00	131.00
C2 (row)	63.90	36.10
C2 (col.)	22.80	23.10
DE (obs.)	336.00	81.00
DE (row)	80.60	19.40
DE (col.)	33.10	14.30

Table 2.169: SEG factor by MDLS (Abs.) (χ^2(NA, 1582) = 74.517, p = 0, Cramer's V = 0.217)

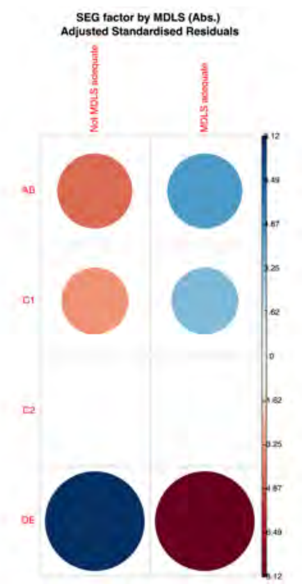

Figure 2.127: Res. Cont. plots-85

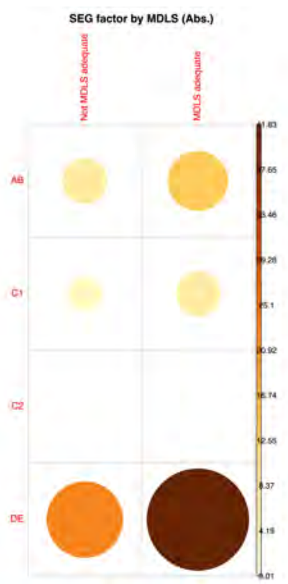

Figure 2.128: Res. Cont. plots-86

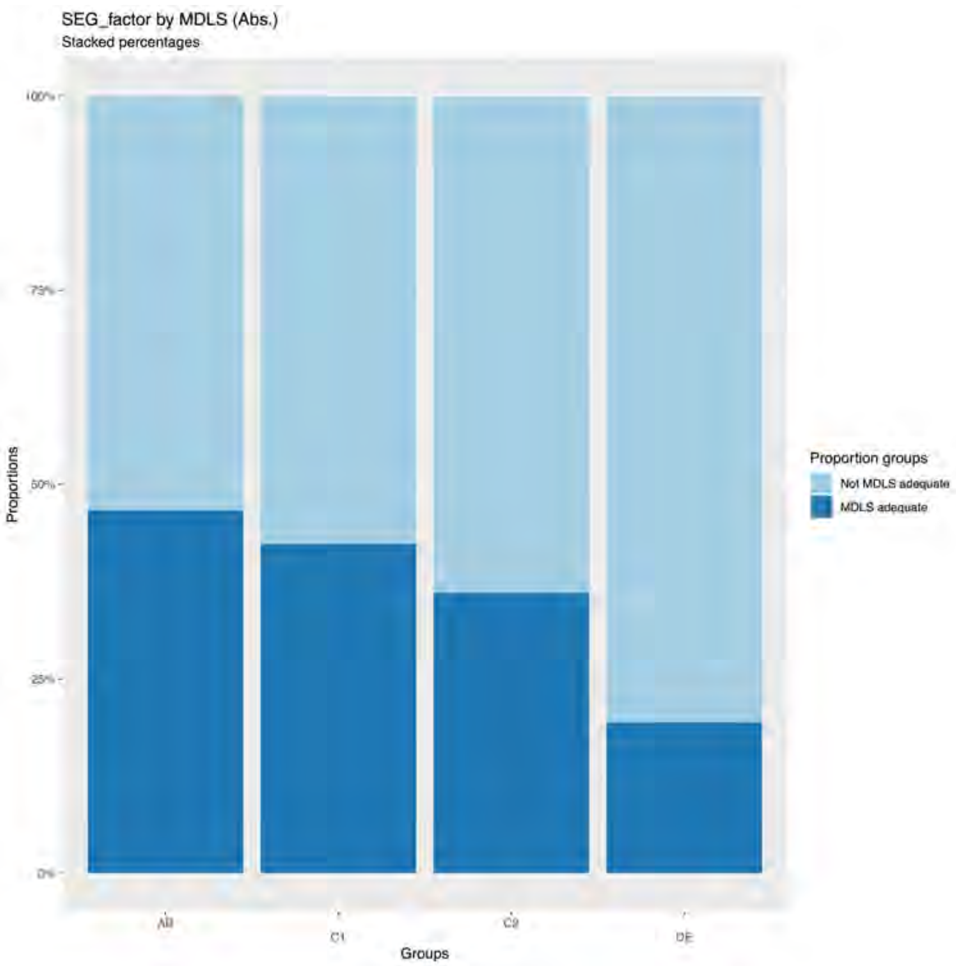

Figure 2.129: Proportions plot-43

2.4.44 HTYPEfactorbyMDLS(Abs.)

The Pearson's Chi-squared test with simulated p-value of independence between variables suggests that the effect is statistically significant and medium ($chi^2 = 101.60, p < .001; AdjustedCramer'sv = 0.24, 95\% CI[0.19, 1.00]$). The following tables 2.171, 2.170, and 2.172 provide detals of the observations, column and row percentages. Figures 2.130 and 2.131 present plots of residuals and contributions. Figure 2.132 presents the data in stacked proprtions.

	Not MDLS adequate	MDLS adequate
1 adult and 1 child (col.)	17.20	11.70
1 adult and 2 children (col.)	10.80	4.60
1 adult and more than 2 children (col.)	5.30	1.10
2 adults and 1 child (col.)	21.60	36.20
2 adults and 2 children (col.)	24.50	33.40
2 adults and more than 2 children (col.)	10.90	6.00
More than 2 adults in HH and 1 child (col.)	4.90	3.50
More than 2 adults in HH and 2 children (col.)	3.10	3.50
More than 2 adults in HH and 2+ children (col.)	1.70	0.00

Table 2.170: HTYPE factor by MDLS (Abs.) (Column Percentages) (χ^2(NA, 1582) = 101.6, p = 0, Cramer's V = 0.253)

	Not MDLS adequate	MDLS adequate
1 adult and 1 child (row)	72.60	27.40
1 adult and 2 children (row)	80.90	19.10
1 adult and more than 2 children (row)	90.00	10.00
2 adults and 1 child (row)	51.70	48.30
2 adults and 2 children (row)	56.80	43.20
2 adults and more than 2 children (row)	76.60	23.40
More than 2 adults in HH and 1 child (row)	71.40	28.60
More than 2 adults in HH and 2 children (row)	60.80	39.20
More than 2 adults in HH and 2+ children (row)	100.00	0.00

Table 2.171: HTYPE factor by MDLS (Abs.) (Row Percentages) (χ^2(NA, 1582) = 101.6, p = 0, Cramer's V = 0.253)

	Not MDLS adequate	MDLS adequate
1 adult and 1 child (obs.)	175.00	66.00
1 adult and 1 child (row)	72.60	27.40
1 adult and 1 child (col.)	17.20	11.70
1 adult and 2 children (obs.)	110.00	26.00
1 adult and 2 children (row)	80.90	19.10
1 adult and 2 children (col.)	10.80	4.60
1 adult and more than 2 children (obs.)	54.00	6.00
1 adult and more than 2 children (row)	90.00	10.00
1 adult and more than 2 children (col.)	5.30	1.10
2 adults and 1 child (obs.)	219.00	205.00
2 adults and 1 child (row)	51.70	48.30
2 adults and 1 child (col.)	21.60	36.20
2 adults and 2 children (obs.)	249.00	189.00
2 adults and 2 children (row)	56.80	43.20
2 adults and 2 children (col.)	24.50	33.40
2 adults and more than 2 children (obs.)	111.00	34.00
2 adults and more than 2 children (row)	76.60	23.40
2 adults and more than 2 children (col.)	10.90	6.00
More than 2 adults in HH and 1 child (obs.)	50.00	20.00
More than 2 adults in HH and 1 child (row)	71.40	28.60
More than 2 adults in HH and 1 child (col.)	4.90	3.50
More than 2 adults in HH and 2 children (obs.)	31.00	20.00
More than 2 adults in HH and 2 children (row)	60.80	39.20
More than 2 adults in HH and 2 children (col.)	3.10	3.50
More than 2 adults in HH and 2+ children (obs.)	17.00	0.00
More than 2 adults in HH and 2+ children (row)	100.00	0.00
More than 2 adults in HH and 2+ children (col.)	1.70	0.00

Table 2.172: HTYPE factor by MDLS (Abs.) (χ^2(NA, 1582) = 101.6, p = 0, Cramer's V = 0.253)

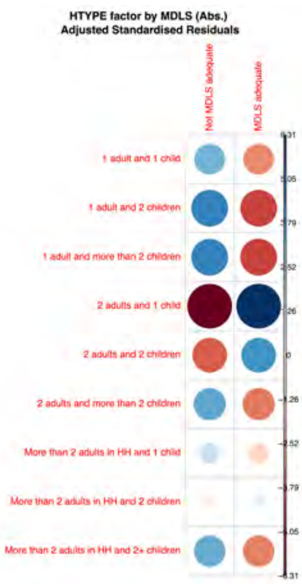

Figure 2.130: Res. Cont. plots-87

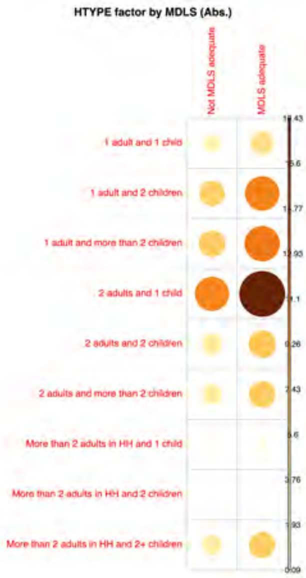

Figure 2.131: Res. Cont. plots-88

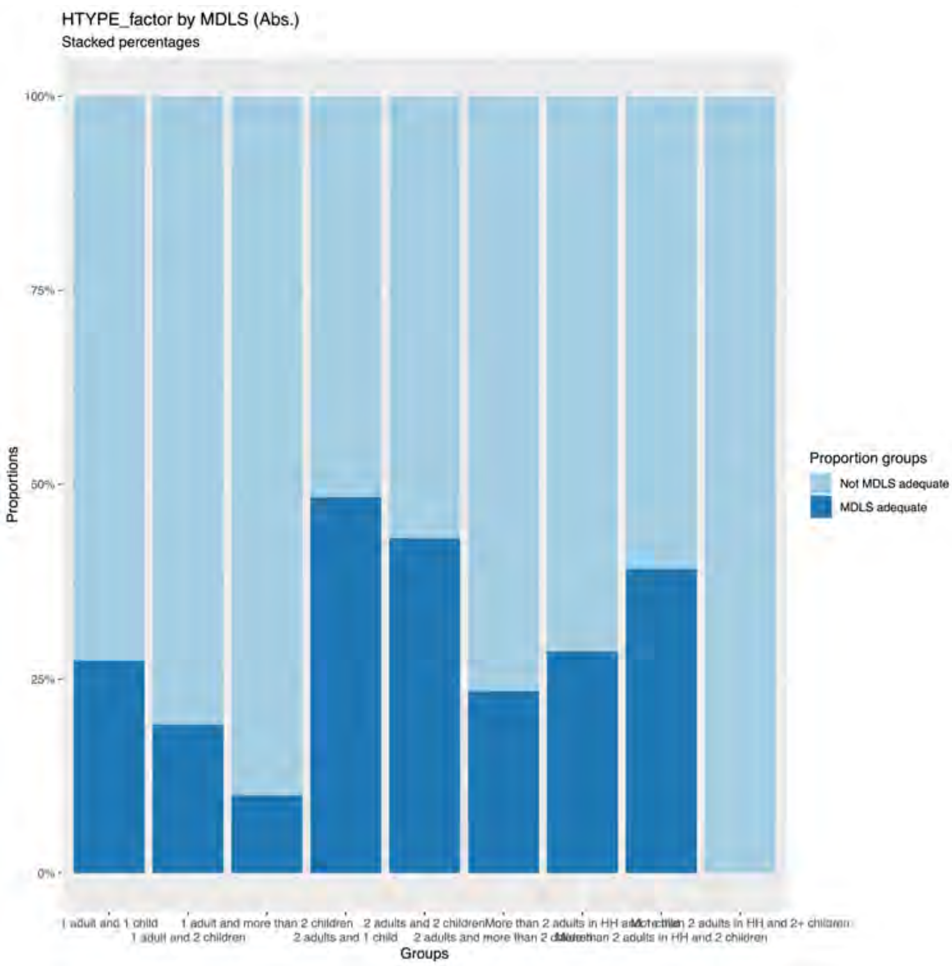

Figure 2.132: Proportions plot-44

2.4.45 REGIONfactorbyMDLS(Abs.)

The Pearson's Chi-squared test with simulated p-value of independence between variables suggests that the effect is statistically significant and small ($chi^2 = 33.46, p < .001; AdjustedCramer'sv = 0.12, 95\%CI[0.00, 1.00]$). The following tables 2.174, 2.173, and 2.175 provide detals of the observations, column and row percentages. Figures 2.133 and 2.134 present plots of residuals and contributions. Figure 2.135 presents the data in stacked proprtions.

	Not MDLS adequate	MDLS adequate
North East (col.)	3.90	3.20
North West (col.)	11.50	6.90
Yorkshire and The Humber (col.)	8.40	8.30
East Midlands (col.)	6.40	6.50
West Midlands (col.)	8.00	11.30
East of England (col.)	7.60	10.40
London (col.)	15.00	13.40
South East (col.)	12.50	15.50
South West (col.)	6.60	9.40
Wales (col.)	4.80	5.50
Northern Ireland (col.)	5.40	2.70
Scotland (col.)	9.90	6.90

Table 2.173: REGION factor by MDLS (Abs.) (Column Percentages) (χ^2(NA, 1582) = 33.456, p = 0.001, Cramer's V = 0.145)

	Not MDLS adequate	MDLS adequate
North East (row)	69.00	31.00
North West (row)	75.00	25.00
Yorkshire and The Humber (row)	64.40	35.60
East Midlands (row)	63.70	36.30
West Midlands (row)	55.90	44.10
East of England (row)	56.60	43.40
London (row)	66.70	33.30
South East (row)	59.10	40.90
South West (row)	55.80	44.20
Wales (row)	61.30	38.80
Northern Ireland (row)	78.60	21.40
Scotland (row)	72.10	27.90

Table 2.174: REGION factor by MDLS (Abs.) (Row Percentages) (χ^2(NA, 1582) = 33.456, p = 0.001, Cramer's V = 0.145)

	Not MDLS adequate	MDLS adequate
North East (obs.)	40.00	18.00
North East (row)	69.00	31.00
North East (col.)	3.90	3.20
North West (obs.)	117.00	39.00
North West (row)	75.00	25.00
North West (col.)	11.50	6.90
Yorkshire and The Humber (obs.)	85.00	47.00
Yorkshire and The Humber (row)	64.40	35.60
Yorkshire and The Humber (col.)	8.40	8.30
East Midlands (obs.)	65.00	37.00
East Midlands (row)	63.70	36.30
East Midlands (col.)	6.40	6.50
West Midlands (obs.)	81.00	64.00
West Midlands (row)	55.90	44.10
West Midlands (col.)	8.00	11.30
East of England (obs.)	77.00	59.00
East of England (row)	56.60	43.40
East of England (col.)	7.60	10.40
London (obs.)	152.00	76.00
London (row)	66.70	33.30
London (col.)	15.00	13.40
South East (obs.)	127.00	88.00
South East (row)	59.10	40.90
South East (col.)	12.50	15.50
South West (obs.)	67.00	53.00
South West (row)	55.80	44.20
South West (col.)	6.60	9.40
Wales (obs.)	49.00	31.00
Wales (row)	61.30	38.80
Wales (col.)	4.80	5.50
Northern Ireland (obs.)	55.00	15.00
Northern Ireland (row)	78.60	21.40
Northern Ireland (col.)	5.40	2.70
Scotland (obs.)	101.00	39.00
Scotland (row)	72.10	27.90
Scotland (col.)	9.90	6.90

Table 2.175: REGION factor by MDLS (Abs.) (χ^2(NA, 1582) = 33.456, p = 0.001, Cramer's V = 0.145)

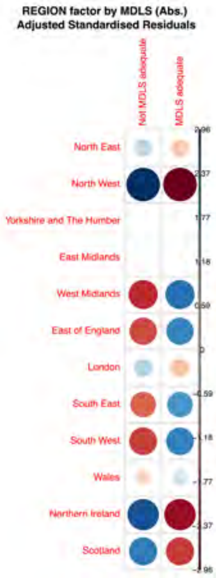

Figure 2.133: Res. Cont. plots-89

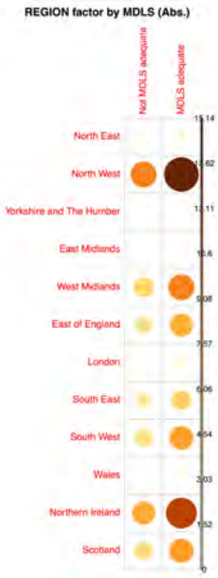

Figure 2.134: Res. Cont. plots-90

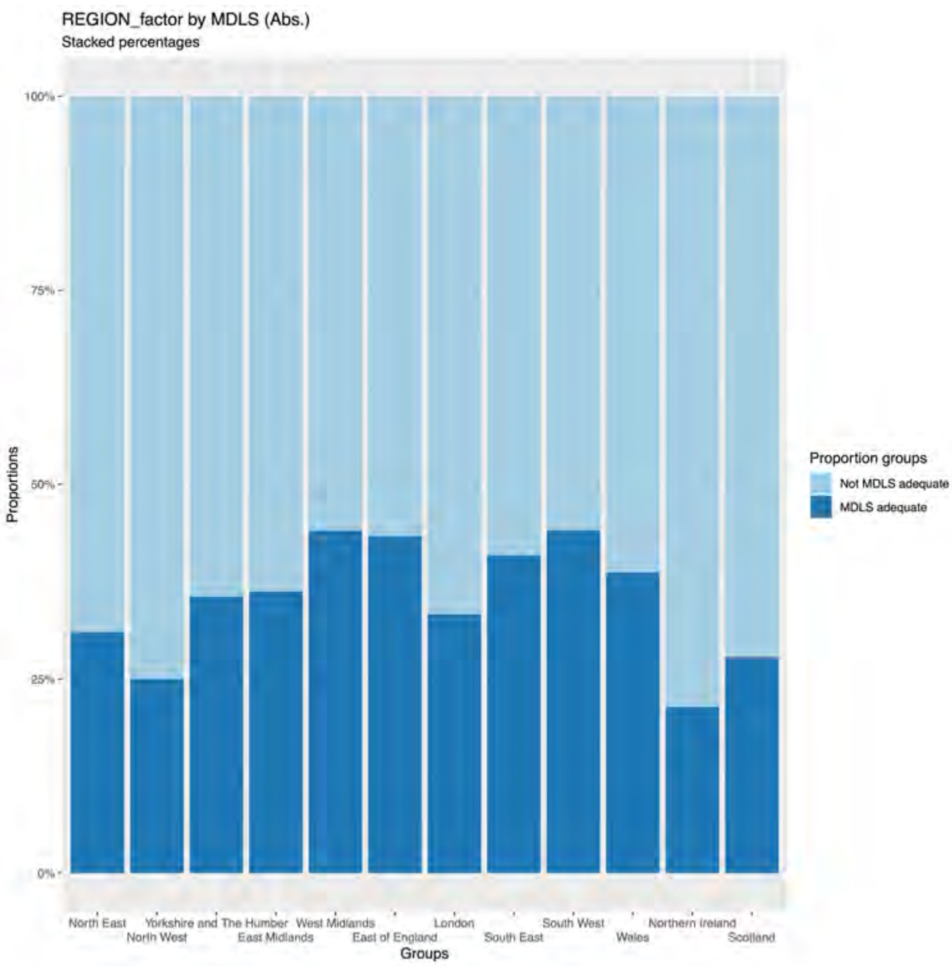

Figure 2.135: Proportions plot-45

2.4.46 OverallhouseholdskillsfactorbyMDLS(Abs.)

The Pearson's Chi-squared test with simulated p-value of independence between variables suggests that the effect is statistically significant and very large ($chi^2 = 562.00, p < .001; AdjustedCramer'sv = 0.59, 95\%CI[0.55, 1.00]$). The following tables 2.177, 2.176, and 2.178 provide detals of the observations, column and row percentages. Figures 2.136 and 2.137 present plots of residuals and contributions. Figure 2.138 presents the data in stacked proprtions.

	Not MDLS adequate	MDLS adequate
Not adequate Skills (col.)	6.90	0.00
Children Have Adequate Skills (col.)	42.50	0.00
Parents Have Adequate Skills (col.)	11.20	0.00
Household Has Adequate Skills (col.)	39.40	100.00

Table 2.176: Overall household skills factor by MDLS (Abs.) (Column Percentages) (χ^2(NA, 1582) = 561.995, p = 0, Cramer's V = 0.596)

	Not MDLS adequate	MDLS adequate
Not adequate Skills (row)	100.00	0.00
Children Have Adequate Skills (row)	100.00	0.00
Parents Have Adequate Skills (row)	100.00	0.00
Household Has Adequate Skills (row)	41.40	58.60

Table 2.177: Overall household skills factor by MDLS (Abs.) (Row Percentages) (χ^2(NA, 1582) = 561.995, p = 0, Cramer's V = 0.596)

	Not MDLS adequate	MDLS adequate
Not adequate Skills (obs.)	70.00	0.00
Not adequate Skills (row)	100.00	0.00
Not adequate Skills (col.)	6.90	0.00
Children Have Adequate Skills (obs.)	432.00	0.00
Children Have Adequate Skills (row)	100.00	0.00
Children Have Adequate Skills (col.)	42.50	0.00
Parents Have Adequate Skills (obs.)	114.00	0.00
Parents Have Adequate Skills (row)	100.00	0.00
Parents Have Adequate Skills (col.)	11.20	0.00
Household Has Adequate Skills (obs.)	400.00	566.00
Household Has Adequate Skills (row)	41.40	58.60
Household Has Adequate Skills (col.)	39.40	100.00

Table 2.178: Overall household skills factor by MDLS (Abs.) (χ^2(NA, 1582) = 561.995, p = 0, Cramer's V = 0.596)

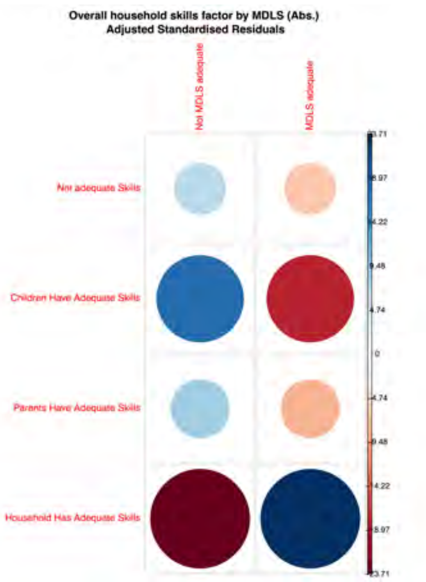

Figure 2.136: Res. Cont. plots-91

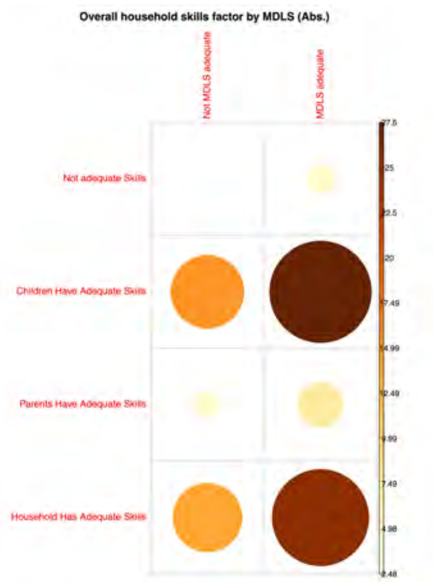

Figure 2.137: Res. Cont. plots-92

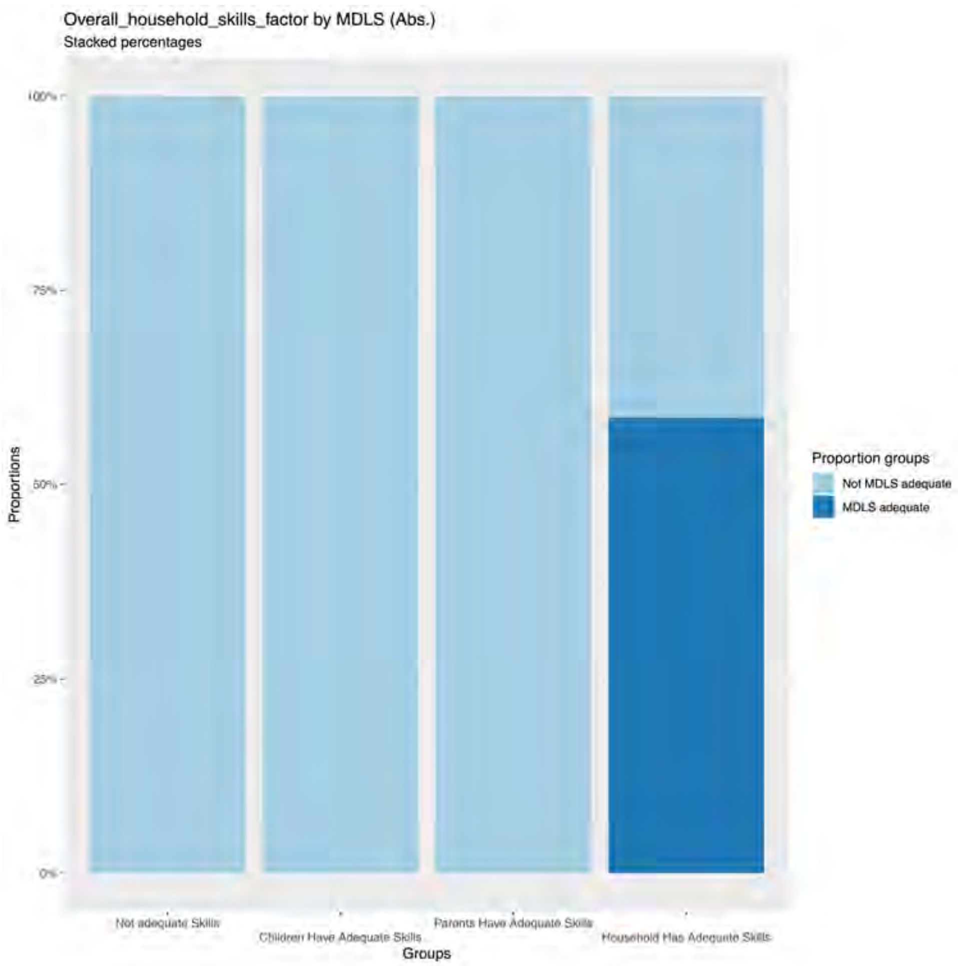

Figure 2.138: Proportions plot-46

2.4.47 BroadbandfactorbyMDLS(Abs.)

The Pearson's Chi-squared test with simulated p-value of independence between variables suggests that the effect is statistically not significant and tiny ($chi^2 = 1.58, p = 0.223; AdjustedCramer'sv = 0.02, 95\%CI[0.00, 1.00]$). The following tables 2.180, 2.179, and 2.181 provide detals of the observations, column and row percentages. Figures 2.139 and 2.140 present plots of residuals and contributions. Figure 2.141 presents the data in stacked proprtions.

	Not MDLS adequate	MDLS adequate
Below average broadband speed (col.)	41.40	44.70
Above average broadband speed (col.)	58.60	55.30

Table 2.179: Broadband factor by MDLS (Abs.) (Column Percentages) (χ^2(NA, 1582) = 1.582, p = 0.223, Cramer's V = 0.032)

	Not MDLS adequate	MDLS adequate
Below average broadband speed (row)	62.50	37.50
Above average broadband speed (row)	65.50	34.50

Table 2.180: Broadband factor by MDLS (Abs.) (Row Percentages) (χ^2(NA, 1582) = 1.582, p = 0.223, Cramer's V = 0.032)

	Not MDLS adequate	MDLS adequate
Below average broadband speed (obs.)	421.00	253.00
Below average broadband speed (row)	62.50	37.50
Below average broadband speed (col.)	41.40	44.70
Above average broadband speed (obs.)	595.00	313.00
Above average broadband speed (row)	65.50	34.50
Above average broadband speed (col.)	58.60	55.30

Table 2.181: Broadband factor by MDLS (Abs.) (χ^2(NA, 1582) = 1.582, p = 0.223, Cramer's V = 0.032)

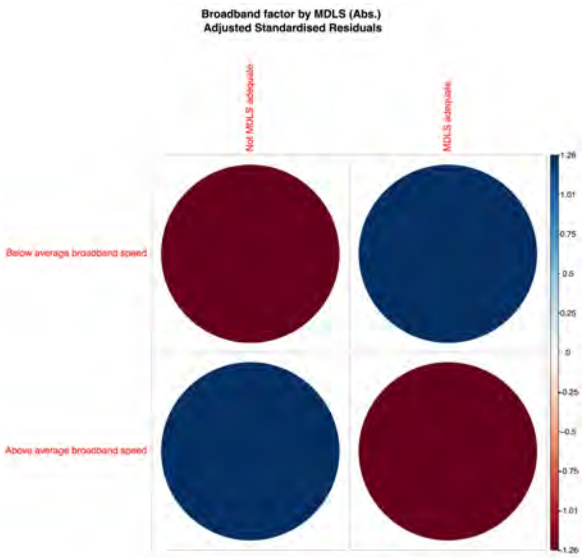

Figure 2.139: Res. Cont. plots-93

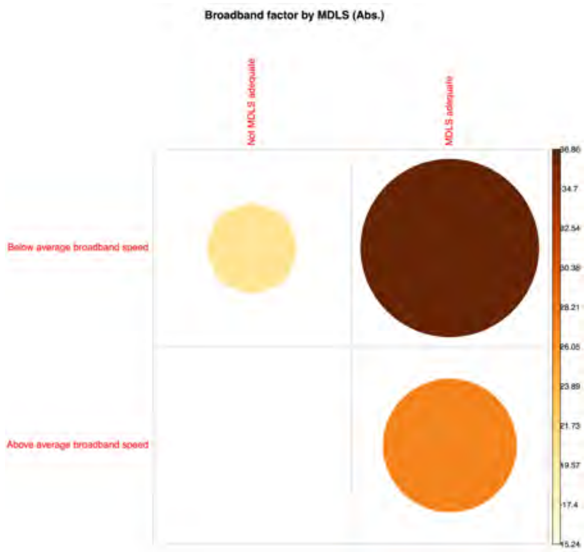

Figure 2.140: Res. Cont. plots-94

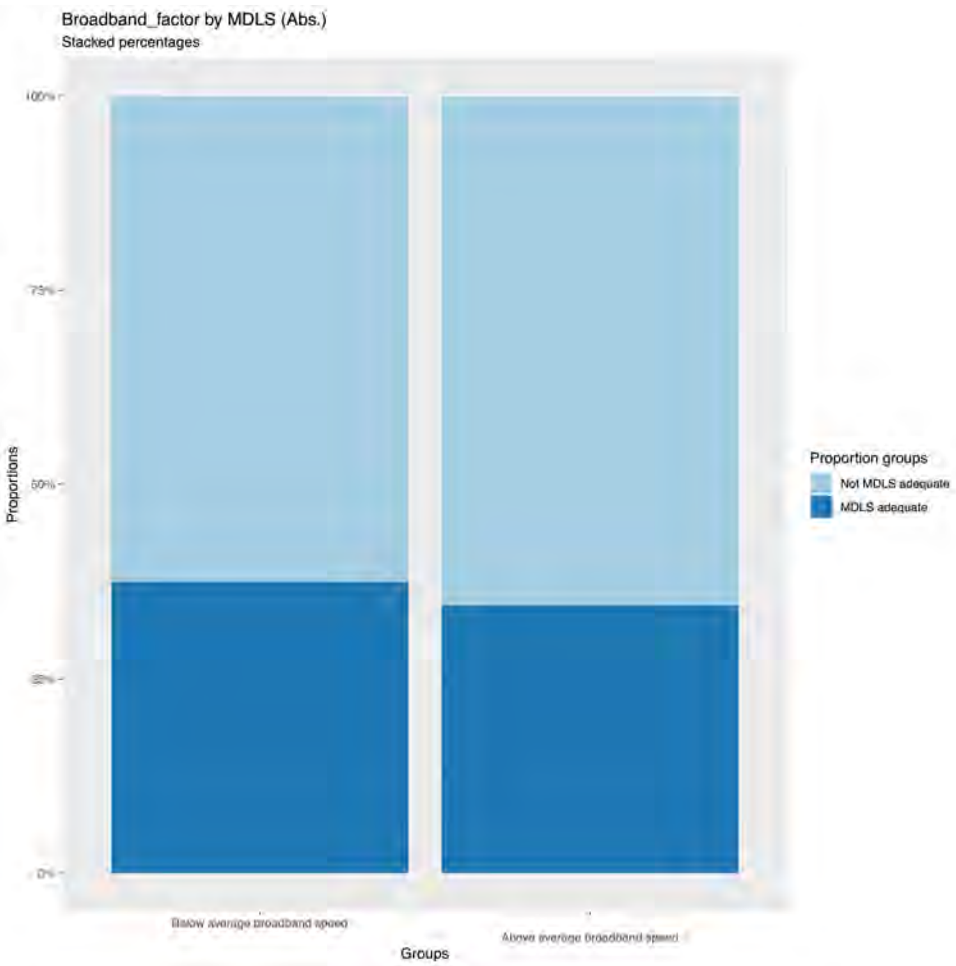

Figure 2.141: Proportions plot-47

2.4.48 URBANfactorbyMDLS(Abs.)

The Pearson's Chi-squared test with simulated p-value of independence between variables suggests that the effect is statistically significant and very small ($chi^2 = 14.32, p = 0.004; AdjustedCramer'sv = 0.08, 95\%CI[0.00, 1.00]$). The following tables 2.183, 2.182, and 2.184 provide detals of the observations, column and row percentages. Figures 2.142 and 2.143 present plots of residuals and contributions. Figure 2.144 presents the data in stacked proprtions.

	Not MDLS adequate	MDLS adequate
Large city (col.)	17.70	14.00
Smaller city or large town (col.)	18.20	14.10
Medium town (col.)	35.20	35.00
Small town (col.)	17.70	23.10
Rural area (col.)	11.10	13.80

Table 2.182: URBAN factor by MDLS (Abs.) (Column Percentages) (χ^2(NA, 1582) = 14.323, p = 0.004, Cramer's V = 0.095)

	Not MDLS adequate	MDLS adequate
Large city (row)	69.50	30.50
Smaller city or large town (row)	69.80	30.20
Medium town (row)	64.40	35.60
Small town (row)	57.90	42.10
Rural area (row)	59.20	40.80

Table 2.183: URBAN factor by MDLS (Abs.) (Row Percentages) (χ^2(NA, 1582) = 14.323, p = 0.004, Cramer's V = 0.095)

	Not MDLS adequate	MDLS adequate
Large city (obs.)	180.00	79.00
Large city (row)	69.50	30.50
Large city (col.)	17.70	14.00
Smaller city or large town (obs.)	185.00	80.00
Smaller city or large town (row)	69.80	30.20
Smaller city or large town (col.)	18.20	14.10
Medium town (obs.)	358.00	198.00
Medium town (row)	64.40	35.60
Medium town (col.)	35.20	35.00
Small town (obs.)	180.00	131.00
Small town (row)	57.90	42.10
Small town (col.)	17.70	23.10
Rural area (obs.)	113.00	78.00
Rural area (row)	59.20	40.80
Rural area (col.)	11.10	13.80

Table 2.184: URBAN factor by MDLS (Abs.) (χ^2(NA, 1582) = 14.323, p = 0.004, Cramer's V = 0.095)

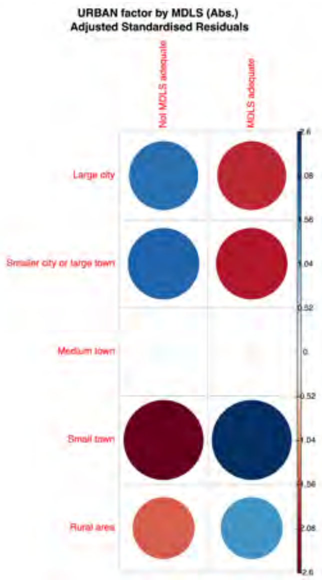

Figure 2.142: Res. Cont. plots-95

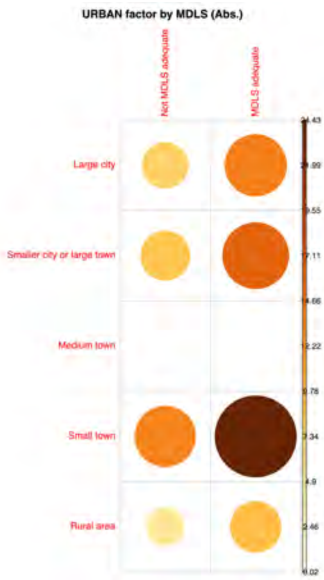

Figure 2.143: Res. Cont. plots-96

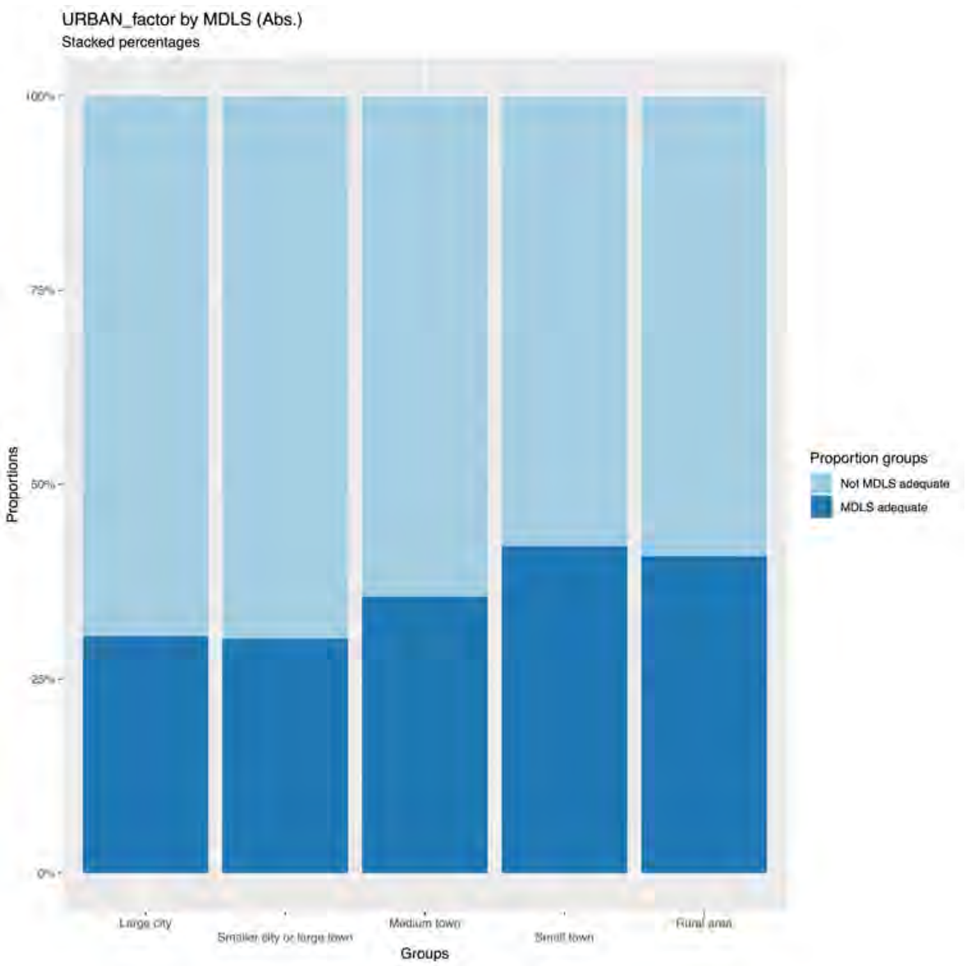

Figure 2.144: Proportions plot-48

2.4.49 URBAN2factorbyMDLS(Abs.)

The Pearson's Chi-squared test with simulated p-value of independence between variables suggests that the effect is statistically not significant and tiny ($chi^2 = 2.42, p = 0.138; AdjustedCramer'sv = 0.03, 95\% CI[0.00, 1.00]$). The following tables 2.186, 2.185, and 2.187 provide detals of the observations, column and row percentages. Figures 2.145 and 2.146 present plots of residuals and contributions. Figure 2.147 presents the data in stacked proprtions.

	Not MDLS adequate	MDLS adequate
Urban (col.)	88.90	86.20
Rural (col.)	11.10	13.80

Table 2.185: URBAN2 factor by MDLS (Abs.) (Column Percentages) (χ^2(NA, 1582) = 2.421, p = 0.138, Cramer's V = 0.039)

	Not MDLS adequate	MDLS adequate
Urban (row)	64.90	35.10
Rural (row)	59.20	40.80

Table 2.186: URBAN2 factor by MDLS (Abs.) (Row Percentages) (χ^2(NA, 1582) = 2.421, p = 0.138, Cramer's V = 0.039)

	Not MDLS adequate	MDLS adequate
Urban (obs.)	903.00	488.00
Urban (row)	64.90	35.10
Urban (col.)	88.90	86.20
Rural (obs.)	113.00	78.00
Rural (row)	59.20	40.80
Rural (col.)	11.10	13.80

Table 2.187: URBAN2 factor by MDLS (Abs.) (χ^2(NA, 1582) = 2.421, p = 0.138, Cramer's V = 0.039)

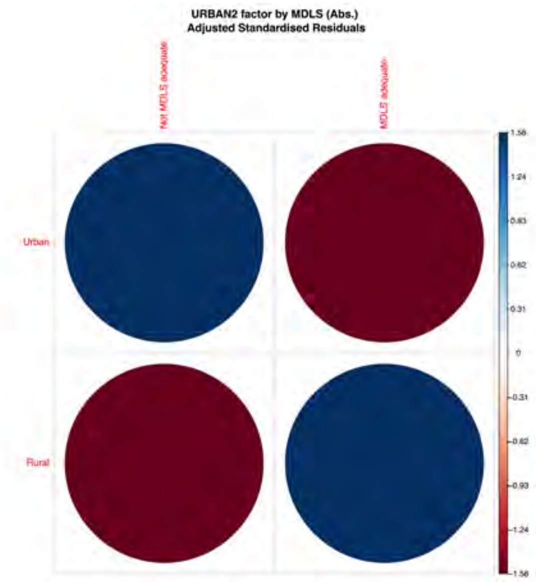

Figure 2.145: Res. Cont. plots-97

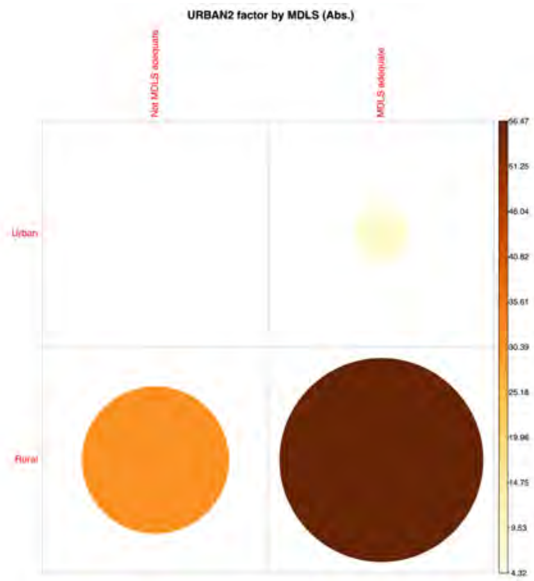

Figure 2.146: Res. Cont. plots-98

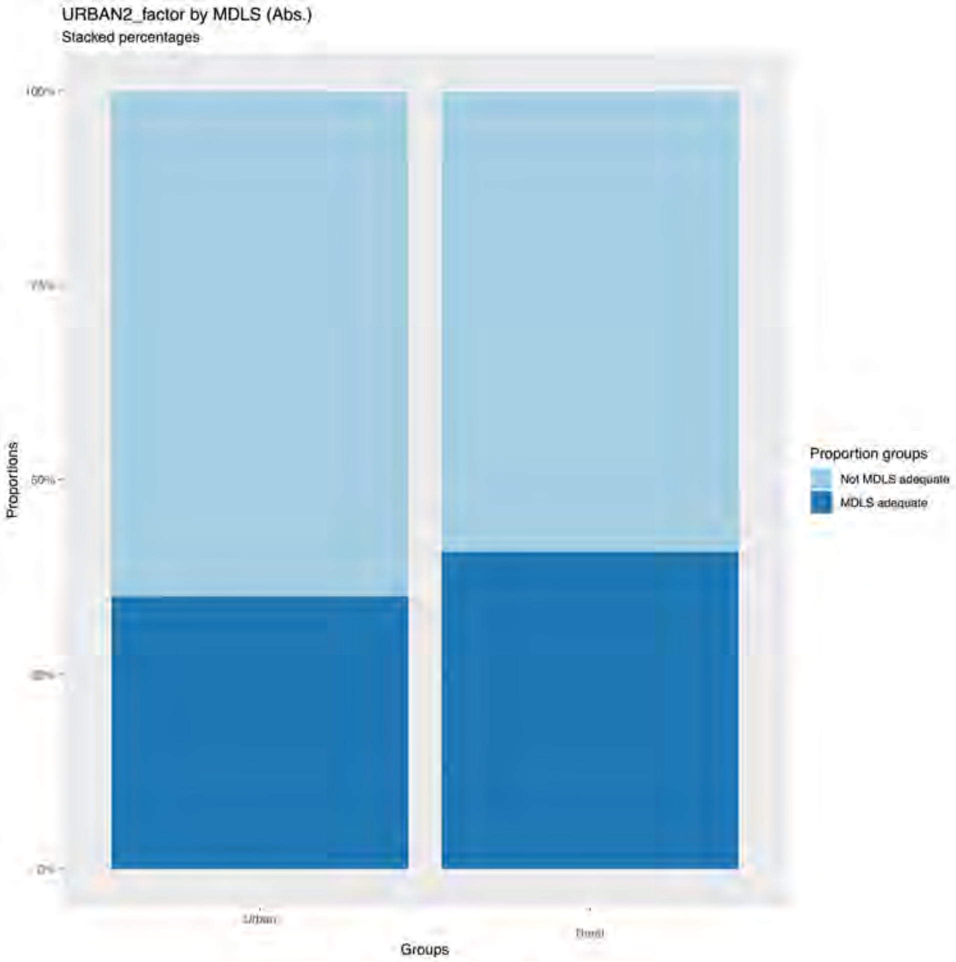

Figure 2.147: Proportions plot-49

2.4.50 iucGRPLBLrfactorbyMDLS(Abs.)

The Pearson's Chi-squared test with simulated p-value of independence between variables suggests that the effect is statistically significant and small ($chi^2 = 38.64, p < .001; AdjustedCramer'sv = 0.14, 95\%CI[0.06, 1.00]$). The following tables 2.189, 2.188, and 2.190 provide detals of the observations, column and row percentages. Figures 2.148 and 2.149 present plots of residuals and contributions. Figure 2.150 presents the data in stacked proprtions.

	Not MDLS adequate	MDLS adequate
Digital Seniors (col.)	9.10	10.50
e-Cultural Creators (col.)	0.30	0.00
e-Mainstream (col.)	13.40	16.30
e-Professionals (col.)	3.50	3.70
e-Rational Utilitarians (col.)	6.30	9.20
e-Veterans (col.)	11.20	15.90
e-Withdrawn (col.)	15.10	8.50
Passive and Uncommitted Users (col.)	29.60	22.90
Settled Offline Communities (col.)	4.60	7.60
Youthful Urban Fringe (col.)	7.10	5.40

Table 2.188: iuc GRP LBLr factor by MDLS (Abs.) (Column Percentages) (χ^2(NA, 1491) = 38.643, p = 0, Cramer's V = 0.161)

	Not MDLS adequate	MDLS adequate
Digital Seniors (row)	60.10	39.90
e-Cultural Creators (row)	100.00	0.00
e-Mainstream (row)	59.10	40.90
e-Professionals (row)	62.30	37.70
e-Rational Utilitarians (row)	54.50	45.50
e-Veterans (row)	55.20	44.80
e-Withdrawn (row)	75.70	24.30
Passive and Uncommitted Users (row)	69.40	30.60
Settled Offline Communities (row)	51.80	48.20
Youthful Urban Fringe (row)	69.80	30.20

Table 2.189: iuc GRP LBLr factor by MDLS (Abs.) (Row Percentages) (χ^2(NA, 1491) = 38.643, p = 0, Cramer's V = 0.161)

	Not MDLS adequate	MDLS adequate
Digital Seniors (obs.)	86.00	57.00
Digital Seniors (row)	60.10	39.90
Digital Seniors (col.)	9.10	10.50
e-Cultural Creators (obs.)	3.00	0.00
e-Cultural Creators (row)	100.00	0.00
e-Cultural Creators (col.)	0.30	0.00
e-Mainstream (obs.)	127.00	88.00
e-Mainstream (row)	59.10	40.90
e-Mainstream (col.)	13.40	16.30
e-Professionals (obs.)	33.00	20.00
e-Professionals (row)	62.30	37.70
e-Professionals (col.)	3.50	3.70
e-Rational Utilitarians (obs.)	60.00	50.00
e-Rational Utilitarians (row)	54.50	45.50
e-Rational Utilitarians (col.)	6.30	9.20
e-Veterans (obs.)	106.00	86.00
e-Veterans (row)	55.20	44.80
e-Veterans (col.)	11.20	15.90
e-Withdrawn (obs.)	143.00	46.00
e-Withdrawn (row)	75.70	24.30
e-Withdrawn (col.)	15.10	8.50
Passive and Uncommitted Users (obs.)	281.00	124.00
Passive and Uncommitted Users (row)	69.40	30.60
Passive and Uncommitted Users (col.)	29.60	22.90
Settled Offline Communities (obs.)	44.00	41.00
Settled Offline Communities (row)	51.80	48.20
Settled Offline Communities (col.)	4.60	7.60
Youthful Urban Fringe (obs.)	67.00	29.00
Youthful Urban Fringe (row)	69.80	30.20
Youthful Urban Fringe (col.)	7.10	5.40

Table 2.190: iuc GRP LBLr factor by MDLS (Abs.) (χ^2(NA, 1491) = 38.643, p = 0, Cramer's V = 0.161)

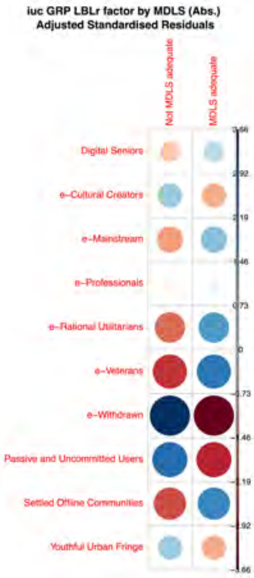

Figure 2.148: Res. Cont. plots-99

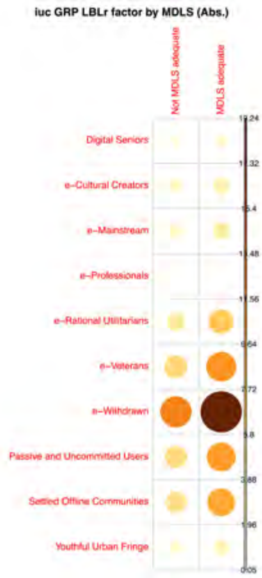

Figure 2.149: Res. Cont. plots-100

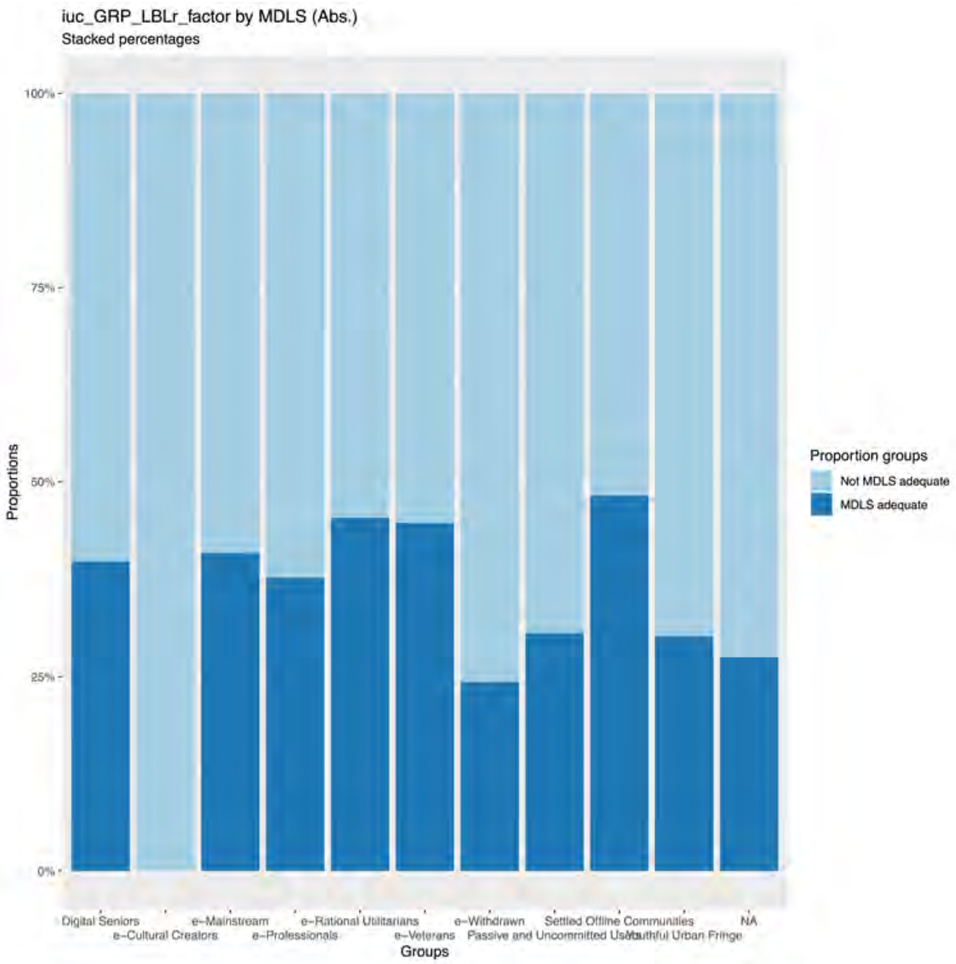

Figure 2.150: Proportions plot-50

2.4.51 oac21SGfactorbyMDLS(Abs.)

The Pearson's Chi-squared test with simulated p-value of independence between variables suggests that the effect is statistically significant and small ($chi^2 = 43.01, p < .001; Adjusted Cramer'sv = 0.16, 95\% CI[0.09, 1.00]$). The following tables 2.192, 2.191, and 2.193 provide detals of the observations, column and row percentages. Figures 2.151 and 2.152 present plots of residuals and contributions. Figure 2.153 presents the data in stacked proprtions.

	Not MDLS adequate	MDLS adequate
Retired Professionals (col.)	6.20	8.50
Suburbanites and Peri-Urbanities (col.)	15.10	21.50
Multicultural and Educated Urbanites (col.)	6.30	4.80
Low-Skilled Migrant and Student Communities (col.)	20.60	12.50
Ethnically Diverse Suburban Professionals (col.)	6.60	13.10
Baseline UK (col.)	22.50	21.10
Semi-and Un-Skilled Workforce (col.)	19.70	17.10
Legacy Communities (col.)	3.00	1.40

Table 2.191: oac21SG factor by MDLS (Abs.) (Column Percentages) (χ^2(NA, 1357) = 43.006, p = 0, Cramer's V = 0.178)

	Not MDLS adequate	MDLS adequate
Retired Professionals (row)	55.20	44.80
Suburbanites and Peri-Urbanities (row)	54.40	45.60
Multicultural and Educated Urbanites (row)	69.20	30.80
Low-Skilled Migrant and Student Communities (row)	73.60	26.40
Ethnically Diverse Suburban Professionals (row)	45.90	54.10
Baseline UK (row)	64.40	35.60
Semi-and Un-Skilled Workforce (row)	66.10	33.90
Legacy Communities (row)	78.80	21.20

Table 2.192: oac21SG factor by MDLS (Abs.) (Row Percentages) (χ^2(NA, 1357) = 43.006, p = 0, Cramer's V = 0.178)

	Not MDLS adequate	MDLS adequate
Retired Professionals (obs.)	53.00	43.00
Retired Professionals (row)	55.20	44.80
Retired Professionals (col.)	6.20	8.50
Suburbanites and Peri-Urbanities (obs.)	129.00	108.00
Suburbanites and Peri-Urbanities (row)	54.40	45.60
Suburbanites and Peri-Urbanities (col.)	15.10	21.50
Multicultural and Educated Urbanites (obs.)	54.00	24.00
Multicultural and Educated Urbanites (row)	69.20	30.80
Multicultural and Educated Urbanites (col.)	6.30	4.80
Low-Skilled Migrant and Student Communities (obs.)	176.00	63.00
Low-Skilled Migrant and Student Communities (row)	73.60	26.40
Low-Skilled Migrant and Student Communities (col.)	20.60	12.50
Ethnically Diverse Suburban Professionals (obs.)	56.00	66.00
Ethnically Diverse Suburban Professionals (row)	45.90	54.10
Ethnically Diverse Suburban Professionals (col.)	6.60	13.10
Baseline UK (obs.)	192.00	106.00
Baseline UK (row)	64.40	35.60
Baseline UK (col.)	22.50	21.10
Semi-and Un-Skilled Workforce (obs.)	168.00	86.00
Semi-and Un-Skilled Workforce (row)	66.10	33.90
Semi-and Un-Skilled Workforce (col.)	19.70	17.10
Legacy Communities (obs.)	26.00	7.00
Legacy Communities (row)	78.80	21.20
Legacy Communities (col.)	3.00	1.40

Table 2.193: oac21SG factor by MDLS (Abs.) (χ^2(NA, 1357) = 43.006, p = 0, Cramer's V = 0.178)

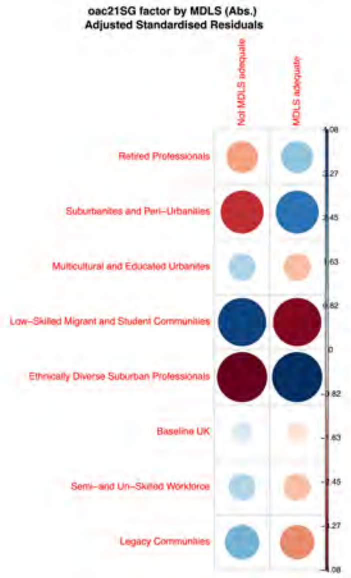

Figure 2.151: Res. Cont. plots-101

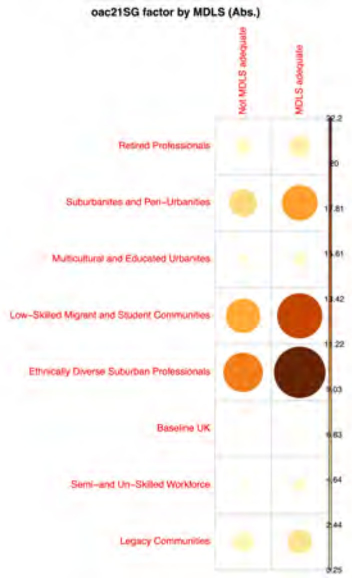

Figure 2.152: Res. Cont. plots-102

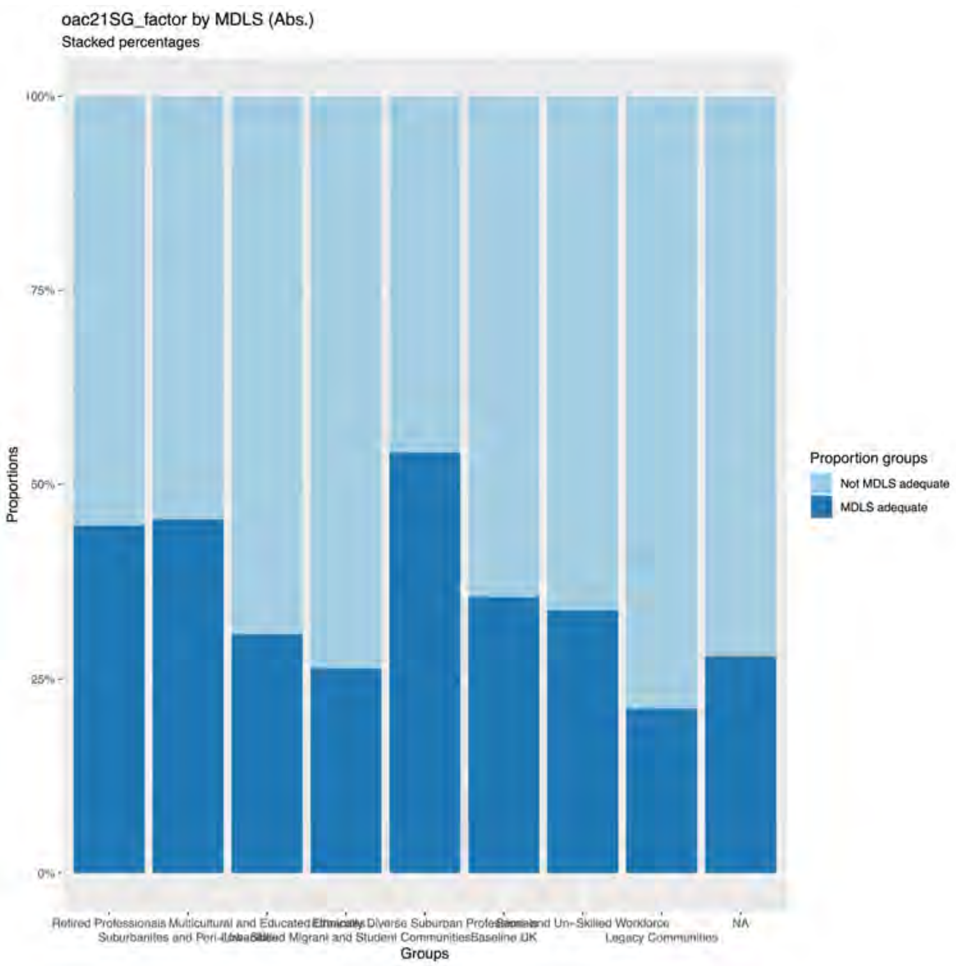

Figure 2.153: Proportions plot-51

2.4.52 aipcsupergroupnamerfactorbyMDLS(Abs.)

The Pearson's Chi-squared test with simulated p-value of independence between variables suggests that the effect is statistically significant and small ($chi^2 = 43.15, p < .001; AdjustedCramer'sv = 0.18, 95\%CI[0.12, 1.00]$). The following tables 2.195, 2.194, and 2.196 provide detals of the observations, column and row percentages. Figures 2.154 and 2.155 present plots of residuals and contributions. Figure 2.156 presents the data in stacked proprtions.

	Not MDLS adequate	MDLS adequate
1 Struggling, More Vulnerable Urbanites (col.)	33.40	22.20
2 Multicultural Central Urban Living (col.)	17.30	10.80
3 Rurban Comfortable Ageing (col.)	13.30	22.40
4 Retired Fringe and Residential Stability (col.)	21.90	24.70
5 Cosmopolitan and Coastal Ageing (col.)	14.20	19.90

Table 2.194: aipc supergroup namer factor by MDLS (Abs.) (Column Percentages) (χ^2(NA, 1278) = 43.145, p = 0, Cramer's V = 0.184)

	Not MDLS adequate	MDLS adequate
1 Struggling, More Vulnerable Urbanites (row)	71.90	28.10
2 Multicultural Central Urban Living (row)	73.20	26.80
3 Rurban Comfortable Ageing (row)	50.20	49.80
4 Retired Fringe and Residential Stability (row)	60.10	39.90
5 Cosmopolitan and Coastal Ageing (row)	54.80	45.20

Table 2.195: aipc supergroup namer factor by MDLS (Abs.) (Row Percentages) (χ^2(NA, 1278) = 43.145, p = 0, Cramer's V = 0.184)

	Not MDLS adequate	MDLS adequate
1 Struggling, More Vulnerable Urbanites (obs.)	269.00	105.00
1 Struggling, More Vulnerable Urbanites (row)	71.90	28.10
1 Struggling, More Vulnerable Urbanites (col.)	33.40	22.20
2 Multicultural Central Urban Living (obs.)	139.00	51.00
2 Multicultural Central Urban Living (row)	73.20	26.80
2 Multicultural Central Urban Living (col.)	17.30	10.80
3 Rurban Comfortable Ageing (obs.)	107.00	106.00
3 Rurban Comfortable Ageing (row)	50.20	49.80
3 Rurban Comfortable Ageing (col.)	13.30	22.40
4 Retired Fringe and Residential Stability (obs.)	176.00	117.00
4 Retired Fringe and Residential Stability (row)	60.10	39.90
4 Retired Fringe and Residential Stability (col.)	21.90	24.70
5 Cosmopolitan and Coastal Ageing (obs.)	114.00	94.00
5 Cosmopolitan and Coastal Ageing (row)	54.80	45.20
5 Cosmopolitan and Coastal Ageing (col.)	14.20	19.90

Table 2.196: aipc supergroup namer factor by MDLS (Abs.) (χ^2(NA, 1278) = 43.145, p = 0, Cramer's V = 0.184)

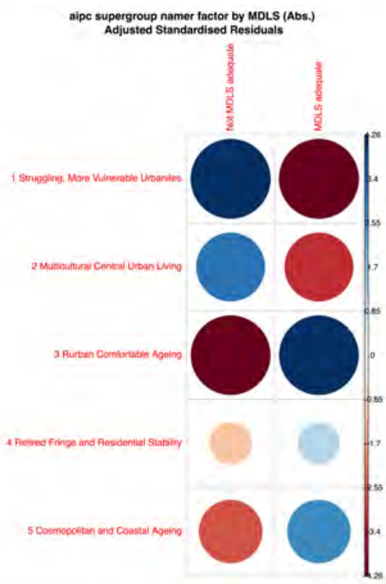

Figure 2.154: Res. Cont. plots-103

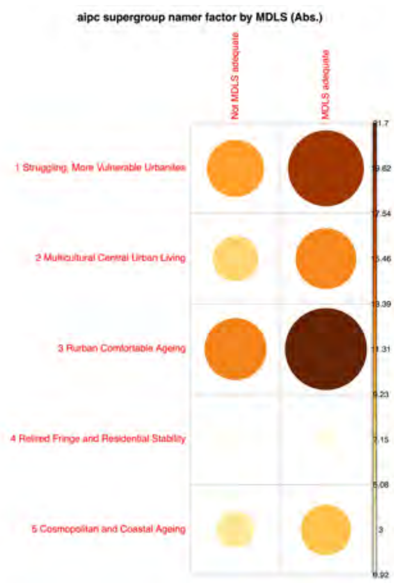

Figure 2.155: Res. Cont. plots-104

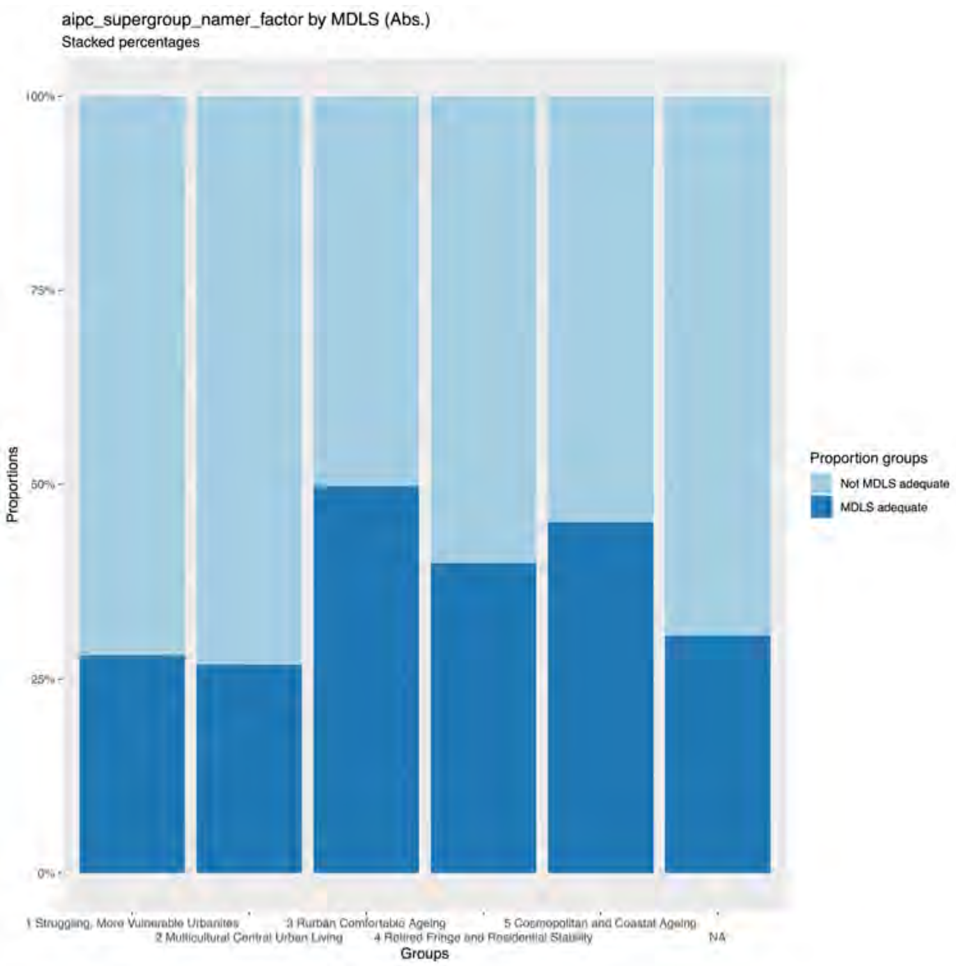

Figure 2.156: Proportions plot-52

2.4.53 BenefitsfactorbyMDLS(Abs.)

The Pearson's Chi-squared test with simulated p-value of independence between variables suggests that the effect is statistically significant and medium ($chi^2 = 73.17, p < .001; AdjustedCramer'sv = 0.21, 95\%CI[0.17, 1.00]$). The following tables 2.198, 2.197, and 2.199 provide detals of the observations, column and row percentages. Figures 2.157 and 2.158 present plots of residuals and contributions. Figure 2.159 presents the data in stacked proprtions.

	Not MDLS adequate	MDLS adequate
Not on any benefits (col.)	59.10	80.20
Receives at least one state benefit (col.)	40.90	19.80

Table 2.197: Benefits factor by MDLS (Abs.) (Column Percentages) (χ^2(NA, 1582) = 73.172, p = 0, Cramer's V = 0.215)

	Not MDLS adequate	MDLS adequate
Not on any benefits (row)	56.90	43.10
Receives at least one state benefit (row)	78.80	21.20

Table 2.198: Benefits factor by MDLS (Abs.) (Row Percentages) (χ^2(NA, 1582) = 73.172, p = 0, Cramer's V = 0.215)

	Not MDLS adequate	MDLS adequate
Not on any benefits (obs.)	600.00	454.00
Not on any benefits (row)	56.90	43.10
Not on any benefits (col.)	59.10	80.20
Receives at least one state benefit (obs.)	416.00	112.00
Receives at least one state benefit (row)	78.80	21.20
Receives at least one state benefit (col.)	40.90	19.80

Table 2.199: Benefits factor by MDLS (Abs.) (χ^2(NA, 1582) = 73.172, p = 0, Cramer's V = 0.215)

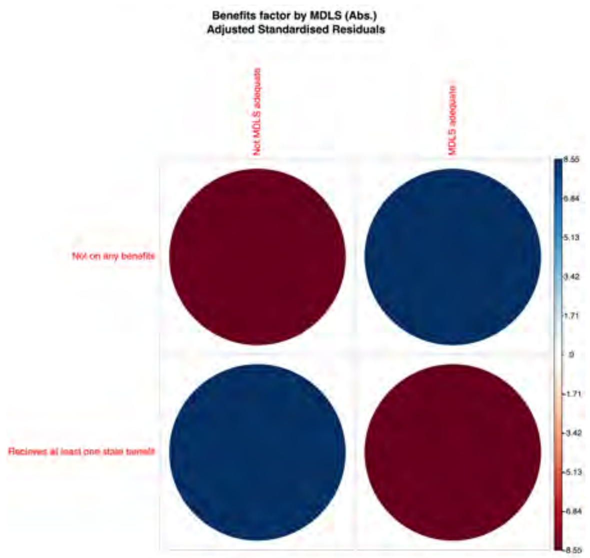

Figure 2.157: Res. Cont. plots-105

Figure 2.158: Res. Cont. plots-106

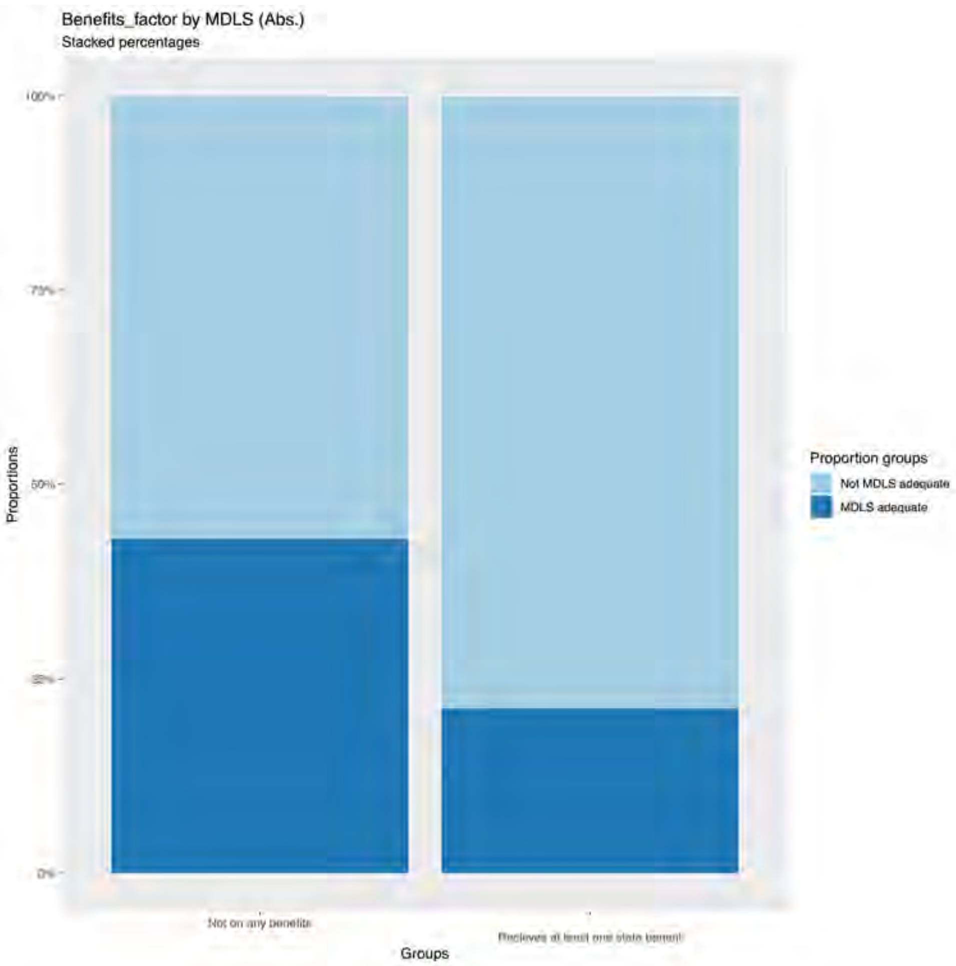

Figure 2.159: Proportions plot-53

2.4.54 WorkingfactorbyMDLS(Abs.)

The Pearson's Chi-squared test with simulated p-value of independence between variables suggests that the effect is statistically significant and small ($chi^2 = 57.70, p < .001; AdjustedCramer'sv = 0.19, 95\%CI[0.15, 1.00]$). The following tables 2.201, 2.200, and 2.202 provide detals of the observations, column and row percentages. Figures 2.160 and 2.161 present plots of residuals and contributions. Figure 2.162 presents the data in stacked proprtions.

	Not MDLS adequate	MDLS adequate
Chief income earner not working (col.)	25.40	9.50
Chief income earner working (col.)	74.60	90.50

Table 2.200: Working factor by MDLS (Abs.) (Column Percentages) (χ^2(NA, 1582) = 57.701, p = 0, Cramer's V = 0.191)

	Not MDLS adequate	MDLS adequate
Chief income earner not working (row)	82.70	17.30
Chief income earner working (row)	59.70	40.30

Table 2.201: Working factor by MDLS (Abs.) (Row Percentages) (χ^2(NA, 1582) = 57.701, p = 0, Cramer's V = 0.191)

	Not MDLS adequate	MDLS adequate
Chief income earner not working (obs.)	258.00	54.00
Chief income earner not working (row)	82.70	17.30
Chief income earner not working (col.)	25.40	9.50
Chief income earner working (obs.)	758.00	512.00
Chief income earner working (row)	59.70	40.30
Chief income earner working (col.)	74.60	90.50

Table 2.202: Working factor by MDLS (Abs.) (χ^2(NA, 1582) = 57.701, p = 0, Cramer's V = 0.191)

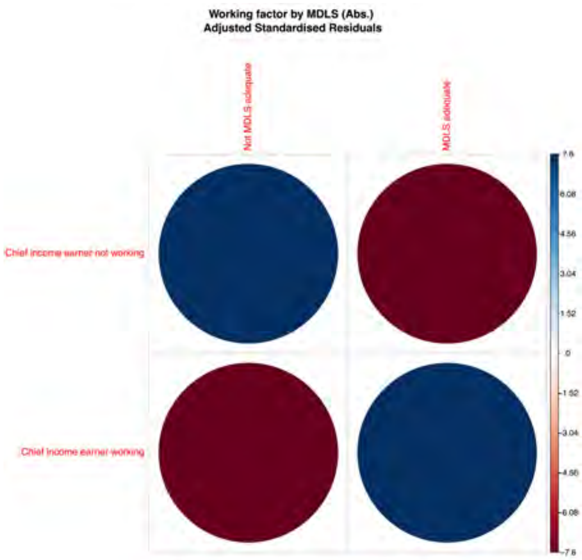

Figure 2.160: Res. Cont. plots-107

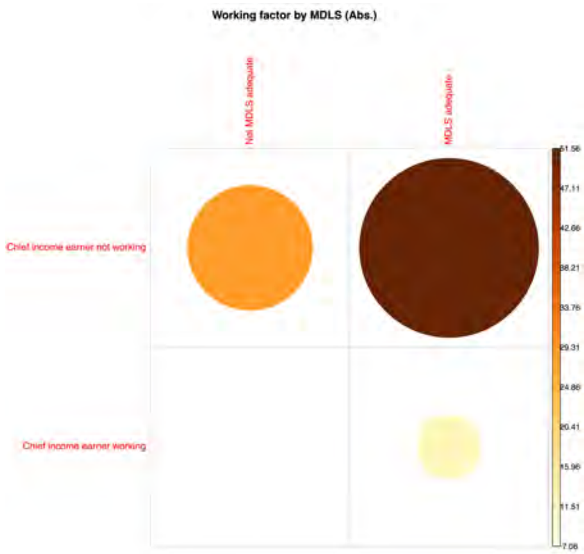

Figure 2.161: Res. Cont. plots-108

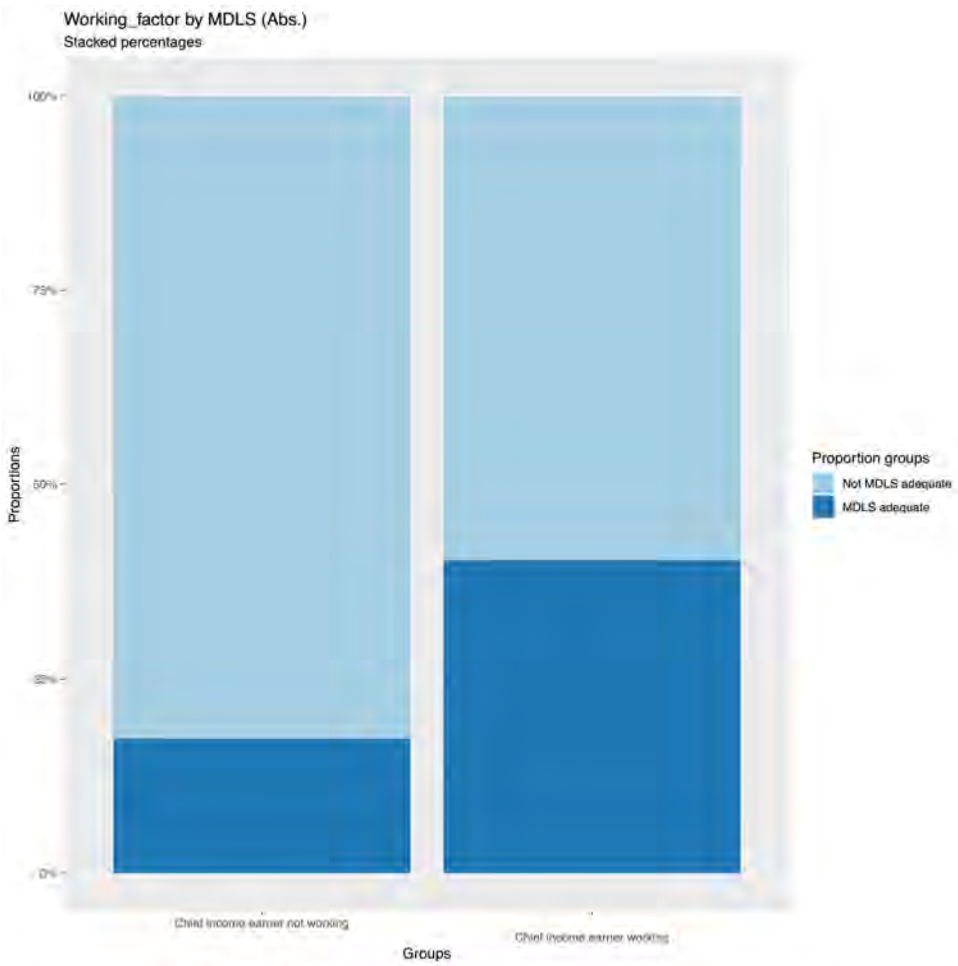

Figure 2.162: Proportions plot-54

2.4.55 HealthlimitationfactorbyMDLS(Abs.)

The Pearson's Chi-squared test with simulated p-value of independence between variables suggests that the effect is statistically significant and small ($chi^2 = 35.47, p < .001; AdjustedCramer'sv = 0.15, 95\%CI[0.11, 1.00]$). The following tables 2.204, 2.203, and 2.205 provide detals of the observations, column and row percentages. Figures 2.163 and 2.164 present plots of residuals and contributions. Figure 2.165 presents the data in stacked proprtions.

	Not MDLS adequate	MDLS adequate
Respondent has **no** health issue (col.)	80.60	91.90
Respondent **has** a health issue (col.)	19.40	8.10

Table 2.203: Health limitation factor by MDLS (Abs.) (Column Percentages) (χ^2(NA, 1582) = 35.465, p = 0, Cramer's V = 0.15)

	Not MDLS adequate	MDLS adequate
Respondent has no health issue(row)	61.20	38.80
Respondent **has** a health issue (row)	81.10	18.90

Table 2.204: Health limitation factor by MDLS (Abs.) (Row Percentages) (χ^2(NA, 1582) = 35.465, p = 0, Cramer's V = 0.15)

	Not MDLS adequate	MDLS adequate
Respondent has no health issue(obs.)	819.00	520.00
Respondent has **no** health issue (row)	61.20	38.80
Respondent has **no** health issue (col.)	80.60	91.90
Respondent **has** a health issue (obs.)	197.00	46.00
Respondent **has** a health issue (row)	81.10	18.90
Respondent **has** a health issue (col.)	19.40	8.10

Table 2.205: Health limitation factor by MDLS (Abs.) (χ^2(NA, 1582) = 35.465, p = 0, Cramer's V = 0.15)

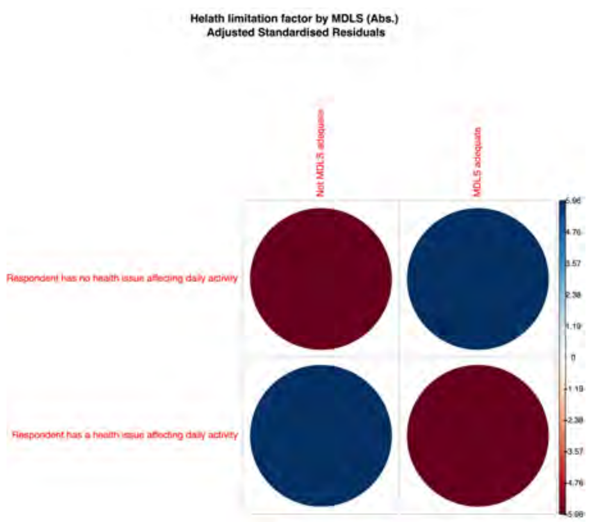

Figure 2.163: Res. Cont. plots-109

Figure 2.164: Res. Cont. plots-110

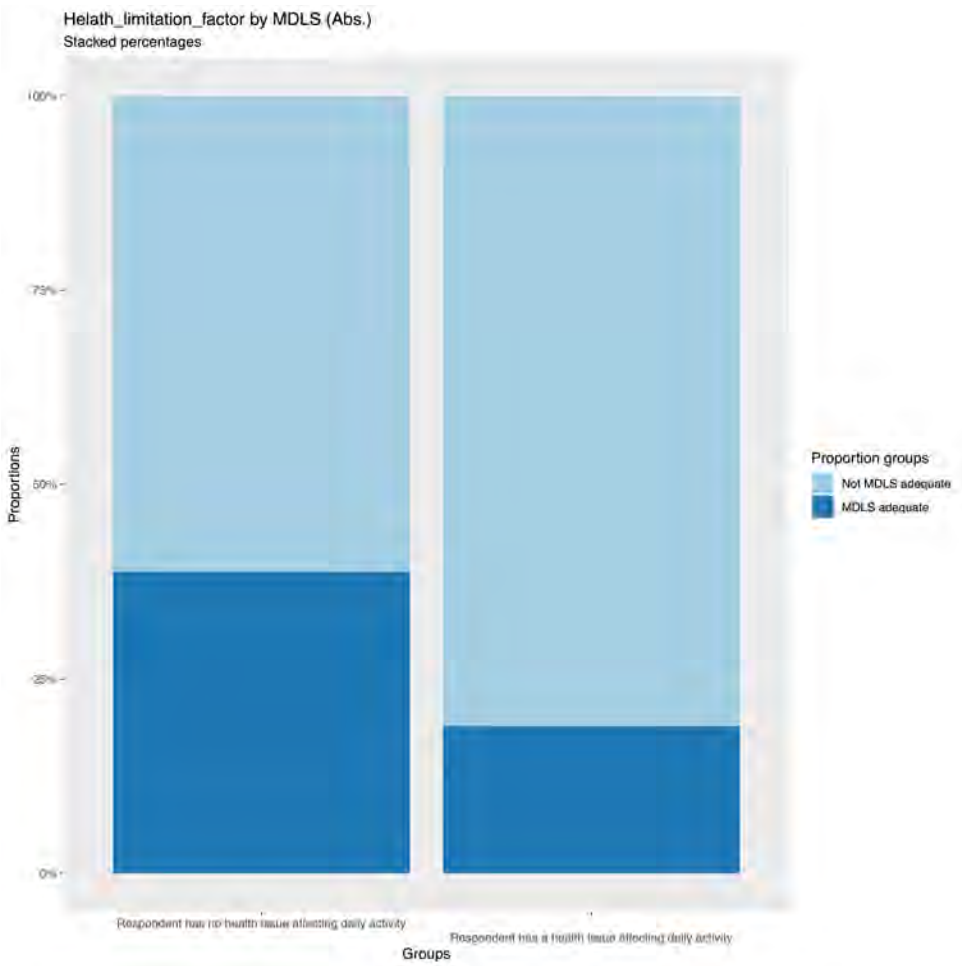

Figure 2.165: Proportions plot-55

2.4.56 EthnicityfactorbyMDLS(Abs.)

The Pearson's Chi-squared test with simulated p-value of independence between variables suggests that the effect is statistically significant and very small ($chi^2 = 12.37, p < .001; AdjustedCramer'sv = 0.08, 95\%CI[0.04, 1.00]$). The following tables 2.207, 2.206, and 2.208 provide detals of the observations, column and row percentages. Figures 2.166 and 2.167 present plots of residuals and contributions. Figure 2.168 presents the data in stacked proprtions.

	Not MDLS adequate	MDLS adequate
Respondent identifies as ethnically white(col.)	74.00	81.80
Respondent identifies as ethnically non-white (col.)	26.00	18.20

Table 2.206: Ethnicity factor by MDLS (Abs.) (Column Percentages) (χ^2(NA, 1582) = 12.369, p = 0.001, Cramer's V = 0.088)

	Not MDLS adequate	MDLS adequate
Respondent identifies as ethnically white(row)	61.90	38.10
Respondent identifies as ethnically non-white (row)	71.90	28.10

Table 2.207: Ethnicity factor by MDLS (Abs.) (Row Percentages) (χ^2(NA, 1582) = 12.369, p = 0.001, Cramer's V = 0.088)

	Not MDLS adequate	MDLS adequate
Respondent identifies as ethnically white(obs.)	752.00	463.00
Respondent identifies as ethnically white(row)	61.90	38.10
Respondent identifies as ethnically white(col.)	74.00	81.80
Respondent identifies as ethnically non-white (obs.)	264.00	103.00
Respondent identifies as ethnically non-white (row)	71.90	28.10
Respondent identifies as ethnically non-white (col.)	26.00	18.20

Table 2.208: Ethnicity factor by MDLS (Abs.) (χ^2(NA, 1582) = 12.369, p = 0.001, Cramer's V = 0.088)

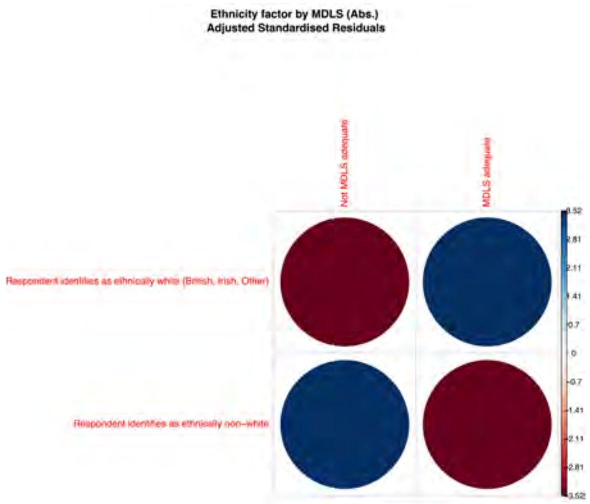

Figure 2.166: Res. Cont. plots-111

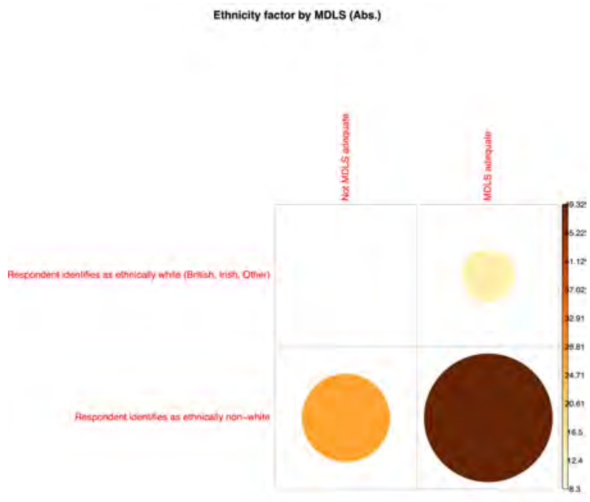

Figure 2.167: Res. Cont. plots-112

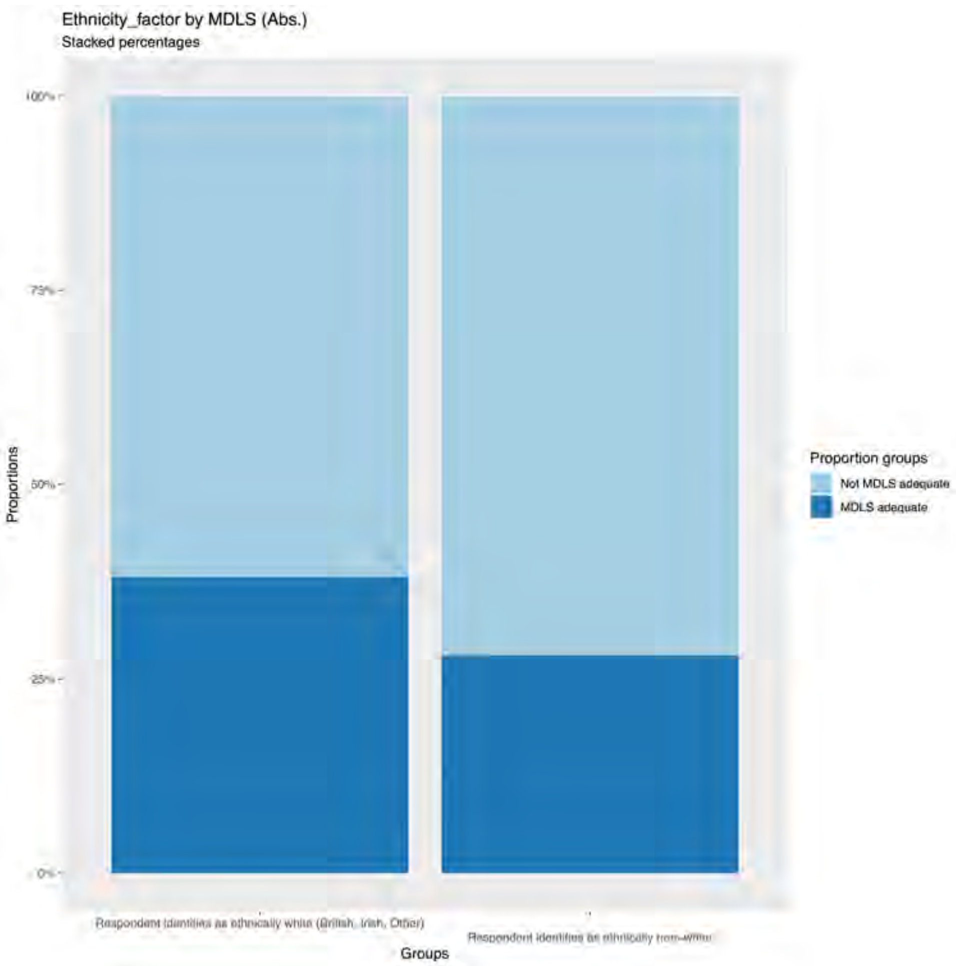

Figure 2.168: Proportions plot-56

2.4.57 SEGfactorbyMDLS(LCA)

The Pearson's Chi-squared test with simulated p-value of independence between variables suggests that the effect is statistically significant and medium ($chi^2 = 105.52, p < .001; Adjusted Cramer'sv = 0.25, 95\% CI [0.21, 1.00]$). The following tables 2.210, 2.209, and 2.211 provide detals of the observations, column and row percentages. Figures 2.169 and 2.170 present plots of residuals and contributions. Figure 2.171 presents the data in stacked proprtions.

	Not MDLS adequate	MDLS adequate
AB (col.)	13.90	25.90
C1 (col.)	25.80	34.40
C2 (col.)	22.50	23.40
DE (col.)	37.80	16.40

Table 2.209: SEG factor by MDLS (LCA) (Column Percentages) (χ^2(NA, 1582) = 105.518, p = 0, Cramer's V = 0.258)

	Not MDLS adequate	MDLS adequate
AB (row)	32.10	67.90
C1 (row)	39.70	60.30
C2 (row)	45.70	54.30
DE (row)	66.90	33.10

Table 2.210: SEG factor by MDLS (LCA) (Row Percentages) (χ^2(NA, 1582) = 105.518, p = 0, Cramer's V = 0.258)

	Not MDLS adequate	MDLS adequate
AB (obs.)	103.00	218.00
AB (row)	32.10	67.90
AB (col.)	13.90	25.90
C1 (obs.)	191.00	290.00
C1 (row)	39.70	60.30
C1 (col.)	25.80	34.40
C2 (obs.)	166.00	197.00
C2 (row)	45.70	54.30
C2 (col.)	22.50	23.40
DE (obs.)	279.00	138.00
DE (row)	66.90	33.10
DE (col.)	37.80	16.40

Table 2.211: SEG factor by MDLS (LCA) (χ^2(NA, 1582) = 105.518, p = 0, Cramer's V = 0.258)

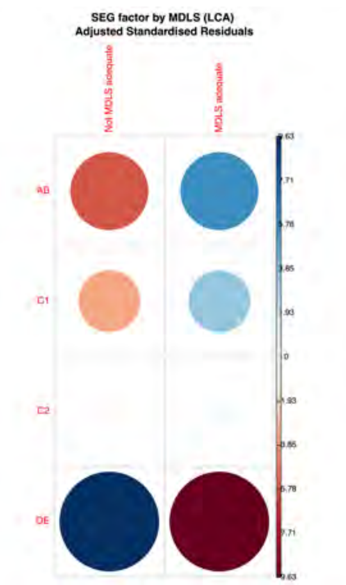

Figure 2.169: Res. Cont. plots-113

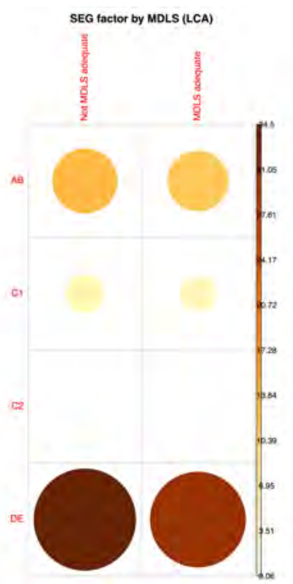

Figure 2.170: Res. Cont. plots-114

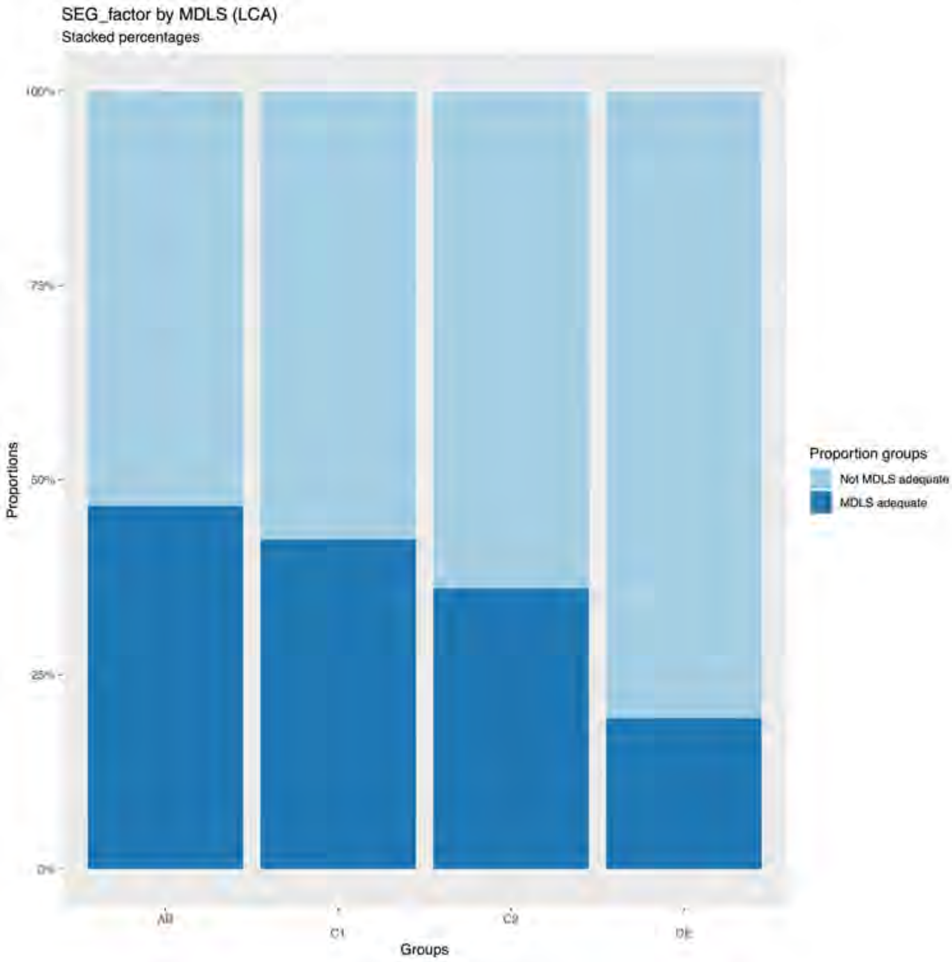

Figure 2.171: Proportions plot-57

2.4.58 HTYPEfactorbyMDLS(LCA)

The Pearson's Chi-squared test with simulated p-value of independence between variables suggests that the effect is statistically significant and medium ($chi^2 = 86.01, p < .001; AdjustedCramer'sv = 0.22, 95\%CI[0.17, 1.00]$). The following tables 2.213, 2.212, and 2.214 provide detals of the observations, column and row percentages. Figures 2.172 and 2.173 present plots of residuals and contributions. Figure 2.174 presents the data in stacked proprtions.

	Not MDLS adequate	MDLS adequate
1 adult and 1 child (col.)	18.70	12.20
1 adult and 2 children (col.)	11.40	6.20
1 adult and more than 2 children (col.)	5.10	2.60
2 adults and 1 child (col.)	20.00	32.70
2 adults and 2 children (col.)	23.30	31.60
2 adults and more than 2 children (col.)	11.60	7.00
More than 2 adults in HH and 1 child (col.)	5.00	3.90
More than 2 adults in HH and 2 children (col.)	2.80	3.60
More than 2 adults in HH and 2+ children (col.)	2.00	0.20

Table 2.212: HTYPE factor by MDLS (LCA) (Column Percentages) (χ^2(NA, 1582) = 86.014, p = 0, Cramer's V = 0.233)

	Not MDLS adequate	MDLS adequate
1 adult and 1 child (row)	57.30	42.70
1 adult and 2 children (row)	61.80	38.20
1 adult and more than 2 children (row)	63.30	36.70
2 adults and 1 child (row)	34.90	65.10
2 adults and 2 children (row)	39.30	60.70
2 adults and more than 2 children (row)	59.30	40.70
More than 2 adults in HH and 1 child (row)	52.90	47.10
More than 2 adults in HH and 2 children (row)	41.20	58.80
More than 2 adults in HH and 2+ children (row)	88.20	11.80

Table 2.213: HTYPE factor by MDLS (LCA) (Row Percentages) (χ^2(NA, 1582) = 86.014, p = 0, Cramer's V = 0.233)

	Not MDLS adequate	MDLS adequate
1 adult and 1 child (obs.)	138.00	103.00
1 adult and 1 child (row)	57.30	42.70
1 adult and 1 child (col.)	18.70	12.20
1 adult and 2 children (obs.)	84.00	52.00
1 adult and 2 children (row)	61.80	38.20
1 adult and 2 children (col.)	11.40	6.20
1 adult and more than 2 children (obs.)	38.00	22.00
1 adult and more than 2 children (row)	63.30	36.70
1 adult and more than 2 children (col.)	5.10	2.60
2 adults and 1 child (obs.)	148.00	276.00
2 adults and 1 child (row)	34.90	65.10
2 adults and 1 child (col.)	20.00	32.70
2 adults and 2 children (obs.)	172.00	266.00
2 adults and 2 children (row)	39.30	60.70
2 adults and 2 children (col.)	23.30	31.60
2 adults and more than 2 children (obs.)	86.00	59.00
2 adults and more than 2 children (row)	59.30	40.70
2 adults and more than 2 children (col.)	11.60	7.00
More than 2 adults in HH and 1 child (obs.)	37.00	33.00
More than 2 adults in HH and 1 child (row)	52.90	47.10
More than 2 adults in HH and 1 child (col.)	5.00	3.90
More than 2 adults in HH and 2 children (obs.)	21.00	30.00
More than 2 adults in HH and 2 children (row)	41.20	58.80
More than 2 adults in HH and 2 children (col.)	2.80	3.60
More than 2 adults in HH and 2+ children (obs.)	15.00	2.00
More than 2 adults in HH and 2+ children (row)	88.20	11.80
More than 2 adults in HH and 2+ children (col.)	2.00	0.20

Table 2.214: HTYPE factor by MDLS (LCA) (χ^2(NA, 1582) = 86.014, p = 0, Cramer's V = 0.233)

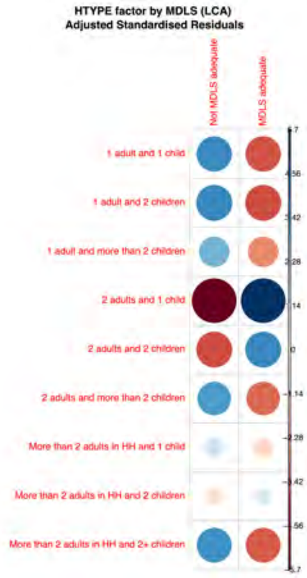

Figure 2.172: Res. Cont. plots-115

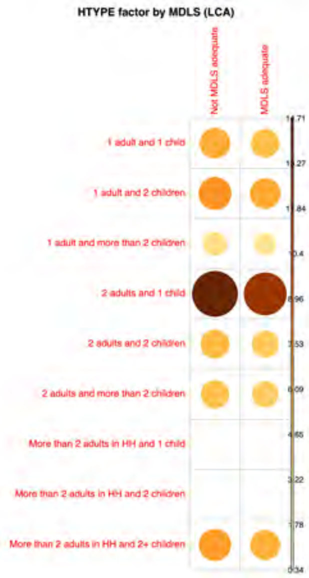

Figure 2.173: Res. Cont. plots-116

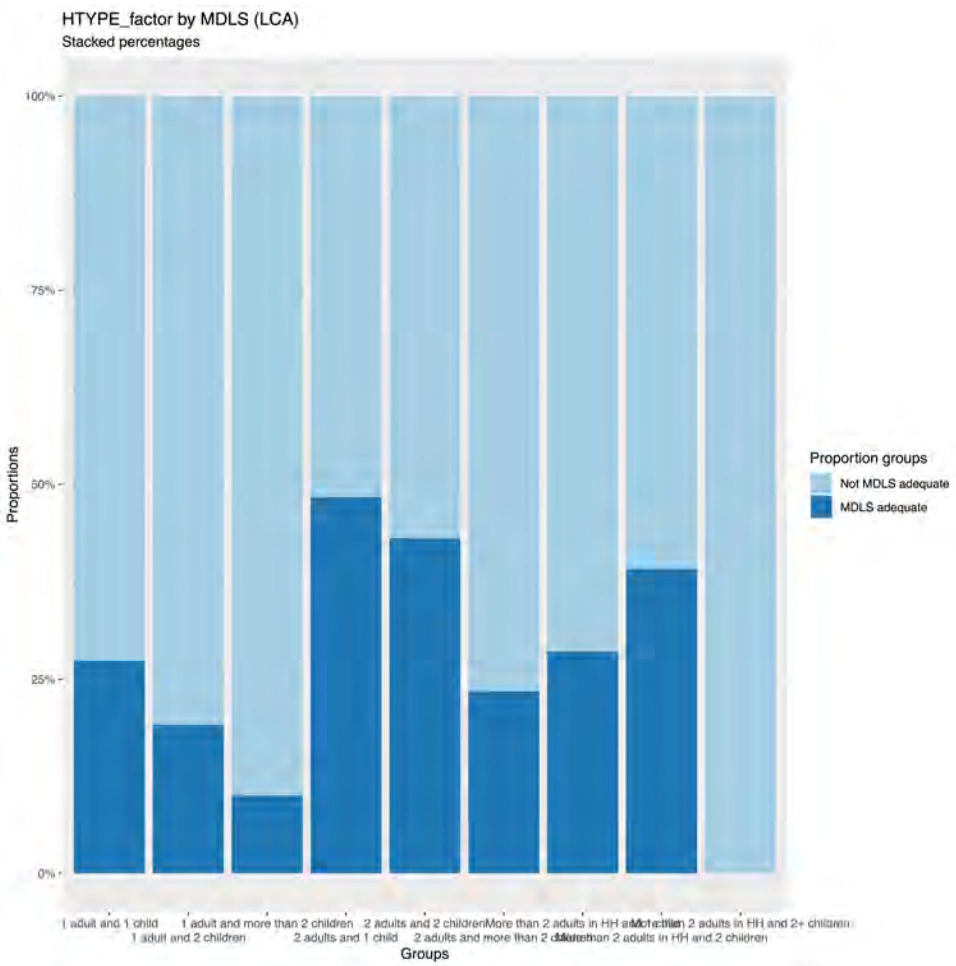

Figure 2.174: Proportions plot-58

2.4.59 REGIONfactorbyMDLS(LCA)

The Pearson's Chi-squared test with simulated p-value of independence between variables suggests that the effect is statistically significant and small ($chi^2 = 45.49, p < .001; AdjustedCramer'sv = 0.15, 95\%CI[0.06, 1.00]$). The following tables 2.216, 2.215, and 2.217 provide detals of the observations, column and row percentages. Figures 2.175 and 2.176 present plots of residuals and contributions. Figure 2.177 presents the data in stacked proprtions.

	Not MDLS adequate	MDLS adequate
North East (col.)	4.20	3.20
North West (col.)	12.40	7.60
Yorkshire and The Humber (col.)	8.40	8.30
East Midlands (col.)	6.50	6.40
West Midlands (col.)	7.40	10.70
East of England (col.)	6.10	10.80
London (col.)	14.50	14.40
South East (col.)	11.40	15.50
South West (col.)	7.30	7.80
Wales (col.)	4.70	5.30
Northern Ireland (col.)	5.70	3.30
Scotland (col.)	11.40	6.60

Table 2.215: REGION factor by MDLS (LCA) (Column Percentages) (χ^2(NA, 1582) = 45.49, p = 0, Cramer's V = 0.17)

	Not MDLS adequate	MDLS adequate
North East (row)	53.40	46.60
North West (row)	59.00	41.00
Yorkshire and The Humber (row)	47.00	53.00
East Midlands (row)	47.10	52.90
West Midlands (row)	37.90	62.10
East of England (row)	33.10	66.90
London (row)	46.90	53.10
South East (row)	39.10	60.90
South West (row)	45.00	55.00
Wales (row)	43.80	56.20
Northern Ireland (row)	60.00	40.00
Scotland (row)	60.00	40.00

Table 2.216: REGION factor by MDLS (LCA) (Row Percentages) (χ^2(NA, 1582) = 45.49, p = 0, Cramer's V = 0.17)

	Not MDLS adequate	MDLS adequate
North East (obs.)	31.00	27.00
North East (row)	53.40	46.60
North East (col.)	4.20	3.20
North West (obs.)	92.00	64.00
North West (row)	59.00	41.00
North West (col.)	12.40	7.60
Yorkshire and The Humber (obs.)	62.00	70.00
Yorkshire and The Humber (row)	47.00	53.00
Yorkshire and The Humber (col.)	8.40	8.30
East Midlands (obs.)	48.00	54.00
East Midlands (row)	47.10	52.90
East Midlands (col.)	6.50	6.40
West Midlands (obs.)	55.00	90.00
West Midlands (row)	37.90	62.10
West Midlands (col.)	7.40	10.70
East of England (obs.)	45.00	91.00
East of England (row)	33.10	66.90
East of England (col.)	6.10	10.80
London (obs.)	107.00	121.00
London (row)	46.90	53.10
London (col.)	14.50	14.40
South East (obs.)	84.00	131.00
South East (row)	39.10	60.90
South East (col.)	11.40	15.50
South West (obs.)	54.00	66.00
South West (row)	45.00	55.00
South West (col.)	7.30	7.80
Wales (obs.)	35.00	45.00
Wales (row)	43.80	56.20
Wales (col.)	4.70	5.30
Northern Ireland (obs.)	42.00	28.00
Northern Ireland (row)	60.00	40.00
Northern Ireland (col.)	5.70	3.30
Scotland (obs.)	84.00	56.00
Scotland (row)	60.00	40.00
Scotland (col.)	11.40	6.60

Table 2.217: REGION factor by MDLS (LCA) (χ^2(NA, 1582) = 45.49, p = 0, Cramer's V = 0.17)

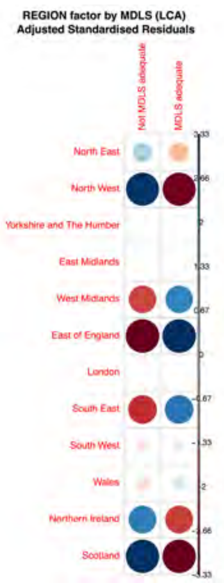

Figure 2.175: Res. Cont. plots-117

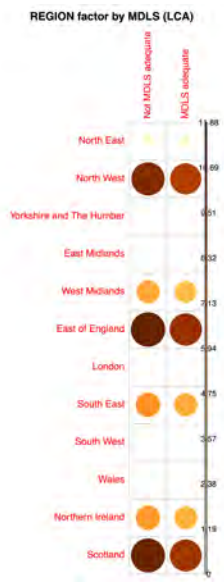

Figure 2.176: Res. Cont. plots-118

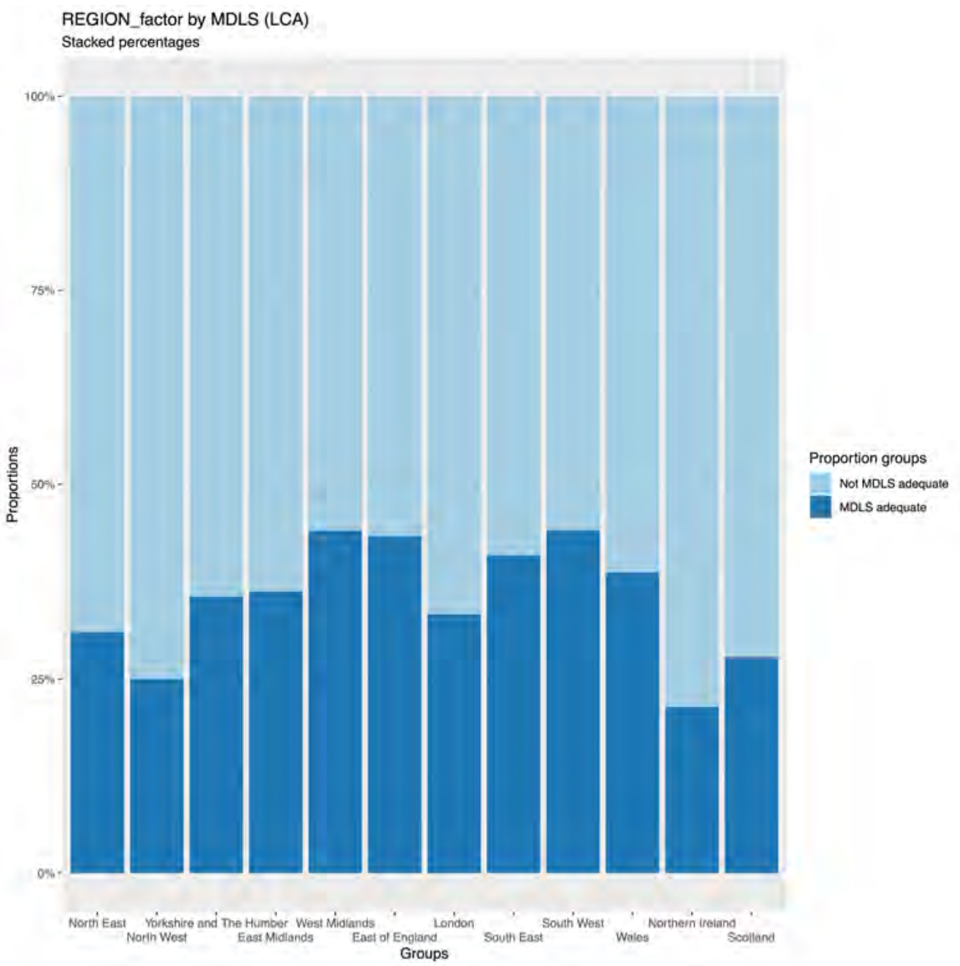

Figure 2.177: Proportions plot-59

2.4.60 OverallhouseholdskillsfactorbyMDLS(LCA)

The Pearson's Chi-squared test with simulated p-value of independence between variables suggests that the effect is statistically significant and very large ($chi^2 = 1150.78, p < .001; AdjustedCramer'sv = 0.85, 95\% CI[0.81, 1.00]$). The following tables 2.219, 2.218, and 2.220 provide detals of the observations, column and row percentages. Figures 2.178 and 2.179 present plots of residuals and contributions. Figure 2.180 presents the data in stacked proprtions.

	Not MDLS adequate	MDLS adequate
Not adequate Skills (col.)	9.50	0.00
Children Have Adequate Skills (col.)	58.50	0.00
Parents Have Adequate Skills (col.)	15.40	0.00
Household Has Adequate Skills (col.)	16.60	100.00

Table 2.218: Overall household skills factor by MDLS (LCA) (Column Percentages) (χ^2(NA, 1582) = 1150.782, p = 0, Cramer's V = 0.853)

	Not MDLS adequate	MDLS adequate
Not adequate Skills (row)	100.00	0.00
Children Have Adequate Skills (row)	100.00	0.00
Parents Have Adequate Skills (row)	100.00	0.00
Household Has Adequate Skills (row)	12.70	87.30

Table 2.219: Overall household skills factor by MDLS (LCA) (Row Percentages) (χ^2(NA, 1582) = 1150.782, p = 0, Cramer's V = 0.853)

	Not MDLS adequate	MDLS adequate
Not adequate Skills (obs.)	70.00	0.00
Not adequate Skills (row)	100.00	0.00
Not adequate Skills (col.)	9.50	0.00
Children Have Adequate Skills (obs.)	432.00	0.00
Children Have Adequate Skills (row)	100.00	0.00
Children Have Adequate Skills (col.)	58.50	0.00
Parents Have Adequate Skills (obs.)	114.00	0.00
Parents Have Adequate Skills (row)	100.00	0.00
Parents Have Adequate Skills (col.)	15.40	0.00
Household Has Adequate Skills (obs.)	123.00	843.00
Household Has Adequate Skills (row)	12.70	87.30
Household Has Adequate Skills (col.)	16.60	100.00

Table 2.220: Overall household skills factor by MDLS (LCA) (χ^2(NA, 1582) = 1150.782, p = 0, Cramer's V = 0.853)

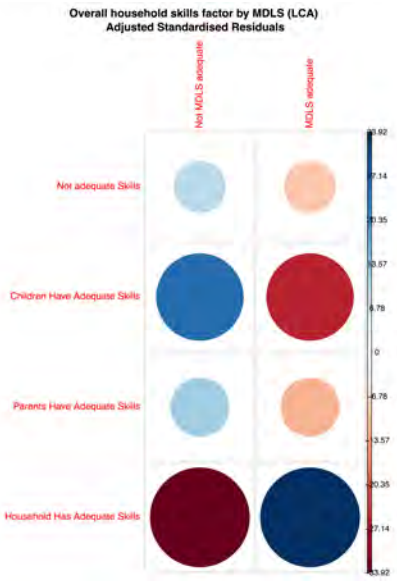

Figure 2.178: Res. Cont. plots-119

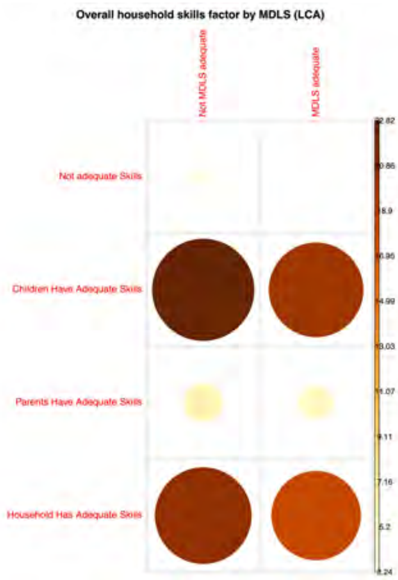

Figure 2.179: Res. Cont. plots-120

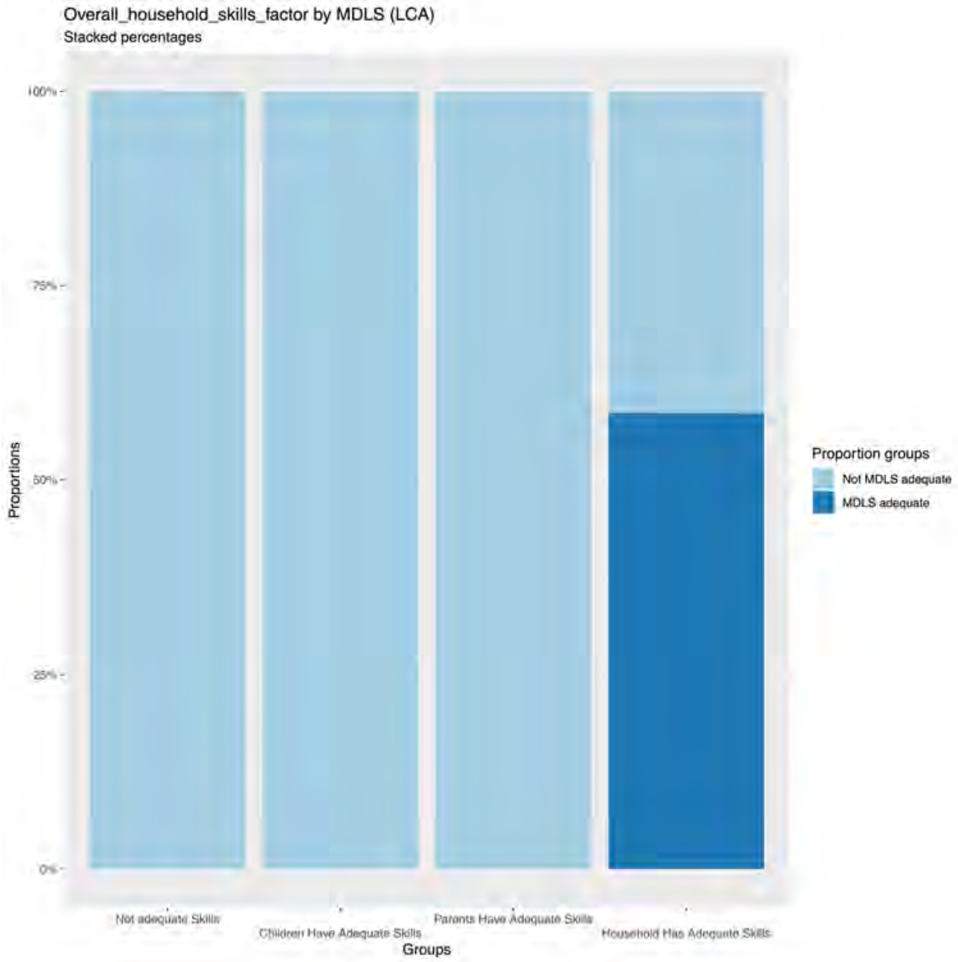

Figure 2.180: Proportions plot-60

2.4.61 BroadbandfactorbyMDLS(LCA)

The Pearson's Chi-squared test with simulated p-value of independence between variables suggests that the effect is statistically not significant and tiny ($chi^2 = 1.71, p = 0.219; AdjustedCramer'sv = 0.02, 95\% CI[0.00, 1.00]$). The following tables 2.222, 2.221, and 2.223 provide detals of the observations, column and row percentages. Figures 2.181 and 2.182 present plots of residuals and contributions. Figure 2.183 presents the data in stacked proprtions.

	Not MDLS adequate	MDLS adequate
Below average broadband speed (col.)	40.90	44.10
Above average broadband speed (col.)	59.10	55.90

Table 2.221: Broadband factor by MDLS (LCA) (Column Percentages) (χ^2(NA, 1582) = 1.714, p = 0.219, Cramer's V = 0.033)

	Not MDLS adequate	MDLS adequate
Below average broadband speed (row)	44.80	55.20
Above average broadband speed (row)	48.10	51.90

Table 2.222: Broadband factor by MDLS (LCA) (Row Percentages) (χ^2(NA, 1582) = 1.714, p = 0.219, Cramer's V = 0.033)

	Not MDLS adequate	MDLS adequate
Below average broadband speed (obs.)	302.00	372.00
Below average broadband speed (row)	44.80	55.20
Below average broadband speed (col.)	40.90	44.10
Above average broadband speed (obs.)	437.00	471.00
Above average broadband speed (row)	48.10	51.90
Above average broadband speed (col.)	59.10	55.90

Table 2.223: Broadband factor by MDLS (LCA) (χ^2(NA, 1582) = 1.714, p = 0.219, Cramer's V = 0.033)

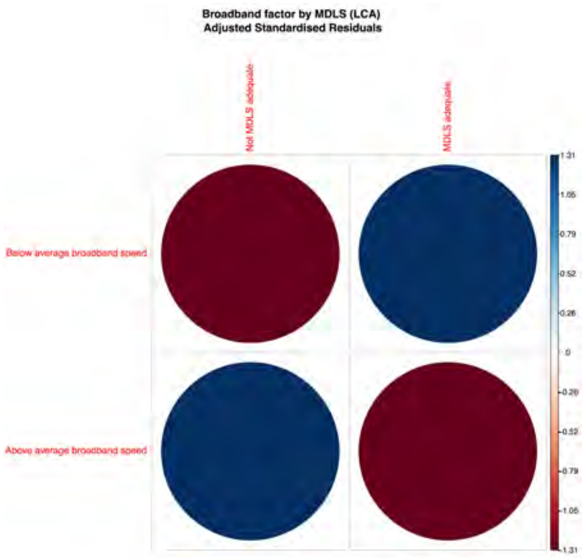

Figure 2.181: Res. Cont. plots-121

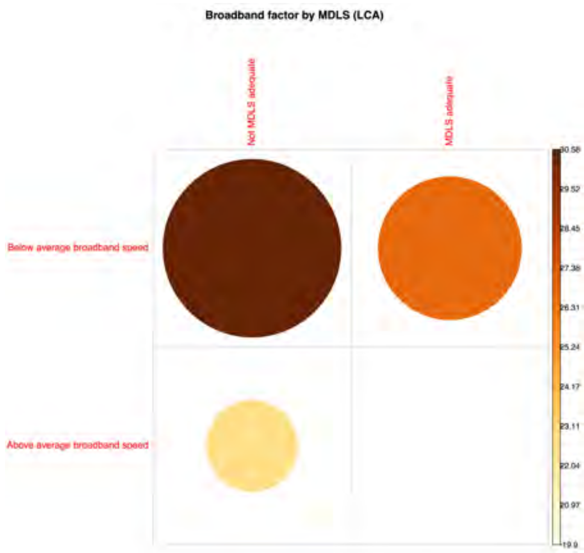

Figure 2.182: Res. Cont. plots-122

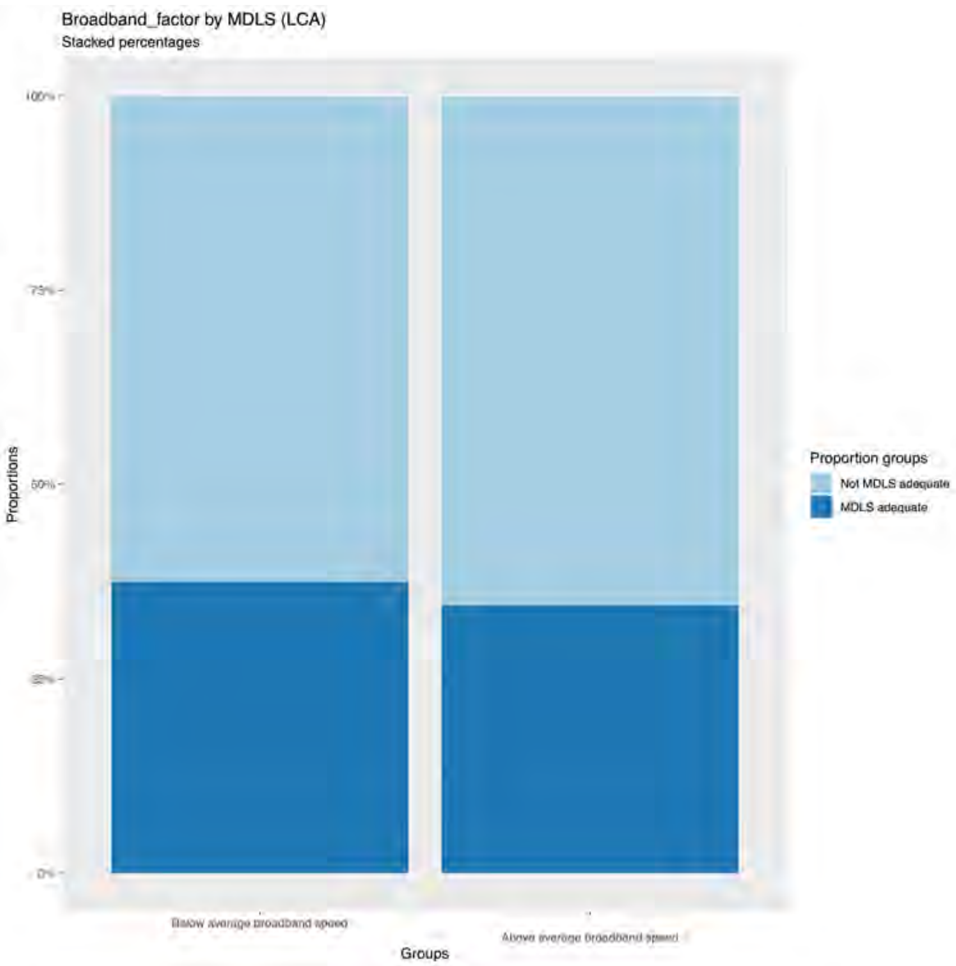

Figure 2.183: Proportions plot-61

2.4.62 URBANfactorbyMDLS(LCA)

The Pearson's Chi-squared test with simulated p-value of independence between variables suggests that the effect is statistically significant and small ($chi^2 = 20.83, p = 0.001; AdjustedCramer'sv = 0.10, 95\%CI[0.04, 1.00]$). The following tables 2.225, 2.224, and 2.226 provide detals of the observations, column and row percentages. Figures 2.184 and 2.185 present plots of residuals and contributions. Figure 2.186 presents the data in stacked proprtions.

	Not MDLS adequate	MDLS adequate
Large city (col.)	18.00	14.90
Smaller city or large town (col.)	20.40	13.50
Medium town (col.)	33.40	36.70
Small town (col.)	18.00	21.10
Rural area (col.)	10.10	13.80

Table 2.224: URBAN factor by MDLS (LCA) (Column Percentages) (χ^2(NA, 1582) = 20.834, p = 0.001, Cramer's V = 0.115)

	Not MDLS adequate	MDLS adequate
Large city (row)	51.40	48.60
Smaller city or large town (row)	57.00	43.00
Medium town (row)	44.40	55.60
Small town (row)	42.80	57.20
Rural area (row)	39.30	60.70

Table 2.225: URBAN factor by MDLS (LCA) (Row Percentages) (χ^2(NA, 1582) = 20.834, p = 0.001, Cramer's V = 0.115)

	Not MDLS adequate	MDLS adequate
Large city (obs.)	133.00	126.00
Large city (row)	51.40	48.60
Large city (col.)	18.00	14.90
Smaller city or large town (obs.)	151.00	114.00
Smaller city or large town (row)	57.00	43.00
Smaller city or large town (col.)	20.40	13.50
Medium town (obs.)	247.00	309.00
Medium town (row)	44.40	55.60
Medium town (col.)	33.40	36.70
Small town (obs.)	133.00	178.00
Small town (row)	42.80	57.20
Small town (col.)	18.00	21.10
Rural area (obs.)	75.00	116.00
Rural area (row)	39.30	60.70
Rural area (col.)	10.10	13.80

Table 2.226: URBAN factor by MDLS (LCA) (χ^2(NA, 1582) = 20.834, p = 0.001, Cramer's V = 0.115)

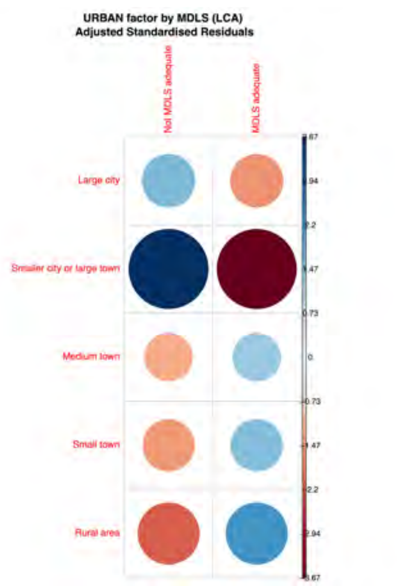

Figure 2.184: Res. Cont. plots-123

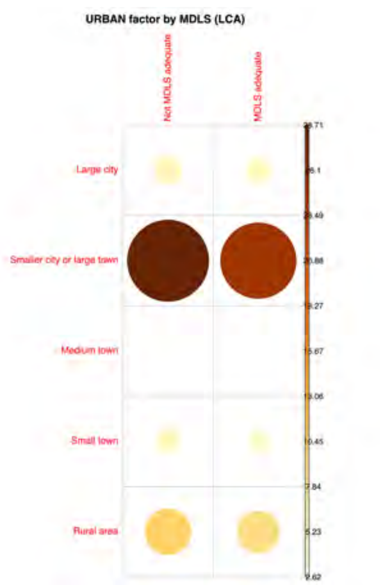

Figure 2.185: Res. Cont. plots-124

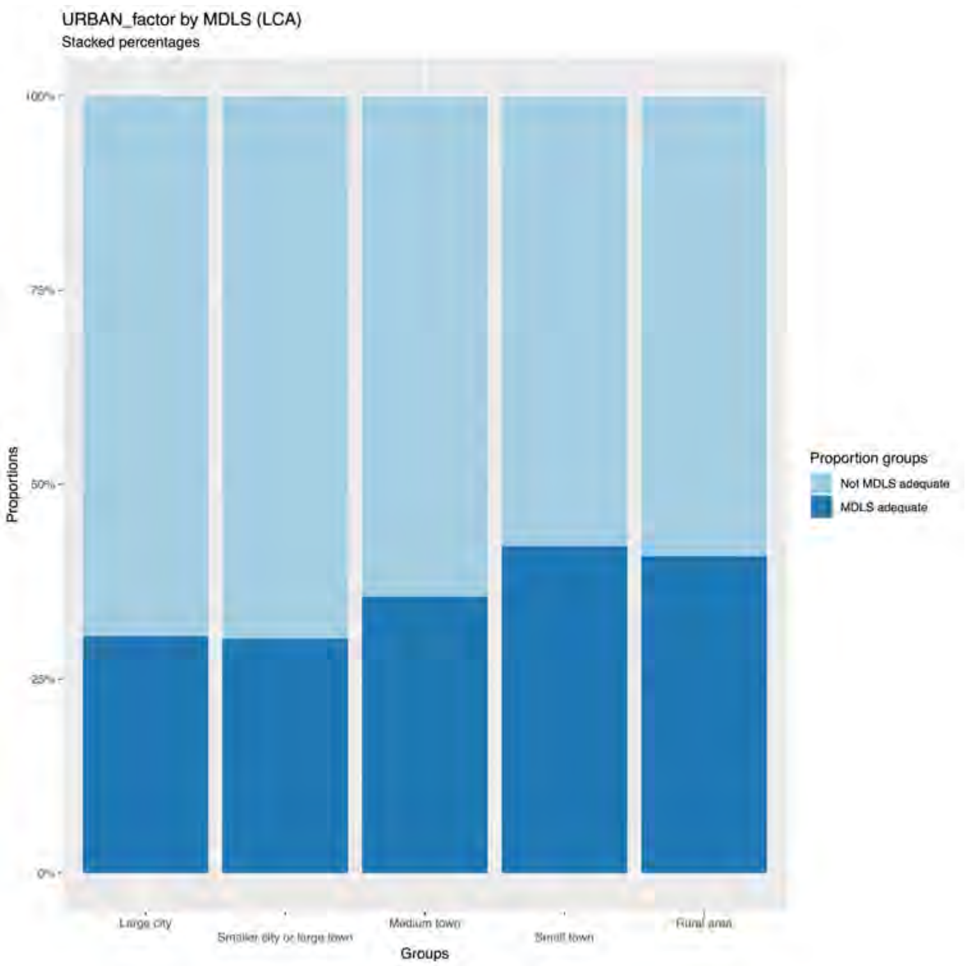

Figure 2.186: Proportions plot-62

2.4.63 URBAN2factorbyMDLS(LCA)

The Pearson's Chi-squared test with simulated p-value of independence between variables suggests that the effect is statistically significant and tiny ($chi^2 = 4.84, p = 0.033; AdjustedCramer'sv = 0.05, 95\%CI[0.00, 1.00]$). The following tables 2.228, 2.227, and 2.229 provide detals of the observations, column and row percentages. Figures 2.187 and 2.188 present plots of residuals and contributions. Figure 2.189 presents the data in stacked proprtions.

	Not MDLS adequate	MDLS adequate
Urban (col.)	89.90	86.20
Rural (col.)	10.10	13.80

Table 2.227: URBAN2 factor by MDLS (LCA) (Column Percentages) (χ^2(NA, 1582) = 4.838, p = 0.033, Cramer's V = 0.055)

	Not MDLS adequate	MDLS adequate
Urban (row)	47.70	52.30
Rural (row)	39.30	60.70

Table 2.228: URBAN2 factor by MDLS (LCA) (Row Percentages) (χ^2(NA, 1582) = 4.838, p = 0.033, Cramer's V = 0.055)

	Not MDLS adequate	MDLS adequate
Urban (obs.)	664.00	727.00
Urban (row)	47.70	52.30
Urban (col.)	89.90	86.20
Rural (obs.)	75.00	116.00
Rural (row)	39.30	60.70
Rural (col.)	10.10	13.80

Table 2.229: URBAN2 factor by MDLS (LCA) (χ^2(NA, 1582) = 4.838, p = 0.033, Cramer's V = 0.055)

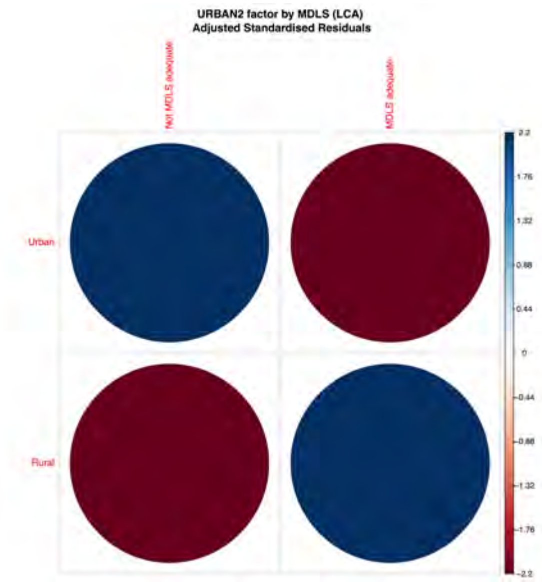

Figure 2.187: Res. and cont. plot-125

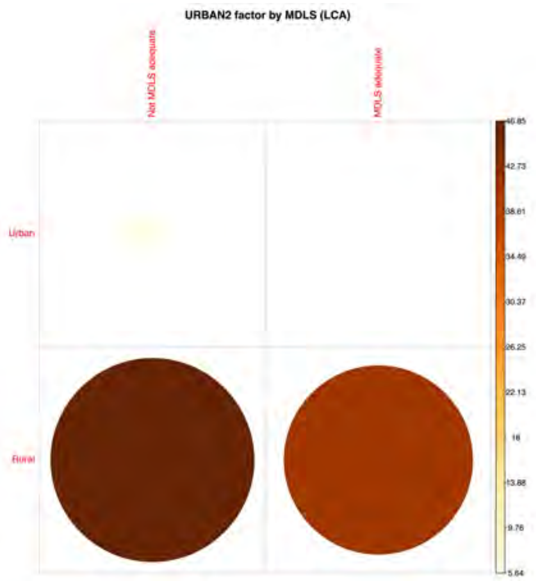

Figure 2.188: Res. and cont. plot-126

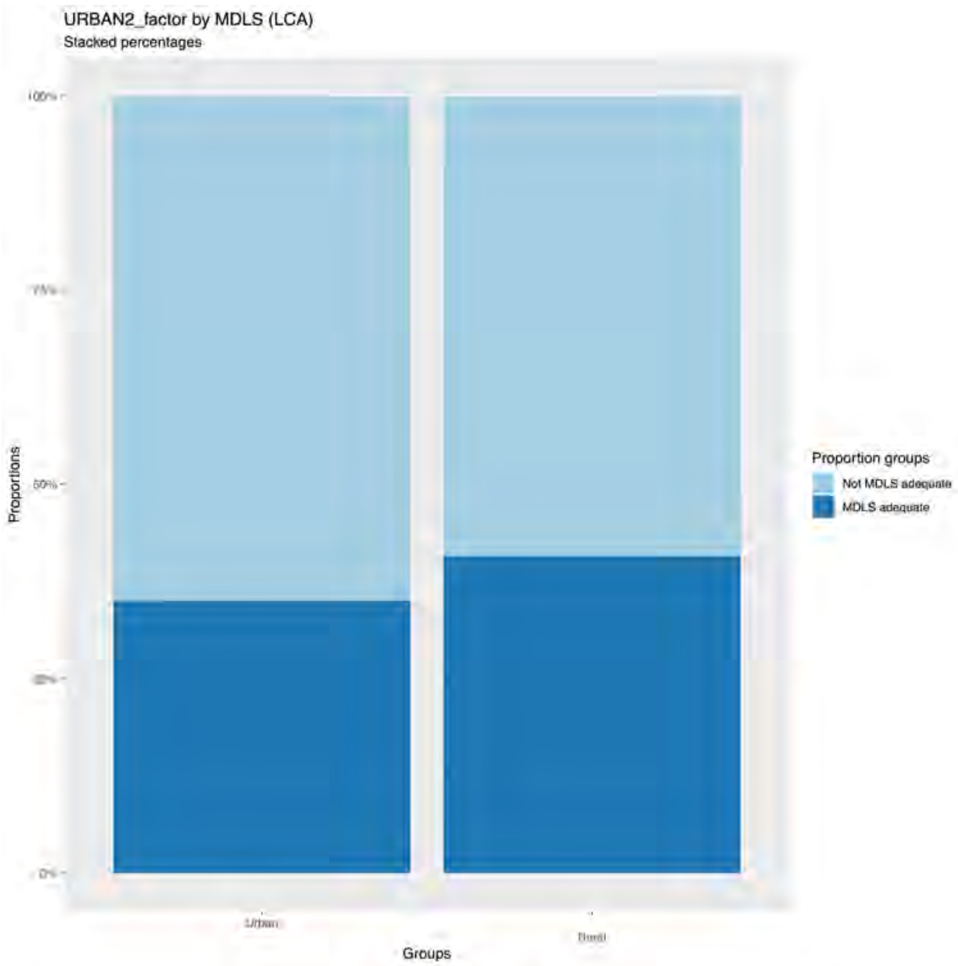

Figure 2.189: Proportions plot-63

2.4.64 iucGRPLBLrfactorbyMDLS(LCA)

The Pearson's Chi-squared test with simulated p-value of independence between variables suggests that the effect is statistically significant and small ($chi^2 = 36.39, p < .001; AdjustedCramer'sv = 0.14, 95\% CI[0.05, 1.00]$). The following tables 2.231, 2.230, and 2.232 provide detals of the observations, column and row percentages. Figures 2.190 and 2.191 present plots of residuals and contributions. Figure 2.192 presents the data in stacked proprtions.

	Not MDLS adequate	MDLS adequate
Digital Seniors (col.)	9.30	9.80
e-Cultural Creators (col.)	0.40	0.00
e-Mainstream (col.)	13.50	15.20
e-Professionals (col.)	3.50	3.60
e-Rational Utilitarians (col.)	6.00	8.60
e-Veterans (col.)	10.50	14.90
e-Withdrawn (col.)	15.70	10.10
Passive and Uncommitted Users (col.)	29.10	25.50
Settled Offline Communities (col.)	3.90	7.20
Youthful Urban Fringe (col.)	8.00	5.10

Table 2.230: iuc GRP LBLr factor by MDLS (LCA) (Column Percentages) (χ^2(NA, 1491) = 36.393, p = 0, Cramer's V = 0.156)

	Not MDLS adequate	MDLS adequate
Digital Seniors (row)	44.80	55.20
e-Cultural Creators (row)	100.00	0.00
e-Mainstream (row)	43.30	56.70
e-Professionals (row)	45.30	54.70
e-Rational Utilitarians (row)	37.30	62.70
e-Veterans (row)	37.50	62.50
e-Withdrawn (row)	57.10	42.90
Passive and Uncommitted Users (row)	49.40	50.60
Settled Offline Communities (row)	31.80	68.20
Youthful Urban Fringe (row)	57.30	42.70

Table 2.231: iuc GRP LBLr factor by MDLS (LCA) (Row Percentages) (χ^2(NA, 1491) = 36.393, p = 0, Cramer's V = 0.156)

	Not MDLS adequate	MDLS adequate
Digital Seniors (obs.)	64.00	79.00
Digital Seniors (row)	44.80	55.20
Digital Seniors (col.)	9.30	9.80
e-Cultural Creators (obs.)	3.00	0.00
e-Cultural Creators (row)	100.00	0.00
e-Cultural Creators (col.)	0.40	0.00
e-Mainstream (obs.)	93.00	122.00
e-Mainstream (row)	43.30	56.70
e-Mainstream (col.)	13.50	15.20
e-Professionals (obs.)	24.00	29.00
e-Professionals (row)	45.30	54.70
e-Professionals (col.)	3.50	3.60
e-Rational Utilitarians (obs.)	41.00	69.00
e-Rational Utilitarians (row)	37.30	62.70
e-Rational Utilitarians (col.)	6.00	8.60
e-Veterans (obs.)	72.00	120.00
e-Veterans (row)	37.50	62.50
e-Veterans (col.)	10.50	14.90
e-Withdrawn (obs.)	108.00	81.00
e-Withdrawn (row)	57.10	42.90
e-Withdrawn (col.)	15.70	10.10
Passive and Uncommitted Users (obs.)	200.00	205.00
Passive and Uncommitted Users (row)	49.40	50.60
Passive and Uncommitted Users (col.)	29.10	25.50
Settled Offline Communities (obs.)	27.00	58.00
Settled Offline Communities (row)	31.80	68.20
Settled Offline Communities (col.)	3.90	7.20
Youthful Urban Fringe (obs.)	55.00	41.00
Youthful Urban Fringe (row)	57.30	42.70
Youthful Urban Fringe (col.)	8.00	5.10

Table 2.232: iuc GRP LBLr factor by MDLS (LCA) (χ^2(NA, 1491) = 36.393, p = 0, Cramer's V = 0.156)

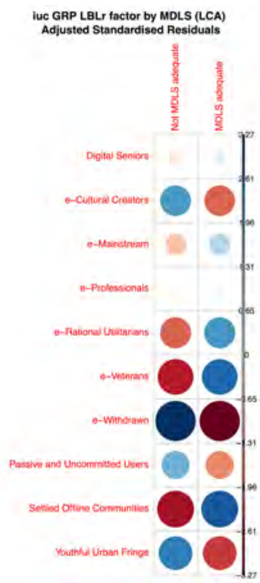

Figure 2.190: Res. Cont. plots-127

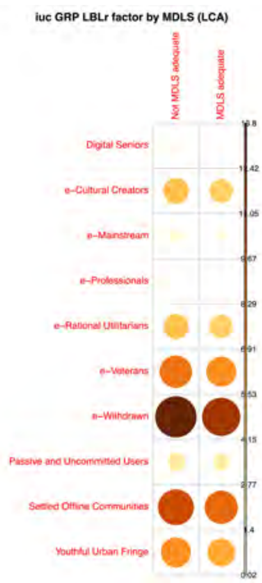

Figure 2.191: Res. Cont. plots-128

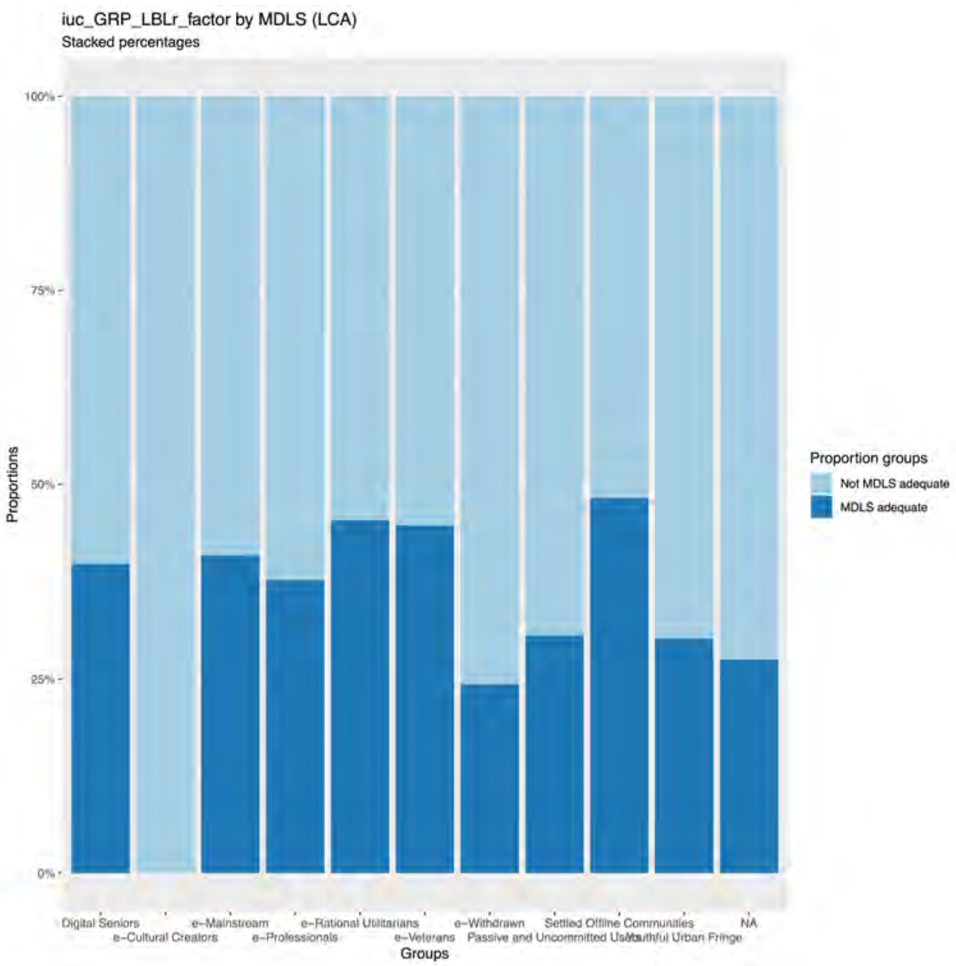

Figure 2.192: Proportions plot-64

2.4.65 oac21SGfactorbyMDLS(LCA)

The Pearson's Chi-squared test with simulated p-value of independence between variables suggests that the effect is statistically significant and small ($chi^2 = 41.78, p < .001; AdjustedCramer'sv = 0.16, 95\% CI[0.09, 1.00]$). The following tables 2.234, 2.233, and 2.235 provide detals of the observations, column and row percentages. Figures 2.193 and 2.194 present plots of residuals and contributions. Figure 2.195 presents the data in stacked proprtions.

	Not MDLS adequate	MDLS adequate
Retired Professionals (col.)	5.30	8.50
Suburbanites and Peri-Urbanities (col.)	14.60	19.80
Multicultural and Educated Urbanites (col.)	5.60	5.90
Low-Skilled Migrant and Student Communities (col.)	22.00	14.00
Ethnically Diverse Suburban Professionals (col.)	5.90	11.50
Baseline UK (col.)	23.40	20.80
Semi-and Un-Skilled Workforce (col.)	19.60	18.00
Legacy Communities (col.)	3.60	1.50

Table 2.233: oac21SG factor by MDLS (LCA) (Column Percentages) (χ^2(NA, 1357) = 41.78, p = 0, Cramer's V = 0.176)

	Not MDLS adequate	MDLS adequate
Retired Professionals (row)	33.30	66.70
Suburbanites and Peri-Urbanities (row)	37.60	62.40
Multicultural and Educated Urbanites (row)	43.60	56.40
Low-Skilled Migrant and Student Communities (row)	56.10	43.90
Ethnically Diverse Suburban Professionals (row)	29.50	70.50
Baseline UK (row)	47.70	52.30
Semi-and Un-Skilled Workforce (row)	46.90	53.10
Legacy Communities (row)	66.70	33.30

Table 2.234: oac21SG factor by MDLS (LCA) (Row Percentages) (χ^2(NA, 1357) = 41.78, p = 0, Cramer's V = 0.176)

	Not MDLS adequate	MDLS adequate
Retired Professionals (obs.)	32.00	64.00
Retired Professionals (row)	33.30	66.70
Retired Professionals (col.)	5.30	8.50
Suburbanites and Peri-Urbanities (obs.)	89.00	148.00
Suburbanites and Peri-Urbanities (row)	37.60	62.40
Suburbanites and Peri-Urbanities (col.)	14.60	19.80
Multicultural and Educated Urbanites (obs.)	34.00	44.00
Multicultural and Educated Urbanites (row)	43.60	56.40
Multicultural and Educated Urbanites (col.)	5.60	5.90
Low-Skilled Migrant and Student Communities (obs.)	134.00	105.00
Low-Skilled Migrant and Student Communities (row)	56.10	43.90
Low-Skilled Migrant and Student Communities (col.)	22.00	14.00
Ethnically Diverse Suburban Professionals (obs.)	36.00	86.00
Ethnically Diverse Suburban Professionals (row)	29.50	70.50
Ethnically Diverse Suburban Professionals (col.)	5.90	11.50
Baseline UK (obs.)	142.00	156.00
Baseline UK (row)	47.70	52.30
Baseline UK (col.)	23.40	20.80
Semi-and Un-Skilled Workforce (obs.)	119.00	135.00
Semi-and Un-Skilled Workforce (row)	46.90	53.10
Semi-and Un-Skilled Workforce (col.)	19.60	18.00
Legacy Communities (obs.)	22.00	11.00
Legacy Communities (row)	66.70	33.30
Legacy Communities (col.)	3.60	1.50

Table 2.235: oac21SG factor by MDLS (LCA) (χ^2(NA, 1357) = 41.78, p = 0, Cramer's V = 0.176)

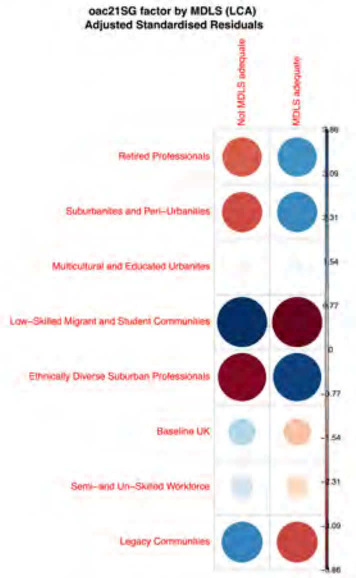

Figure 2.193: Res. Cont. plots-129

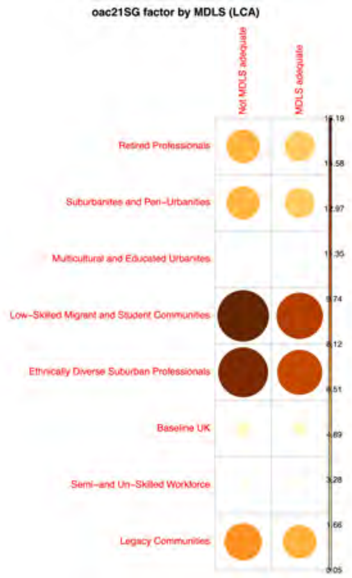

Figure 2.194: Res. Cont. plots-130

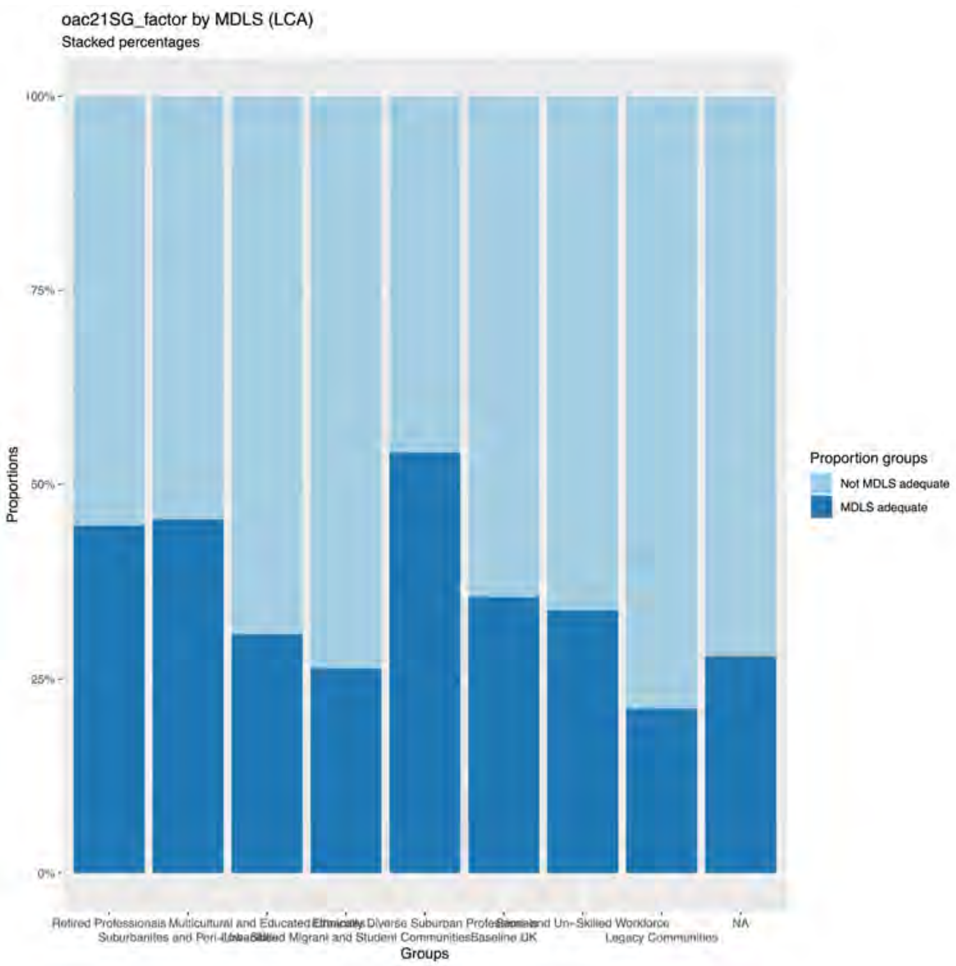

Figure 2.195: Proportions plot-65

2.4.66 aipcsupergroupnamerfactorbyMDLS(LCA)

The Pearson's Chi-squared test with simulated p-value of independence between variables suggests that the effect is statistically significant and small ($chi^2 = 35.79, p < .001; AdjustedCramer'sv = 0.16, 95\%CI[0.10, 1.00]$). The following tables 2.237, 2.236, and 2.238 provide detals of the observations, column and row percentages. Figures 2.196 and 2.197 present plots of residuals and contributions. Figure 2.198 presents the data in stacked proprtions.

	Not MDLS adequate	MDLS adequate
1 Struggling, More Vulnerable Urbanites (col.)	34.90	24.70
2 Multicultural Central Urban Living (col.)	17.50	12.80
3 Rurban Comfortable Ageing (col.)	11.50	20.90
4 Retired Fringe and Residential Stability (col.)	22.00	23.70
5 Cosmopolitan and Coastal Ageing (col.)	14.10	18.00

Table 2.236: aipc supergroup namer factor by MDLS (LCA) (Column Percentages) (χ^2(NA, 1278) = 35.795, p = 0, Cramer's V = 0.167)

	Not MDLS adequate	MDLS adequate
1 Struggling, More Vulnerable Urbanites (row)	53.50	46.50
2 Multicultural Central Urban Living (row)	52.60	47.40
3 Rurban Comfortable Ageing (row)	31.00	69.00
4 Retired Fringe and Residential Stability (row)	43.00	57.00
5 Cosmopolitan and Coastal Ageing (row)	38.90	61.10

Table 2.237: aipc supergroup namer factor by MDLS (LCA) (Row Percentages) (χ^2(NA, 1278) = 35.795, p = 0, Cramer's V = 0.167)

	Not MDLS adequate	MDLS adequate
1 Struggling, More Vulnerable Urbanites (obs.)	200.00	174.00
1 Struggling, More Vulnerable Urbanites (row)	53.50	46.50
1 Struggling, More Vulnerable Urbanites (col.)	34.90	24.70
2 Multicultural Central Urban Living (obs.)	100.00	90.00
2 Multicultural Central Urban Living (row)	52.60	47.40
2 Multicultural Central Urban Living (col.)	17.50	12.80
3 Rurban Comfortable Ageing (obs.)	66.00	147.00
3 Rurban Comfortable Ageing (row)	31.00	69.00
3 Rurban Comfortable Ageing (col.)	11.50	20.90
4 Retired Fringe and Residential Stability (obs.)	126.00	167.00
4 Retired Fringe and Residential Stability (row)	43.00	57.00
4 Retired Fringe and Residential Stability (col.)	22.00	23.70
5 Cosmopolitan and Coastal Ageing (obs.)	81.00	127.00
5 Cosmopolitan and Coastal Ageing (row)	38.90	61.10
5 Cosmopolitan and Coastal Ageing (col.)	14.10	18.00

Table 2.238: aipc supergroup namer factor by MDLS (LCA) (χ^2(NA, 1278) = 35.795, p = 0, Cramer's V = 0.167)

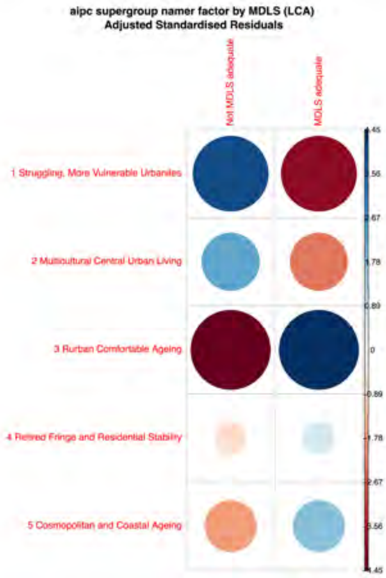

Figure 2.196: Res. Cont. plots-131

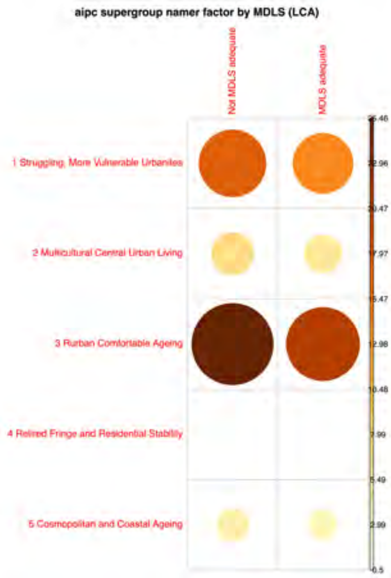

Figure 2.197: Res. Cont. plots-132

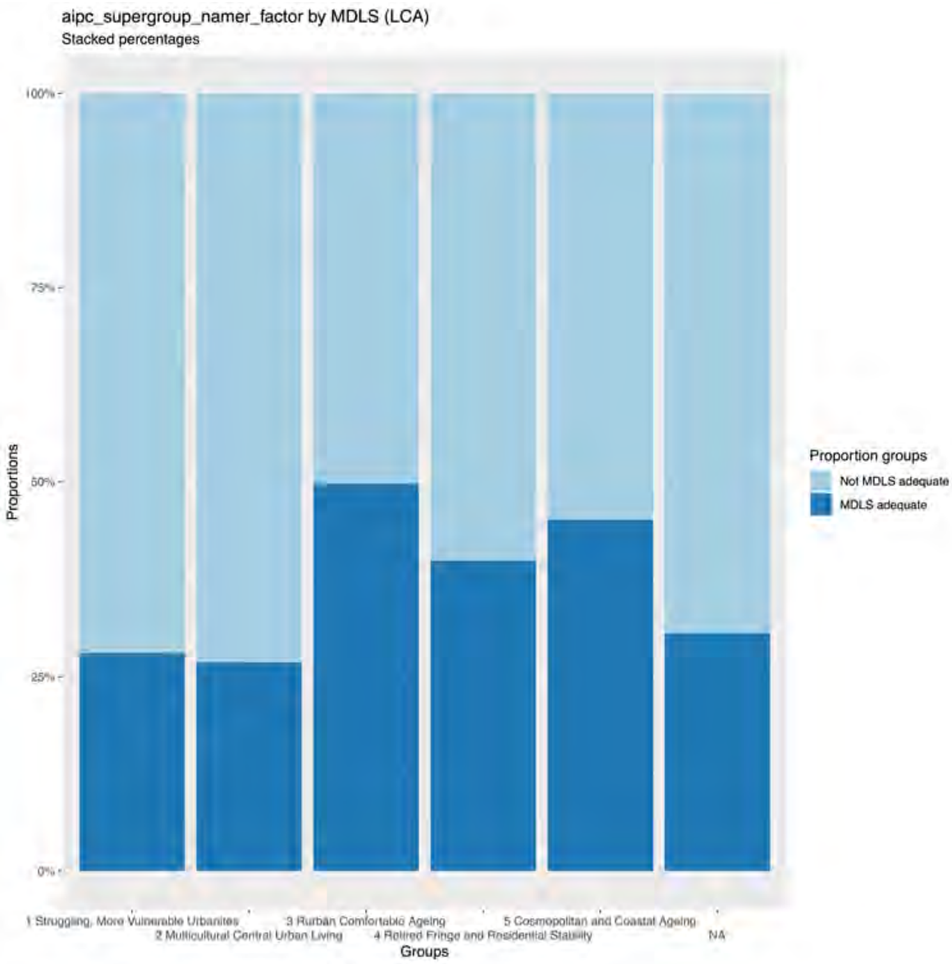

Figure 2.198: Proportions plot-66

2.4.67 BenefitsfactorbyMDLS(LCA)

The Pearson's Chi-squared test with simulated p-value of independence between variables suggests that the effect is statistically significant and medium ($chi^2 = 79.35, p < .001; AdjustedCramer'sv = 0.22, 95\% CI[0.18, 1.00]$). The following tables 2.240, 2.239, and 2.241 provide detals of the observations, column and row percentages. Figures 2.199 and 2.200 present plots of residuals and contributions. Figure 2.201 presents the data in stacked proprtions.

	Not MDLS adequate	MDLS adequate
Not on any benefits (col.)	55.30	76.50
Receives at least one state benefit (col.)	44.70	23.50

Table 2.239: Benefits factor by MDLS (LCA) (Column Percentages) (χ^2(NA, 1582) = 79.349, p = 0, Cramer's V = 0.224)

	Not MDLS adequate	MDLS adequate
Not on any benefits (row)	38.80	61.20
Receives at least one state benefit (row)	62.50	37.50

Table 2.240: Benefits factor by MDLS (LCA) (Row Percentages) (χ^2(NA, 1582) = 79.349, p = 0, Cramer's V = 0.224)

	Not MDLS adequate	MDLS adequate
Not on any benefits (obs.)	409.00	645.00
Not on any benefits (row)	38.80	61.20
Not on any benefits (col.)	55.30	76.50
Receives at least one state benefit (obs.)	330.00	198.00
Receives at least one state benefit (row)	62.50	37.50
Receives at least one state benefit (col.)	44.70	23.50

Table 2.241: Benefits factor by MDLS (LCA) (χ^2(NA, 1582) = 79.349, p = 0, Cramer's V = 0.224)

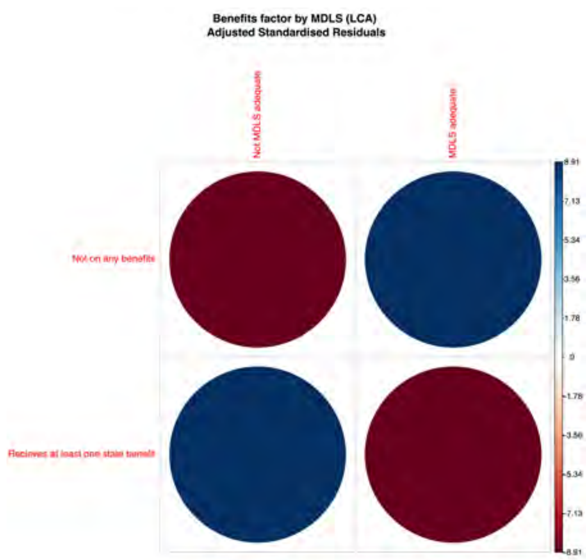

Figure 2.199: Res. Cont. plots-133

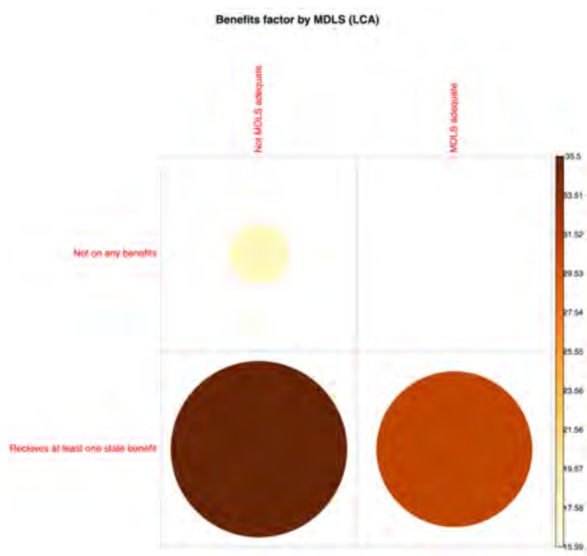

Figure 2.200: Res. Cont. plots-134

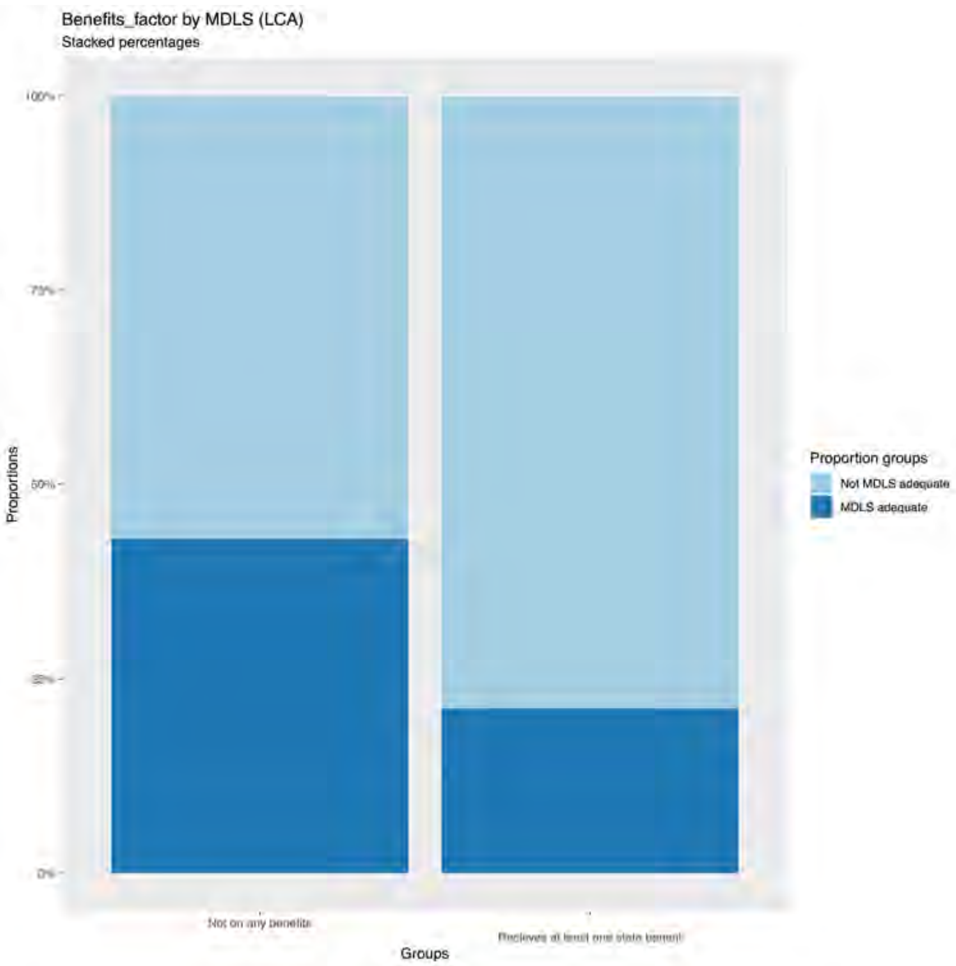

Figure 2.201: Proportions plot-67

2.4.68 WorkingfactorbyMDLS(LCA)

The Pearson's Chi-squared test with simulated p-value of independence between variables suggests that the effect is statistically significant and medium ($chi^2 = 81.44, p < .001; Adjusted Cramer'sv = 0.23, 95\% CI[0.18, 1.00]$). The following tables 2.243, 2.242, and 2.244 provide detals of the observations, column and row percentages. Figures 2.202 and 2.203 present plots of residuals and contributions. Figure 2.204 presents the data in stacked proprtions.

	Not MDLS adequate	MDLS adequate
Chief income earner not working (col.)	29.40	11.30
Chief income earner working (col.)	70.60	88.70

Table 2.242: Working factor by MDLS (LCA) (Column Percentages) (χ^2(NA, 1582) = 81.437, p = 0, Cramer's V = 0.227)

	Not MDLS adequate	MDLS adequate
Chief income earner not working (row)	69.60	30.40
Chief income earner working (row)	41.10	58.90

Table 2.243: Working factor by MDLS (LCA) (Row Percentages) (χ^2(NA, 1582) = 81.437, p = 0, Cramer's V = 0.227)

	Not MDLS adequate	MDLS adequate
Chief income earner not working (obs.)	217.00	95.00
Chief income earner not working (row)	69.60	30.40
Chief income earner not working (col.)	29.40	11.30
Chief income earner working (obs.)	522.00	748.00
Chief income earner working (row)	41.10	58.90
Chief income earner working (col.)	70.60	88.70

Table 2.244: Working factor by MDLS (LCA) (χ^2(NA, 1582) = 81.437, p = 0, Cramer's V = 0.227)

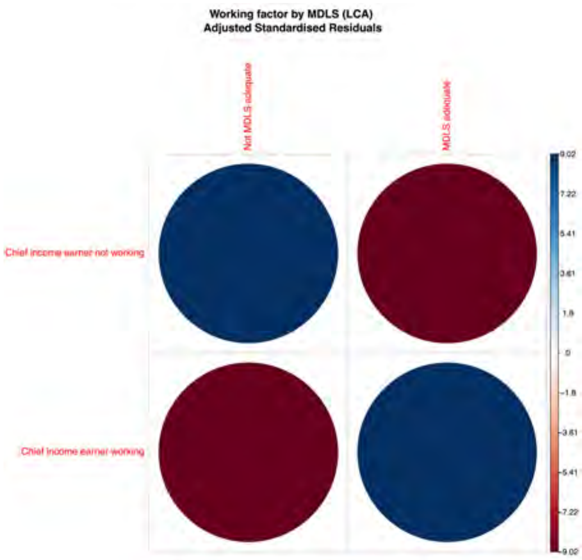

Figure 2.202: Res. Cont. plots-135

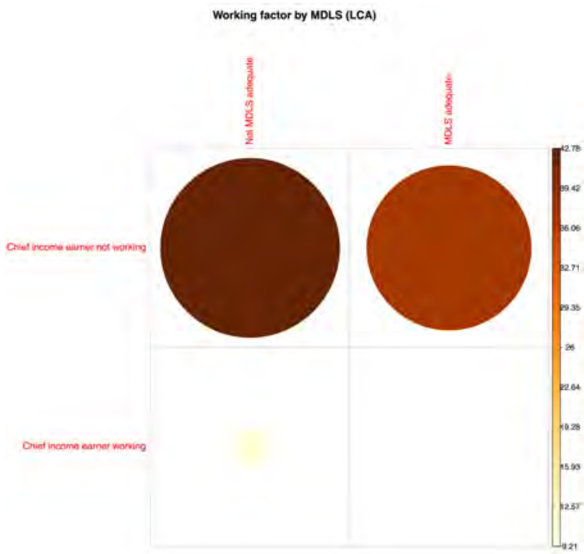

Figure 2.203: Res. Cont. plots-136

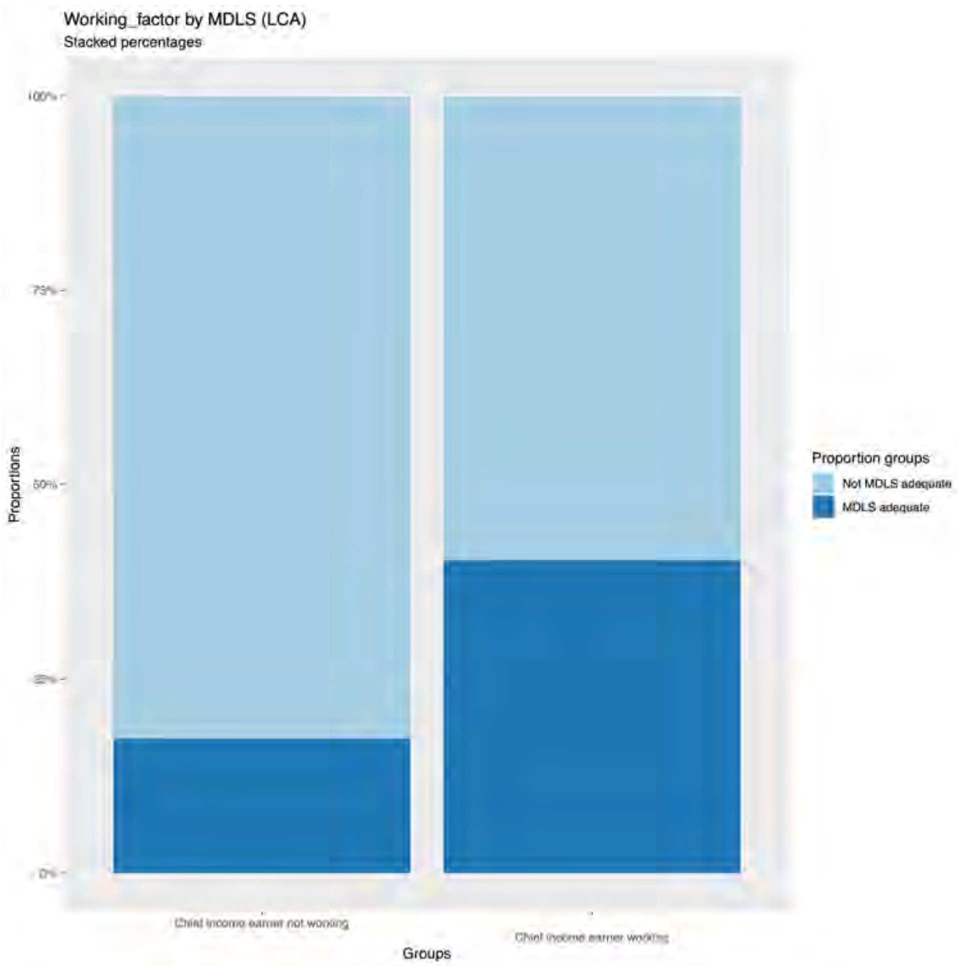

Figure 2.204: Proportions plot-68

2.4.69 HealthlimitationfactorbyMDLS(LCA)

The Pearson's Chi-squared test with simulated p-value of independence between variables suggests that the effect is statistically significant and small ($chi^2 = 42.21, p < .001; Adjusted Cramer's v = 0.16, 95\% CI [0.12, 1.00]$). The following tables 2.246, 2.245, and 2.247 provide detals of the observations, column and row percentages. Figures 2.205 and 2.206 present plots of residuals and contributions. Figure 2.207 presents the data in stacked proprtions.

	Not MDLS adequate	MDLS adequate
Respondent has **no** health issue (col.)	78.30	90.20
Respondent **has** a health issue (col.)	21.70	9.80

Table 2.245: Health limitation factor by MDLS (LCA) (Column Percentages) (χ^2(NA, 1582) = 42.211, p = 0, Cramer's V = 0.163)

	Not MDLS adequate	MDLS adequate
Respondent has no health issue(row)	43.20	56.80
Respondent **has** a health issue (row)	65.80	34.20

Table 2.246: Health limitation factor by MDLS (LCA) (Row Percentages) (χ^2(NA, 1582) = 42.211, p = 0, Cramer's V = 0.163)

	Not MDLS adequate	MDLS adequate
Respondent has no health issue(obs.)	579.00	760.00
Respondent has **no** health issue (row)	43.20	56.80
Respondent has **no** health issue (col.)	78.30	90.20
Respondent **has** a health issue (obs.)	160.00	83.00
Respondent **has** a health issue (row)	65.80	34.20
Respondent **has** a health issue (col.)	21.70	9.80

Table 2.247: Health limitation factor by MDLS (LCA) (χ^2(NA, 1582) = 42.211, p = 0, Cramer's V = 0.163)

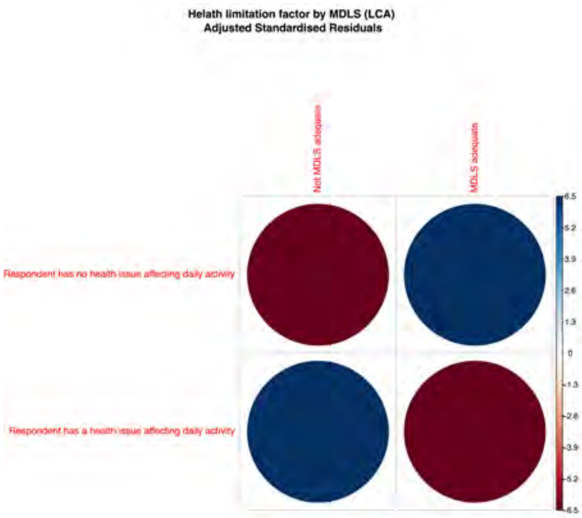

Figure 2.205: Res. Cont. plots-137

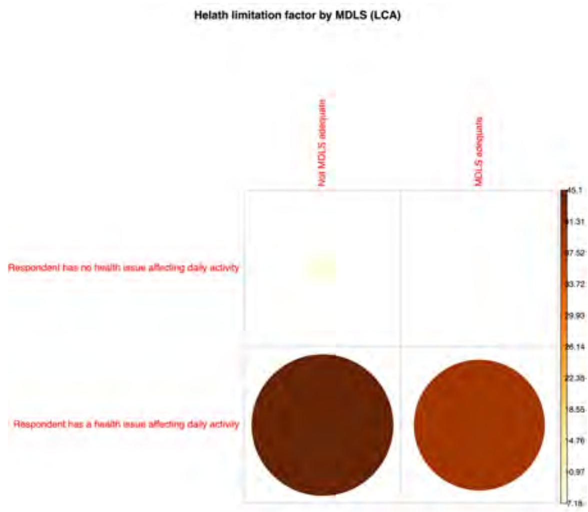

Figure 2.206: Res. Cont. plots-138

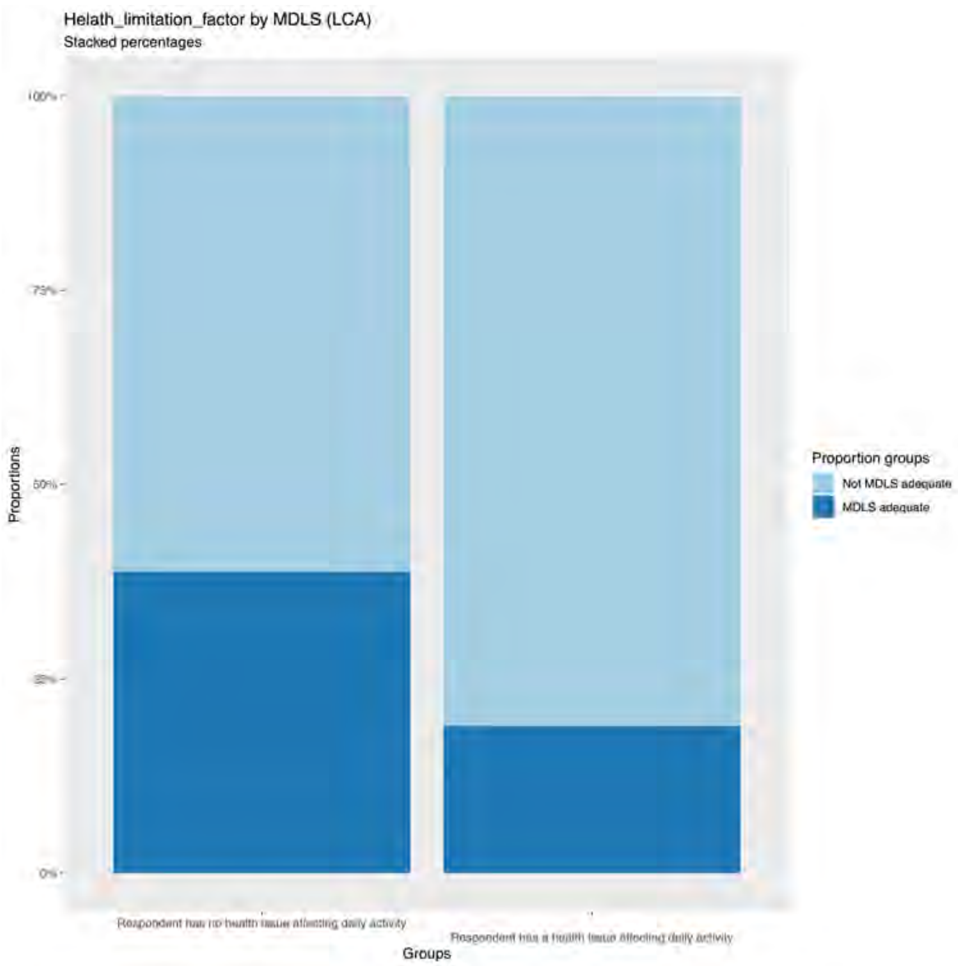

Figure 2.207: Proportions plot-69

2.4.70 EthnicityfactorbyMDLS(LCA)

The Pearson's Chi-squared test with simulated p-value of independence between variables suggests that the effect is statistically significant and very small ($chi^2 = 14.20, p < .001; AdjustedCramer'sv = 0.09, 95\% CI[0.05, 1.00]$). The following tables 2.249, 2.248, and 2.250 provide detals of the observations, column and row percentages. Figures 2.208 and 2.209 present plots of residuals and contributions. Figure 2.210 presents the data in stacked proprtions.

	Not MDLS adequate	MDLS adequate
Respondent identifies as ethnically white(col.)	72.50	80.50
Respondent identifies as ethnically non-white (col.)	27.50	19.50

Table 2.248: Ethnicity factor by MDLS (LCA) (Column Percentages) (χ^2(NA, 1582) = 14.199, p = 0, Cramer's V = 0.095)

	Not MDLS adequate	MDLS adequate
Respondent identifies as ethnically white(row)	44.10	55.90
Respondent identifies as ethnically non-white (row)	55.30	44.70

Table 2.249: Ethnicity factor by MDLS (LCA) (Row Percentages) (χ^2(NA, 1582) = 14.199, p = 0, Cramer's V = 0.095)

	Not MDLS adequate	MDLS adequate
Respondent identifies as ethnically white(obs.)	536.00	679.00
Respondent identifies as ethnically white(row)	44.10	55.90
Respondent identifies as ethnically white(col.)	72.50	80.50
Respondent identifies as ethnically non-white (obs.)	203.00	164.00
Respondent identifies as ethnically non-white (row)	55.30	44.70
Respondent identifies as ethnically non-white (col.)	27.50	19.50

Table 2.250: Ethnicity factor by MDLS (LCA) (χ^2(NA, 1582) = 14.199, p = 0, Cramer's V = 0.095)

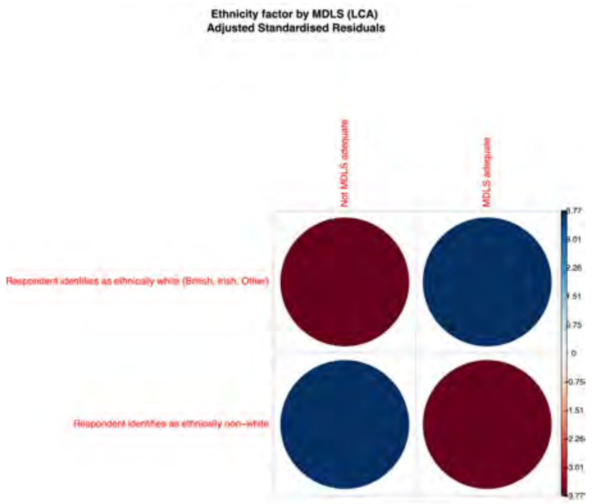

Figure 2.208: Res. Cont. plots-139

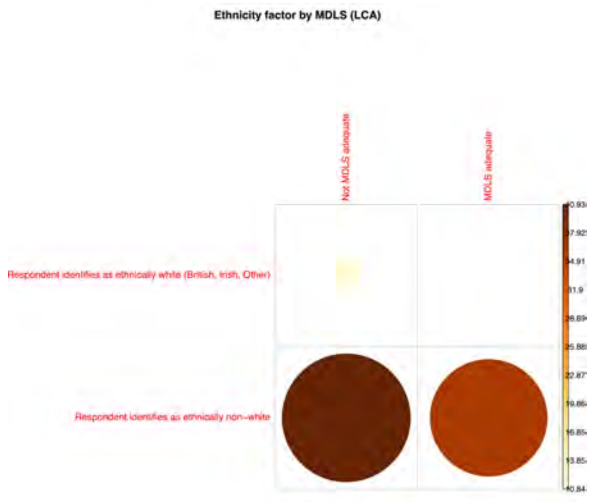

Figure 2.209: Res. Cont. plots-140

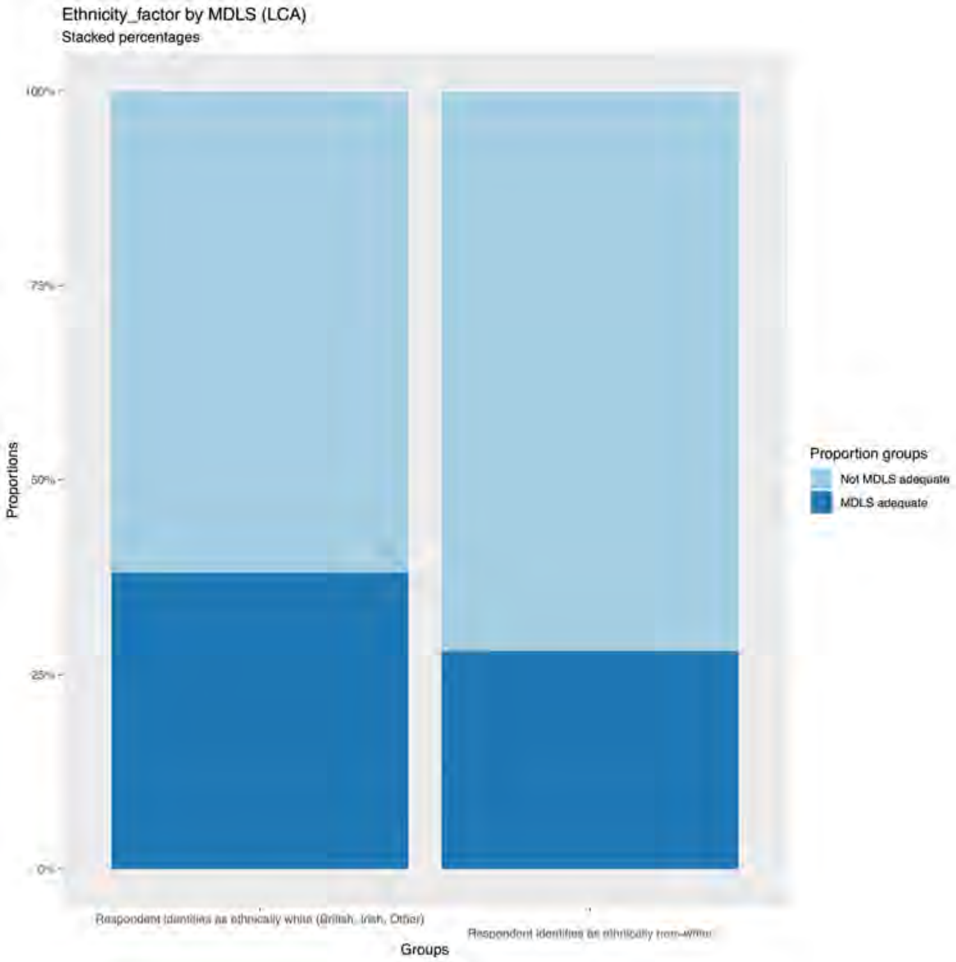

Figure 2.210: Proportions plot-70

2.4.71 Modeling MDLS

Binary regression on simple MDLS equipment cutoff - socio-economic predictors

We fitted a logistic model (estimated using ML) to predict MDLS Abs. Equipment (no skills) with:

- SEGfactor
- Singleparentdummyfactor
- Twopluschildrendummyfactor and
- imd2019RANKnamode

Formula:

$$MDLS2factor\ SEGfactor + Singleparentdummyfactor + Twopluschildrendummyfactor + imd2019RANKnamode \tag{2.1}$$

The model's explanatory power is weak (Tjur's $R^2 = 0.07$). The model's intercept, corresponding to SEGfactor = AB, Singleparentdummyfactor = Not single parent, Twopluschildrendummyfactor = Not more than two children, and imd2019RANKnamode = 0, is at $-0.38(95\%CI[-0.70, -0.05], p = 0.023)$. Within this model:

- The effect of SEG factor [C1] is statistically non-significant and positive ($beta = 0.06, 95\%CI[-0.24, 0.35], p = 0.703; Std.beta = 0.06, 95\%CI[-0.24, 0.35]$)
- The effect of SEG factor [C2] is statistically significant and negative ($beta = -0.33, 95\%CI[-0.65, -0.02], p = 0.039; Std.beta = -0.33, 95\%CI[-0.65, -0.02]$)
- The effect of SEG factor [DE] is statistically significant and negative ($beta = -0.57, 95\%CI[-0.90, -0.25], p < .001; Std.beta = -0.57, 95\%CI[-0.90, -0.25]$)

- The effect of Single parent dummy factor [linear] is statistically significant and negative ($beta = -0.43, 95\%CI[-0.61, -0.26], p <$ $.001; Std.beta = -0.43, 95\%CI[-0.61, -0.26]$)

- The effect of Two plus children dummy factor [linear] is statistically significant and negative ($beta = -0.53, 95\%CI[-0.75, -0.32]$ $.001; Std.beta - 0.53, 95\%CI[-0.75, -0.32]$)

- The effect of imd2019RANK namode is statistically significant and positive ($beta = 1.55e - 05, 95\%CI[4.58e - 06, 2.64e - 05], p = 0.005; Std.beta = 0.15, 95\%CI[0.05, 0.26]$)

Standardized parameters were obtained by fitting the model on a standardized version of the dataset. 95% Confidence Intervals (CIs) and p-values were computed using a Wald z-distribution approximation.

Table 2.251

	Dependent variable:
	MDLS Equipment (Abs.)
C1	0.058
	(0.152)
C2	-0.331^{**}
	(0.161)
DE	-0.573^{***}
	(0.166)
Single parent family	-0.435^{***}
	(0.087)
More than two children	-0.534^{***}
	(0.110)
Index of Multiple Deprivation Rank	0.00002^{***}
	(0.00001)
Constant	-0.376^{**}
	(0.165)
Observations	1,582
Log Likelihood	−1,039.017
Akaike Inf. Crit.	2,092.033
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 2.252

	e^B	2.5 %	97.5 %
(Intercept)	0.69	0.50	0.95
C1	1.06	0.79	1.43
C2	0.72	0.52	0.98
DE	0.56	0.41	0.78
Single parent family	0.65	0.55	0.77
More than two children	0.59	0.47	0.73
Index of Multiple Deprivation Rank	1.00	1.00	1.00

Table 2.253: MDLS Binary GLM confidence intervals

Binary regression on absolute MDLS - socio-economic predictors

We fitted a logistic model (estimated using ML) to predict MDLS (Abs.) with:

- SEGfactor
- Singleparentdummyfactor
- Twopluschildrendummyfactor
- imd2019RANKnamode

Formula:

$$MDLSAbsEquipmentSkills\ SEGfactor + Singleparentdummyfactor + Twopluschildrendummyfactor + imd2019RANKn$$ (2.2)

The model's explanatory power is weak (Tjur's $R^2 = 0.09$). The model's intercept, corresponding to SEGfactor = AB, Singleparentdummyfactor = Not single parent, Twopluschildrendummyfactor = Not more than two children, and imd2019RANKnamode = 0, is at $-1.12(95\%CI[-1.47, -0.78], p < .001)$. Within this model:

- The effect of SEG factor [C1] is statistically non-significant and negative ($beta = -0.01, 95\%CI[-0.31, 0.28], p = 0.926; Std.beta = -0.01, 95\%CI[-0.31, 0.28]$)
- The effect of SEG factor [C2] is statistically non-significant and negative ($beta = -0.28, 95\%CI[-0.60, 0.04], p = 0.089; Std.beta = -0.28, 95\%CI[-0.60, 0.04]$)
- The effect of SEG factor [DE] is statistically significant and negative ($beta = -0.87, 95\%CI[-1.23, -0.52], p < .001; Std.beta = -0.87, 95\%CI[-1.23, -0.52]$)
- The effect of Single parent dummy factor [linear] is statistically significant and negative ($beta = -0.46, 95\%CI[-0.65, -0.27], p <$ $.001; Std.beta = -0.46, 95\%CI[-0.65, -0.27]$)
- The effect of Two plus children dummy factor [linear] is statistically significant and negative ($beta = -0.71, 95\%CI[-0.98, -0.46]$ $.001; Std.beta = -0.71, 95\%CI[-0.98, -0.46]$)
- The effect of imd2019RANK namode is statistically significant and positive ($beta = 2.03e - 05, 95\%CI[9.00e - 06, 3.15e - 05], p < .001; Std.beta = 0.20, 95\%CI[0.09, 0.31]$)

Standardized parameters were obtained by fitting the model on a standardized version of the dataset. 95% Confidence Intervals (CIs) and p-values were computed using a Wald z-distribution approximation.

	Dependent variable:
	MDLS (Abs.)
C1	-0.014
	(0.151)
C2	-0.277^{*}
	(0.163)
DE	-0.870^{***}
	(0.180)
Single parent family	-0.457^{***}
	(0.097)
More than two children	-0.713^{***}
	(0.133)
Index of Multiple Deprivation Rank	0.00002^{***}
	(0.00001)
Constant	-1.123^{***}
	(0.177)
Observations	1,582
Log Likelihood	-956.808
Akaike Inf. Crit.	1,927.615
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 2.254

	e^B	2.5 %	97.5 %
(Intercept)	0.33	0.23	0.46
C1	0.99	0.73	1.33
C2	0.76	0.55	1.04
DE	0.42	0.29	0.60
Single parent family	0.63	0.52	0.76
More than two children	0.49	0.37	0.63
Index of Multiple Deprivation Rank	1.00	1.00	1.00

Table 2.255: MDLS Binary GLM confidence intervals

Binary regression on LCA MDLS - socio-economic predictors

We fitted a logistic model (estimated using ML) to predict MDLS (LCA) with:

- SEGfactor
- Singleparentdummyfactor,
- Twopluschildrendummyfactor
- imd2019RANKnamode

Formula:

$$MDLSLCAEquipmentSkills\ SEGfactor+Singleparentdummyfactor+Twopluschildrendummyfactor+imd2019RANK \tag{2.3}$$

The model's explanatory power is weak (Tjur's $R^2 = 0.09$). The model's intercept, corresponding to SEGfactor = AB, Singleparentdummyfactor = Not single parent, Twopluschildrendummyfactor = Not more than two children, and imd2019RANKnamode = 0, is at $0.07(95\%CI[-0.26, 0.40], p = 0.674)$. Within this model:

- The effect of SEG factor [C1] is statistically non-significant and negative ($beta = -0.22, 95\%CI[-0.52, 0.09], p = 0.165; Std.beta = -0.22, 95\%CI[-0.52, 0.09]$)
- The effect of SEG factor [C2] is statistically significant and negative ($beta = -0.46, 95\%CI[-0.78, -0.14], p = 0.005; Std.beta = -0.46, 95\%CI[-0.78, -0.14]$)
- The effect of SEG factor [DE] is statistically significant and negative ($beta = -1.14, 95\%CI[-1.48, -0.81], p < .001; Std.beta = -1.14, 95\%CI[-1.48, -0.81]$)
- The effect of the Single parent dummy factor [linear] is statistically significant and negative ($beta = -0.31, 95\%CI[-0.48, -0.14]$ $.001; Std.beta = -0.31, 95\%CI[-0.48, -0.14]$)
- The effect of Two plus children dummy factor [linear] is statistically significant and negative ($beta = -0.48, 95\%CI[-0.70, -0.27]$ $.001; Std.beta = -0.48, 95\%CI[-0.70, -0.27]$)
- The effect of imd2019RANK namode is statistically significant and positive ($beta = 1.57e-05, 95\%CI[4.69e-06, 2.68e-05], p = 0.005; Std.beta = 0.16, 95\%CI[0.05, 0.27]$)

Standardized parameters were obtained by fitting the model on a standardized version of the dataset. 95% Confidence Intervals (CIs) and p-values were computed using a Wald z-distribution approximation.

	Dependent variable:
	MDLS (LCA)
C1	−0.216
	(0.156)
C2	−0.458***
	(0.164)
DE	−1.140***
	(0.170)
Single parent family	−0.313***
	(0.087)
More than two children	−0.480***
	(0.110)
Index of Multiple Deprivation Rank	0.00002***
	(0.00001)
Constant	0.070
	(0.167)
Observations	1,582
Log Likelihood	−1,018.586
Akaike Inf. Crit.	2,051.172
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 2.256

	e^B	2.5 %	97.5 %
(Intercept)	1.07	0.77	1.49
C1	0.81	0.59	1.09
C2	0.63	0.46	0.87
DE	0.32	0.23	0.45
Single parent family	0.73	0.62	0.87
More than two children	0.62	0.50	0.77
Index of Multiple Deprivation Rank	1.00	1.00	1.00

Table 2.257: MDLS Binary GLM confidence intervals

Binary regression on LCA MDLS demographic factors

We fitted a logistic model (estimated using ML) to predict MDLS (LCA) with:

- Benefitsfactor
- Workingfactor,
- Healthlimitationfactor
- Ethnicityfactor

Formula:

$$MDLSLCAEquipmentSkills\ Benefitsfactor + Workingfactor + Healthlimitationfactor + Ethnicityfactor) \tag{2.4}$$

The model's explanatory power is weak (Tjur's $R^2 = 0.09$). The model's intercept, corresponding to Benefitsfactor = Not on any benefits, Workingfactor = Chiefincome earner not working, Healthlimitationfactor = Respondent has **no** health issue and Ethnicityfactor = Respondent identifies as ethnically white (British, Irish, Other), is at $-9.89e-03(95\%CI[-0.34, 0.31], p = 0.953)$. Within this model:

- The effect of Benefits factor [Receives at least one state benefit] is statistically significant and negative ($beta = -0.64, 95\%CI[-0.89, -0.38], p < .001; Std.beta = -0.64, 95\%CI[-0.89, -0.38]$)
- The effect of Working factor [Chief income earner working] is statistically significant and positive ($beta = 0.71, 95\%CI[0.41, 1.01]$ $.001; Std.beta = 0.71, 95\%CI[0.41, 1.01]$)
- The effect of Health limitation factor [Respondent has a health issue affecting daily activity] is statistically significant and negative ($beta = -0.51, 95\%CI[-0.83, -0.19], p = 0.002; Std.beta = -0.51, 95\%CI[-0.83, -0.19]$)
- The effect of Ethnicity factor [Respondent identifies as ethnically non-white] is statistically significant and negative ($beta = -0.61, 95\%CI[-0.85, -0.36], p < .001; Std.beta = -0.61, 95\%CI[-0.85, -0.36]$)

Standardized parameters were obtained by fitting the model on a standardized version of the dataset. 95% Confidence Intervals (CIs) and p-values were computed using a Wald z-distribution approximation.

	e^B	2.5 %	97.5 %
(Intercept)	0.99	0.71	1.37
Receives at least one state benefit	0.53	0.41	0.68
Chief income earner working	2.03	1.50	2.76
Respondent **has** a health issue	0.60	0.44	0.83
Respondent identifies as ethnically non-white	0.55	0.43	0.70

Table 2.260: MDLS Binary GLM confidence intervals

Binary regression on LCA MDLS - geographic factors

We fitted a logistic model (estimated using ML) to predict MDLS (LCA) with:

- URBANfactor
- REGIONshortfactor
- oacLSMSdummyfactor

Table 2.258

	Dependent variable:
	MDLS (LCA)
Receives at least one state benefit	-0.637^{***}
	(0.129)
Chief income earner working	0.710^{***}
	(0.154)
Respondent **has** a health issue	-0.507^{***}
	(0.163)
Respondent identifies as ethnically non-white	-0.605^{***}
	(0.126)
Constant	-0.010
	(0.166)
Observations	1,582
Log Likelihood	$-1,022.448$
Akaike Inf. Crit.	2,054.895
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 2.259

- oacLegacydummyfactor
- oacRetireddummyfactor
- oacSPUdummyfactor
- oacEDSPdummyfactor
- IUCEWdummyfactor,
- IUCYUFdummyfactor
- IUCERUdummyfactor
- IUCEVdummyfactor
- IUCSOCdummyfactor

Formula:

$$MDLSLCAEquipmentSkills\,URBANfactor+REGIONshortfactor+oacLSMSdummyfactor+oacLegacydummyfactor \tag{2.5}$$

The model's explanatory power is weak (Tjur's R^2 = 0.07). The model's intercept, corresponding to URBANfactor = Large city, REGIONshortfactor = Lon, oacLSMSdummyfactor = Not Low-Skilled, Migrant, and Student Communities, oacLegacydummyfactor = Not Legacy Communities, oacRetireddummyfactor = Not Retired Professionals, oacSPUdummyfactor = Not Suburbanites and Peri-Urbanities, oacEDSPdummyfactor = Not Ethnically Diverse Suburban Professionals, IUCEWdummyfactor = Not e-Withdrawn, IUCYUFdummyfactor = Not Youthful Urban Fringe, IUCERUdummyfactor = Not e-Rational Utilitarians, IUCEVdummyfactor = Not e-Veterans and IUCSOCdummyfactor = Not Settled Offline Communities, is at $0.43(95\%CI[0.07, 0.80], p = 0.021)$. Within this model:

- The effect of URBAN factor [Smaller city or large town] is statistically significant and positive ($beta = 1.16, 95\%CI[0.19, 2.30], p = 0.028; Std.beta = 1.16, 95\%CI[0.19, 2.30]$)
- The effect of URBAN factor [Medium town] is statistically significant and positive ($beta = 1.52, 95\%CI[0.57, 2.66], p = 0.004; Std.beta = 1.52, 95\%CI[0.57, 2.66]$)
- The effect of URBAN factor [Small town] is statistically significant and positive ($beta = 1.63, 95\%CI[0.68, 2.76], p = 0.002; Std.beta = 1.63, 95\%CI[0.68, 2.76]$)
- The effect of URBAN factor [Rural area] is statistically significant and positive ($beta = 1.49, 95\%CI[0.50, 2.66], p = 0.006; Std.beta = 1.49, 95\%CI[0.50, 2.66]$)

- The effect of REGION short factor [EE] is statistically significant and negative ($beta = -1.37, 95\%CI[-2.58, -0.30], p = 0.017; Std.beta = -1.37, 95\%CI[-2.58, -0.30]$)
- The effect of REGION short factor [WM] is statistically significant and negative ($beta = -1.39, 95\%CI[-2.58, -0.36], p = 0.013; Std.beta = -1.39, 95\%CI[-2.58, -0.36]$)
- The effect of REGION short factor [SE] is statistically significant and negative ($beta = -1.51, 95\%CI[-2.71, -0.48], p = 0.007; Std.beta = -1.51, 95\%CI[-2.71, -0.48]$)
- The effect of REGION short factor [YH] is statistically significant and negative ($beta = -1.72, 95\%CI[-2.93, -0.65], p = 0.003; Std.beta = -1.72, 95\%CI[-2.93, -0.65]$)
- The effect of REGION short factor [W] is statistically significant and negative ($beta = -1.73, 95\%CI[-2.97, -0.63], p = 0.003; Std.beta = -1.73, 95\%CI[-2.97, -0.63]$)
- The effect of REGION short factor [SW] is statistically significant and negative ($beta = -1.86, 95\%CI[-3.08, -0.80], p = 0.001; Std.beta = -1.86, 95\%CI[-3.08, -0.80]$)
- The effect of REGION short factor [EM] is statistically significant and negative ($beta = -1.89, 95\%CI[-3.12, -0.81], p = 0.001; Std.beta = -1.89, 95\%CI[-3.12, -0.81]$)
- The effect of REGION short factor [S] is statistically significant and negative ($beta = -2.14, 95\%CI[-3.28, -1.18], p < .001; Std.beta = -2.14, 95\%CI[-3.28, -1.18]$)
- The effect of REGION short factor [NE] is statistically significant and negative ($beta = -2.20, 95\%CI[-3.49, -1.05], p < .001; Std.beta = -2.20, 95\%CI[-3.49, -1.05]$)
- The effect of REGION short factor [NW] is statistically significant and negative ($beta = -2.26, 95\%CI[-3.47, -1.22], p < .001; Std.beta = -2.26, 95\%CI[-3.47, -1.22]$)
- The effect of REGION short factor [NI] is statistically significant and negative ($beta = -2.31, 95\%CI[-3.56, -1.20], p < .001; Std.beta = -2.31, 95\%CI[-3.56, -1.20]$)
- The effect of oac LSMS dummy factor [Low-Skilled, Migrant, and Student Communities] is statistically significant and negative ($beta = -0.37, 95\%CI[-0.73, -0.01], p = 0.044; Std.beta = -0.37, 95\%CI[-0.73, -0.01]$)
- The effect of oac Legacy dummy factor [Legacy Communities] is statistically significant and negative ($beta = -0.88, 95\%CI[-1.68$ $0.024; Std.beta = -0.88, 95\%CI[-1.68, -0.14]$)
- The effect of oac Retired dummy factor [Retired Professionals] is statistically significant and positive ($beta = 0.59, 95\%CI[0.10, 1.10], p = 0.020; Std.beta = 0.59, 95\%CI[0.10, 1.10]$)
- The effect of oac SPU dummy factor [Suburbanites and Peri-Urbanities] is statistically non-significant and positive ($beta = 0.18, 95\%CI[-0.17, 0.54], p = 0.314; Std.beta = 0.18, 95\%CI[-0.17, 0.54]$)
- The effect of oac EDSP dummy factor [Ethnically Diverse Suburban Professionals] is statistically significant and positive ($beta = 0.61, 95\%CI[0.15, 1.08], p = 0.010; Std.beta = 0.61, 95\%CI[0.15, 1.08]$)
- The effect of IUC EW dummy factor [e-Withdrawn] is statistically non-significant and negative ($beta = -0.14, 95\%CI[-0.49, 0.21$ $0.434; Std.beta = -0.14, 95\%CI[-0.49, 0.21]$)
- The effect of IUC YUF dummy factor [Youthful Urban Fringe] is statistically non-significant and negative ($beta = -0.39, 95\%CI[-0.88, 0.10], p = 0.120; Std.beta = -0.39, 95\%CI[-0.88, 0.10]$)
- The effect of IUC ERU dummy factor [e-Rational Utilitarians] is statistically non-significant and positive ($beta = 0.08, 95\%CI[-0.40, 0.57], p = 0.751; Std.beta = 0.08, 95\%CI[-0.40, 0.57]$)
- The effect of IUC EV dummy factor [e-Veterans] is statistically non-significant and negative ($beta = -0.02, 95\%CI[-0.40, 0.36], p$ $0.913; Std.beta = -0.02, 95\%CI[-0.40, 0.36]$)
- The effect of IUC SOC dummy factor [Settled Offline Communities] is statistically non-significant and positive ($beta = 0.34, 95\%CI[-0.18, 0.88], p = 0.209; Std.beta = 0.34, 95\%CI[-0.18, 0.88]$)

Standardized parameters were obtained by fitting the model on a standardized version of the dataset. 95% Confidence Intervals (CIs) and p-values were computed using a Wald z-distribution approximation.

Table 2.261

	Dependent variable:
	MDLS (LCA)
Smaller city or large town	1.156**
	(0.528)
Medium town	1.523***
	(0.524)
Small town	1.630***
	(0.521)
Rural area	1.492***
	(0.541)
EE	−1.365**
	(0.573)
WM	−1.390**
	(0.557)
SE	−1.510***
	(0.560)
YH	−1.715***
	(0.573)
W	−1.726***
	(0.587)
SW	−1.859***
	(0.573)
EM	−1.892***
	(0.581)
S	−2.138***
	(0.525)
NE	−2.201***
	(0.615)
NW	−2.264***
	(0.567)
NI	−2.310***
	(0.594)
Low-Skilled, Migrant, and Student Communities	−0.372**
	(0.185)
Legacy Communities	−0.883**
	(0.391)
Retired Professionals	0.590**
	(0.254)
Suburbanites and Peri-Urbanities	0.183
	(0.181)
Ethnically Diverse Suburban Professionals	0.611***
	(0.237)
e-Withdrawn	−0.140
	(0.180)
Youthful Urban Fringe	−0.389
	(0.251)
e-Rational Utilitarians	0.078
	(0.247)
e-Veterans	−0.021
	(0.195)
Settled Offline Communities	0.338
	(0.269)
Constant	0.429**
	(0.186)
Observations	1,582
Log Likelihood	−1,036.710
Akaike Inf. Crit.	2,125.420
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 2.262

	e^B	2.5 %	97.5 %
(Intercept)	1.54	1.07	2.22
Smaller city or large town	3.18	1.21	9.99
Medium town	4.59	1.77	14.32
Small town	5.11	1.98	15.86
Rural area	4.44	1.65	14.26
EE	0.26	0.08	0.74
WM	0.25	0.08	0.70
SE	0.22	0.07	0.62
Y&H	0.18	0.05	0.52
W	0.18	0.05	0.53
SW	0.16	0.05	0.45
EM	0.15	0.04	0.44
S	0.12	0.04	0.31
NE	0.11	0.03	0.35
NW	0.10	0.03	0.30
NI	0.10	0.03	0.30
Low-Skilled, Migrant, and Student Communities	0.69	0.48	0.99
Legacy Communities	0.41	0.19	0.87
Retired Professionals	1.80	1.10	3.00
Suburbanites and Peri-Urbanities	1.20	0.84	1.72
Ethnically Diverse Suburban Professionals	1.84	1.17	2.95
e-Withdrawn	0.87	0.61	1.24
Youthful Urban Fringe	0.68	0.41	1.10
e-Rational Utilitarians	1.08	0.67	1.76
e-Veterans	0.98	0.67	1.44
Settled Offline Communities	1.40	0.83	2.40

Table 2.263: MDLS Binary GLM confidence intervals

Binary regression on LCA MDLS - all predictors

We fitted a logistic model (estimated using ML) to predict MDLS (LCA) with:

- SEGfactor
- Singleparentdummyfactor
- Twopluschildrendummyfactor
- imd2019RANKnamode
- Benefitsfactor,
- Workingfactor
- Healthlimitationfactor
- Ethnicityfactor
- URBANfactor
- REGIONshortfactor
- oacLSMSdummyfactor
- oacLegacydummyfactor
- oacRetireddummyfactor
- oacEDSPdummyfactor

Formula:

$$MDLSLCAEquipmentSkills\ SEGfactor + Singleparentdummyfactor + Twopluschildrendummyfactor + imd2019RANKn \tag{2.6}$$

The model's explanatory power is moderate (Tjur's $R^2 = 0.15$). The model's intercept, corresponding to SEGfactor = AB, Singleparentdummyfactor = Not single parent, Twopluschildrendummyfactor = Not more than two children, imd2019RANKnamode = 0, Benefitsfactor = Not on any benefits, Workingfactor = Chief income earner not working, Healthlimitationfactor = Respondent has **no** health issue, Ethnicityfactor = Respondent identifies as ethnically white (British, Irish, Other), URBANfactor = Large city, REGIONshortfactor = Lon, oacLSMSdummyfactor = Not Low-Skilled, Migrant, and Student Communities, oacLegacydummyfactor = Not Legacy Communities, oacRetireddummyfactor = Not Retired Professionals and oacEDSPdummyfactor = Not Ethnically Diverse Suburban Professionals, is at $0.87 (95\% CI [0.25, 1.51], p = 0.007)$. Within this model:

- The effect of SEG factor [C1] is statistically non-significant and negative ($beta = -0.24, 95\% CI [-0.56, 0.08], p = 0.138; Std.beta = -0.24, 95\% CI [-0.56, 0.08]$)
- The effect of SEG factor [C2] is statistically significant and negative ($beta = -0.51, 95\% CI [-0.85, -0.17], p = 0.003; Std.beta = -0.51, 95\% CI [-0.85, -0.17]$)
- The effect of SEG factor [DE] is statistically significant and negative ($beta = -0.86, 95\% CI [-1.26, -0.47], p < .001; Std.beta = -0.86, 95\% CI [-1.26, -0.47]$)
- The effect of Single parent dummy factor [linear] is statistically significant and negative ($beta = -0.25, 95\% CI [-0.44, -0.06]$, $p = 0.010; Std.beta = -0.25, 95\% CI [-0.44, -0.06]$)
- The effect of Two plus children dummy factor [linear] is statistically significant and negative ($beta = -0.45$, $95\% CI [-0.68, -0.23], p < .001; Std.beta = -0.45, 95\% CI [-0.68, -0.23]$)
- The effect of imd2019RANK namode is statistically significant and negative ($beta = -1.77e-05, 95\% CI [-3.42e-05, -1.21e-06], p = 0.036; Std.beta = -0.18, 95\% CI [-0.34, -0.01]$)
- The effect of Benefits factor [Receives at least one state benefit] is statistically non-significant and negative ($beta = -0.24, 95\% CI [-0.54, 0.05], p = 0.100; Std.beta = -0.24, 95\% CI [-0.54, 0.05]$)
- The effect of Working factor [Chief income earner working] is statistically non-significant and positive ($beta = 0.34, 95\% CI [-9.76e-03, 0.70], p = 0.056; Std.beta = 0.34, 95\% CI [-9.76e-03, 0.70]$)
- The effect of Health limitation factor [Respondent has a health issue affecting daily activity] is statistically significant and negative ($beta = -0.51, 95\% CI [-0.85, -0.17], p = 0.003; Std.beta = -0.51, 95\% CI [-0.85, -0.17]$)
- The effect of Ethnicity factor [Respondent identifies as ethnically non-white] is statistically significant and negative ($beta = -0.69, 95\% CI [-0.99, -0.39], p < .001; Std.beta = -0.69, 95\% CI [-0.99, -0.39]$)
- The effect of URBAN factor [Smaller city or large town] is statistically significant and positive ($beta = 1.15, 95\% CI [0.15, 2.33]$, $p = 0.035; Std.beta = 1.15, 95\% CI [0.15, 2.33]$)
- The effect of URBAN factor [Medium town] is statistically significant and positive ($beta = 1.45, 95\% CI [0.45, 2.62], p = 0.008; Std.beta = 1.45, 95\% CI [0.45, 2.62]$)
- The effect of URBAN factor [Small town] is statistically significant and positive ($beta = 1.69, 95\% CI [0.70, 2.85], p = 0.002; Std.beta = 1.69, 95\% CI [0.70, 2.85]$)
- The effect of URBAN factor [Rural area] is statistically significant and positive ($beta = 1.53, 95\% CI [0.50, 2.73], p = 0.006; Std.beta = 1.53, 95\% CI [0.50, 2.73]$)
- The effect of REGION short factor [EE] is statistically significant and negative ($beta = -1.30, 95\% CI [-2.54, -0.21], p = 0.027; Std.beta = -1.30, 95\% CI [-2.54, -0.21]$)
- The effect of REGION short factor [WM] is statistically significant and negative ($beta = -1.40, 95\% CI [-2.61, -0.35], p = 0.014; Std.beta = -1.40, 95\% CI [-2.61, -0.35]$)
- The effect of REGION short factor [SE] is statistically significant and negative ($beta = -1.49, 95\% CI [-2.71, -0.42], p = 0.010; Std.beta = -1.49, 95\% CI [-2.71, -0.42]$)
- The effect of REGION short factor [YH] is statistically significant and negative ($beta = -1.64, 95\% CI [-2.88, -0.54], p = 0.005; Std.beta = -1.64, 95\% CI [-2.88, -0.54]$)
- The effect of REGION short factor [W] is statistically significant and negative ($beta = -1.88, 95\% CI [-3.17, -0.72], p = 0.002; Std.beta = -1.88, 95\% CI [-3.17, -0.72]$)
- The effect of REGION short factor [SW] is statistically significant and negative ($beta = -2.03, 95\% CI [-3.28, -0.94], p < .001; Std.beta = -2.03, 95\% CI [-3.28, -0.94]$)

- The effect of REGION short factor [EM] is statistically significant and negative ($beta = -1.79, 95\%CI[-3.04, -0.69], p = 0.003; Std.beta = -1.79, 95\%CI[-3.04, -0.69]$)
- The effect of REGION short factor [S] is statistically significant and negative ($beta = -2.39, 95\%CI[-3.56, -1.39], p < .001; Std.beta = -2.39, 95\%CI[-3.56, -1.39]$)
- The effect of REGION short factor [NE] is statistically significant and negative ($beta = -2.16, 95\%CI[-3.46, -0.98], p < .001; Std.beta = -2.16, 95\%CI[-3.46, -0.98]$)
- The effect of REGION short factor [NW] is statistically significant and negative ($beta = -2.30, 95\%CI[-3.54, -1.21], p < .001; Std.beta = -2.30, 95\%CI[-3.54, -1.21]$)
- The effect of REGION short factor [NI] is statistically significant and negative ($beta = -2.75, 95\%CI[-4.06, -1.58], p < .001; Std.beta = -2.75, 95\%CI[-4.06, -1.58]$)
- The effect of oac LSMS dummy factor [Low-Skilled, Migrant, and Student Communities] is statistically significant and negative ($beta = -0.38, 95\%CI[-0.76, -6.00e-03], p = 0.047; Std.beta = -0.38, 95\%CI[-0.76, -6.00e-03]$)
- The effect of oac Legacy dummy factor [Legacy Communities] is statistically non-significant and negative ($beta = -0.58, 95\%CI[-1.44, 0.24], p = 0.172; Std.beta = -0.58, 95\%CI[-1.44, 0.24]$)
- The effect of oac Retired dummy factor [Retired Professionals] is statistically non-significant and positive ($beta = 0.32, 95\%CI[-0.18, 0.83], p = 0.221; Std.beta = 0.32, 95\%CI[-0.18, 0.83]$)
- The effect of oac EDSP dummy factor [Ethnically Diverse Suburban Professionals] is statistically significant and positive ($beta = 0.50, 95\%CI[0.02, 1.00], p = 0.044; Std.beta = 0.50, 95\%CI[0.02, 1.00]$)

Standardized parameters were obtained by fitting the model on a standardized version of the dataset. 95% Confidence Intervals (CIs) and p-values were computed using a Wald z-distribution approximation.

Eq. Form	*Dependent variable:*	MDLS (LCA)
C1	−0.241	(0.162)
C2	−0.508***	(0.173)
DE	−0.861***	(0.201)
Single parent family	−0.249**	(0.097)
More than two children	−0.452***	(0.116)
Index of Multiple Deprivation Rank	−0.00002**	(0.00001)
Receives at least one state benefit	−0.245	(0.149)
Chief income earner working	0.343*	(0.180)
Respondent **has** a health issue	−0.512***	(0.173)
Respondent identifies as ethnically non-white	−0.690***	(0.152)
Smaller city or large town	1.150**	(0.546)
Medium town	1.446***	(0.543)
Small town	1.686***	(0.539)
Rural area	1.531***	(0.561)
EE	−1.298**	(0.585)
WM	−1.398**	(0.568)
SE	−1.489***	(0.576)
YH	−1.636***	(0.588)
W	−1.876***	(0.615)
SW	−2.034***	(0.589)
EM	−1.788***	(0.592)
S	−2.388***	(0.543)
NE	−2.156***	(0.626)
NW	−2.295***	(0.586)
NI	−2.749***	(0.625)
Low-Skilled, Migrant, and Student Communities	−0.381**	(0.192)
Legacy Communities	−0.579	(0.424)
Retired Professionals	0.315	(0.258)
Ethnically Diverse Suburban Professionals	0.502**	(0.249)
Constant	0.873***	(0.321)
Observations	1,582	
Log Likelihood	−964.153	
Akaike Inf. Crit.	1,988.306	
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 2.264: Significant regression coefficients for predictors of LCA-based MDLS

	e^B	2.5 %	97.5 %
(Intercept)	2.40	1.28	4.51
C1	0.79	0.57	1.08
C2	0.60	0.43	0.84
DE	0.42	0.28	0.63
Single parent family	0.78	0.64	0.94
More than two children	0.64	0.51	0.80
Index of Multiple Deprivation Rank	1.00	1.00	1.00
Receives at least one state benefit	0.78	0.58	1.05
Chief income earner working	1.41	0.99	2.01
Respondent **has** a health issue	0.60	0.43	0.84
Respondent identifies as ethnically non-white	0.50	0.37	0.67
Smaller city or large town	3.16	1.16	10.23
Medium town	4.25	1.57	13.67
Small town	5.40	2.01	17.28
Rural area	4.62	1.64	15.32
EE	0.27	0.08	0.81
WM	0.25	0.07	0.70
SE	0.23	0.07	0.66
Y&H	0.19	0.06	0.58
W	0.15	0.04	0.48
SW	0.13	0.04	0.39
EM	0.17	0.05	0.50
S	0.09	0.03	0.25
NE	0.12	0.03	0.37
NW	0.10	0.03	0.30
NI	0.06	0.02	0.21
Low-Skilled, Migrant, and Student Communities	0.68	0.47	0.99
Legacy Communities	0.56	0.24	1.27
Retired Professionals	1.37	0.83	2.29
Ethnically Diverse Suburban Professionals	1.65	1.02	2.72

Table 2.265: MDLS Binary GLM confidence intervals

Final binary regression model of LCA MDLS - all significant variables

We fitted a logistic model (estimated using ML) to predict MDLS (LCA) with:

- SEGfactor
- Singleparentdummyfactor
- Twopluschildrendummyfactor
- imd2019RANKnamode
- Benefitsfactor,
- Workingfactor
- Healthlimitationfactor
- Ethnicityfactor
- URBANfactor
- REGIONshortfactor
- oacLSMSdummyfactor
- oacEDSPdummyfactor

The model's intercept, corresponding to SEGfactor = AB, Singleparentdummyfactor = Not single parent, Twopluschildren-dummyfactor = Not more than two children, imd2019RANKnamode = 0, Benefitsfactor = Not on any benefits, Workingfactor = Chief income earner not working, Healthlimitationfactor = Respondent has **no** health issue, Ethnicityfactor

= Respondent identifies as ethnically white (British, Irish, Other), URBANfactor = Large city, REGIONshortfactor = Lon, oacLSMSdummyfactor = Not Low-Skilled, Migrant, and Student Communities and oacEDSPdummyfactor = Not Ethnically Diverse Suburban Professionals, is at $0.85(95\%CI[0.22, 1.48], p = 0.008)$. Within this model:

- The effect of SEG factor [C1] is statistically non-significant and negative ($beta = -0.25, 95\%CI[-0.57, 0.07], p = 0.123; Std.beta = -0.25, 95\%CI[-0.57, 0.07]$)
- The effect of SEG factor [C2] is statistically significant and negative ($beta = -0.52, 95\%CI[-0.86, -0.18], p = 0.003; Std.beta = -0.52, 95\%CI[-0.86, -0.18]$)
- The effect of SEG factor [DE] is statistically significant and negative ($beta = -0.88, 95\%CI[-1.27, -0.49], p < .001; Std.beta = -0.88, 95\%CI[-1.27, -0.49]$)
- The effect of Single parent dummy factor [linear] is statistically significant and negative ($beta = -0.26, 95\%CI[-0.45, -0.07], p = 0.008; Std.beta = -0.26, 95\%CI[-0.45, -0.07]$)
- The effect of Two plus children dummy factor [linear] is statistically significant and negative ($beta = -0.45, 95\% CI[-0.68, -0.22], p < .001; Std.beta = -0.45, 95\%CI[-0.68, -0.22]$)
- The effect of imd2019RANK namode is statistically non-significant and negative ($beta = -1.42e-05, 95\%CI[-3.00e-05, 1.60e-06], p = 0.079; Std.beta = -0.14, 95\%CI[-0.30, 0.02]$)
- The effect of Benefits factor [Receives at least one state benefit] is statistically non-significant and negative ($beta = -0.25, 95\%CI[-0.54, 0.04], p = 0.090; Std.beta = -0.25, 95\%CI[-0.54, 0.04]$)
- The effect of Working factor [Chief income earner working] is statistically non-significant and positive ($beta = 0.35, 95\%CI[-7.54e-03, 0.70], p = 0.055; Std.beta = 0.35, 95\%CI[-7.54e-03, 0.70]$)
- The effect of Health limitation factor [Respondent has a health issue affecting daily activity] is statistically significant and negative ($beta = -0.53, 95\%CI[-0.87, -0.19], p = 0.002; Std.beta = -0.53, 95\%CI[-0.87, -0.19]$)
- The effect of Ethnicity factor [Respondent identifies as ethnically non-white] is statistically significant and negative ($beta = -0.69, 95\%CI[-0.99, -0.40], p < .001; Std.beta = -0.69, 95\%CI[-0.99, -0.40]$)
- The effect of URBAN factor [Smaller city or large town] is statistically significant and positive ($beta = 1.16, 95\% CI[0.15, 2.33], p = 0.035; Std.beta = 1.16, 95\%CI[0.15, 2.33]$)
- The effect of URBAN factor [Medium town] is statistically significant and positive ($beta = 1.45, 95\%CI[0.45, 2.62], p = 0.008; Std.beta = 1.45, 95\%CI[0.45, 2.62]$)
- The effect of URBAN factor [Small town] is statistically significant and positive ($beta = 1.67, 95\%CI[0.69, 2.84], p = 0.002; Std.beta = 1.67, 95\%CI[0.69, 2.84]$)
- The effect of URBAN factor [Rural area] is statistically significant and positive ($beta = 1.53, 95\%CI[0.50, 2.73], p = 0.006; Std.beta = 1.53, 95\%CI[0.50, 2.73]$)
- The effect of REGION short factor [EE] is statistically significant and negative ($beta = -1.32, 95\%CI[-2.56, -0.23], p = 0.025; Std.beta = -1.32, 95\%CI[-2.56, -0.23]$)
- The effect of REGION short factor [WM] is statistically significant and negative ($beta = -1.41, 95\%CI[-2.62, -0.36], p = 0.013; Std.beta = -1.41, 95\%CI[-2.62, -0.36]$)
- The effect of REGION short factor [SE] is statistically significant and negative ($beta = -1.51, 95\%CI[-2.73, -0.44], p = 0.009; Std.beta = -1.51, 95\%CI[-2.73, -0.44]$)
- The effect of REGION short factor [YH] is statistically significant and negative ($beta = -1.63, 95\%CI[-2.88, -0.54], p = 0.006; Std.beta = -1.63, 95\%CI[-2.88, -0.54]$)
- The effect of REGION short factor [W] is statistically significant and negative ($beta = -1.85, 95\%CI[-3.13, -0.70], p = 0.003; Std.beta = -1.85, 95\%CI[-3.13, -0.70]$)
- The effect of REGION short factor [SW] is statistically significant and negative ($beta = -2.04, 95\%CI[-3.28, -0.94], p < .001; Std.beta = -2.04, 95\%CI[-3.28, -0.94]$)
- The effect of REGION short factor [EM] is statistically significant and negative ($beta = -1.77, 95\%CI[-3.02, -0.66], p = 0.003; Std.beta = -1.77, 95\%CI[-3.02, -0.66]$)
- The effect of REGION short factor [S] is statistically significant and negative ($beta = -2.35, 95\%CI[-3.52, -1.36], p < .001; Std.beta = -2.35, 95\%CI[-3.52, -1.36]$)

- The effect of REGION short factor [NE] is statistically significant and negative ($beta = -2.08, 95\%CI[-3.38, -0.91], p < .001; Std.beta = -2.08, 95\%CI[-3.38, -0.91]$)
- The effect of REGION short factor [NW] is statistically significant and negative ($beta = -2.28, 95\%CI[-3.52, -1.19], p < .001; Std.beta = -2.28, 95\%CI[-3.52, -1.19]$)
- The effect of REGION short factor [NI] is statistically significant and negative ($beta = -2.71, 95\%CI[-4.02, -1.54], p < .001; Std.beta = -2.71, 95\%CI[-4.02, -1.54]$)
- The effect of oac LSMS dummy factor [Low-Skilled, Migrant, and Student Communities] is statistically non-significant and negative ($beta = -0.37, 95\%CI[-0.75, 5.11e-04], p = 0.051; Std.beta = -0.37, 95\%CI[-0.75, 5.11e-04]$)
- The effect of oac EDSP dummy factor [Ethnically Diverse Suburban Professionals] is statistically non-significant and positive ($beta = 0.45, 95\%CI[-0.02, 0.94], p = 0.066; Std.beta = 0.45, 95\%CI[-0.02, 0.94]$)

Standardized parameters were obtained by fitting the model on a standardized version of the dataset. 95% Confidence Intervals (CIs) and p-values were computed using a Wald z-distribution approximation.

Eq. Form	*Dependent variable:*	MDLS (LCA)
C1	-0.250	(0.162)
C2	-0.518^{***}	(0.172)
DE	-0.880^{***}	(0.200)
Single parent family	-0.256^{***}	(0.097)
More than two children	-0.448^{***}	(0.116)
Index of Multiple Deprivation Rank	-0.00001^{*}	(0.00001)
Receives at least one state benefit	-0.252^{*}	(0.149)
Chief income earner working	0.345^{*}	(0.180)
Respondent **has** a health issue	-0.527^{***}	(0.172)
Respondent identifies as ethnically non-white	-0.692^{***}	(0.152)
Smaller city or large town	1.156^{**}	(0.547)
Medium town	1.450^{***}	(0.543)
Small town	1.675^{***}	(0.540)
Rural area	1.535^{***}	(0.561)
EE	-1.317^{**}	(0.586)
WM	-1.409^{**}	(0.568)
SE	-1.508^{***}	(0.576)
YH	-1.632^{***}	(0.588)
W	-1.848^{***}	(0.614)
SW	-2.037^{***}	(0.589)
EM	-1.766^{***}	(0.592)
S	-2.351^{***}	(0.543)
NE	-2.080^{***}	(0.623)
NW	-2.279^{***}	(0.586)
NI	-2.714^{***}	(0.626)
Low-Skilled, Migrant, and Student Communities	-0.375^{*}	(0.192)
Ethnically Diverse Suburban Professionals	0.452^{*}	(0.246)
Constant	0.848^{***}	(0.321)
Observations	1,582	
Log Likelihood	-965.961	
Akaike Inf. Crit.	1,987.923	
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 2.266: Significant regression coefficients for predictors of LCA-based MDLS

	e^B	2.5 %	97.5 %
(Intercept)	2.34	1.25	4.40
C1	0.78	0.57	1.07
C2	0.60	0.42	0.83
DE	0.41	0.28	0.61
Single parent family	0.77	0.64	0.94
More than two children	0.64	0.51	0.80
Index of Multiple Deprivation Rank	1.00	1.00	1.00
Receives at least one state benefit	0.78	0.58	1.04
Chief income earner working	1.41	0.99	2.01
Respondent **has** a health issue	0.59	0.42	0.83
Respondent identifies as ethnically non-white	0.50	0.37	0.67
Smaller city or large town	3.18	1.16	10.30
Medium town	4.26	1.57	13.73
Small town	5.34	1.98	17.10
Rural area	4.64	1.65	15.39
EE	0.27	0.08	0.80
WM	0.24	0.07	0.70
SE	0.22	0.07	0.64
Y&H	0.20	0.06	0.58
W	0.16	0.04	0.50
SW	0.13	0.04	0.39
EM	0.17	0.05	0.52
S	0.10	0.03	0.26
NE	0.12	0.03	0.40
NW	0.10	0.03	0.30
NI	0.07	0.02	0.21
Low-Skilled, Migrant, and Student Communities	0.69	0.47	1.00
Ethnically Diverse Suburban Professionals	1.57	0.98	2.57

Table 2.267: MDLS Binary GLM confidence intervals

Chapter 3

Appendix 3

3.1 Data preparation code

```
## sink output to ovearll results file
sink("Initial_Setup_MDLS.txt",
     append = FALSE,
     split = TRUE)

set.seed(1680) # for reproducibility

library("ca")
library("cluster") # for gower similarity and pam
library("corrplot")
library("descr")
library("DescTools")
library("dplyr")
library("effects")
library("factoextra")
library("FactoMineR")
library("flextable")
library("forcats")
library("generalhoslem")
library("ggparallel")
library("ggplot2")
library("ggpubr")
library("gmodels")
library("haven")
library("hexbin")
library("Hmisc")
library("hrbrthemes")
library("huxtable")
library("igraph")
library("jtools")
library("knitr")
library("labelled")
library("lattice")
library("logistf")
library("nnet")
library("officer")
library("OneR")
library("plot3D")
library("plyr")
library("poLCA")
library("pwr")
library("psych")
library("RcmdrMisc")
```

```r
library("RColorBrewer")
library("rcompanion")
library("reshape2")
library("rms")
library("Rtsne") # for t-SNE plot
library("sandwich")
library("scales")
library("scatterplot3d")
library("sjlabelled")
library("stargazer")
library("tidyr")
library("vcdExtra")
library("xtable")
library("ggsci")
library("weights")
library("pals")

##Function for Latex contingency tables
latext.table.function <- function(data_for_table) {
  result <-
    xtable(round(100 * prop.table(table(data_for_table)), digits = 2))
  return(result)
}

# Function to convert results to an MDLS biary factor
create.factor <- function(column) {
  # Converting the column to a factor
  result <- factor(
    column + 1,
    levels = c(1, 2),
    labels = c("Not-MDLS-adequate",
               "MDLS-adequate"),
    ordered = FALSE)
  return(result)
}


##Import processed SPSS file
X2023MDLS_Survey2 <- read_sav("Original-Data/SPSSv2recodenewgeog.sav")


##Set all blank cells in raw geo data to NA
X2023MDLS_Survey2$I1a_Postcode[X2023MDLS_Survey2$I1a_Postcode == ""] <- NA
X2023MDLS_Survey2$postcode[X2023MDLS_Survey2$postcode == ""] <- NA
X2023MDLS_Survey2$pcds[X2023MDLS_Survey2$pcds == ""] <- NA
X2023MDLS_Survey2$pcdss[X2023MDLS_Survey2$pcdss == ""] <- NA
X2023MDLS_Survey2$oa11[X2023MDLS_Survey2$oa11 == ""] <- NA
X2023MDLS_Survey2$lsoa11[X2023MDLS_Survey2$lsoa11 == ""] <- NA
X2023MDLS_Survey2$msoa11[X2023MDLS_Survey2$msoa11 == ""] <- NA
X2023MDLS_Survey2$oa21[X2023MDLS_Survey2$oa21 == ""] <- NA
X2023MDLS_Survey2$lsoa21[X2023MDLS_Survey2$lsoa21 == ""] <- NA
X2023MDLS_Survey2$msoa21[X2023MDLS_Survey2$msoa21 == ""] <- NA
X2023MDLS_Survey2$oac21SG[X2023MDLS_Survey2$oac21SG == ""] <- NA
X2023MDLS_Survey2$oac21G[X2023MDLS_Survey2$oac21G == ""] <- NA
X2023MDLS_Survey2$oac21SBG[X2023MDLS_Survey2$oac21SBG == ""] <- NA
X2023MDLS_Survey2$loac21SG[X2023MDLS_Survey2$loac21SG == ""] <- NA
X2023MDLS_Survey2$loac21G[X2023MDLS_Survey2$loac21G == ""] <- NA
X2023MDLS_Survey2$imd2019RANK[X2023MDLS_Survey2$imd2019RANK == ""] <- NA
X2023MDLS_Survey2$iuc_2018_GRP_CD[X2023MDLS_Survey2$iuc_2018_GRP_CD == ""] <- NA
X2023MDLS_Survey2$iuc_GRP_LBL[X2023MDLS_Survey2$iuc_GRP_LBL == ""] <- NA
X2023MDLS_Survey2$dwe_p45pc[X2023MDLS_Survey2$dwe_p45pc == ""] <- NA
```

```
X2023MDLS_Survey2$dwe_p16pc[X2023MDLS_Survey2$dwe_p16pc == ""] <- NA
X2023MDLS_Survey2$dwe_modbp[X2023MDLS_Survey2$dwe_modbp == ""] <- NA
X2023MDLS_Survey2$dwe_mo20bp[X2023MDLS_Survey2$dwe_mo20bp == ""] <- NA
X2023MDLS_Survey2$dwe_medbp[X2023MDLS_Survey2$dwe_medbp == ""] <- NA
X2023MDLS_Survey2$dwe_mdargb[X2023MDLS_Survey2$dwe_mdargb == ""] <- NA
X2023MDLS_Survey2$hpmd202003[X2023MDLS_Survey2$hpmd202003 == ""] <- NA
X2023MDLS_Survey2$hpmd202103[X2023MDLS_Survey2$hpmd202103 == ""] <- NA
X2023MDLS_Survey2$media_download_speed_Mbitxsec[X2023MDLS_Survey2$media_download
    _speed_Mbitxsec == ""] <- NA
X2023MDLS_Survey2$aipc_supergroup_code[X2023MDLS_Survey2$aipc_supergroup_code ==
    ""] <- NA
X2023MDLS_Survey2$aipc_supergroup_me[X2023MDLS_Survey2$aipc_supergroup_me == ""]
    <- NA
X2023MDLS_Survey2$aipc_group_code[X2023MDLS_Survey2$aipc_group_code == ""] <- NA
X2023MDLS_Survey2$aipc_group_me[X2023MDLS_Survey2$aipc_group_me == ""] <- NA
X2023MDLS_Survey2$ah3ahah[X2023MDLS_Survey2$ah3ahah == ""] <- NA
X2023MDLS_Survey2$ah3ahah_rn[X2023MDLS_Survey2$ah3ahah_rn == ""] <- NA
X2023MDLS_Survey2$ah3ahah_pc[X2023MDLS_Survey2$ah3ahah_pc == ""] <- NA
X2023MDLS_Survey2$epc_inspection_date[X2023MDLS_Survey2$epc_inspection_date == "
    "] <- NA
X2023MDLS_Survey2$epc_band[X2023MDLS_Survey2$epc_band == ""] <- NA
X2023MDLS_Survey2$epc_score[X2023MDLS_Survey2$epc_score == ""] <- NA

##Create working file for set up
X2023MDLS.data <- X2023MDLS_Survey2

##Initial MDLS variables set up

##Clean up child numbers in households
##Replace 7 with NA as some are 7 not NA
X2023MDLS.data$PCOUNT2[X2023MDLS.data$PCOUNT2 == 7] <- NA
X2023MDLS.data$PCOUNT3[X2023MDLS.data$PCOUNT3 == 7] <- NA
X2023MDLS.data$PCOUNT4[X2023MDLS.data$PCOUNT4 == 7] <- NA
X2023MDLS.data$PCOUNT5[X2023MDLS.data$PCOUNT5 == 7] <- NA
##Replace NA with 0
X2023MDLS.data$PCOUNT2[is.na(X2023MDLS.data$PCOUNT2)] <- 0
X2023MDLS.data$PCOUNT3[is.na(X2023MDLS.data$PCOUNT3)] <- 0
X2023MDLS.data$PCOUNT4[is.na(X2023MDLS.data$PCOUNT4)] <- 0
X2023MDLS.data$PCOUNT5[is.na(X2023MDLS.data$PCOUNT5)] <- 0
##Calculate total school and pre-school age children in the home
X2023MDLS.data$Total_school_age_children <-
  X2023MDLS.data$PCOUNT3 + X2023MDLS.data$PCOUNT4
X2023MDLS.data$Total_preschool_age_children <-
  X2023MDLS.data$PCOUNT5

##Clean up device numbers
X2023MDLS.data$Laptops <- X2023MDLS.data$IC2
X2023MDLS.data$Laptops[is.na(X2023MDLS.data$IC2)] <- 0
X2023MDLS.data$Tablets <- X2023MDLS.data$IC3
X2023MDLS.data$Tablets[is.na(X2023MDLS.data$IC3)] <- 0

##Total large scree devices
X2023MDLS.data$Large_screen_devices <- 0
##Have desktop PC
X2023MDLS.data$Large_screen_devices <- X2023MDLS.data$C1A
##Add laptops and tablets
X2023MDLS.data$Large_screen_devices <-
  X2023MDLS.data$Large_screen_devices + X2023MDLS.data$Laptops + X2023MDLS.data$
      Tablets

##Total devices needed
```

```
X2023MDLS.data$Large_screen_devices_needed <- 1
## IGNORE OTHER ADULTS X2023MDLS.data$Large_screen_devices_needed <- X2023MDLS.
    data$Large_screen_devices_needed + X2023MDLS.data$PCOUNT2
X2023MDLS.data$Large_screen_devices_needed[X2023MDLS.data$Total_school_age_
    children > 1] <-
  X2023MDLS.data$Total_school_age_children[X2023MDLS.data$Total_school_age_
      children > 1]

X2023MDLS.data$Large_screen_devices_needed[X2023MDLS.data$Large_screen_devices_
    needed > 2] <-
  3
##Meet MDLS for large screen devices
X2023MDLS.data$Large_screen_devices_MDLS <- 0
X2023MDLS.data$Large_screen_devices_MDLS[(X2023MDLS.data$Large_screen_devices -
    X2023MDLS.data$Large_screen_devices_needed) >= 0] <-
  1

##Smartphones
X2023MDLS.data$Smartphones_MDLS <- 0
X2023MDLS.data$Smartphones_MDLS[X2023MDLS.data$C5_01 == 1] <- 1
X2023MDLS.data$Smartphones_MDLS[(!is.na(X2023MDLS.data$C5_02)) &
                                 (X2023MDLS.data$C5_02 != 1) &
                                 (X2023MDLS.data$Smartphones_MDLS == 1)] <-
  0
X2023MDLS.data$Smartphones_MDLS[(!is.na(X2023MDLS.data$C5_08)) &
                                 (X2023MDLS.data$C5_08 != 1) &
                                 (X2023MDLS.data$Smartphones_MDLS == 1)] <-
  0
X2023MDLS.data$Smartphones_MDLS[(!is.na(X2023MDLS.data$C5_09)) &
                                 (X2023MDLS.data$C5_09 != 1) &
                                 (X2023MDLS.data$Smartphones_MDLS == 1)] <-
  0
X2023MDLS.data$Smartphones_MDLS[(!is.na(X2023MDLS.data$C5_10)) &
                                 (X2023MDLS.data$C5_10 != 1) &
                                 (X2023MDLS.data$Smartphones_MDLS == 1)] <-
  0
X2023MDLS.data$Smartphones_MDLS[(!is.na(X2023MDLS.data$C5_11)) &
                                 (X2023MDLS.data$C5_11 != 1) &
                                 (X2023MDLS.data$Smartphones_MDLS == 1)] <-
  0
X2023MDLS.data$Smartphones_MDLS[(!is.na(X2023MDLS.data$C5_12)) &
                                 (X2023MDLS.data$C5_12 != 1) &
                                 (X2023MDLS.data$Smartphones_MDLS == 1)] <-
  0

##Datapackage
X2023MDLS.data$Data_package_MDLS <- 1
X2023MDLS.data$Data_package_MDLS[X2023MDLS.data$C9A == 1] <- 0
X2023MDLS.data$Data_package_MDLS[X2023MDLS.data$C9B == 1] <- 0
X2023MDLS.data$Data_package_MDLS[X2023MDLS.data$C9H == 1] <- 0
X2023MDLS.data$Data_package_MDLS[X2023MDLS.data$C9I == 1] <- 0
X2023MDLS.data$Data_package_MDLS[X2023MDLS.data$C9J == 1] <- 0
X2023MDLS.data$Data_package_MDLS[X2023MDLS.data$C9K == 1] <- 0
X2023MDLS.data$Data_package_MDLS[X2023MDLS.data$C9L == 1] <- 0

##SmartTV
X2023MDLS.data$Smart_TV__MDLS <- 0
X2023MDLS.data$Smart_TV__MDLS[X2023MDLS.data$C1E == 1] <- 1
X2023MDLS.data$Smart_TV__MDLS[X2023MDLS.data$C11 == 1] <- 1

##Games console
```

```
X2023MDLS.data$Games_console_MDLS <- 0
X2023MDLS.data$Games_console_MDLS[X2023MDLS.data$C1D == 1] <- 1
X2023MDLS.data$Games_console_MDLS[X2023MDLS.data$C1A == 1] <- 1
X2023MDLS.data$Games_console_MDLS[X2023MDLS.data$Laptops > 0] <- 1
X2023MDLS.data$Games_console_MDLS[(X2023MDLS.data$Total_preschool_age_children >
    0) &
                                  (X2023MDLS.data$Total_school_age_children ==
                                      0) &
                                  (X2023MDLS.data$Tablets > 0)] <-
  1
##Smart speaker
X2023MDLS.data$Smart_speaker_MDLS <- 0
X2023MDLS.data$Smart_speaker_MDLS[X2023MDLS.data$C4 == 1] <- 1

##TV service
X2023MDLS.data$TV_service_MDLS <- 0
X2023MDLS.data$TV_service_MDLS[X2023MDLS.data$C11 == 1] <- 1

##Games service
X2023MDLS.data$Games_service_MDLS <- 0
X2023MDLS.data$Games_service_MDLS[X2023MDLS.data$C10 == 1] <- 1

##Broadband
X2023MDLS.data$Broadband_MDLS <- 0
X2023MDLS.data$Broadband_MDLS[X2023MDLS.data$C13A == 1] <- 1

##Internet speed
X2023MDLS.data$Internet_speed_MDLS <- 0
X2023MDLS.data$Internet_speed_MDLS[X2023MDLS.data$C14 == 3] <- 1
X2023MDLS.data$Internet_speed_MDLS[X2023MDLS.data$C14 == 4] <- 1
X2023MDLS.data$Internet_speed_MDLS[X2023MDLS.data$C14 == 5] <- 1

##Create factor versions with lowest value 1 for LCA and MCA analyses
X2023MDLS.data$Large_screen_devices_MDLS_factor <- factor(
  X2023MDLS.data$Large_screen_devices_MDLS + 1,
  levels = c(1, 2),
  labels = c("Not adequate LSD", "Adequate LSD"),
  ordered = FALSE
)

X2023MDLS.data$Smartphones_MDLS_factor <- factor(
  X2023MDLS.data$Smartphones_MDLS + 1,
  levels = c(1, 2),
  labels = c("Not adequate SM", "Adequate SM"),
  ordered = FALSE
)

X2023MDLS.data$Data_package_MDLS_factor <- factor(
  X2023MDLS.data$Data_package_MDLS + 1,
  levels = c(1, 2),
  labels = c("Not adequate data", "Adequate data"),
  ordered = FALSE
)

X2023MDLS.data$Smart_TV__MDLS_factor <- factor(
  X2023MDLS.data$Smart_TV__MDLS + 1,
  levels = c(1, 2),
  labels = c("Not adequate STV", "Adequate STV"),
  ordered = FALSE
)
```

```
X2023MDLS.data$TV_service_MDLS_factor <- factor(
  X2023MDLS.data$TV_service_MDLS + 1,
  levels = c(1, 2),
  labels = c("Not adequate TVS", "Adequate TVS"),
  ordered = FALSE
)

X2023MDLS.data$Broadband_MDLS_factor <- factor(
  X2023MDLS.data$Broadband_MDLS + 1,
  levels = c(1, 2),
  labels = c("Not adequate BB", "Adequate BB"),
  ordered = FALSE
)

X2023MDLS.data$Internet_speed_MDLS_factor <- factor(
  X2023MDLS.data$Internet_speed_MDLS + 1,
  levels = c(1, 2),
  labels = c("Not adequate BB speed", "Adequate BB speed"),
  ordered = FALSE
)
PercTable(X2023MDLS.data$Internet_speed_MDLS_factor)
latext.table.function(X2023MDLS.data$Internet_speed_MDLS_factor)

X2023MDLS.data$Games_console_MDLS_factor <- factor(
  X2023MDLS.data$Games_console_MDLS + 1,
  levels = c(1, 2),
  labels = c("Not adequate GC", "Adequate GC"),
  ordered = FALSE
)

X2023MDLS.data$Games_service_MDLS_factor <- factor(
  X2023MDLS.data$Games_service_MDLS + 1,
  levels = c(1, 2),
  labels = c("Not adequate GS", "Adequate GS"),
  ordered = FALSE
)

X2023MDLS.data$Smart_speaker_MDLS_factor <- factor(
  X2023MDLS.data$Smart_speaker_MDLS + 1,
  levels = c(1, 2),
  labels = c("Not adequate SS", "Adequate sS"),
  ordered = FALSE
)

##MDLS equipment as a score
X2023MDLS.data$MDLS_total_noSSGS <-
  X2023MDLS.data$Large_screen_devices_MDLS +
  X2023MDLS.data$Smartphones_MDLS +
  X2023MDLS.data$Data_package_MDLS +
  X2023MDLS.data$Smart_TV__MDLS +
  X2023MDLS.data$TV_service_MDLS +
  X2023MDLS.data$Broadband_MDLS +
  X2023MDLS.data$Internet_speed_MDLS +
  X2023MDLS.data$Games_console_MDLS

X2023MDLS.data$MDLS_total <-
  X2023MDLS.data$MDLS_total_noSSGS +
  X2023MDLS.data$Games_service_MDLS +
  X2023MDLS.data$Smart_speaker_MDLS

##MDLS as a binary result with tables as each item checked
```

```
X2023MDLS.data$MDLS <- 1
X2023MDLS.data$MDLS[X2023MDLS.data$Smartphones_MDLS == 0] <- 0
X2023MDLS.data$MDLS_SP <- X2023MDLS.data$MDLS
X2023MDLS.data$MDLS_SP_factor <- create.factor(X2023MDLS.data$MDLS_SP)
X2023MDLS.data$MDLS[X2023MDLS.data$Data_package_MDLS == 0] <- 0
X2023MDLS.data$MDLS_SP_DP <- X2023MDLS.data$MDLS
X2023MDLS.data$MDLS_SP_DP_factor <- create.factor(X2023MDLS.data$MDLS_SP_DP)
X2023MDLS.data$MDLS[X2023MDLS.data$Broadband_MDLS == 0] <- 0
X2023MDLS.data$MDLS_SP_DP_BB <- X2023MDLS.data$MDLS
X2023MDLS.data$MDLS_SP_DP_BB_factor <- create.factor(X2023MDLS.data$MDLS_SP_DP_
    BB)
X2023MDLS.data$MDLS[X2023MDLS.data$TV_service_MDLS == 0] <- 0
X2023MDLS.data$MDLS_SP_DP_BB_TV <- X2023MDLS.data$MDLS
X2023MDLS.data$MDLS_SP_DP_BB_TV_factor <- create.factor(X2023MDLS.data$MDLS_SP_
    DP_BB_TV)
X2023MDLS.data$MDLS[X2023MDLS.data$Internet_speed_MDLS == 0] <- 0
X2023MDLS.data$MDLS_SP_DP_BB_TV_IS <- X2023MDLS.data$MDLS
X2023MDLS.data$MDLS_SP_DP_BB_TV_IS_factor <- create.factor(X2023MDLS.data$MDLS_
    SP_DP_BB_TV_IS)
X2023MDLS.data$MDLS[X2023MDLS.data$Large_screen_devices_MDLS == 0] <-
  0
X2023MDLS.data$MDLS_SP_DP_BB_TV_IS_LS <- X2023MDLS.data$MDLS
X2023MDLS.data$MDLS_SP_DP_BB_TV_IS_LS_factor <- create.factor(X2023MDLS.data$
    MDLS_SP_DP_BB_TV_IS_LS)
X2023MDLS.data$MDLS[X2023MDLS.data$Smart_TV__MDLS == 0] <- 0
X2023MDLS.data$MDLS_SP_DP_BB_TV_IS_LS_ST <- X2023MDLS.data$MDLS
X2023MDLS.data$MDLS_SP_DP_BB_TV_IS_LS_ST_factor <- create.factor(X2023MDLS.data$
    MDLS_SP_DP_BB_TV_IS_LS_ST)
X2023MDLS.data$MDLS[X2023MDLS.data$Games_console_MDLS == 0] <- 0
X2023MDLS.data$MDLS_SP_DP_BB_TV_IS_LS_ST_GC <- X2023MDLS.data$MDLS
X2023MDLS.data$MDLS_SP_DP_BB_TV_IS_LS_ST_GC_factor <- create.factor(X2023MDLS.
    data$MDLS_SP_DP_BB_TV_IS_LS_ST_GC)
X2023MDLS.data$MDLS2 <- X2023MDLS.data$MDLS
X2023MDLS.data$MDLS[X2023MDLS.data$Games_service_MDLS == 0] <- 0
X2023MDLS.data$MDLS_SP_DP_BB_TV_IS_LS_ST_GC_GS <-
  X2023MDLS.data$MDLS
X2023MDLS.data$MDLS_SP_DP_BB_TV_IS_LS_ST_GC_GS_factor <- create.factor(X2023MDLS
    .data$MDLS_SP_DP_BB_TV_IS_LS_ST_GC_GS)
X2023MDLS.data$MDLS[X2023MDLS.data$Smart_speaker_MDLS == 0] <- 0
X2023MDLS.data$MDLS_SP_DP_BB_TV_IS_LS_ST_GC_GS_SS <-
  X2023MDLS.data$MDLS
X2023MDLS.data$MDLS_SP_DP_BB_TV_IS_LS_ST_GC_GS_SS_factor <- create.factor(
    X2023MDLS.data$MDLS_SP_DP_BB_TV_IS_LS_ST_GC_GS_SS)

X2023MDLS.data$MDLS2_factor <- factor(
  X2023MDLS.data$MDLS2 + 1,
  levels = c(1, 2),
  labels = c("Not-MDLS-adequate", "MDLS-adequate"),
  ordered = FALSE
)

X2023MDLS.data$B1_08_age <- NA
X2023MDLS.data$B1_09_age <- NA
X2023MDLS.data$B1_10_age <- NA
X2023MDLS.data$B1_11_age <- NA
X2023MDLS.data$B1_12_age <- NA
X2023MDLS.data$B1_13_age <- NA
X2023MDLS.data$B1_14_age <- NA
X2023MDLS.data$B1_15_age <- NA
X2023MDLS.data$B1_16_age <- NA
X2023MDLS.data$B1_17_age <- NA
```

```
X2023MDLS.data$CL2_18_age <- NA
X2023MDLS.data$CL2_19_age <- NA
X2023MDLS.data$CL2_20_age <- NA
X2023MDLS.data$CL2_21_age <- NA
X2023MDLS.data$CL2_22_age <- NA

X2023MDLS.data$B1_08_level <- NA
X2023MDLS.data$B1_09_level <- NA
X2023MDLS.data$B1_10_level <- NA
X2023MDLS.data$B1_11_level <- NA
X2023MDLS.data$B1_12_level <- NA
X2023MDLS.data$B1_13_level <- NA
X2023MDLS.data$B1_14_level <- NA
X2023MDLS.data$B1_15_level <- NA
X2023MDLS.data$B1_16_level <- NA
X2023MDLS.data$B1_17_level <- NA
X2023MDLS.data$CL2_18_level <- NA
X2023MDLS.data$CL2_19_level <- NA
X2023MDLS.data$CL2_20_level <- NA
X2023MDLS.data$CL2_21_level <- NA
X2023MDLS.data$CL2_22_level <- NA

##Create childrens age variables by converting measure into simple age number
    and then allocating children to specific groups by UK Key stage
X2023MDLS.data$Child_1_age <-
  labelled::remove_labels(X2023MDLS.data$S4_1) - 1
##Remove 'no other children coding'
X2023MDLS.data$Child_2_age <-
  labelled::remove_labels(X2023MDLS.data$S4_2) - 1
X2023MDLS.data$Child_2_age[X2023MDLS.data$Child_2_age > 17] <- NA
X2023MDLS.data$Child_3_age <-
  labelled::remove_labels(X2023MDLS.data$S4_3) - 1
X2023MDLS.data$Child_3_age[X2023MDLS.data$Child_3_age > 17] <- NA
X2023MDLS.data$Child_4_age <-
  labelled::remove_labels(X2023MDLS.data$S4_4) - 1
X2023MDLS.data$Child_4_age[X2023MDLS.data$Child_4_age > 17] <- NA
X2023MDLS.data$Child_5_age <-
  labelled::remove_labels(X2023MDLS.data$S4_5) - 1
X2023MDLS.data$Child_5_age[X2023MDLS.data$Child_5_age > 17] <- NA

allocate.ages.function <-
  function(n, school_group, school_type, ages, df) {
    ##Loop through the variables for school level skills
    for (item in school_group) {
      ##Create output list for results return
      output <- list()
      print(school_type)
      ##Create a variable storing the name of the target variable for child age
      child_age <- paste0(item, "_age")
      ##Create a variable storing the name of the target variable for child
          level
      school_level <- paste0(item, "_level")
      ##Print for debugging
      print(child_age)
      ##Create a varibale that holds a value we can check to see if the child
      ##is in the row-column locaiton or not. Use BX for SS and PS, use CL2 for
          PRS
      if (substr(item, 1, 2) == "CL") {
        child_col <- item
      } else
      {
```

```
        child_col <- paste0(item, "_1")
      }
      ##Print for debugging
      print(child_col)
      ##Loop through all rows in df
      for (i in 1:nrow(df)) {
        ##Possibly unneccessay check we have not gone past 5 child max
        if (n[i] < 6) {
          ##Use child allocated score to select right age column for icase if
              valid
          current_child_age <- paste0("Child_", n[i], "_age")
          ##Check if valid case at cell
          if (!is.na(df[i, child_col])) {
            ##Allocate age
            df[i, child_age] <- df[i, current_child_age]
            ##Increase child allocated score
            n[i] <- n[i] + 1
            ##Use age and school type to allocate to Key Stage
            if (school_type == "SS") {
              print("Inside SS if")
              if (df[i, child_age] > 13) {
                df[i, school_level] <- 4
              } else {
                df[i, school_level] <- 3
              }
              print(df[i, school_level])
            }
            if (school_type == "PS") {
              if (df[i, child_age] > 6) {
                df[i, school_level] <- 2
              } else {
                df[i, school_level] <- 1
              }
            }
            if (school_type == "PRS") {
              df[i, school_level] <- 0
            }
          }
        }
      }
    }
    output$n <- n
    output$df <- df
    return(output)
  }

ages.check.function <- function(df, vars) {
  for (item in vars) {
    item <- paste0(item, "_age")
    print(table(df[[item]]))
  }
}
X2023MDLS.data$Child_age_allocation <- 1

ages <-
  c("Child_1_age",
    "Child_2_age",
    "Child_3_age",
    "Child_4_age",
    "Child_5_age")
```

```
secondary <- c("B1_08",
               "B1_09",
               "B1_10",
               "B1_11",
               "B1_12")

results <-
  allocate.ages.function(X2023MDLS.data$Child_age_allocation,
                         secondary,
                         "SS",
                         ages,
                         X2023MDLS.data)
ages.check.function(results$df, secondary)

primary <- c("B1_13",
             "B1_14",
             "B1_15",
             "B1_16",
             "B1_17")

results <-
  allocate.ages.function(results$n, primary, "PS", ages, results$df)
ages.check.function(results$df, primary)

preschool <- c("CL2_18",
               "CL2_19",
               "CL2_20",
               "CL2_21",
               "CL2_22")

results <-
  allocate.ages.function(results$n, preschool, "PRS", ages, results$df)
ages.check.function(results$df, preschool)

X2023MDLS.data <- results$df

##Functional skills
##Respondent functional skills as a binary
X2023MDLS.data$Respondent_functional <- 1
X2023MDLS.data$Respondent_functional[X2023MDLS.data$B1_01_1 > 2] <-
  0
X2023MDLS.data$Respondent_functional[X2023MDLS.data$B1_01_2 > 2] <-
  0
X2023MDLS.data$Respondent_functional[X2023MDLS.data$B1_01_3 > 2] <-
  0
X2023MDLS.data$Respondent_functional[X2023MDLS.data$B1_01_4 > 2] <-
  0
X2023MDLS.data$Respondent_functional[X2023MDLS.data$B1_01_5 > 2] <-
  0
X2023MDLS.data$Respondent_functional[X2023MDLS.data$B1_01_6 > 2] <-
  0

##Other parent functional skills
X2023MDLS.data$Other_parent_functional <- NA
X2023MDLS.data$Other_parent_functional[!is.na(X2023MDLS.data$B1_02_1)] <-
  1
X2023MDLS.data$Other_parent_functional[X2023MDLS.data$B1_02_1 > 2] <-
  0
X2023MDLS.data$Other_parent_functional[X2023MDLS.data$B1_02_2 > 2] <-
  0
X2023MDLS.data$Other_parent_functional[X2023MDLS.data$B1_02_3 > 2] <-
```

```
  0
X2023MDLS.data$Other_parent_functional[X2023MDLS.data$B1_02_4 > 2] <-
  0
X2023MDLS.data$Other_parent_functional[X2023MDLS.data$B1_02_5 > 2] <-
  0
X2023MDLS.data$Other_parent_functional[X2023MDLS.data$B1_02_6 > 2] <-
  0

##Secondary school children
##Secondary school child 1
X2023MDLS.data$SS_child_1_functional <- NA
X2023MDLS.data$SS_child_1_functional[!is.na(X2023MDLS.data$B1_08_1)] <-
  1
X2023MDLS.data$SS_child_1_functional[X2023MDLS.data$B1_08_1 > 2] <-
  0
X2023MDLS.data$SS_child_1_functional[X2023MDLS.data$B1_08_2 > 2] <-
  0
X2023MDLS.data$SS_child_1_functional[(X2023MDLS.data$B1_08_2 > 2) &
                                     (X2023MDLS.data$B1_08_level == 4)] <-
  0
X2023MDLS.data$SS_child_1_functional[(X2023MDLS.data$B1_08_4 > 2) &
                                     (X2023MDLS.data$B1_08_level == 4)] <-
  0
X2023MDLS.data$SS_child_1_functional[X2023MDLS.data$B1_08_5 > 2] <-
  0

##Secondary school child 2
X2023MDLS.data$SS_child_2_functional <- NA
X2023MDLS.data$SS_child_2_functional[!is.na(X2023MDLS.data$B1_09_1)] <-
  1
X2023MDLS.data$SS_child_2_functional[X2023MDLS.data$B1_09_1 > 2] <-
  0
X2023MDLS.data$SS_child_2_functional[X2023MDLS.data$B1_09_2 > 2] <-
  0
X2023MDLS.data$SS_child_1_functional[(X2023MDLS.data$B1_09_2 > 2) &
                                     (X2023MDLS.data$B1_09_level == 4)] <-
  0
X2023MDLS.data$SS_child_1_functional[(X2023MDLS.data$B1_09_4 > 2) &
                                     (X2023MDLS.data$B1_09_level == 4)] <-
  0
X2023MDLS.data$SS_child_1_functional[X2023MDLS.data$B1_09_5 > 2] <-
  0

##Secondary school child 3
X2023MDLS.data$SS_child_3_functional <- NA
X2023MDLS.data$SS_child_3_functional[!is.na(X2023MDLS.data$B1_10_1)] <-
  1
X2023MDLS.data$SS_child_3_functional[X2023MDLS.data$B1_10_1 > 2] <-
  0
X2023MDLS.data$SS_child_3_functional[X2023MDLS.data$B1_10_2 > 2] <-
  0
X2023MDLS.data$SS_child_1_functional[(X2023MDLS.data$B1_10_2 > 2) &
                                     (X2023MDLS.data$B1_10_level == 4)] <-
  0
X2023MDLS.data$SS_child_1_functional[(X2023MDLS.data$B1_10_4 > 2) &
                                     (X2023MDLS.data$B1_10_level == 4)] <-
  0
X2023MDLS.data$SS_child_1_functional[X2023MDLS.data$B1_10_5 > 2] <-
  0
```

```
##Secondary school child 4
X2023MDLS.data$SS_child_4_functional <- NA
X2023MDLS.data$SS_child_4_functional[!is.na(X2023MDLS.data$B1_11_1)] <-
  1
X2023MDLS.data$SS_child_4_functional[X2023MDLS.data$B1_11_1 > 2] <-
  0
X2023MDLS.data$SS_child_4_functional[X2023MDLS.data$B1_11_2 > 2] <-
  0
X2023MDLS.data$SS_child_1_functional[(X2023MDLS.data$B1_11_2 > 2) &
                                      (X2023MDLS.data$B1_11_level == 4)] <-
  0
X2023MDLS.data$SS_child_1_functional[(X2023MDLS.data$B1_11_4 > 2) &
                                      (X2023MDLS.data$B1_11_level == 4)] <-
  0
X2023MDLS.data$SS_child_1_functional[X2023MDLS.data$B1_11_5 > 2] <-
  0

##Secondary school child 5
X2023MDLS.data$SS_child_5_functional <- NA
X2023MDLS.data$SS_child_5_functional[!is.na(X2023MDLS.data$B1_12_1)] <-
  1
X2023MDLS.data$SS_child_5_functional[X2023MDLS.data$B1_12_1 > 2] <-
  0
X2023MDLS.data$SS_child_5_functional[X2023MDLS.data$B1_12_2 > 2] <-
  0
X2023MDLS.data$SS_child_1_functional[(X2023MDLS.data$B1_12_2 > 2) &
                                      (X2023MDLS.data$B1_12_level == 4)] <-
  0
X2023MDLS.data$SS_child_1_functional[(X2023MDLS.data$B1_12_4 > 2) &
                                      (X2023MDLS.data$B1_12_level == 4)] <-
  0
X2023MDLS.data$SS_child_1_functional[X2023MDLS.data$B1_12_5 > 2] <-
  0

##Primary school children - only MDLS relevant items
##Primary school child 1
X2023MDLS.data$PS_child_1_functional <- NA
X2023MDLS.data$PS_child_1_functional[!is.na(X2023MDLS.data$B1_13_1)] <-
  1
X2023MDLS.data$PS_child_1_functional[(X2023MDLS.data$B1_13_8 > 2)]  <-
  0
X2023MDLS.data$PS_child_1_functional[(X2023MDLS.data$B1_13_1 > 2) &
                                      (X2023MDLS.data$B1_13_level == 2)]  <-
  0
X2023MDLS.data$PS_child_1_functional[(X2023MDLS.data$B1_13_2 > 2) &
                                      (X2023MDLS.data$B1_13_level == 2)]  <-
  0
X2023MDLS.data$PS_child_1_functional[(X2023MDLS.data$B1_13_7 > 2) &
                                      (X2023MDLS.data$B1_13_level == 2)]  <-
  0


##Primary school child 2
X2023MDLS.data$PS_child_2_functional <- NA
X2023MDLS.data$PS_child_2_functional[!is.na(X2023MDLS.data$B1_14_1)] <-
  1
X2023MDLS.data$PS_child_2_functional[(X2023MDLS.data$B1_14_8 > 2)]  <-
  0

X2023MDLS.data$PS_child_2_functional[(X2023MDLS.data$B1_14_1 > 2) &
                                      (X2023MDLS.data$B1_14_level == 2)]  <-
```

```
  0
X2023MDLS.data$PS_child_2_functional[(X2023MDLS.data$B1_14_2 > 2) &
                                      (X2023MDLS.data$B1_14_level == 2)] <-
  0
X2023MDLS.data$PS_child_2_functional[(X2023MDLS.data$B1_14_7 > 2) &
                                      (X2023MDLS.data$B1_14_level == 2)] <-
  0

##Primary school child 3
X2023MDLS.data$PS_child_3_functional <- NA
X2023MDLS.data$PS_child_3_functional[!is.na(X2023MDLS.data$B1_15_1)] <-
  1
X2023MDLS.data$PS_child_3_functional[(X2023MDLS.data$B1_15_8 > 2)] <-
  0
X2023MDLS.data$PS_child_3_functional[(X2023MDLS.data$B1_15_1 > 2) &
                                      (X2023MDLS.data$B1_14_level == 2)] <-
  0
X2023MDLS.data$PS_child_3_functional[(X2023MDLS.data$B1_15_2 > 2) &
                                      (X2023MDLS.data$B1_15_level == 2)] <-
  0
X2023MDLS.data$PS_child_3_functional[(X2023MDLS.data$B1_15_7 > 2) &
                                      (X2023MDLS.data$B1_15_level == 2)] <-
  0

##Primary school child 4
X2023MDLS.data$PS_child_4_functional <- NA
X2023MDLS.data$PS_child_4_functional[!is.na(X2023MDLS.data$B1_16_1)] <-
  1
X2023MDLS.data$PS_child_4_functional[(X2023MDLS.data$B1_16_8 > 2)] <-
  0
X2023MDLS.data$PS_child_4_functional[(X2023MDLS.data$B1_16_1 > 2) &
                                      (X2023MDLS.data$B1_16_level == 2)] <-
  0
X2023MDLS.data$PS_child_4_functional[(X2023MDLS.data$B1_16_2 > 2) &
                                      (X2023MDLS.data$B1_16_level == 2)] <-
  0
X2023MDLS.data$PS_child_4_functional[(X2023MDLS.data$B1_16_7 > 2) &
                                      (X2023MDLS.data$B1_16_level == 2)] <-
  0


##Primary school child 5
X2023MDLS.data$PS_child_5_functional <- NA
X2023MDLS.data$PS_child_5_functional[!is.na(X2023MDLS.data$B1_17_1)] <-
  1
X2023MDLS.data$PS_child_5_functional[(X2023MDLS.data$B1_17_8 > 2)] <-
  0
X2023MDLS.data$PS_child_5_functional[(X2023MDLS.data$B1_17_1 > 2) &
                                      (X2023MDLS.data$B1_17_level == 2)] <-
  0
X2023MDLS.data$PS_child_5_functional[(X2023MDLS.data$B1_17_2 > 2) &
                                      (X2023MDLS.data$B1_17_level == 2)] <-
  0
X2023MDLS.data$PS_child_5_functional[(X2023MDLS.data$B1_17_7 > 2) &
                                      (X2023MDLS.data$B1_17_level == 2)] <-
  0

##Create factor versions with lowest value 1 for LCA and MCA analyses
X2023MDLS.data$Respondent_functional_factor <- factor(
  X2023MDLS.data$Respondent_functional + 1,
  levels = c(1, 2),
```

```
  labels = c("Not adequate Functional", "Adequate Functional"),
  ordered = FALSE
)

X2023MDLS.data$Other_parent_functional_factor <- factor(
  X2023MDLS.data$Other_parent_functional + 1,
  levels = c(1, 2),
  labels = c("Not adequate Functional", "Adequate Functional"),
  ordered = FALSE
)

X2023MDLS.data$SS_child_1_functional_factor <- factor(
  X2023MDLS.data$SS_child_1_functional + 1,
  levels = c(1, 2),
  labels = c("Not adequate Functional", "Adequate Functional"),
  ordered = FALSE
)

X2023MDLS.data$SS_child_2_functional_factor <- factor(
  X2023MDLS.data$SS_child_2_functional + 1,
  levels = c(1, 2),
  labels = c("Not adequate Functional", "Adequate Functional"),
  ordered = FALSE
)

X2023MDLS.data$SS_child_3_functional_factor <- factor(
  X2023MDLS.data$SS_child_3_functional + 1,
  levels = c(1, 2),
  labels = c("Not adequate Functional", "Adequate Functional"),
  ordered = FALSE
)

X2023MDLS.data$SS_child_4_functional_factor <- factor(
  X2023MDLS.data$SS_child_4_functional + 1,
  levels = c(1, 2),
  labels = c("Not adequate Functional", "Adequate Functional"),
  ordered = FALSE
)

X2023MDLS.data$SS_child_5_functional_factor <- factor(
  X2023MDLS.data$SS_child_5_functional + 1,
  levels = c(1, 2),
  labels = c("Not adequate Functional", "Adequate Functional"),
  ordered = FALSE
)

X2023MDLS.data$PS_child_1_functional_factor <- factor(
  X2023MDLS.data$PS_child_1_functional + 1,
  levels = c(1, 2),
  labels = c("Not adequate Functional", "Adequate Functional"),
  ordered = FALSE
)

X2023MDLS.data$PS_child_2_functional_factor <- factor(
  X2023MDLS.data$PS_child_2_functional + 1,
  levels = c(1, 2),
  labels = c("Not adequate Functional", "Adequate Functional"),
  ordered = FALSE
)

X2023MDLS.data$PS_child_3_functional_factor <- factor(
```

```
  X2023MDLS.data$PS_child_3_functional + 1,
  levels = c(1, 2),
  labels = c("Not-adequate-Functional", "Adequate-Functional"),
  ordered = FALSE
)

X2023MDLS.data$PS_child_4_functional_factor <- factor(
  X2023MDLS.data$PS_child_4_functional + 1,
  levels = c(1, 2),
  labels = c("Not-adequate-Functional", "Adequate-Functional"),
  ordered = FALSE
)

X2023MDLS.data$PS_child_5_functional_factor <- factor(
  X2023MDLS.data$PS_child_5_functional + 1,
  levels = c(1, 2),
  labels = c("Not-adequate-Functional", "Adequate-Functional"),
  ordered = FALSE
)

##Create functional skills binary varibales
##Overall household functional skills
X2023MDLS.data$Functional_skills <- 1
X2023MDLS.data$Functional_skills[X2023MDLS.data$Respondent_functional != 1] <-
  0
X2023MDLS.data$Functional_skills[(!is.na(X2023MDLS.data$Other_parent_functional)
    ) &
                                  (X2023MDLS.data$Other_parent_functional != 1)
                                     ] <-
  0
X2023MDLS.data$Functional_skills[(!is.na(X2023MDLS.data$SS_child_1_functional))
    &
                                  (X2023MDLS.data$SS_child_1_functional != 1)]
                                    <-
  0
X2023MDLS.data$Functional_skills[(!is.na(X2023MDLS.data$SS_child_2_functional))
    &
                                  (X2023MDLS.data$SS_child_2_functional != 1)]
                                    <-
  0
X2023MDLS.data$Functional_skills[(!is.na(X2023MDLS.data$SS_child_3_functional))
    &
                                  (X2023MDLS.data$SS_child_3_functional != 1)]
                                    <-
  0
X2023MDLS.data$Functional_skills[(!is.na(X2023MDLS.data$SS_child_4_functional))
    &
                                  (X2023MDLS.data$SS_child_4_functional != 1)]
                                    <-
  0
X2023MDLS.data$Functional_skills[(!is.na(X2023MDLS.data$SS_child_5_functional))
    &
                                  (X2023MDLS.data$SS_child_5_functional != 1)]
                                    <-
  0
X2023MDLS.data$Functional_skills[(!is.na(X2023MDLS.data$PS_child_1_functional))
    &
                                  (X2023MDLS.data$PS_child_1_functional != 1)]
                                    <-
  0
X2023MDLS.data$Functional_skills[(!is.na(X2023MDLS.data$PS_child_2_functional))
```

```
&
                                        (X2023MDLS.data$PS_child_2_functional != 1)]
                                            <-
 0
X2023MDLS.data$Functional_skills[(!is.na(X2023MDLS.data$PS_child_3_functional))
   &
                                        (X2023MDLS.data$PS_child_3_functional != 1)]
                                            <-
 0
X2023MDLS.data$Functional_skills[(!is.na(X2023MDLS.data$PS_child_4_functional))
   &
                                        (X2023MDLS.data$PS_child_4_functional != 1)]
                                            <-
 0
X2023MDLS.data$Functional_skills[(!is.na(X2023MDLS.data$PS_child_5_functional))
   &
                                        (X2023MDLS.data$PS_child_5_functional != 1)]
                                            <-
 0

##Adults functional skills - meets MDLS at least one adult has skills
tempVar <- X2023MDLS.data$Other_parent_functional
tempVar[is.na(X2023MDLS.data$Other_parent_functional)] <- 0
X2023MDLS.data$Adult_functional_skills <-
  X2023MDLS.data$Respondent_functional + tempVar
X2023MDLS.data$Adult_functional_skills[X2023MDLS.data$Adult_functional_skills >
    0] <-
  1

##Secondary school children functional skills
X2023MDLS.data$SS_children_functional_skills <- 1
X2023MDLS.data$SS_children_functional_skills[(!is.na(X2023MDLS.data$SS_child_1_
    functional)) &
                                                   (X2023MDLS.data$SS_child_1_
                                                      functional != 1)] <-
 0
X2023MDLS.data$SS_children_functional_skills[(!is.na(X2023MDLS.data$SS_child_2_
    functional)) &
                                                   (X2023MDLS.data$SS_child_2_
                                                      functional != 1)] <-
 0
X2023MDLS.data$SS_children_functional_skills[(!is.na(X2023MDLS.data$SS_child_3_
    functional)) &
                                                   (X2023MDLS.data$SS_child_3_
                                                      functional != 1)] <-
 0
X2023MDLS.data$SS_children_functional_skills[(!is.na(X2023MDLS.data$SS_child_4_
    functional)) &
                                                   (X2023MDLS.data$SS_child_4_
                                                      functional != 1)] <-
 0
X2023MDLS.data$SS_children_functional_skills[(!is.na(X2023MDLS.data$SS_child_5_
    functional)) &
                                                   (X2023MDLS.data$SS_child_5_
                                                      functional != 1)] <-
 0
X2023MDLS.data$SS_children_functional_skills[(!is.na(X2023MDLS.data$SS_child_1_
    functional)) &
                                                   (X2023MDLS.data$SS_child_1_
                                                      functional == 1)] <-
 1
```

```
X2023MDLS.data$SS_children_functional_skills[(!is.na(X2023MDLS.data$SS_child_2_
    functional)) &
                                                   (X2023MDLS.data$SS_child_2_
                                                      functional == 1)] <-
  1
X2023MDLS.data$SS_children_functional_skills[(!is.na(X2023MDLS.data$SS_child_3_
    functional)) &
                                                   (X2023MDLS.data$SS_child_3_
                                                      functional == 1)] <-
  1
X2023MDLS.data$SS_children_functional_skills[(!is.na(X2023MDLS.data$SS_child_4_
    functional)) &
                                                   (X2023MDLS.data$SS_child_4_
                                                      functional == 1)] <-
  1
X2023MDLS.data$SS_children_functional_skills[(!is.na(X2023MDLS.data$SS_child_5_
    functional)) &
                                                   (X2023MDLS.data$SS_child_5_
                                                      functional == 1)] <-
  1

##Primary school children functional skills
X2023MDLS.data$PS_children_functional_skills <- 1
X2023MDLS.data$PS_children_functional_skills[(!is.na(X2023MDLS.data$PS_child_1_
    functional)) &
                                                   (X2023MDLS.data$PS_child_1_
                                                      functional != 1)] <-
  0
X2023MDLS.data$PS_children_functional_skills[(!is.na(X2023MDLS.data$PS_child_2_
    functional)) &
                                                   (X2023MDLS.data$PS_child_2_
                                                      functional != 1)] <-
  0
X2023MDLS.data$PS_children_functional_skills[(!is.na(X2023MDLS.data$PS_child_3_
    functional)) &
                                                   (X2023MDLS.data$PS_child_3_
                                                      functional != 1)] <-
  0
X2023MDLS.data$PS_children_functional_skills[(!is.na(X2023MDLS.data$PS_child_4_
    functional)) &
                                                   (X2023MDLS.data$PS_child_4_
                                                      functional != 1)] <-
  0
X2023MDLS.data$PS_children_functional_skills[(!is.na(X2023MDLS.data$PS_child_5_
    functional)) &
                                                   (X2023MDLS.data$PS_child_5_
                                                      functional != 1)] <-
  0
X2023MDLS.data$PS_children_functional_skills[(!is.na(X2023MDLS.data$PS_child_1_
    functional)) &
                                                   (X2023MDLS.data$PS_child_1_
                                                      functional == 1)] <-
  1
X2023MDLS.data$PS_children_functional_skills[(!is.na(X2023MDLS.data$PS_child_2_
    functional)) &
                                                   (X2023MDLS.data$PS_child_2_
                                                      functional == 1)] <-
  1
X2023MDLS.data$PS_children_functional_skills[(!is.na(X2023MDLS.data$PS_child_3_
    functional)) &
                                                   (X2023MDLS.data$PS_child_3_
```

```
                                                        functional == 1)] <-
  1
X2023MDLS.data$PS_children_functional_skills[(!is.na(X2023MDLS.data$PS_child_4_
    functional)) &
                                                        (X2023MDLS.data$PS_child_4_
                                                        functional == 1)] <-
  1
X2023MDLS.data$PS_children_functional_skills[(!is.na(X2023MDLS.data$PS_child_5_
    functional)) &
                                                        (X2023MDLS.data$PS_child_5_
                                                        functional == 1)] <-
  1

##Create factor versions with lowest value 1 for LCA and MCA analyses
X2023MDLS.data$Adult_functional_skills_factor <- factor(
  X2023MDLS.data$Adult_functional_skills + 1,
  levels = c(1, 2),
  labels = c("Not adequate Functional", "Adequate Functional"),
  ordered = FALSE
)

X2023MDLS.data$SS_children_functional_skills_factor <- factor(
  X2023MDLS.data$SS_children_functional_skills + 1,
  levels = c(1, 2),
  labels = c("Not adequate Functional", "Adequate Functional"),
  ordered = FALSE
)

X2023MDLS.data$PS_children_functional_skills_factor <- factor(
  X2023MDLS.data$PS_children_functional_skills + 1,
  levels = c(1, 2),
  labels = c("Not adequate Functional", "Adequate Functional"),
  ordered = FALSE
)

##Critical skills
##Respondent critical skills as a binary
X2023MDLS.data$Respondent_critical <- 1
X2023MDLS.data$Respondent_critical[X2023MDLS.data$B2_01_1 > 2] <-
  0
X2023MDLS.data$Respondent_critical[X2023MDLS.data$B2_01_2 > 2] <-
  0
X2023MDLS.data$Respondent_critical[X2023MDLS.data$B2_01_3 > 2] <-
  0
X2023MDLS.data$Respondent_critical[X2023MDLS.data$B2_01_4 > 2] <-
  0
X2023MDLS.data$Respondent_critical[X2023MDLS.data$B2_01_5 > 2] <-
  0
X2023MDLS.data$Respondent_critical[X2023MDLS.data$B2_01_6 > 2] <-
  0
X2023MDLS.data$Respondent_critical[X2023MDLS.data$B2_01_7 > 2] <-
  0
X2023MDLS.data$Respondent_critical[X2023MDLS.data$B2_01_8 > 2] <-
  0
X2023MDLS.data$Respondent_critical[X2023MDLS.data$B2_01_9 > 2] <-
  0

##Other parent critical skills
X2023MDLS.data$Other_parent_critical <- NA
X2023MDLS.data$Other_parent_critical[!is.na(X2023MDLS.data$B2_02_1)] <-
  1
```

```
X2023MDLS.data$Other_parent_critical[X2023MDLS.data$B2_02_1 > 2] <-
  0
X2023MDLS.data$Other_parent_critical[X2023MDLS.data$B2_02_2 > 2] <-
  0
X2023MDLS.data$Other_parent_critical[X2023MDLS.data$B2_02_3 > 2] <-
  0
X2023MDLS.data$Other_parent_critical[X2023MDLS.data$B2_02_4 > 2] <-
  0
X2023MDLS.data$Other_parent_critical[X2023MDLS.data$B2_02_5 > 2] <-
  0
X2023MDLS.data$Other_parent_critical[X2023MDLS.data$B2_02_6 > 2] <-
  0
X2023MDLS.data$Other_parent_critical[X2023MDLS.data$B2_02_7 > 2] <-
  0
X2023MDLS.data$Other_parent_critical[X2023MDLS.data$B2_02_8 > 2] <-
  0
X2023MDLS.data$Other_parent_critical[X2023MDLS.data$B2_02_9 > 2] <-
  0

##Secondary school children
##Secondary school child 1
X2023MDLS.data$SS_child_1_critical <- NA
X2023MDLS.data$SS_child_1_critical[!is.na(X2023MDLS.data$B2_08_1)] <-
  1
X2023MDLS.data$SS_child_1_critical[X2023MDLS.data$B2_08_1 > 2] <-
  0
X2023MDLS.data$SS_child_1_critical[X2023MDLS.data$B2_08_2 > 2] <-
  0
X2023MDLS.data$SS_child_1_critical[X2023MDLS.data$B2_08_3 > 2] <-
  0
X2023MDLS.data$SS_child_1_critical[X2023MDLS.data$B2_08_4 > 2] <-
  0
X2023MDLS.data$SS_child_1_critical[X2023MDLS.data$B2_08_5 > 2] <-
  0
X2023MDLS.data$SS_child_1_critical[X2023MDLS.data$B2_08_6 > 2] <-
  0
X2023MDLS.data$SS_child_1_critical[X2023MDLS.data$B2_08_7 > 2] <-
  0
##Secondary school child 2
X2023MDLS.data$SS_child_2_critical <- NA
X2023MDLS.data$SS_child_2_critical[!is.na(X2023MDLS.data$B2_09_1)] <-
  1
X2023MDLS.data$SS_child_2_critical[X2023MDLS.data$B2_09_1 > 2] <-
  0
X2023MDLS.data$SS_child_2_critical[X2023MDLS.data$B2_09_2 > 2] <-
  0
X2023MDLS.data$SS_child_2_critical[X2023MDLS.data$B2_09_3 > 2] <-
  0
X2023MDLS.data$SS_child_2_critical[X2023MDLS.data$B2_09_4 > 2] <-
  0
X2023MDLS.data$SS_child_2_critical[X2023MDLS.data$B2_09_5 > 2] <-
  0
X2023MDLS.data$SS_child_2_critical[X2023MDLS.data$B2_09_6 > 2] <-
  0
X2023MDLS.data$SS_child_2_critical[X2023MDLS.data$B2_09_7 > 2] <-
  0

##Secondary school child 3
X2023MDLS.data$SS_child_3_critical <- NA
X2023MDLS.data$SS_child_3_critical[!is.na(X2023MDLS.data$B2_10_1)] <-
  1
```

```
X2023MDLS.data$SS_child_3_critical[X2023MDLS.data$B2_10_1 > 2] <-
  0
X2023MDLS.data$SS_child_3_critical[X2023MDLS.data$B2_10_2 > 2] <-
  0
X2023MDLS.data$SS_child_3_critical[X2023MDLS.data$B2_10_3 > 2] <-
  0
X2023MDLS.data$SS_child_3_critical[X2023MDLS.data$B2_10_4 > 2] <-
  0
X2023MDLS.data$SS_child_3_critical[X2023MDLS.data$B2_10_5 > 2] <-
  0
X2023MDLS.data$SS_child_3_critical[X2023MDLS.data$B2_10_6 > 2] <-
  0
X2023MDLS.data$SS_child_3_critical[X2023MDLS.data$B2_10_7 > 2] <-
  0

##Secondary school child 4
X2023MDLS.data$SS_child_4_critical <- NA
X2023MDLS.data$SS_child_4_critical[!is.na(X2023MDLS.data$B2_11_1)] <-
  1
X2023MDLS.data$SS_child_4_critical[X2023MDLS.data$B2_11_1 > 2] <-
  0
X2023MDLS.data$SS_child_4_critical[X2023MDLS.data$B2_11_2 > 2] <-
  0
X2023MDLS.data$SS_child_4_critical[X2023MDLS.data$B2_11_3 > 2] <-
  0
X2023MDLS.data$SS_child_4_critical[X2023MDLS.data$B2_11_4 > 2] <-
  0
X2023MDLS.data$SS_child_4_critical[X2023MDLS.data$B2_11_5 > 2] <-
  0
X2023MDLS.data$SS_child_4_critical[X2023MDLS.data$B2_11_6 > 2] <-
  0
X2023MDLS.data$SS_child_4_critical[X2023MDLS.data$B2_11_7 > 2] <-
  0

##Secondary school child 5
X2023MDLS.data$SS_child_5_critical <- NA
X2023MDLS.data$SS_child_5_critical[!is.na(X2023MDLS.data$B2_12_1)] <-
  1
X2023MDLS.data$SS_child_5_critical[X2023MDLS.data$B2_12_1 > 2] <-
  0
X2023MDLS.data$SS_child_5_critical[X2023MDLS.data$B2_12_2 > 2] <-
  0
X2023MDLS.data$SS_child_5_critical[X2023MDLS.data$B2_12_3 > 2] <-
  0
X2023MDLS.data$SS_child_5_critical[X2023MDLS.data$B2_12_4 > 2] <-
  0
X2023MDLS.data$SS_child_5_critical[X2023MDLS.data$B2_12_5 > 2] <-
  0
X2023MDLS.data$SS_child_5_critical[X2023MDLS.data$B2_12_6 > 2] <-
  0
X2023MDLS.data$SS_child_5_critical[X2023MDLS.data$B2_12_7 > 2] <-
  0

##Primary school children - only MDLS relevant items
##Primary school child 1
X2023MDLS.data$PS_child_1_critical <- NA
X2023MDLS.data$PS_child_1_critical[!is.na(X2023MDLS.data$B2_13_1)] <-
  1
X2023MDLS.data$PS_child_1_critical[X2023MDLS.data$B2_13_3 > 2] <-
  0
X2023MDLS.data$PS_child_1_critical[(X2023MDLS.data$B2_13_1 > 2) &
```

```
                                        (X2023MDLS.data$B1_13_level == 2)] <-
  0
X2023MDLS.data$PS_child_1_critical[(X2023MDLS.data$B2_13_5 > 2) &
                                        (X2023MDLS.data$B1_13_level == 2)] <-
  0
X2023MDLS.data$PS_child_1_critical[(X2023MDLS.data$B2_13_9 > 2) &
                                        (X2023MDLS.data$B1_13_level == 2)] <-
  0

##Primary school child 2
X2023MDLS.data$PS_child_2_critical <- NA
X2023MDLS.data$PS_child_2_critical[!is.na(X2023MDLS.data$B2_14_1)] <-
  1
X2023MDLS.data$PS_child_2_critical[X2023MDLS.data$B2_14_3 > 2] <-
  0
X2023MDLS.data$PS_child_2_critical[(X2023MDLS.data$B2_14_1 > 2) &
                                        (X2023MDLS.data$B1_14_level == 2)] <-
  0
X2023MDLS.data$PS_child_2_critical[(X2023MDLS.data$B2_14_5 > 2) &
                                        (X2023MDLS.data$B1_14_level == 2)] <-
  0
X2023MDLS.data$PS_child_2_critical[(X2023MDLS.data$B2_14_9 > 2) &
                                        (X2023MDLS.data$B1_14_level == 2)] <-
  0

##Primary school child 3
X2023MDLS.data$PS_child_3_critical <- NA
X2023MDLS.data$PS_child_3_critical[!is.na(X2023MDLS.data$B2_15_1)] <-
  1
X2023MDLS.data$PS_child_3_critical[X2023MDLS.data$B2_15_3 > 2] <-
  0
X2023MDLS.data$PS_child_3_critical[(X2023MDLS.data$B2_15_1 > 2) &
                                        (X2023MDLS.data$B1_15_level == 2)] <-
  0
X2023MDLS.data$PS_child_3_critical[(X2023MDLS.data$B2_15_5 > 2) &
                                        (X2023MDLS.data$B1_15_level == 2)] <-
  0
X2023MDLS.data$PS_child_3_critical[(X2023MDLS.data$B2_15_9 > 2) &
                                        (X2023MDLS.data$B1_15_level == 2)] <-
  0

##Primary school child 4
X2023MDLS.data$PS_child_4_critical <- NA
X2023MDLS.data$PS_child_4_critical[!is.na(X2023MDLS.data$B2_16_1)] <-
  1
X2023MDLS.data$PS_child_4_critical[X2023MDLS.data$B2_16_3 > 2] <-
  0
X2023MDLS.data$PS_child_4_critical[(X2023MDLS.data$B2_16_1 > 2) &
                                        (X2023MDLS.data$B1_16_level == 2)] <-
  0
X2023MDLS.data$PS_child_4_critical[(X2023MDLS.data$B2_16_5 > 2) &
                                        (X2023MDLS.data$B1_16_level == 2)] <-
  0
X2023MDLS.data$PS_child_4_critical[(X2023MDLS.data$B2_16_9 > 2) &
                                        (X2023MDLS.data$B1_16_level == 2)] <-
  0

##Primary school child 5
X2023MDLS.data$PS_child_5_critical <- NA
X2023MDLS.data$PS_child_5_critical[!is.na(X2023MDLS.data$B2_17_1)] <-
  1
```

```
X2023MDLS.data$PS_child_5_critical[X2023MDLS.data$B2_17_3 > 2] <-
  0
X2023MDLS.data$PS_child_5_critical[(X2023MDLS.data$B2_17_1 > 2) &
                                        (X2023MDLS.data$B1_17_level == 2)] <-
  0
X2023MDLS.data$PS_child_5_critical[(X2023MDLS.data$B2_17_5 > 2) &
                                        (X2023MDLS.data$B1_17_level == 2)] <-
  0
X2023MDLS.data$PS_child_5_critical[(X2023MDLS.data$B2_17_9 > 2) &
                                        (X2023MDLS.data$B1_17_level == 2)] <-
  0
##Create factor versions with lowest value 1 for LCA and MCA analyses
X2023MDLS.data$Respondent_critical_factor <- factor(
  X2023MDLS.data$Respondent_critical + 1,
  levels = c(1, 2),
  labels = c("Not adequate Critical", "Adequate Critical"),
  ordered = FALSE
)

X2023MDLS.data$Other_parent_critical_factor <- factor(
  X2023MDLS.data$Other_parent_critical + 1,
  levels = c(1, 2),
  labels = c("Not adequate Critical", "Adequate Critical"),
  ordered = FALSE
)

X2023MDLS.data$SS_child_1_critical_factor <- factor(
  X2023MDLS.data$SS_child_1_critical + 1,
  levels = c(1, 2),
  labels = c("Not adequate Critical", "Adequate Critical"),
  ordered = FALSE
)

X2023MDLS.data$SS_child_2_critical_factor <- factor(
  X2023MDLS.data$SS_child_2_critical + 1,
  levels = c(1, 2),
  labels = c("Not adequate Critical", "Adequate Critical"),
  ordered = FALSE
)

X2023MDLS.data$SS_child_3_critical_factor <- factor(
  X2023MDLS.data$SS_child_3_critical + 1,
  levels = c(1, 2),
  labels = c("Not adequate Critical", "Adequate Critical"),
  ordered = FALSE
)

X2023MDLS.data$SS_child_4_critical_factor <- factor(
  X2023MDLS.data$SS_child_4_critical + 1,
  levels = c(1, 2),
  labels = c("Not adequate Critical", "Adequate Critical"),
  ordered = FALSE
)

X2023MDLS.data$SS_child_5_critical_factor <- factor(
  X2023MDLS.data$SS_child_5_critical + 1,
  levels = c(1, 2),
  labels = c("Not adequate Critical", "Adequate Critical"),
  ordered = FALSE
)
```

```
X2023MDLS.data$PS_child_1_critical_factor <- factor(
  X2023MDLS.data$PS_child_1_critical + 1,
  levels = c(1, 2),
  labels = c("Not adequate Critical", "Adequate Critical"),
  ordered = FALSE
)

X2023MDLS.data$PS_child_2_critical_factor <- factor(
  X2023MDLS.data$PS_child_2_critical + 1,
  levels = c(1, 2),
  labels = c("Not adequate Critical", "Adequate Critical"),
  ordered = FALSE
)

X2023MDLS.data$PS_child_3_critical_factor <- factor(
  X2023MDLS.data$PS_child_3_critical + 1,
  levels = c(1, 2),
  labels = c("Not adequate Critical", "Adequate Critical"),
  ordered = FALSE
)

X2023MDLS.data$PS_child_4_critical_factor <- factor(
  X2023MDLS.data$PS_child_4_critical + 1,
  levels = c(1, 2),
  labels = c("Not adequate Critical", "Adequate Critical"),
  ordered = FALSE
)

X2023MDLS.data$PS_child_5_critical_factor <- factor(
  X2023MDLS.data$PS_child_5_critical + 1,
  levels = c(1, 2),
  labels = c("Not adequate Critical", "Adequate Critical"),
  ordered = FALSE
)

##Create critical skills binary varibales
##Overall household critical skills
X2023MDLS.data$Critical_skills <- 1
X2023MDLS.data$Critical_skills[X2023MDLS.data$Respondent_critical != 1] <-
  0
X2023MDLS.data$Critical_skills[(!is.na(X2023MDLS.data$Other_parent_critical)) &
                               (X2023MDLS.data$Other_parent_critical != 1)] <-
  0
X2023MDLS.data$Critical_skills[(!is.na(X2023MDLS.data$SS_child_1_critical)) &
                               (X2023MDLS.data$SS_child_1_critical != 1)] <-
  0
X2023MDLS.data$Critical_skills[(!is.na(X2023MDLS.data$SS_child_2_critical)) &
                               (X2023MDLS.data$SS_child_2_critical != 1)] <-
  0
X2023MDLS.data$Critical_skills[(!is.na(X2023MDLS.data$SS_child_3_critical)) &
                               (X2023MDLS.data$SS_child_3_critical != 1)] <-
  0
X2023MDLS.data$Critical_skills[(!is.na(X2023MDLS.data$SS_child_4_critical)) &
                               (X2023MDLS.data$SS_child_4_critical != 1)] <-
  0
X2023MDLS.data$Critical_skills[(!is.na(X2023MDLS.data$SS_child_5_critical)) &
                               (X2023MDLS.data$SS_child_5_critical != 1)] <-
  0
X2023MDLS.data$Critical_skills[(!is.na(X2023MDLS.data$PS_child_1_critical)) &
                               (X2023MDLS.data$PS_child_1_critical != 1)] <-
  0
```

```
X2023MDLS.data$Critical_skills[(!is.na(X2023MDLS.data$PS_child_2_critical)) &
                                (X2023MDLS.data$PS_child_2_critical != 1)] <-
  0
X2023MDLS.data$Critical_skills[(!is.na(X2023MDLS.data$PS_child_3_critical)) &
                                (X2023MDLS.data$PS_child_3_critical != 1)] <-
  0
X2023MDLS.data$Critical_skills[(!is.na(X2023MDLS.data$PS_child_4_critical)) &
                                (X2023MDLS.data$PS_child_4_critical != 1)] <-
  0
X2023MDLS.data$Critical_skills[(!is.na(X2023MDLS.data$PS_child_5_critical)) &
                                (X2023MDLS.data$PS_child_5_critical != 1)] <-
  0

##Adults critical skills - at least one parent has skills
tempVar <- X2023MDLS.data$Other_parent_critical
tempVar[is.na(X2023MDLS.data$Other_parent_critical)] <- 0
X2023MDLS.data$Adult_critical_skills <-
  X2023MDLS.data$Respondent_critical + tempVar
X2023MDLS.data$Adult_critical_skills[X2023MDLS.data$Adult_critical_skills > 0]
   <-
  1


##Secondary school children critical skills
X2023MDLS.data$SS_children_critical_skills <- 1
X2023MDLS.data$SS_children_critical_skills[(!is.na(X2023MDLS.data$SS_child_1_
    critical)) &
                                            (X2023MDLS.data$SS_child_1_critical
                                                != 1)] <-
  0
X2023MDLS.data$SS_children_critical_skills[(!is.na(X2023MDLS.data$SS_child_2_
    critical)) &
                                            (X2023MDLS.data$SS_child_2_critical
                                                != 1)] <-
  0
X2023MDLS.data$SS_children_critical_skills[(!is.na(X2023MDLS.data$SS_child_3_
    critical)) &
                                            (X2023MDLS.data$SS_child_3_critical
                                                != 1)] <-
  0
X2023MDLS.data$SS_children_critical_skills[(!is.na(X2023MDLS.data$SS_child_4_
    critical)) &
                                            (X2023MDLS.data$SS_child_4_critical
                                                != 1)] <-
  0
X2023MDLS.data$SS_children_critical_skills[(!is.na(X2023MDLS.data$SS_child_5_
    critical)) &
                                            (X2023MDLS.data$SS_child_5_critical
                                                != 1)] <-
  0

##Primary school children critical skills - Corrected Data
X2023MDLS.data$PS_children_critical_skills <- 1
X2023MDLS.data$PS_children_critical_skills[(!is.na(X2023MDLS.data$PS_child_1_
    critical)) &
                                            (X2023MDLS.data$PS_child_1_critical
                                                != 1)] <-
  0
X2023MDLS.data$PS_children_critical_skills[(!is.na(X2023MDLS.data$PS_child_2_
    critical)) &
                                            (X2023MDLS.data$PS_child_2_critical
```

```
                                                     != 1)] <-
  0
X2023MDLS.data$PS_children_critical_skills[(!is.na(X2023MDLS.data$PS_child_3_
    critical)) &
                                                (X2023MDLS.data$PS_child_3_critical
                                                     != 1)] <-
  0
X2023MDLS.data$PS_children_critical_skills[(!is.na(X2023MDLS.data$PS_child_4_
    critical)) &
                                                (X2023MDLS.data$PS_child_4_critical
                                                     != 1)] <-
  0
X2023MDLS.data$PS_children_critical_skills[(!is.na(X2023MDLS.data$PS_child_5_
    critical)) &
                                                (X2023MDLS.data$PS_child_5_critical
                                                     != 1)] <-
  0

##Create factor versions with lowest value 1 for LCA and MCA analyses
X2023MDLS.data$Adult_critical_skills_factor <- factor(
  X2023MDLS.data$Adult_critical_skills + 1,
  levels = c(1, 2),
  labels = c("Not adequate Critical", "Adequate Critical"),
  ordered = FALSE
)

X2023MDLS.data$SS_children_critical_skills_factor <- factor(
  X2023MDLS.data$SS_children_critical_skills + 1,
  levels = c(1, 2),
  labels = c("Not adequate Critical", "Adequate Critical"),
  ordered = FALSE
)

X2023MDLS.data$PS_children_critical_skills_factor <- factor(
  X2023MDLS.data$PS_children_critical_skills + 1,
  levels = c(1, 2),
  labels = c("Not adequate Critical", "Adequate Critical"),
  ordered = FALSE
)

X2023MDLS.data$Overall_children_functional_skills <- 0
X2023MDLS.data$Overall_children_functional_skills[X2023MDLS.data$PS_children_
    functional_skills == 1] <-
  1
X2023MDLS.data$Overall_children_functional_skills[X2023MDLS.data$SS_children_
    functional_skills == 1] <-
  1

X2023MDLS.data$Overall_children_functional_skills_factor <- factor(
  X2023MDLS.data$Overall_children_functional_skills + 1,
  levels = c(1, 2),
  labels = c("Not adequate Functional", "Adequate Functional"),
  ordered = FALSE
)

X2023MDLS.data$Overall_children_critical_skills <- 0
X2023MDLS.data$Overall_children_critical_skills[X2023MDLS.data$PS_children_
    critical_skills == 1] <-
  1
X2023MDLS.data$Overall_children_critical_skills[X2023MDLS.data$SS_children_
    critical_skills == 1] <-
```

```
  1

X2023MDLS.data$Overall_children_critical_skills_factor <- factor(
  X2023MDLS.data$Overall_children_critical_skills + 1,
  levels = c(1, 2),
  labels = c("Not adequate Critical", "Adequate Critical"),
  ordered = FALSE
)

X2023MDLS.data$Overall_skills <- 0
X2023MDLS.data$Overall_skills[X2023MDLS.data$Functional_skills == 1] <-
  1
X2023MDLS.data$Overall_skills[X2023MDLS.data$Critical_skills == 1] <-
  2
X2023MDLS.data$Overall_skills[(X2023MDLS.data$Functional_skills + X2023MDLS.data
   $Critical_skills) == 2] <-
  3

X2023MDLS.data$Overall_skills_factor <- factor(
  X2023MDLS.data$Overall_skills + 1,
  levels = c(1, 2, 3, 4),
  labels = c(
    "Not adequate Skills",
    "Adequate Functional Skills",
    "Adequate Critical Skills",
    "Adequate Total Skills"
  ),
  ordered = FALSE
)

X2023MDLS.data$Overall_children_skills <- 0
X2023MDLS.data$Overall_children_skills[(
  X2023MDLS.data$Overall_children_functional_skills + X2023MDLS.data$Overall_
      children_critical_skills
) == 2] <- 1
X2023MDLS.data$Overall_children_skills_factor <- factor(
  X2023MDLS.data$Overall_children_skills + 1,
  levels = c(1, 2),
  labels = c(
    "Not adequate Skills",
    "Adequate Total Skills"
  ),
  ordered = FALSE
)

X2023MDLS.data$Overall_parent_skills <- 0
X2023MDLS.data$Overall_parent_skills[(X2023MDLS.data$Adult_functional_skills +
    X2023MDLS.data$Adult_critical_skills) == 2] <-
    1
X2023MDLS.data$Overall_parent_skills_factor <- factor(
  X2023MDLS.data$Overall_parent_skills + 1,
  levels = c(1, 2),
  labels = c(
    "Not adequate Skills",
    "Adequate Total Skills"
  ),
  ordered = FALSE
)

X2023MDLS.data$Overall_household_skills <- 0
X2023MDLS.data$Overall_household_skills[(
```

```
  X2023MDLS.data$Overall_children_functional_skills + X2023MDLS.data$Overall_
      children_critical_skills
) == 2] <- 1
X2023MDLS.data$Overall_household_skills[(X2023MDLS.data$Adult_functional_skills
    + X2023MDLS.data$Adult_critical_skills) == 2] <-
  2
X2023MDLS.data$Overall_household_skills[(
  X2023MDLS.data$Adult_functional_skills + X2023MDLS.data$Adult_critical_skills
      +
    X2023MDLS.data$Overall_children_functional_skills + X2023MDLS.data$Overall_
        children_critical_skills
) == 4] <- 3

X2023MDLS.data$Overall_household_skills_factor <- factor(
  X2023MDLS.data$Overall_household_skills + 1,
  levels = c(1, 2, 3, 4),
  labels = c(
    "Not adequate Skills",
    "Children Have Adequate Skills",
    "Parents Have Adequate Skills",
    "Household Has Adequate Skills"
  ),
  ordered = FALSE
)

X2023MDLS.data$Overall_household_skills_binary <- 0
X2023MDLS.data$Overall_household_skills_binary[X2023MDLS.data$Overall_household_
    skills == 3] <- 1
X2023MDLS.data$Overall_household_skills_binary_factor <- factor(
  X2023MDLS.data$Overall_household_skills + 1,
  levels = c(1, 2),
  labels = c(
    "Household Does Not Have Adequate Skills",
    "Household Has Adequate Skills"
  ),
  ordered = FALSE
)

X2023MDLS.data$SEG_factor <-
  haven::as_factor(X2023MDLS.data$SEG, levels = "labels")
X2023MDLS.data$URBAN_factor <-
  haven::as_factor(X2023MDLS.data$URBAN, levels = "labels")
X2023MDLS.data$URBAN2_factor <-
  haven::as_factor(X2023MDLS.data$URBAN2, levels = "labels")
X2023MDLS.data$REGION_factor <-
  haven::as_factor(X2023MDLS.data$REGION, levels = "labels")
X2023MDLS.data$REGION_short_factor <- X2023MDLS.data$REGION_factor
levels(X2023MDLS.data$REGION_short_factor) <- c("NE",
                                                 "NW",
                                                 "YH",
                                                 "EM",
                                                 "WM",
                                                 "EE",
                                                 "Lon",
                                                 "SE",
                                                 "SW",
                                                 "W",
                                                 "NI",
                                                 "S")
X2023MDLS.data$REGION_short_factor <-
  factor(
```

```
    X2023MDLS.data$REGION_short_factor,
    levels = c(
      "Lon",
      "EE",
      "WM",
      "SE",
      "YH",
      "W",
      "SW",
      "EM",
      "S",
      "NE",
      "NW",
      "NI"
    )
  )
X2023MDLS.data$HTYPE_factor <-
  haven::as_factor(X2023MDLS.data$HTYPE, levels = "labels")
X2023MDLS.data$iuc_GRP_LBLr_factor <-
  haven::as_factor(X2023MDLS.data$iuc_GRP_LBLr, levels = "labels")
X2023MDLS.data$oac21SG_factor <-
  haven::as_factor(X2023MDLS.data$oac21SG)
levels(X2023MDLS.data$oac21SG_factor) <- c(
  "Retired Professionals",
  "Suburbanites and Peri-Urbanities",
  "Multicultural and Educated Urbanites",
  "Low-Skilled Migrant and Student Communities",
  "Ethnically Diverse Suburban Professionals",
  "Baseline UK",
  "Semi-and Un-Skilled Workforce",
  "Legacy Communities"
)
X2023MDLS.data$oac21Gr_factor <-
  droplevels(haven::as_factor(X2023MDLS.data$oac21Gr, levels = "labels"))
X2023MDLS.data$oac21SBGr_factor <-
  droplevels(haven::as_factor(X2023MDLS.data$oac21SBGr, levels = "labels"))
# X2023MDLS.data$aipc_supergroup_namer_factor <-
#   droplevels(haven::as_factor(X2023MDLS.data$aipc_supergroup_namer, levels = "
    labels"))
# X2023MDLS.data$aipc_group_namer_factor <-
#   droplevels(haven::as_factor(X2023MDLS.data$aipc_group_namer, levels = "
    labels"))
X2023MDLS.data$urban_size_factor <-
  droplevels(haven::as_factor(X2023MDLS.data$URBAN, levels = "labels"))
X2023MDLS.data$urban_rural_factor <-
  droplevels(haven::as_factor(X2023MDLS.data$URBAN2, levels = "labels"))

##Split broadband speed by UK median speed (69.4mbs)
X2023MDLS.data$Broadband <- 0
X2023MDLS.data$Broadband[X2023MDLS.data$media_download_speed_Mbitxsec > 69.4] <-
  1
X2023MDLS.data$Broadband_factor <- factor(
  X2023MDLS.data$Broadband + 1,
  levels = c(1, 2),
  labels = c("Below average broadband speed",
             "Above average broadband speed"),
  ordered = FALSE
)
##Create dummy variables for regression
X2023MDLS.data$Single_parent_dummy <- 0
X2023MDLS.data$Single_parent_dummy[X2023MDLS.data$HTYPE < 4] <-
```

```
  1
X2023MDLS.data$Single_parent_dummy_factor <- factor(
  X2023MDLS.data$Single_parent_dummy + 1,
  levels = c(1, 2),
  labels = c("Not Single Parent",
             "Single Parent"),
  ordered = TRUE
)
X2023MDLS.data$Two_plus_children_dummy <- 0
X2023MDLS.data$Two_plus_children_dummy[X2023MDLS.data$HTYPE == 3] <-
  1
X2023MDLS.data$Two_plus_children_dummy[X2023MDLS.data$HTYPE == 6] <-
  1
X2023MDLS.data$Two_plus_children_dummy[X2023MDLS.data$HTYPE == 9] <-
  1
X2023MDLS.data$Two_plus_children_dummy_factor <- factor(
  X2023MDLS.data$Two_plus_children_dummy + 1,
  levels = c(1, 2),
  labels = c("Not 2+ children",
             "2+ children"),
  ordered = TRUE
)
##Create dummy variables for key geodemograophic variables
X2023MDLS.data$oac_LSMS_dummy <- 0
X2023MDLS.data$oac_LSMS_dummy[X2023MDLS.data$oac21SG == 4] <- 1
X2023MDLS.data$oac_LSMS_dummy_factor <- factor(
  X2023MDLS.data$oac_LSMS_dummy + 1,
  levels = c(1, 2),
  labels = c(
    "Not Low-Skilled, Migrant, and Student Communities",
    "Low-Skilled, Migrant, and Student Communities"
  ),
  ordered = FALSE
)
X2023MDLS.data$oac_Legacy_dummy <- 0
X2023MDLS.data$oac_Legacy_dummy[X2023MDLS.data$oac21SG == 8] <- 1
X2023MDLS.data$oac_Legacy_dummy_factor <- factor(
  X2023MDLS.data$oac_Legacy_dummy + 1,
  levels = c(1, 2),
  labels = c("Not Legacy Communities",
             "Legacy Communities"),
  ordered = FALSE
)
X2023MDLS.data$oac_Retired_dummy <- 0
X2023MDLS.data$oac_Retired_dummy[X2023MDLS.data$oac21SG == 1] <- 1
X2023MDLS.data$oac_Retired_dummy_factor <- factor(
  X2023MDLS.data$oac_Retired_dummy + 1,
  levels = c(1, 2),
  labels = c("Not Retired Professionals",
             "Retired Professionals"),
  ordered = FALSE
)
X2023MDLS.data$oac_SPU_dummy <- 0
X2023MDLS.data$oac_SPU_dummy[X2023MDLS.data$oac21SG == 2] <- 1
X2023MDLS.data$oac_SPU_dummy_factor <- factor(
  X2023MDLS.data$oac_SPU_dummy + 1,
  levels = c(1, 2),
  labels = c(
    "Not Suburbanites and Peri-Urbanities",
    "Suburbanites and Peri-Urbanities"
  ),
```

```
  ordered = FALSE
)
X2023MDLS.data$oac_EDSP_dummy <- 0
X2023MDLS.data$oac_EDSP_dummy[X2023MDLS.data$oac21SG == 5] <- 1
X2023MDLS.data$oac_EDSP_dummy_factor <- factor(
  X2023MDLS.data$oac_EDSP_dummy + 1,
  levels = c(1, 2),
  labels = c(
    "Not Ethnically Diverse Suburban Professionals",
    "Ethnically Diverse Suburban Professionals"
  ),
  ordered = FALSE
)
X2023MDLS.data$IUC_EW_dummy <- 0
X2023MDLS.data$IUC_EW_dummy[X2023MDLS.data$iuc_2018_GRP_CD == 10] <-
  1
X2023MDLS.data$IUC_EW_dummy_factor <- factor(
  X2023MDLS.data$IUC_EW_dummy + 1,
  levels = c(1, 2),
  labels = c("Not e-Withdrawn",
             "e-Withdrawn"),
  ordered = FALSE
)
X2023MDLS.data$IUC_YUF_dummy <- 0
X2023MDLS.data$IUC_YUF_dummy[X2023MDLS.data$iuc_2018_GRP_CD == 4] <-
  1
X2023MDLS.data$IUC_YUF_dummy_factor <- factor(
  X2023MDLS.data$IUC_YUF_dummy + 1,
  levels = c(1, 2),
  labels = c("Not Youthful Urban Fringe",
             "Youthful Urban Fringe"),
  ordered = FALSE
)
X2023MDLS.data$IUC_ERU_dummy <- 0
X2023MDLS.data$IUC_ERU_dummy[X2023MDLS.data$iuc_2018_GRP_CD == 5] <-
  1
X2023MDLS.data$IUC_ERU_dummy_factor <- factor(
  X2023MDLS.data$IUC_ERU_dummy + 1,
  levels = c(1, 2),
  labels = c("Not e-Rational Utilitarians",
             "e-Rational Utilitarians"),
  ordered = FALSE
)
X2023MDLS.data$IUC_EV_dummy <- 0
X2023MDLS.data$IUC_EV_dummy[X2023MDLS.data$iuc_2018_GRP_CD == 3] <-
  1
X2023MDLS.data$IUC_EV_dummy_factor <- factor(
  X2023MDLS.data$IUC_EV_dummy + 1,
  levels = c(1, 2),
  labels = c("Not e-Veterans",
             "e-Veterans"),
  ordered = FALSE
)
X2023MDLS.data$IUC_SOC_dummy <- 0
X2023MDLS.data$IUC_SOC_dummy[X2023MDLS.data$iuc_2018_GRP_CD == 9] <-
  1
X2023MDLS.data$IUC_SOC_dummy_factor <- factor(
  X2023MDLS.data$IUC_SOC_dummy + 1,
  levels = c(1, 2),
  labels = c("Not Settled Offline Communities",
             "Settled Offline Communities"),
```

```
  ordered = FALSE
)

X2023MDLS.data$Benefits <- X2023MDLS.data$CL4L
X2023MDLS.data$Benefits_factor <- factor(
  X2023MDLS.data$CL4L + 1,
  levels = c(1, 2),
  labels = c("Not on any benefits",
             "Recieves at least one state benefit"),
  ordered = FALSE
)

X2023MDLS.data$Working_factor <- factor(
  X2023MDLS.data$CL5I + 1,
  levels = c(1, 2),
  labels = c("Chief income earner not working",
             "Chief income earner working"),
  ordered = FALSE
)


X2023MDLS.data$Helath_limitation <- X2023MDLS.data$CL6BK
X2023MDLS.data$Helath_limitation_factor <- factor(
  X2023MDLS.data$CL6BK + 1,
  levels = c(1, 2),
  labels = c(
    "Respondent has no health issue affecting daily activity",
    "Respondent has a health issue affecting daily activity"
  ),
  ordered = FALSE
)

X2023MDLS.data$Ethnicity <- 0
X2023MDLS.data$Ethnicity[X2023MDLS.data$CL7B > 2] <- 1
X2023MDLS.data$Ethnicity[X2023MDLS.data$CL7B == 4] <- 0
X2023MDLS.data$Ethnicity_factor <- factor(
  X2023MDLS.data$Ethnicity + 1,
  levels = c(1, 2),
  labels = c(
    "Respondent identifies as ethnically white (British, Irish, Other)",
    "Respondent identifies as ethnically non-white"
  ),
  ordered = FALSE
)

##Replace imd2019RANK NA with mode
X2023MDLS.data$imd2019RANK_namode <- X2023MDLS.data$imd2019RANK
X2023MDLS.data$imd2019RANK_namode[is.na(X2023MDLS.data$imd2019RANK)] <-
  Mode(!is.na(X2023MDLS.data$imd2019RANK))

write_sav(X2023MDLS.data,
          "2023_MDLS_data_no_LCA.sav")
sink()
```

Chapter 4

Latent Class analysis

```
# Sink output to ovearll results file
sink("MDLS_comparisons.tex",
     append = FALSE,
     split = TRUE)
pdf("MDLS_comparisons.pdf",
    width = 10,
    height = 10)
set.seed(1680) # for reproducibility

library("ca")
library("cluster") # for gower similarity and pam
library("corrplot")
library("descr")
library("DescTools")
library("dplyr")
library("effects")
library("factoextra")
library("FactoMineR")
library("flextable")
library("forcats")
library("generalhoslem")
library("ggparallel")
library("ggplot2")
library("ggpubr")
library("ggsurvey")
library("gmodels")
library("gdata")
library("haven")
library("hexbin")
library("Hmisc")
library("hrbrthemes")
library("huxtable")
library("igraph")
library("jtools")
library("knitr")
library("labelled")
library("lattice")
library("logistf")
library("nnet")
library("officer")
library("OneR")
library("plot3D")
library("plyr")
library("poLCA")
library("pwr")
```

```
library("psych")
library("RcmdrMisc")
library("RColorBrewer")
library("rcompanion")
library("reshape2")
library("rms")
library("Rtsne") # for t-SNE plot
library("sandwich")
library("scales")
library("scatterplot3d")
library("sjlabelled")
library("stargazer")
library("survey")
library("tidyr")
library("vcdExtra")
library("xtable")
library("ggsci")
library("weights")
library("pals")
library("report")
library("lmtest")

##Set up functions to be used in the analysis

##Set up function for entropy calculation
entropy <- function (var.p) {
  sum(-var.p * log(var.p))
}

overalllatex <- list()

model_equation <- function(model) {
  format_args <- list()

  model_coeff <- model$coefficients
  format_args$x <- abs(model$coefficients)
  model_coeff_sign <- sign(model_coeff)
  model_coeff_prefix <- case_when(model_coeff_sign == -1 ~ " - ",
                                  model_coeff_sign == 1 ~ " + ",
                                  model_coeff_sign == 0 ~ " + ")
  model_eqn <-
    paste(strsplit(as.character(model$call$formula), "~")[[2]],
          # 'y'
          "=",
          paste(
            if_else(model_coeff[1] < 0, "- ", ""),
            do.call(format, format_args)[1],
            paste(
              model_coeff_prefix[-1],
              do.call(format, format_args)[-1],
              " * ",
              names(model_coeff[-1]),
              sep = "",
              collapse = ""
            ),
            sep = ""
          ))
  return(model_eqn)
}

##Function to calculate Chi2 and corrplots
```

```
chisquaretest.predictions.survey.function <-
  function(indfactor.data,
           predclass.data,
           design.ps,
           df,
           plot.title,
           type_test) {
    plot.title <- gsub("_", " ", plot.title)
    plot.label <- gsub(" ", "", plot.title)
    output.list <- list()
    if (type_test == "Svy") {
      chisquare.results <-
        svychisq(
          as.formula(paste(
            "~", indfactor.data, "+", predclass.data
          )),
          design = design.ps,
          statistic = "Chisq",
          data = df
        )
    }
    else
    {
      chisquare.results <-
        chisq.test(df[[indfactor.data]], df[[predclass.data]], simulate.p.value
           = TRUE)
    }
    residuals.data <- chisquare.results$residuals
    stdres.data <- chisquare.results$stdres
    stdres.plot <-
      corrplot(
        stdres.data,
        is.cor = FALSE,
        title = paste(plot.title,
                      "\nAdjusted Standardised Residuals"),
        mar = c(0, 0, 3, 0)
      )
    if (chisquare.results$p.value != "NaN") {
      contrib.data <-
        100 * residuals.data ^ 2 / chisquare.results$statistic
      round(contrib.data, 3)
      contribution.plot <-
        corrplot(
          contrib.data,
          is.cor = FALSE,
          title = plot.title,
          mar = c(0, 0, 2, 0)
        )
    }
    else
    {
      contrib.data <-
        0.1 * residuals.data / residuals.data
      contribution.plot <-
        corrplot(
          contrib.data,
          is.cor = FALSE,
          title = paste(plot.title, "This plot is invalid as obs = expected p=
             NaN"),
          mar = c(0, 0, 2, 0)
        )
```

```
}
obs.table <- round(chisquare.results$observed, digits = 0)
rownames(obs.table) <- paste0(rownames(obs.table), " (obs.)")
ltx.table.obs <- xtable(obs.table,
                        caption = plot.title)
row.table <-
  round(100 * prop.table(chisquare.results$observed, 1), digits = 1)
rownames(row.table) <- paste0(rownames(row.table), " (row %)")
ltx.table.rpct <-
  xtable(
    row.table,
    caption = paste(
      plot.title,
      " (Row Percentages)",
      " ($\\chi^2$(",
      chisquare.results$parameter,
      ", ",
      sum(chisquare.results$observed),
      ") = ",
      round(chisquare.results$statistic, digits = 3),
      ", p = ",
      round(chisquare.results$p.value, digits = 3),
      ", Cramer's V = ",
      round(cramerV(chisquare.results$observed), digits = 3),
      ")",
      sep = ""
    ),
    label = paste("tab:", plot.label, "1", sep = "")
  )
col.table <-
  round(100 * prop.table(chisquare.results$observed, 2), digits = 1)
rownames(col.table) <- paste0(rownames(col.table), " (col. %)")
ltx.table.cpct <-
  xtable(
    col.table,
    caption = paste(
      plot.title,
      " (Column Percentages)",
      " ($\\chi^2$(",
      chisquare.results$parameter,
      ", ",
      sum(chisquare.results$observed),
      ") = ",
      round(chisquare.results$statistic, digits = 3),
      ", p = ",
      round(chisquare.results$p.value, digits = 3),
      ", Cramer's V = ",
      round(cramerV(chisquare.results$observed), digits = 3),
      ")",
      sep = ""
    ),
    label = paste("tab:", plot.label, "2", sep = "")
  )
ltx.table.all <-
  xtable(
    interleave(obs.table,
               row.table,
               col.table),
    caption = paste(
      plot.title,
      " ($\\chi^2$(",
```

```
          chisquare.results$parameter,
          ", ",
          sum(chisquare.results$observed),
          ") = ",
          round(chisquare.results$statistic, digits = 3),
          ", p = ",
          round(chisquare.results$p.value, digits = 3),
          ", Cramer's V = ",
          round(cramerV(chisquare.results$observed), digits = 3),
          ")",
          sep = ""
        ),
        label = paste("tab:", plot.label, "3", sep = "")
      )
    output.list <-
      list(
        contplot = contribution.plot,
        stdresplot = stdres.plot,
        chires = chisquare.results,
        obsltx = ltx.table.obs,
        cpctltx = ltx.table.cpct,
        rpctltx = ltx.table.rpct,
        allltx = ltx.table.all,
        ##rep = report(chisquare.results),
        lab = plot.label
      )
    return(output.list)
  }

##Function to generate Cramers V as needed
cv.test = function(x, y) {
  CV = sqrt(chisq.test(x, y, correct = FALSE)$statistic /
              (length(x) * (min(
                length(unique(x)), length(unique(y))
              ) - 1)))
  print.noquote("Cramer V / Phi:")
  return(as.numeric(CV))
}

gvarlist = c(
  "SEG_factor",
  "HTYPE_factor",
  "REGION_factor",
  "Overall_household_skills_factor",
  "Broadband_factor",
  "urban_size_factor",
  "urban_rural_factor",
  "iuc_GRP_LBLr_factor",
  "oac21SG_factor",
  "Benefits_factor",
  "Working_factor",
  "Helath_limitation_factor",
  "Ethnicity_factor"
)

hvarlist = c(
  "MDLS_LCA_factor_short",
  "MDLS2_factor",
  "Overall_household_skills_factor",
  "MDLS_Abs_Equipment_Skills_factor",
  "MDLS_LCA_Equipment_Skills_factor"
```

```
)

##create weighted data set with survey package
design.ps <-
  svydesign(ids = ~ 1,
            weights = X2023MDLS.data.ordered$WT,
            data = X2023MDLS.data.ordered)

overallchitables <- list()
figNolist <- list()
figNo <- 0
for (hitem in hvarlist) {
  for (gitem in gvarlist) {
    if (gitem != hitem) {
      print(paste("Chi-square-on:-", hitem, "-by-", gitem))
      if (hitem == "Overall_household_skills_factor" &
          gitem == "HTYPE_factor") {
        type_test <- "Chi"
      } else{
        type_test <- "Svy"
      }
      overallchitables[[hitem]][[gitem]] <-
        chisquaretest.predictions.survey.function(
    gitem,
    hitem,
    design.ps,
    X2023MDLS.data.ordered,
    paste0(gitem, "-by-", hitem),
    type_test
        )
      figNolist[[hitem]][[gitem]] <- figNo + 1
      figNo <- figNo + 2
    }
  }
}

##Binary logistic regression using factors on equipment
fit.glmlogit.equipment <- svyglm(
  MDLS2_factor ~
    SEG_factor +
    Single_parent_dummy_factor +
    Two_plus_children_dummy_factor +
    imd2019RANK_namode,
  family = binomial(link = "logit"),
  design = design.ps
)

summary(fit.glmlogit.equipment)
logitgof(
  fit.glmlogit.equipment$y,
  fitted(fit.glmlogit.equipment),
  g = 10,
  ord = FAlSE
)

fit.glmlogit.equipment0 <- svyglm(MDLS2_factor ~ 1,
                                  family = binomial(link = "logit"),
                                  design = design.ps)
anova(fit.glmlogit.equipment0,
      fit.glmlogit.equipment,
      test = "Chisq")
```

```
confint <- exp(cbind(
  coef(fit.glmlogit.equipment),
  confint(fit.glmlogit.equipment)
))
confint

overalllatex$MDLS2confint <-
  xtable(confint, caption = "MDLS Binary GLM confidence intervals")

plot(Effect("SEG_factor", fit.glmlogit.equipment))
plot(Effect("Single_parent_dummy_factor", fit.glmlogit.equipment))
plot(Effect("Two_plus_children_dummy_factor", fit.glmlogit.equipment))
plot(Effect("imd2019RANK_namode", fit.glmlogit.equipment))

##Binary logistic regression using factors on skills
fit.glmlogit.skills <- svyglm(
  Overall_household_skills_binary_factor ~
    SEG_factor +
    Single_parent_dummy_factor +
    Two_plus_children_dummy_factor +
    imd2019RANK_namode,
  family = binomial(link = "logit"),
  design = design.ps
)

summary(fit.glmlogit.skills)
logitgof(fit.glmlogit.skills$y,
         fitted(fit.glmlogit.skills),
         g = 10,
         ord = FAlSE)

fit.glmlogit.skills0 <- svyglm(MDLS2_factor ~ 1,
                              family = binomial(link = "logit"),
                              design = design.ps)
anova(fit.glmlogit.skills0,
      fit.glmlogit.skills,
      test = "Chisq")

confint <- exp(cbind(coef(fit.glmlogit.skills),
                     confint(fit.glmlogit.skills)))
confint

overalllatex$MDLSskillsconfint <-
  xtable(confint, caption = "MDLS Binary GLM confidence intervals")

plot(Effect("SEG_factor", fit.glmlogit.skills))
plot(Effect("Single_parent_dummy_factor", fit.glmlogit.skills))
plot(Effect("Two_plus_children_dummy_factor", fit.glmlogit.skills))
plot(Effect("imd2019RANK_namode", fit.glmlogit.skills))


##Binary logistic regression using factors on skills and equipment
fit.glmlogit.abs <- svyglm(
  MDLS_Abs_Equipment_Skills ~
    SEG_factor +
    Single_parent_dummy_factor +
    Two_plus_children_dummy_factor +
    imd2019RANK_namode,
  family = binomial(link = "logit"),
  design = design.ps
```

```
)

summary(fit.glmlogit.abs)
logitgof(fit.glmlogit.abs$y,
         fitted(fit.glmlogit.abs),
         g = 10,
         ord = FAlSE)

fit.glmlogit.abs0 <- svyglm(MDLS_Abs_Equipment_Skills ~ 1,
                            family = binomial(link = "logit"),
                            design = design.ps)
anova(fit.glmlogit.abs0,
      fit.glmlogit.abs,
      test = "Chisq")

confint <- exp(cbind(coef(fit.glmlogit.abs),
                     confint(fit.glmlogit.abs)))
confint

overalllatex$MDLSabsconfint <-
  xtable(confint, caption = "MDLS Binary GLM confidence intervals")

plot(Effect("SEG_factor", fit.glmlogit.abs))
plot(Effect("Single_parent_dummy_factor", fit.glmlogit.abs))
plot(Effect("Two_plus_children_dummy_factor", fit.glmlogit.abs))
plot(Effect("imd2019RANK_namode", fit.glmlogit.abs))

##Binary logistic regression using factors on skills and equipment
fit.glmlogit.lca <- svyglm(
  MDLS_LCA_Equipment_Skills ~
    SEG_factor +
    Single_parent_dummy_factor +
    Two_plus_children_dummy_factor +
    imd2019RANK_namode,
  family = binomial(link = "logit"),
  design = design.ps
)

summary(fit.glmlogit.lca)
logitgof(fit.glmlogit.lca$y,
         fitted(fit.glmlogit.lca),
         g = 10,
         ord = FAlSE)

fit.glmlogit.lca0 <- svyglm(MDLS_LCA_Equipment_Skills ~ 1,
                            family = binomial(link = "logit"),
                            design = design.ps)

confint <- exp(cbind(coef(fit.glmlogit.lca),
                     confint(fit.glmlogit.lca)))
confint

overalllatex$MDLSLCAconfint <-
  xtable(confint, caption = "MDLS Binary GLM confidence intervals")

anova(fit.glmlogit.lca0,
      fit.glmlogit.lca,
      test = "Chisq")

plot(Effect("SEG_factor", fit.glmlogit.lca))
plot(Effect("Single_parent_dummy_factor", fit.glmlogit.lca))
```

```
plot(Effect("Two_plus_children_dummy_factor", fit.glmlogit.lca))
plot(Effect("imd2019RANK_namode", fit.glmlogit.lca))

fit.glmlogit.dem.lca <- svyglm(
  MDLS_LCA_Equipment_Skills ~
     Benefits_factor +
     Working_factor +
     Helath_limitation_factor +
     Ethnicity_factor,
  family = binomial(link = "logit"),
  design = design.ps
)
summary(fit.glmlogit.dem.lca)
logitgof(
  fit.glmlogit.dem.lca$y,
  fitted(fit.glmlogit.dem.lca),
  g = 10,
  ord = FAlSE
)

fit.glmlogit.dem.lca0 <- svyglm(MDLS_LCA_Equipment_Skills ~ 1,
                                 family = binomial(link = "logit"),
                                 design = design.ps)

confint <- exp(cbind(coef(fit.glmlogit.dem.lca),
                      confint(fit.glmlogit.dem.lca)))
confint

overalllatex$MDLSLCAdemconfint <-
  xtable(confint, caption = "MDLS Binary GLM confidence intervals")

anova(fit.glmlogit.dem.lca0,
      fit.glmlogit.dem.lca,
      test = "Chisq")

plot(Effect("Benefits_factor", fit.glmlogit.dem.lca))
plot(Effect("Working_factor", fit.glmlogit.dem.lca))
plot(Effect("Helath_limitation_factor", fit.glmlogit.dem.lca))
plot(Effect("Ethnicity_factor", fit.glmlogit.dem.lca))

##Binary logistic regression of geographic factors on LCA-MDLS
fit.glmlogit.geo.lca <- svyglm(
  MDLS_LCA_Equipment_Skills ~
     URBAN_factor +
     REGION_short_factor +
     oac_LSMS_dummy_factor +
     oac_Legacy_dummy_factor +
     oac_Retired_dummy_factor +
     oac_SPU_dummy_factor +
     oac_EDSP_dummy_factor +
     IUC_EW_dummy_factor +
     IUC_YUF_dummy_factor +
     IUC_ERU_dummy_factor +
     IUC_EV_dummy_factor +
     IUC_SOC_dummy_factor,
  family = binomial(link = "logit"),
  design = design.ps
)

summary(fit.glmlogit.geo.lca)
logitgof(
```

```
  fit.glmlogit.geo.lca$y,
  fitted(fit.glmlogit.geo.lca),
  g = 10,
  ord = FAlSE
)

fit.glmlogit.geo.lca0 <- svyglm(MDLS_LCA_Equipment_Skills ~ 1,
                                family = binomial(link = "logit"),
                                design = design.ps)

confint <- exp(cbind(coef(fit.glmlogit.geo.lca),
                     confint(fit.glmlogit.geo.lca)))
confint

overalllatex$MDLSLCAgeoconfint <-
  xtable(confint, caption = "MDLS Binary GLM confidence intervals")

anova(fit.glmlogit.geo.lca0,
      fit.glmlogit.geo.lca,
      test = "Chisq")

##Binary logistic regression overall model
fit.glmlogit.lca.overall <- svyglm(
  MDLS_LCA_Equipment_Skills ~
    SEG_factor +
    Single_parent_dummy_factor +
    Two_plus_children_dummy_factor +
    imd2019RANK_namode +
    Benefits_factor +
    Working_factor +
    Helath_limitation_factor +
    Ethnicity_factor +
    URBAN_factor +
    REGION_short_factor +
    oac_LSMS_dummy_factor +
    oac_Legacy_dummy_factor +
    oac_Retired_dummy_factor +
    oac_EDSP_dummy_factor,
  family = binomial(link = "logit"),
  design = design.ps
)

summary(fit.glmlogit.lca.overall)
logitgof(
  fit.glmlogit.lca.overall$y,
  fitted(fit.glmlogit.lca.overall),
  g = 10,
  ord = FAlSE
)

fit.glmlogit.lca.overall0 <- svyglm(MDLS_LCA_Equipment_Skills ~ 1,
                                    family = binomial(link = "logit"),
                                    design = design.ps)

confint <- exp(cbind(
  coef(fit.glmlogit.lca.overall),
  confint(fit.glmlogit.lca.overall)
))
confint

overalllatex$MDLSLCAoverallconfint <-
```

```
  xtable(confint, caption = "MDLS Binary GLM confidence intervals")

anova(fit.glmlogit.lca.overall0,
      fit.glmlogit.lca.overall,
      test = "Chisq")

plot(Effect("SEG_factor", fit.glmlogit.lca.overall))
plot(Effect("Single_parent_dummy_factor", fit.glmlogit.lca.overall))
plot(Effect("Two_plus_children_dummy_factor", fit.glmlogit.lca.overall))
plot(Effect("imd2019RANK_namode", fit.glmlogit.lca.overall))
plot(Effect("URBAN_factor", fit.glmlogit.lca.overall))
plot(Effect("REGION_short_factor", fit.glmlogit.lca.overall))
plot(Effect("Benefits_factor", fit.glmlogit.lca.overall))
plot(Effect("Working_factor", fit.glmlogit.lca.overall))
plot(Effect("Helath_limitation_factor", fit.glmlogit.lca.overall))
plot(Effect("Ethnicity_factor", fit.glmlogit.lca.overall))

##Binary logistic regression overall model
fit.glmlogit.lca.overall2 <- svyglm(
  MDLS_LCA_Equipment_Skills ~
    SEG_factor +
    Single_parent_dummy_factor +
    Two_plus_children_dummy_factor +
    imd2019RANK_namode +
    Benefits_factor +
    Working_factor +
    Helath_limitation_factor +
    Ethnicity_factor +
    URBAN_factor +
    REGION_short_factor +
    oac_LSMS_dummy_factor +
    oac_EDSP_dummy_factor,
  family = binomial(link = "logit"),
  design = design.ps
)

summary(fit.glmlogit.lca.overall2)
logitgof(
  fit.glmlogit.lca.overall2$y,
  fitted(fit.glmlogit.lca.overall2),
  g = 10,
  ord = FAlSE
)

fit.glmlogit.lca.overall20 <- svyglm(MDLS_LCA_Equipment_Skills ~ 1,
                                     family = binomial(link = "logit"),
                                     design = design.ps)

confint <- exp(cbind(
  coef(fit.glmlogit.lca.overall2),
  confint(fit.glmlogit.lca.overall2)
))
confint

overalllatex$MDLSLCAoverall2confint <-
  xtable(confint, caption = "MDLS Binary GLM confidence intervals")

anova(fit.glmlogit.lca.overall20,
      fit.glmlogit.lca.overall2,
      test = "Chisq")
```

```
model_equation(fit.glmlogit.lca.overall2)

##Binary logistic regression overall model
fit.glmlogit.lca.overall3 <- svyglm(
  MDLS_LCA_Equipment_Skills ~
     SEG +
     Single_parent_dummy_factor +
     Two_plus_children_dummy_factor +
     imd2019RANK_namode +
     Benefits_factor +
     Working_factor +
     Helath_limitation_factor +
     Ethnicity_factor +
     URBAN +
     REGION +
     oac21SG,
  family = binomial(link = "logit"),
  design = design.ps
)

vif_check <- vif(fit.glmlogit.lca.overall3)
bp_check <- bptest(fit.glmlogit.lca.overall2)
hl_check <- logitgof(
  fit.glmlogit.lca.overall2$y,
  fitted(fit.glmlogit.lca.overall2),
  g = 10,
  ord = FAlSE
)

plot(Effect("SEG_factor", fit.glmlogit.lca.overall2))
plot(Effect("Single_parent_dummy_factor", fit.glmlogit.lca.overall2))
plot(Effect("Two_plus_children_dummy_factor", fit.glmlogit.lca.overall2))
plot(Effect("imd2019RANK_namode", fit.glmlogit.lca.overall2))
plot(Effect("URBAN_factor", fit.glmlogit.lca.overall2))
plot(Effect("REGION_short_factor", fit.glmlogit.lca.overall2))
plot(Effect("Benefits_factor", fit.glmlogit.lca.overall2))
plot(Effect("Working_factor", fit.glmlogit.lca.overall2))
plot(Effect("Helath_limitation_factor", fit.glmlogit.lca.overall2))
plot(Effect("Ethnicity_factor", fit.glmlogit.lca.overall2))
plot(Effect("oac_LSMS_dummy_factor", fit.glmlogit.lca.overall2))
plot(Effect("oac_EDSP_dummy_factor", fit.glmlogit.lca.overall2))

ggboxweight2d_svy(design.ps, imd2019RANK_namode, MDLS_LCA_Equipment_Skills_
    factor) + aes(fill = MDLS_LCA_Equipment_Skills_factor) + ylab("Combined Index
    of Multiple Deprivation Rank") + xlab("MDLS")

absMDLSIMD.aov <-
  svyglm(imd2019RANK_namode ~ MDLS_Abs_Equipment_Skills_factor, design = design.
     ps)
summary(absMDLSIMD.aov)

ggboxweight2d_svy(design.ps, imd2019RANK_namode, SEG_factor) +aes(fill=MDLS_LCA_
    Equipment_Skills_factor) + ylab("Combined Index of Multiple Deprivation Rank"
    ) + xlab("NRS grade") + labs(fill = "MDLS")

absMDLSIMD2.aov <-
  svyglm(imd2019RANK_namode ~ SEG_factor + MDLS_Abs_Equipment_Skills_factor,
         design = design.ps)
summary(absMDLSIMD2.aov)

ggboxweight2d_svy(design.ps, media_download_speed_Mbitxsec, Broadband_MDLS_
```

```
    factor) + ylab("Broadband speed") + xlab("Adequate Broadband") + aes(fill =
    Broadband_MDLS_factor)

bb.aov <-
  svyglm(media_download_speed_Mbitxsec ~ Broadband_MDLS_factor,
      design = design.ps)
summary(bb.aov)

dev.off()
sink()
```

Chapter 5

Skills analysis

```
library("broom")
library("car")
library("corrplot")
library("dplyr")
library("factoextra")
library("FactoMineR")
library("FactoInvestigate")
library("forcats")
library("ggparallel")
library("ggplot2")
library("GPArotation")
library("haven")
library("Hmisc")
library("igraph")
library("knitr")
library("labelled")
library("lattice")
library("LCAvarsel")
library("OneR")
library("plyr")
library("poLCA")
library("psych")
library("reshape2")
library("scales")
library("sjlabelled")
library("tidyr")
library("xtable")
library("tidyverse")

##Functions to recode Critical likert data into a binary variable
likert.column.reverse <- function(column) {
  dplyr::recode(
    column,
    '1' = 2,
    '2' = 2,
    '3' = 1,
    '4' = 1,
    '5' = 1,
    '6' = 1,
    .combine_value_labels = TRUE
  )
}

# Function to recode all likert columns in a data frame
likert.df.reverse <- function(df) {
```

```r
  df %>%
    mutate_all(likert.column.reverse)
}

# Function to convert results to a factor
create.factor2 <- function(column) {
  # Converting the column to a factor
  result <- factor(
    column,
    levels = c(1, 2),
    labels = c("Not-MDLS-adequate",
               "MDLS-adequate"),
    ordered = FALSE)
  return(result)
}


# Function to create a table with percentages for each skill in the set
calculate.percentage.table.function <- function(data) {
  # Initialize an empty data frame to store results
  result_df <- data.frame()
  # Loop through each column in the data frame
  for (col in names(data)) {
    # Calculate percentage for each factor level
    percentages <- prop.table(table(data[[col]])) * 100
    # Combine factor levels and percentages into a data frame
    col_result <- data.frame(
      Skill = col,
      MDLS = names(percentages),
      Percentage = as.vector(percentages)
    )
    # Bind the result to the final data frame
    result_df <- rbind(result_df, col_result)
  }
  return(result_df)
}

col_namesPF <-
  c("B1c01",
    "B1c02",
    "B1c03",
    "B1c04",
    "B1c05",
    "B1c06",
    "B1c07",
    "B1c08")

col_namesPC <-
  c("B2c01",
    "B2c02",
    "B2c03",
    "B2c04",
    "B2c05",
    "B2c06",
    "B2c07",
    "B2c08",
    "B2c09")

col_namesCF <-
  c("B1c01",
    "B1c02",
```

```
      "B1c03",
      "B1c04",
      "B1c05",
      "B1c06",
      "B1c07",
      "B1c08",
      "Level")

col_namesCC <-
  c("B2c01",
      "B2c02",
      "B2c03",
      "B2c04",
      "B2c05",
      "B2c06",
      "B2c07",
      "B2c08",
      "B2c09",
      "Level")

B1_01 <- subset(
  X2023MDLS.data.ordered,
  select = c(
    B1_01_1,
    B1_01_2,
    B1_01_3,
    B1_01_4,
    B1_01_5,
    B1_01_6,
    B1_01_7,
    B1_01_8
  )
)
colnames(B1_01) <- col_namesPF

B1_02 <- subset(
  X2023MDLS.data.ordered,
  select = c(
    B1_02_1,
    B1_02_2,
    B1_02_3,
    B1_02_4,
    B1_02_5,
    B1_02_6,
    B1_02_7,
    B1_02_8
  )
)
colnames(B1_02) <- col_namesPF

B1_03 <- subset(
  X2023MDLS.data.ordered,
  select = c(
    B1_03_1,
    B1_03_2,
    B1_03_3,
    B1_03_4,
    B1_03_5,
    B1_03_6,
    B1_03_7,
    B1_03_8
```

```
  )
)
colnames(B1_03) <- col_namesPF

B1_04 <- subset(
  X2023MDLS.data.ordered,
  select = c(
    B1_04_1,
    B1_04_2,
    B1_04_3,
    B1_04_4,
    B1_04_5,
    B1_04_6,
    B1_04_7,
    B1_04_8
  )
)
colnames(B1_04) <- col_namesPF

B1_05 <- subset(
  X2023MDLS.data.ordered,
  select = c(
    B1_05_1,
    B1_05_2,
    B1_05_3,
    B1_05_4,
    B1_05_5,
    B1_05_6,
    B1_05_7,
    B1_05_8
  )
)
colnames(B1_05) <- col_namesPF

B1_06 <- subset(
  X2023MDLS.data.ordered,
  select = c(
    B1_06_1,
    B1_06_2,
    B1_06_3,
    B1_06_4,
    B1_06_5,
    B1_06_6,
    B1_06_7,
    B1_06_8
  )
)
colnames(B1_06) <- col_namesPF

B1_07 <- subset(
  X2023MDLS.data.ordered,
  select = c(
    B1_07_1,
    B1_07_2,
    B1_07_3,
    B1_07_4,
    B1_07_5,
    B1_07_6,
    B1_07_7,
    B1_07_8
  )
```

```
)
colnames(B1_07) <- col_namesPF

B1_08 <- subset(
  X2023MDLS.data.ordered,
  select = c(
    B1_08_1,
    B1_08_2,
    B1_08_3,
    B1_08_4,
    B1_08_5,
    B1_08_6,
    B1_08_7,
    B1_08_8,
    B1_08_level
  )
)
colnames(B1_08) <- col_namesCF

B1_09 <- subset(
  X2023MDLS.data.ordered,
  select = c(
    B1_09_1,
    B1_09_2,
    B1_09_3,
    B1_09_4,
    B1_09_5,
    B1_09_6,
    B1_09_7,
    B1_09_8,
    B1_09_level
  )
)
colnames(B1_09) <- col_namesCF

B1_10 <- subset(
  X2023MDLS.data.ordered,
  select = c(
    B1_10_1,
    B1_10_2,
    B1_10_3,
    B1_10_4,
    B1_10_5,
    B1_10_6,
    B1_10_7,
    B1_10_8,
    B1_10_level
  )
)
colnames(B1_10) <- col_namesCF

B1_11 <- subset(
  X2023MDLS.data.ordered,
  select = c(
    B1_11_1,
    B1_11_2,
    B1_11_3,
    B1_11_4,
    B1_11_5,
    B1_11_6,
    B1_11_7,
```

```
    B1_11_8,
    B1_11_level
  )
)
colnames(B1_11) <- col_namesCF

B1_12 <- subset(
  X2023MDLS.data.ordered,
  select = c(
    B1_12_1,
    B1_12_2,
    B1_12_3,
    B1_12_4,
    B1_12_5,
    B1_12_6,
    B1_12_7,
    B1_12_8,
    B1_12_level
  )
)
colnames(B1_12) <- col_namesCF

B1_13 <- subset(
  X2023MDLS.data.ordered,
  select = c(
    B1_13_1,
    B1_13_2,
    B1_13_3,
    B1_13_4,
    B1_13_5,
    B1_13_6,
    B1_13_7,
    B1_13_8,
    B1_13_level
  )
)
colnames(B1_13) <- col_namesCF

B1_14 <- subset(
  X2023MDLS.data.ordered,
  select = c(
    B1_14_1,
    B1_14_2,
    B1_14_3,
    B1_14_4,
    B1_14_5,
    B1_14_6,
    B1_14_7,
    B1_14_8,
    B1_14_level
  )
)
colnames(B1_14) <- col_namesCF

B1_15 <- subset(
  X2023MDLS.data.ordered,
  select = c(
    B1_15_1,
    B1_15_2,
    B1_15_3,
    B1_15_4,
```

```
      B1_15_5,
      B1_15_6,
      B1_15_7,
      B1_15_8,
      B1_15_level
   )
)
colnames(B1_15) <- col_namesCF

B1_16 <- subset(
   X2023MDLS.data.ordered,
   select = c(
      B1_16_1,
      B1_16_2,
      B1_16_3,
      B1_16_4,
      B1_16_5,
      B1_16_6,
      B1_16_7,
      B1_16_8,
      B1_16_level
   )
)
colnames(B1_16) <- col_namesCF

B1_17 <- subset(
   X2023MDLS.data.ordered,
   select = c(
      B1_17_1,
      B1_17_2,
      B1_17_3,
      B1_17_4,
      B1_17_5,
      B1_17_6,
      B1_17_7,
      B1_17_8,
      B1_17_level
   )
)
colnames(B1_17) <- col_namesCF

B2_01 <- subset(
   X2023MDLS.data.ordered,
   select = c(
      B2_01_1,
      B2_01_2,
      B2_01_3,
      B2_01_4,
      B2_01_5,
      B2_01_6,
      B2_01_7,
      B2_01_8,
      B2_01_9
   )
)
colnames(B2_01) <- col_namesPC

B2_02 <- subset(
   X2023MDLS.data.ordered,
   select = c(
      B2_02_1,
```

```
    B2_02_2,
    B2_02_3,
    B2_02_4,
    B2_02_5,
    B2_02_6,
    B2_02_7,
    B2_02_8,
    B2_02_9
  )
)
colnames(B2_02) <- col_namesPC

B2_03 <- subset(
  X2023MDLS.data.ordered,
  select = c(
    B2_03_1,
    B2_03_2,
    B2_03_3,
    B2_03_4,
    B2_03_5,
    B2_03_6,
    B2_03_7,
    B2_03_8,
    B2_03_9
  )
)
colnames(B2_03) <- col_namesPC

B2_04 <- subset(
  X2023MDLS.data.ordered,
  select = c(
    B2_04_1,
    B2_04_2,
    B2_04_3,
    B2_04_4,
    B2_04_5,
    B2_04_6,
    B2_04_7,
    B2_04_8,
    B2_04_9
  )
)
colnames(B2_04) <- col_namesPC

B2_05 <- subset(
  X2023MDLS.data.ordered,
  select = c(
    B2_05_1,
    B2_05_2,
    B2_05_3,
    B2_05_4,
    B2_05_5,
    B2_05_6,
    B2_05_7,
    B2_05_8,
    B2_05_9
  )
)
colnames(B2_05) <- col_namesPC

B2_06 <- subset(
```

```
  X2023MDLS.data.ordered,
  select = c(
    B2_06_1,
    B2_06_2,
    B2_06_3,
    B2_06_4,
    B2_06_5,
    B2_06_6,
    B2_06_7,
    B2_06_8,
    B2_06_9
  )
)
colnames(B2_06) <- col_namesPC

B2_07 <- subset(
  X2023MDLS.data.ordered,
  select = c(
    B2_07_1,
    B2_07_2,
    B2_07_3,
    B2_07_4,
    B2_07_5,
    B2_07_6,
    B2_07_7,
    B2_07_8,
    B2_07_9
  )
)
colnames(B2_07) <- col_namesPC

B2_08 <- subset(
  X2023MDLS.data.ordered,
  select = c(
    B2_08_1,
    B2_08_2,
    B2_08_3,
    B2_08_4,
    B2_08_5,
    B2_08_6,
    B2_08_7,
    B2_08_8,
    B2_08_9,
    B1_08_level
  )
)
colnames(B2_08) <- col_namesCC

B2_09 <- subset(
  X2023MDLS.data.ordered,
  select = c(
    B2_09_1,
    B2_09_2,
    B2_09_3,
    B2_09_4,
    B2_09_5,
    B2_09_6,
    B2_09_7,
    B2_09_8,
    B2_09_9,
    B1_09_level
```

```
  )
)
colnames(B2_09) <- col_namesCC

B2_10 <- subset(
  X2023MDLS.data.ordered,
  select = c(
    B2_10_1,
    B2_10_2,
    B2_10_3,
    B2_10_4,
    B2_10_5,
    B2_10_6,
    B2_10_7,
    B2_10_8,
    B2_10_9,
    B1_10_level
  )
)
colnames(B2_10) <- col_namesCC

B2_11 <- subset(
  X2023MDLS.data.ordered,
  select = c(
    B2_11_1,
    B2_11_2,
    B2_11_3,
    B2_11_4,
    B2_11_5,
    B2_11_6,
    B2_11_7,
    B2_11_8,
    B2_11_9,
    B1_11_level
  )
)
colnames(B2_11) <- col_namesCC

B2_12 <- subset(
  X2023MDLS.data.ordered,
  select = c(
    B2_12_1,
    B2_12_2,
    B2_12_3,
    B2_12_4,
    B2_12_5,
    B2_12_6,
    B2_12_7,
    B2_12_8,
    B2_12_9,
    B1_12_level
  )
)
colnames(B2_12) <- col_namesCC

B2_13 <- subset(
  X2023MDLS.data.ordered,
  select = c(
    B2_13_1,
    B2_13_2,
    B2_13_3,
```

```
    B2_13_4,
    B2_13_5,
    B2_13_6,
    B2_13_7,
    B2_13_8,
    B2_13_9,
    B1_13_level
  )
)
colnames(B2_13) <- col_namesCC

B2_14 <- subset(
  X2023MDLS.data.ordered,
  select = c(
    B2_14_1,
    B2_14_2,
    B2_14_3,
    B2_14_4,
    B2_14_5,
    B2_14_6,
    B2_14_7,
    B2_14_8,
    B2_14_9,
    B1_14_level
  )
)
colnames(B2_14) <- col_namesCC

B2_15 <- subset(
  X2023MDLS.data.ordered,
  select = c(
    B2_15_1,
    B2_15_2,
    B2_15_3,
    B2_15_4,
    B2_15_5,
    B2_15_6,
    B2_15_7,
    B2_15_8,
    B2_15_9,
    B1_15_level
  )
)
colnames(B2_15) <- col_namesCC

B2_16 <- subset(
  X2023MDLS.data.ordered,
  select = c(
    B2_16_1,
    B2_16_2,
    B2_16_3,
    B2_16_4,
    B2_16_5,
    B2_16_6,
    B2_16_7,
    B2_16_8,
    B2_16_9,
    B1_16_level
  )
)
colnames(B2_16) <- col_namesCC
```

```
B2_17 <- subset(
  X2023MDLS.data.ordered,
  select = c(
    B2_17_1,
    B2_17_2,
    B2_17_3,
    B2_17_4,
    B2_17_5,
    B2_17_6,
    B2_17_7,
    B2_17_8,
    B2_17_9,
    B1_17_level
  )
)
colnames(B2_17) <- col_namesCC

B1_parents <- rbind(B1_01, B1_02)
B1_all_adults <- rbind(B1_parents, B1_03)
B1_all_adults <- rbind(B1_all_adults, B1_04)
B1_all_adults <- rbind(B1_all_adults, B1_05)
B1_all_adults <- rbind(B1_all_adults, B1_06)
B1_all_adults <- rbind(B1_all_adults, B1_07)
B1_parents <- subset(B1_parents,
                     select = c(B1c01,
                                B1c02,
                                B1c03,
                                B1c04,
                                B1c05,
                                B1c06))

B1_all_adults <- subset(B1_all_adults,
                        select = c(B1c01,
                                   B1c02,
                                   B1c03,
                                   B1c04,
                                   B1c05))

B1_parents <-
  filter(B1_parents, rowSums(is.na(B1_parents)) != ncol(B1_parents))
B1_all_adults <-
  filter(B1_all_adults, rowSums(is.na(B1_all_adults)) != ncol(B1_all_adults))

B1_parents <- likert.df.reverse(B1_parents)
B1_parents <- B1_parents %>% mutate_all(~ create.factor2(.))
B1_all_adults <- likert.df.reverse(B1_all_adults)
B1_all_adults <- B1_all_adults %>% mutate_all(~ create.factor2(.))

B1_parents_result_table <- calculate.percentage.table.function(B1_parents)
B1_all_adults_result_table <- calculate.percentage.table.function(B1_all_adults)

B1_secondary <- rbind(B1_08, B1_09)
B1_secondary <- rbind(B1_secondary, B1_10)
B1_secondary <- rbind(B1_secondary, B1_11)
B1_secondary <- rbind(B1_secondary, B1_12)
B1_secondary_older <- subset(B1_secondary,
                             Level == 4,
                             select = c(B1c01,
                                        B1c02,
                                        B1c03,
```

```
                                  B1c04,
                                  B1c05))
B1_secondary_younger <- subset(B1_secondary,
                               Level == 3,
                               select = c(B1c01,
                                  B1c02,
                                  B1c05))

B1_secondary_older <-
  filter(B1_secondary_older, rowSums(is.na(B1_secondary_older)) != ncol(B1_
     secondary_older))

B1_secondary_older <- likert.df.reverse(B1_secondary_older)
B1_secondary_older <- B1_secondary_older %>% mutate_all(~ create.factor2(.))

B1_secondary_younger <-
  filter(B1_secondary_younger, rowSums(is.na(B1_secondary_younger)) != ncol(B1_
     secondary_younger))

B1_secondary_younger <- likert.df.reverse(B1_secondary_younger)
B1_secondary_younger <- B1_secondary_younger %>% mutate_all(~ create.factor2(.))

B1_secondary_older_result_table <- calculate.percentage.table.function(B1_
    secondary_older)
B1_secondary_younger_result_table <- calculate.percentage.table.function(B1_
    secondary_younger)

B1_primary <- rbind(B1_13, B1_14)
B1_primary <- rbind(B1_primary, B1_15)
B1_primary <- rbind(B1_primary, B1_16)
B1_primary <- rbind(B1_primary, B1_17)
B1_primary_older <- subset(B1_primary,
                           Level == 2,
                       select = c(B1c01,
                              B1c02,
                              B1c07,
                              B1c08))

B1_primary_younger <- subset(B1_primary,
                           Level == 1,
                             select = c(B1c08))
B1_primary_older <-
  filter(B1_primary_older, rowSums(is.na(B1_primary_older)) != ncol(B1_primary_
     older))

B1_primary_older <- likert.df.reverse(B1_primary_older)
B1_primary_older <- B1_primary_older %>% mutate_all(~ create.factor2(.))

B1_primary_younger <-
  filter(B1_primary_younger, rowSums(is.na(B1_primary_younger)) != ncol(B1_
     primary_younger))

B1_primary_younger <- likert.df.reverse(B1_primary_younger)
B1_primary_younger <- B1_primary_younger %>% mutate_all(~ create.factor2(.))

B1_primary_older_result_table <- calculate.percentage.table.function(B1_primary_
    older)
B1_primary_younger_result_table <- calculate.percentage.table.function(B1_
    primary_younger)

B2_parents <- rbind(B2_01, B2_02)
```

```r
B2_all_adults <- rbind(B2_parents, B2_03)
B2_all_adults <- rbind(B2_all_adults, B2_04)
B2_all_adults <- rbind(B2_all_adults, B2_05)
B2_all_adults <- rbind(B2_all_adults, B2_06)
B2_all_adults <- rbind(B2_all_adults, B2_07)
B2_parents <- subset(B2_parents,
                     select = c(B2c01,
                                B2c02,
                                B2c03,
                                B2c04,
                                B2c05,
                                B2c06,
                                B2c07,
                                B2c08))
B2_all_adults <- subset(B2_all_adults,
                        select = c(B2c01,
                                   B2c02,
                                   B2c03,
                                   B2c04,
                                   B2c05,
                                   B2c06,
                                   B2c07))
B2_all_adults <-
  filter(B2_all_adults, rowSums(is.na(B2_all_adults)) != ncol(B2_all_adults))
B2_parents <-
  filter(B2_parents, rowSums(is.na(B2_parents)) != ncol(B2_parents))

B2_parents <- likert.df.reverse(B2_parents)
B2_parents <- B2_parents %>% mutate_all(~ create.factor2(.))

B2_all_adults <- likert.df.reverse(B2_all_adults)
B2_all_adults <- B2_all_adults %>% mutate_all(~ create.factor2(.))

B2_parents_result_table <- calculate.percentage.table.function(B2_parents)
B2_all_adults_result_table <- calculate.percentage.table.function(B2_all_adults)

B2_secondary <- rbind(B2_08, B2_09)
B2_secondary <- rbind(B2_secondary, B2_10)
B2_secondary <- rbind(B2_secondary, B2_11)
B2_secondary <- rbind(B2_secondary, B2_12)
B2_secondary_older <- subset(B2_secondary,
                             Level == 4,
                        select = c(B2c01,
                                   B2c02,
                                   B2c03,
                                   B2c04,
                                   B2c05,
                                   B2c06,
                                   B2c07))

B2_secondary_younger <- subset(B2_secondary,
                             Level == 3,
                             select = c(B2c01,
                                        B2c02,
                                        B2c03,
                                        B2c04,
                                        B2c05,
                                        B2c06,
                                        B2c07))

B2_secondary_older <-
```

```
  filter(B2_secondary_older, rowSums(is.na(B2_secondary_older)) != ncol(B2_
     secondary_older))

B2_secondary_older <- likert.df.reverse(B2_secondary_older)
B2_secondary_older <- B2_secondary_older %>% mutate_all(~ create.factor2(.))

B2_secondary_younger <-
  filter(B2_secondary_younger, rowSums(is.na(B2_secondary_younger)) != ncol(B2_
     secondary_younger))

B2_secondary_younger <- likert.df.reverse(B2_secondary_younger)
B2_secondary_younger <- B2_secondary_younger %>% mutate_all(~ create.factor2(.))

B2_secondary_older_result_table <- calculate.percentage.table.function(B2_
    secondary_older)
B2_secondary_younger_result_table <- calculate.percentage.table.function(B2_
    secondary_younger)

B2_primary <- rbind(B2_13, B2_14)
B2_primary <- rbind(B2_primary, B2_15)
B2_primary <- rbind(B2_primary, B2_16)
B2_primary <- rbind(B2_primary, B2_17)
B2_primary_older <- subset(B2_primary,
                     Level == 2,
                       select = c(B2c01,
                                  B2c03,
                                  B2c05,
                                  B2c09))

B2_primary_younger <- subset(B2_primary,
                             Level == 1,
                             select = c(B2c03))

B2_primary_older <-
  filter(B2_primary_older, rowSums(is.na(B2_primary_older)) != ncol(B2_primary_
     older))

B2_primary_older <- likert.df.reverse(B2_primary_older)
B2_primary_older <- B2_primary_older %>% mutate_all(~ create.factor2(.))

B2_primary_younger <-
  filter(B2_primary_younger, rowSums(is.na(B2_primary_younger)) != ncol(B2_
     primary_younger))

B2_primary_younger <- likert.df.reverse(B2_primary_younger)
B2_primary_younger <- B2_primary_younger %>% mutate_all(~ create.factor2(.))

B2_primary_older_result_table <- calculate.percentage.table.function(B2_primary_
    older)
B2_primary_younger_result_table <- calculate.percentage.table.function(B2_
    primary_younger)
```

Chapter 6

Output

```
library("ca")
library("cluster") # for gower similarity and pam
library("corrplot")
library("descr")
library("DescTools")
library("dplyr")
library("effects")
library("factoextra")
library("FactoMineR")
library("flextable")
library("forcats")
library("generalhoslem")
library("ggparallel")
library("ggplot2")
library("ggpubr")
library("gmodels")
library("haven")
library("hexbin")
library("Hmisc")
library("hrbrthemes")
library("huxtable")
library("igraph")
library("jtools")
library("knitr")
library("labelled")
library("lattice")
library("logistf")
library("nnet")
library("officer")
library("OneR")
library("plot3D")
library("plyr")
library("poLCA")
library("pwr")
library("psych")
library("RcmdrMisc")
library("RColorBrewer")
library("rcompanion")
library("reshape2")
library("rms")
library("Rtsne") # for t-SNE plot
library("sandwich")
library("scales")
library("scatterplot3d")
library("sjlabelled")
```

```
library("stargazer")
library("survey")
library("tidyr")
library("vcdExtra")
library("xtable")
library("ggsci")
library("weights")
library("pals")
library("texreg")
library("report")


##Function for Latex contingency tables
latext.table.pct.function <- function(Pct, title, lab) {
  Print(
    xtable(
      round(100 * prop.table(table(Pct)), digits = 1),
      caption = title,
      label = lab
    ),
    table.placement = "H"
  )
}


##Function for Latex contingency tables
latext.table.pct.survey.function <-
  function(Pct, title, lab, design.ps) {
    print(
      xtable(
        round(100 * prop.table(
          svytable(as.formula(paste("~", Pct)), design = design.ps)
        ), digits = 1),
        caption = title,
        label = lab
      ),
      table.placement = "H"
    )
  }

##Function for Latex contingency tables
latext.table.function <- function(Pct, title, lab) {
  print(
    xtable(Pct,
           caption = title,
           label = lab),
    table.placement = "H",
    include.rownames = FALSE
  )
}

##Function for graphics latex
chitbales.figures.function <- function(F1, G1, title_text) {
  F2 <- F1 + 1
  result <- cat(
    "\\begin{figure}\n",
    "\\centering\n",
    "\\begin{minipage}{.45\\linewidth}\n",
    "\\includegraphics[width=\\linewidth]{Figure-",
    F1,
    ".pdf}\n",
```

```
    "\\captionof{figure}{Residuals plot of ",
    title_text,
    "}\n",
    "\\label{fig:Figure-",
    F1,
    "}\n",
    "\\end{minipage}\n",
    "\\hspace{.05\\linewidth}\n",
    "\\begin{minipage}{.45\\linewidth}\n",
    "\\includegraphics[width=\\linewidth]{Figure-",
    F2,
    ".pdf}\n",
    "\\captionof{figure}{Contributions plot of ",
    title_text,
    "}\n",
    "\\label{fig:Figure-",
    F2,
    "}\n",
    "\\end{minipage}\n",
    "\\end{figure}\n",
    "\\begin{figure}[hbt!]\n",
    "\\centering\n",
    "\\includegraphics[width=0.75\\linewidth]{PropFigure-",
    G1,
    ".pdf}\n",
    "\\caption{Proportions plot of ",
    title_text,
    "}\n",
    "\\label{fig:PropFigure-",
    G1,
    "}\n",
    "\\end{figure}\n",
    sep = ""
  )
  return(result)
}

chitables.labels.function <- function(plot.label, F1, G1) {
  result <- cat(
    "The following tables \\ref{tab:",
    plot.label,
    "1}, \\ref{tab:",
    plot.label,
    "2}, and \\ref{tab:",
    plot.label,
    "3} provide detals of the observations, column and row percentages. Figures
       \\ref{fig:Figure-",
    F1,
    "} and \\ref{fig:Figure-",
    F1 + 1,
    "} present plots of residuals and contributions. Figure \\ref{fig:PropFigure
       -",
    G1,
    "} presents the data in stacked proprtions.",
    sep = ""
  )
  return(result)
}

model_equation <- function(model) {
  format_args <- list()
```

```r
  model_coeff <- model$coefficients
  format_args$x <- abs(model$coefficients)
  model_coeff_sign <- sign(model_coeff)
  model_coeff_prefix <- case_when(model_coeff_sign == -1 ~ " - ",
                                  model_coeff_sign == 1 ~ " + ",
                                  model_coeff_sign == 0 ~ " + ")
  model_eqn <-
    paste(strsplit(as.character(model$call$formula), "~")[[2]],
          # 'y'
          "=",
          paste(
            if_else(model_coeff[1] < 0, "- ", ""),
            do.call(format, format_args)[1],
            paste(
              model_coeff_prefix[-1],
              do.call(format, format_args)[-1],
              " * ",
              names(model_coeff[-1]),
              sep = "",
              collapse = ""
            ),
            sep = ""
          ))
  return(model_eqn)
}


print.tables.function <- function(tablestoprint, F1, G1) {
  cat("%########################################\n")
  cat("%#                                      #\n")
  cat("%#",
      gsub(" ", "", tablestoprint$lab),
      "#\n", sep = "")
  cat("%#                                      #\n")
  cat("%########################################\n")
  cat("\\subsection{",
      tablestoprint$lab,
      "}\n",
      sep = "")
  print(tablestoprint$rep)
  cat("%########################################\n")
  print(chitables.labels.function(tablestoprint$lab, F1, G1))
  print(tablestoprint$cpctltx,
        table.placement = "H",
  )
  print(tablestoprint$rpctltx,
        table.placement = "H",
  )
  print(tablestoprint$allltx,
        table.placement = "H",
  )
  chitbales.figures.function(F1, G1, tablestoprint$lab)
}

plot.data.function <-
  function(df, x_factor, fill_factor, plot.title) {
    polt.result <- ggplot(df,
                          aes(x = x_factor, fill = fill_factor)) +
      geom_bar(stat = "count", position = "fill", ) +
      scale_fill_brewer(palette = "Paired") +
```

```
    labs(
      y = "Proportions",
      x = "Groups",
      title = plot.title,
      subtitle = "Stacked percentages",
      fill = "Proportion groups"
    ) +
    scale_x_discrete(guide = guide_axis(n.dodge = 2)) +
    scale_y_continuous(labels = scales::percent)
  return(polt.result)
}

sink("Output.tex",
     append = FALSE,
     split = TRUE)

pdf("Output.pdf",
    width = 10,
    height = 10)

cat("\\documentclass{report}\n")
cat("% Language setting\n")
cat("% Replace `english' with e.g. `spanish' to change the document language\n")
cat("\\usepackage[english]{babel}\n")
cat("% Set page size and margins\n")
cat("% Replace `letterpaper' with `a4paper' for UK/EU standard size\n")
cat(
  "\\usepackage[a4paper,top=2cm,bottom=2cm,left=2cm,right=2cm,marginparwidth
    =1.75cm]{geometry}\n"
)
cat("\n")
cat("% Useful packages\n")
cat("\\usepackage{amsmath}\n")
cat("\\usepackage[colorlinks=true, allcolors=blue]{hyperref}\n")
cat("\\usepackage{graphicx} % Required for inserting images\n")
cat("\\usepackage{float} % Keep tables and figures within sections\n")
cat("\\usepackage{longtable}\n")
cat("\\usepackage[width=.75\\textwidth]{caption} % Reduce caption widths\n")
cat("\\title{MDLS Overall Data Analysis}\n")
cat("\\author{Simeon Yates}\n")
cat("\\date{January 2024}\n")
cat("\\begin{document}\n")
cat("\\maketitle\n")
cat("\\section{Introduction}\n")
cat("\\section{Devices and services}\n")
cat("%############################################\n")
cat("%#                                          #\n")
cat("%#Large Screen Devices                      #\n")
cat("%#                                          #\n")
cat("%############################################\n")
cat("\\subsection{Large Screen Device}\n")
latext.table.pct.survey.function(
    "Large_screen_devices_MDLS_factor",
    "MDLS large screen devices",
    "tab:LSDperc",
    design.ps
)
cat("%############################################\n")
cat("%#                                          #\n")
cat("%#Broadband                                 #\n")
cat("%#                                          #\n")
```

```
cat("%########################################\n")
cat("\\subsection{Broadband}\n")
latext.table.pct.survey.function("Broadband_MDLS_factor",
                                 "MDLS broadband",
                                 "tab:BBperc",
                                 design.ps)
cat("%########################################\n")
cat("%#                                      #\n")
cat("%#Internet speed                                    #\n")
cat("%#                                      #\n")
cat("%########################################\n")
cat("\\subsection{Internet speed}\n")
latext.table.pct.survey.function("Internet_speed_MDLS_factor",
                                 "MDLS internet speed",
                                 "tab:ISperc",
                                 design.ps)
cat("%########################################\n")
cat("%#                                      #\n")
cat("%#Data Package                          #\n")
cat("%#                                      #\n")
cat("%########################################\n")
cat("\\subsection{Data Package}\n")
latext.table.pct.survey.function("Data_package_MDLS_factor",
                                 "MDLS data",
                                 "tab:Dataperc",
                                 design.ps)
cat("%########################################\n")
cat("%#                                      #\n")
cat("%#Games Console                         #\n")
cat("%#                                      #\n")
cat("%########################################\n")
cat("\\subsection{Games Console}\n")
latext.table.pct.survey.function("Games_console_MDLS_factor",
                                 "MDLS gaming device",
                                 "tab:GDperc",
                                 design.ps)
cat("%########################################\n")
cat("%#                                      #\n")
cat("%#Games Service                         #\n")
cat("%#                                      #\n")
cat("%########################################\n")
cat("\\subsection{Games Service}\n")
latext.table.pct.survey.function("Games_service_MDLS_factor",
                                 "MDLS games service",
                                 "tab:GSperc",
                                 design.ps)
cat("%########################################\n")
cat("%#                                      #\n")
cat("%#Smart Speaker                         #\n")
cat("%#                                      #\n")
cat("%########################################\n")
cat("\\subsection{Smart Speaker}\n")
latext.table.pct.survey.function("Smart_speaker_MDLS_factor",
                                 "MDLS smart speaker",
                                 "tab:SSperc",
                                 design.ps)
cat("%########################################\n")
cat("%#                                      #\n")
cat("%#Smart TV                              #\n")
cat("%#                                      #\n")
cat("%########################################\n")
```

```
cat("\\subsection{Smart TV}\n")
latext.table.pct.survey.function("Smart_TV__MDLS_factor",
                                 "MDLS smart TV",
                                 "tab:TVperc",
                                 design.ps)
cat("%##########################################\n")
cat("%#                                        #\n")
cat("%#Smart Phone                             #\n")
cat("%#                                        #\n")
cat("%##########################################\n")
cat("\\subsection{Smart Phone}\n")
latext.table.pct.survey.function("Smartphones_MDLS_factor",
                                 "MDLS smart phone",
                                 "tab:SPperc",
                                 design.ps)
cat("%##########################################\n")
cat("%#                                        #\n")
cat("%#TV Service                              #\n")
cat("%#                                        #\n")
cat("%##########################################\n")
cat("\\subsection{TV Service}\n")
latext.table.pct.survey.function("TV_service_MDLS_factor",
                                 "MDLS digital TV service",
                                 "tab:TVSperc",
                                 design.ps)
cat("%##########################################\n")
cat("%#                                        #\n")
cat("%#MDLS equipment totals                   #\n")
cat("%#                                        #\n")
cat("%##########################################\n")
cat("\\subsection{MDLS equipment totals}\n")
latext.table.pct.survey.function("MDLS_total",
                                 "MDLS equipment overall",
                                 "tab:MDLSeqip",
                                 design.ps)
cat("%##########################################\n")
cat("%#                                        #\n")
cat("%#MDLS equipment (no SS or full GS)       #\n")
cat("%#                                        #\n")
cat("%##########################################\n")
cat("\\subsection{MDLS equipment (no smart speaker or full games service)}\n")
latext.table.pct.survey.function(
    "X2023MDLS.data$MDLS_total_noSSGS",
    "MDLS equipment (no smart speaker or games service)",
    "tab:MDLSeqipSSGC",
    design.ps
)
cat("%##########################################\n")
cat("%#                                        #\n")
cat("%#How we get to this figure               #\n")
cat("%#                                        #\n")
cat("%##########################################\n")
cat("\\subsection{How we get to this figure}\n")
cat("\\subsubsection{Those households with adequate smartphone access}\n")
latext.table.pct.survey.function("MDLS_SP_factor",
                                 "MDLS equipment step through adding SP",
                                 "tab:MDLSstep1",
                                 design.ps)
cat(
  "\\subsubsection{Those households in the prior table with adequate smartphone
     data package}\n"
```

```
)
latext.table.pct.survey.function(
    "MDLS_SP_DP_factor",
    "MDLS equipment step through adding DP",
    "tab:MDLSstep2",
    design.ps
)
cat("\\subsubsection{Those households in the prior table with broadband access}\n")
latext.table.pct.survey.function(
    "MDLS_SP_DP_BB_factor",
    "MDLS equipment step through adding BB",
    "tab:MDLSstep3",
    design.ps
)
cat("\\subsubsection{Those households in the prior table with adequate TV service}\n")
latext.table.pct.survey.function(
    "MDLS_SP_DP_BB_TV_factor",
    "MDLS equipment step through adding TV",
    "tab:MDLSstep4",
    design.ps
)
cat("\\subsubsection{Those households in the prior table with adequate broadband speed}\n")
latext.table.pct.survey.function(
    "MDLS_SP_DP_BB_TV_IS_factor",
    "MDLS equipment step through adding IS",
    "tab:MDLSstep5",
    design.ps
)
cat(
  "\\subsubsection{Those households in the prior table with adequate large screen devices}\n"
)
latext.table.pct.survey.function(
    "MDLS_SP_DP_BB_TV_IS_LS_factor",
    "MDLS equipment step through adding LS",
    "tab:MDLSstep6",
    design.ps
)
cat("\\subsubsection{Those households in the prior table with adequate smart TV}\n")
latext.table.pct.survey.function(
    "MDLS_SP_DP_BB_TV_IS_LS_ST_factor",
    "MDLS equipment step through adding ST",
    "tab:MDLSstep7",
    design.ps
)
cat("\\subsubsection{Those households in the prior table with access to gaming}\n")
latext.table.pct.survey.function(
    "MDLS_SP_DP_BB_TV_IS_LS_ST_GC_factor",
    "MDLS equipment step through adding GC",
    "tab:MDLSstep8",
    design.ps
)
cat("\\subsubsection{Those households in the prior table with access to gaming service}\n")
latext.table.pct.survey.function(
    "MDLS_SP_DP_BB_TV_IS_LS_ST_GC_GS_factor",
```

```
    "MDLS equipment step through adding GS",
    "tab:MDLSstep9",
    design.ps
)
cat("\\subsubsection{Those households in the prior table with access to smart
    speaker}\n")
latext.table.pct.survey.function(
    "MDLS_SP_DP_BB_TV_IS_LS_ST_GC_GS_SS_factor",
    "MDLS equipment step through adding SS",
    "tab:MDLSstep10",
    design.ps
)
cat("\\section{Skills}\n")
cat("%##########################################\n")
cat("%#                                       #\n")
cat("%#Parents - Functional skills            #\n")
cat("%#                                       #\n")
cat("%##########################################\n")
cat("\\subsection{Adults with parental responsibilites - Functional skills}\n")
latext.table.pct.survey.function(
    "Respondent_functional_factor",
    "MDLS respondent functional skills",
    "tab:MDLSrfs",
    design.ps
)
latext.table.pct.survey.function(
    "Other_parent_functional_factor",
    "MDLS orther parent functional skills",
    "tab:MDLSopfs",
    design.ps
)
latext.table.function(
    B1_parents_result_table,
    "MDLS Parents functional skills breakdown",
    "tab:MDLSpfsbd"
)
latext.table.pct.survey.function(
    "Adult_functional_skills_factor",
    "MDLS all parents functional skills",
    "tab:MDLSapfs",
    design.ps
)
cat("%##########################################\n")
cat("%#                                       #\n")
cat("%#SS older children - Functional skills  #\n")
cat("%#                                       #\n")
cat("%##########################################\n")
cat("\\subsection{Older secondary school children - Functional skills}\n")
latext.table.function(
    B1_secondary_older_result_table,
    "MDLS Older SS children functional skills",
    "tab:MDLSssofs"
)

cat("%##########################################\n")
cat("%#                                       #\n")
cat("%#SS younger children - Functional skills  #\n")
cat("%#                                       #\n")
cat("%##########################################\n")
cat("\\subsection{Younger secondary school children - Functional skills}\n")
latext.table.function(
```

```
    B1_secondary_younger_result_table,
    "MDLS youngerSS children functional skills",
    "tab:MDLSssyfs"
)

cat("%###########################################\n")
cat("%#                                      #\n")
cat("%#SS overall children — Functional skills#\n")
cat("%#                                      #\n")
cat("%###########################################\n")
cat("\\subsection{Secondary school children — Functional skills}\n")
latext.table.pct.survey.function(
    "SS_children_functional_skills_factor",
    "MDLS Overall SS children functional skills",
    "tab:MDLSssfs",
    design.ps
)
cat("%###########################################\n")
cat("%#                                      #\n")
cat("%#PS older children — Functional skills  #\n")
cat("%#                                      #\n")
cat("%###########################################\n")
cat("\\subsection{Older primary school children — Functional skills}\n")
latext.table.function(B1_primary_older_result_table,
                      "MDLS PS children functional skills",
                      "tab:MDLSpsofs")

cat("%###########################################\n")
cat("%#                                      #\n")
cat("%#PS younger children — Functional skills#\n")
cat("%#                                      #\n")
cat("%###########################################\n")
cat("\\subsection{Younger primary school children — Functional skills}\n")
latext.table.function(
    B1_primary_younger_result_table,
    "MDLS PS children functional skills",
    "tab:MDLSpsyfs"
)

cat("%###########################################\n")
cat("%#                                      #\n")
cat("%#PS children — Functional skills        #\n")
cat("%#                                      #\n")
cat("%###########################################\n")
cat("\\subsection{Primary school children — Functional skills}\n")
latext.table.pct.survey.function(
    "PS_children_functional_skills_factor",
    "MDLS ovearll PS children functional skills",
    "tab:MDLSpsfs",
    design.ps
)
cat("%###########################################\n")
cat("%#                                      #\n")
cat("%#Parents — Critical skills              #\n")
cat("%#                                      #\n")
cat("%###########################################\n")
cat("\\subsection{Adults with parental responsibilites — Critical skills}\n")
latext.table.pct.survey.function(
    "Respondent_critical_factor",
    "MDLS respondent critical skills",
    "tab:MDLSrcs",
```

```
    design.ps
)
latext.table.pct.survey.function(
    "Other_parent_critical_factor",
    "MDLS other parent critical skills",
    "tab:MDLSopcs",
    design.ps
)
latext.table.function(
    B2_parents_result_table,
    "MDLS Parents critical skills breakdown",
    "tab:MDLSpcsbd"
)
latext.table.pct.survey.function(
    "Adult_critical_skills_factor",
    "MDLS all parents critical skills",
    "tab:MDLSapcs",
    design.ps
)
cat("%##########################################\n")
cat("%#                                        #\n")
cat("%#SS older children — Critical skills    #\n")
cat("%#                                        #\n")
cat("%##########################################\n")
cat("\\subsection{Secondary school children — Critical skills}\n")
latext.table.function(
    B2_secondary_older_result_table,
    "MDLS older SS children critical skills",
    "tab:MDLSssocs"
)
cat("%##########################################\n")
cat("%#                                        #\n")
cat("%#SS younger children — Critical skills          #\n")
cat("%#                                        #\n")
cat("%##########################################\n")
cat("\\subsection{Secondary school children — Critical skills}\n")
latext.table.function(
    B2_secondary_younger_result_table,
    "MDLS younger SS children critical skills",
    "tab:MDLSssycs"
)

cat("%##########################################\n")
cat("%#                                        #\n")
cat("%#SS children — Critical skills          #\n")
cat("%#                                        #\n")
cat("%##########################################\n")
cat("\\subsection{Secondary school children — Critical skills}\n")
latext.table.pct.survey.function(
    "SS_children_critical_skills_factor",
    "MDLS overall SS children critical skills",
    "tab:MDLSsscs",
    design.ps
)
cat("%##########################################\n")
cat("%#                                        #\n")
cat("%#PS older children — critical skills    #\n")
cat("%#                                        #\n")
cat("%##########################################\n")
cat("\\subsection{Primary school children — Functional skills}\n")
latext.table.function(
```

```
    B2_primary_older_result_table,
    "MDLS older PS children critical skills",
    "tab:MDLSpsocs"
)

cat("%##########################################\n")
cat("%#                                        #\n")
cat("%#PS younger children -- Critical skills. #\n")
cat("%#                                        #\n")
cat("%##########################################\n")
cat("\\subsection{Primary school children -- Functional skills}\n")
latext.table.function(
    B2_primary_younger_result_table,
    "MDLS younger PS children critical skills",
    "tab:MDLSpsycs"
)

cat("%##########################################\n")
cat("%#                                        #\n")
cat("%#PS children -- Critical skills          #\n")
cat("%#                                        #\n")
cat("%##########################################\n")
cat("\\subsection{Primary school children -- Functional skills}\n")
latext.table.pct.survey.function(
    "PS_children_critical_skills_factor",
    "MDLS PS children critical skills",
    "tab:MDLSpscs",
    design.ps
)
cat("%##########################################\n")
cat("%#                                        #\n")
cat("%#OVerall  skills                         #\n")
cat("%#                                        #\n")
cat("%##########################################\n")
cat("\\subsection{Overall  skills}\n")
latext.table.pct.survey.function("Overall_skills_factor",
                                 "Overall skills",
                                 "tab:MDLSoas",
                                 design.ps)
cat("%##########################################\n")
cat("%#                                        #\n")
cat("%#Overall household skills                #\n")
cat("%#                                        #\n")
cat("%##########################################\n")
cat("\\subsection{OVerall household skills}\n")
latext.table.pct.survey.function(
    "Overall_household_skills_factor",
    "Overall household skills",
    "tab:MDLSoahs",
    design.ps
)
cat("\\section{
  Categorising households
}\n")
cat("%##########################################\n")
cat("%#                                        #\n")
cat("%#Simple (Absolute) MDLS Equipment        #\n")
cat("%#                                        #\n")
cat("%##########################################\n")
cat("\\subsection{Simple (Absolute) MDLS Equipment cutoff}\n")
latext.table.pct.survey.function("MDLS2_factor",
```

```
                                        "Absolute MDLS",
                                        "tab:MDLSabs",
                                        design.ps)
cat("%###########################################\n")
cat("%#                                         #\n")
cat("%#Grouped MDLS equipment LCA               #\n")
cat("%#                                         #\n")
cat("%###########################################\n")
cat("\\subsection{Grouped MDLS equioment using Latent Class Analysis}\n")
MDLSTypesLCAresults2023Latex
cat("\\subsubsection{MDLS LCA Graphs}\n")
cat("\\subsubsection{MDLS LCA Proportions}\n")
latext.table.pct.survey.function("MDLS_LCA_factor",
                                        "MDLS LCA based equipment",
                                        "tab:LCAequip",
                                        design.ps)
cat("%###########################################\n")
cat("%#                                         #\n")
cat("%#MDLS abs Equipment and Skills            #\n")
cat("%#                                         #\n")
cat("%###########################################\n")
cat("\\subsection{Combinging MDLS abs Equipment and Skills}\n")
latext.table.pct.survey.function(
    "MDLS_Abs_Equipment_Skills_factor",
    "MDLS (abs.) equipment",
    "tab:LCAequipabs",
    design.ps
)
cat("%###########################################\n")
cat("%#                                         #\n")
cat("%#MDLS LCA Equipment and Skills            #\n")
cat("%#                                         #\n")
cat("%###########################################\n")
cat("\\subsection{Combinging MDLS LCA Equipment and Skills}\n")
latext.table.pct.survey.function(
    "MDLS_LCA_Equipment_Skills_factor",
    "MDLS LCA based equipment and skills",
    "tab:LCAMDLSskills",
    design.ps
)
cat("\\section{
  Analyses and comparisons
}\n")
cat("%###########################################\n")
cat("%#                                         #\n")
cat("%#MDLS LCA Equipment and SEG               #\n")
cat("%#                                         #\n")
cat("%###########################################\n")
cat("\\subsection{MDLS LCA Equipment and SEG}\n")
gvarlist = c(
  "SEG_factor",
  "HTYPE_factor",
  "REGION_factor",
  "Overall_household_skills_factor",
  "Broadband_factor",
  "urban_size_factor",
  "urban_rural_factor",
  "iuc_GRP_LBLr_factor",
  "oac21SG_factor",
  "Benefits_factor",
  "Working_factor",
```

```
  "Helath_limitation_factor",
  "Ethnicity_factor"
)

hvarlist = c(
  "MDLS_LCA_factor_short",
  "MDLS2_factor",
  "Overall_household_skills_factor",
  "MDLS_Abs_Equipment_Skills_factor",
  "MDLS_LCA_Equipment_Skills_factor"
)


G1 <- 0
for (hitem in hvarlist) {
  for (gitem in gvarlist) {
    if (gitem != hitem) {
      G1 <- G1 + 1
      print.tables.function(overallchitables[[hitem]][[gitem]],
                            figNolist[[hitem]][[gitem]],
                            G1)
      print(
        plot.data.function(
    X2023MDLS.data.ordered,
    X2023MDLS.data.ordered[[gitem]],
    X2023MDLS.data.ordered[[hitem]],
    paste0(gitem, "-by-", hitem)
        )
      )
    }
  }
}


# for (gitem in gvarlist) {
#   G1 <- G1 + 1
#   print.tables.function(overallchitables$EqCutoff[[gitem]],
#                         figNolist$EqCutoff[[gitem]], G1)
#   print(
#     plot.data.function(
    #       X2023MDLS.data.ordered,
#     X2023MDLS.data.ordered[[gitem]],
#     X2023MDLS.data.ordered$MDLS2_factor,
#     paste0(gitem, " by Equipment (Abs.)")
#     )
#   )
# }
#
# for (gitem in gvarlist) {
#   G1 <- G1 + 1
#   print.tables.function(overallchitables$Skills[[gitem]],
#                         figNolist$Skills[[gitem]], G1)
#   print(
#     plot.data.function(
    #       X2023MDLS.data.ordered,
#     X2023MDLS.data.ordered[[gitem]],
#     X2023MDLS.data.ordered$Overall_household_skills_factor,
#     paste0(gitem, " by household skills")
#     )
#   )
# }
```

```
#
# for (gitem in gvarlist) {
#   G1 <- G1 + 1
#   print.tables.function(overallchitables$MDLSABSCutoff[[gitem]],
#                         figNolist$MDLSABSCutoff[[gitem]],
#                         G1)
#   print(
#     plot.data.function(
  #       X2023MDLS.data.ordered,
#     X2023MDLS.data.ordered[[gitem]],
#     X2023MDLS.data.ordered$MDLS_Abs_Equipment_Skills_factor,
#     paste0(gitem, " by MDLS (Abs.)")
#     )
#   )
# }
#
# for (gitem in gvarlist) {
#   G1 <- G1 + 1
#   print.tables.function(overallchitables$MDLSLCACutoff[[gitem]],
#                         figNolist$MDLSLCACutoff[[gitem]],
#                         G1)
#   print(
#     plot.data.function(
  #       X2023MDLS.data.ordered,
#     X2023MDLS.data.ordered[[gitem]],
#     X2023MDLS.data.ordered$MDLS_Abs_Equipment_Skills_factor,
#     paste0(gitem, " by MDLS (LCA)")
#     )
#   )
# }
cat("%############################################\n")
cat("%#                                         #\n")
cat("%#Models                                   #\n")
cat("%#                                         #\n")
cat("%############################################\n")
cat("\\subsection{Modeling MDLS}\n")
cat("%############################################\n")
cat("%#                                         #\n")
cat("%#Regression on MDLS equipment cutoff     #\n")
cat("%#                                         #\n")
cat("%############################################\n")
cat("\\subsubsection{Binary regression on simple MDLS equipment cutoff}\n")
stargazer(
  fit.glmlogit.equipment,
  single.row = TRUE,
  no.space = TRUE,
  label = "MDLSabsequipment",
  title = "Regression with all covariates on absolute MDLS equipment"
)
overalllatex$MDLS2confint
cat("%############################################\n")
cat("%#                                         #\n")
cat("%#Regression on MDLS skills cutoff        #\n")
cat("%#                                         #\n")
cat("%############################################\n")
cat("\\subsubsection{Binary regression on simple MDLS equipment cutoff}\n")
stargazer(
  fit.glmlogit.skills,
  single.row = TRUE,
  no.space = TRUE,
  label = "MDLSskills",
```

```
  title = "Regression with all covariates on overall MDLS skills"
)
overalllatex$MDLSskillsconfint
cat("%#########################################\n")
cat("%#------------------------------------#\n")
cat("%#Regression abs MDLS and skills ---------#\n")
cat("%#------------------------------------#\n")
cat("%#########################################\n")
cat("\\subsubsection{Binary regression on simple MDLS equipment and skills
    cutoff}\n")
stargazer(
  fit.glmlogit.abs,
  single.row = TRUE,
  no.space = TRUE,
  label = "RegressionMDLSabs",
  title = "Regression with S and E covariates on absolute MDLS"
)
overalllatex$MDLSabsconfint
cat("%#########################################\n")
cat("%#------------------------------------#\n")
cat("%#Regression on LCA MDLS skills ----------#\n")
cat("%#------------------------------------#\n")
cat("%#########################################\n")
cat("\\subsubsection{Binary regression on LCA MDLS equipment and skills cutoff}\
    n")
stargazer(
  fit.glmlogit.lca,
  single.row = TRUE,
  no.space = TRUE,
  label = "RegressionMDLSoverall1",
  title = "Regression with S and E covariates on LCA-based MDLS"
)
overalllatex$MDLSLCAconfint
cat("%#########################################\n")
cat("%#------------------------------------#\n")
cat("%#Regression on LCA dem MDLS skills ------#\n")
cat("%#------------------------------------#\n")
cat("%#########################################\n")
cat("\\subsubsection{Binary regression on LCA MDLS equipment and skills cutoff}\
    n")
stargazer(
  fit.glmlogit.dem.lca,
  single.row = TRUE,
  no.space = TRUE,
  label = "RegressionMDLSdemog",
  title = "Regression with demographic covariates on LCA-based MDLS"
)
overalllatex$MDLSLCAdemconfint
cat("%#########################################\n")
cat("%#------------------------------------#\n")
cat("%#Regression on LCA geo MDLS skills ------#\n")
cat("%#------------------------------------#\n")
cat("%#########################################\n")
cat("\\subsubsection{Binary regression on LCA MDLS equipment and skills cutoff}\
    n")
stargazer(
  fit.glmlogit.geo.lca,
  single.row = TRUE,
  no.space = TRUE,
  label = "RegressionMDLSgeog",
  title = "Regression with geographic covariates on LCA-based MDLS"
```

```
)
overalllatex$MDLSLCAgeoconfint
cat("%############################################\n")
cat("%#                                         #\n")
cat("%#Regression on LCA MDLS skills            #\n")
cat("%#                                         #\n")
cat("%############################################\n")
cat("\\subsubsection{Binary regression on LCA MDLS equipment and skills cutoff}\
    n")
stargazer(
  fit.glmlogit.lca.overall,
  single.row = TRUE,
  no.space = TRUE,
  label = "RegressionMDLSoverall2",
  title = "Regression with all covariates on LCA-based MDLS"
)
overalllatex$MDLSLCAoverallconfint
cat("%############################################\n")
cat("%#                                         #\n")
cat("%#Regression on LCA MDLS skills            #\n")
cat("%#                                         #\n")
cat("%############################################\n")
cat("\\subsubsection{Binary regression on LCA MDLS equipment and skills cutoff}\
    n")
stargazer(
  fit.glmlogit.lca.overall2,
  single.row = TRUE,
  no.space = TRUE,
  label = "RegressionMDLSoverallfinal",
  title = "Final regression with all covariates on LCA-based MDLS"
)
overalllatex$MDLSLCAoverall2confint
cat("\\begin{equation}\n")
cat("\\begin{split}\n")
model_equation(fit.glmlogit.lca.overall2)
cat("\\end{split}\n")
cat("\\end{equation}\n")
hl_check
stargazer(vif_check, flip=TRUE)
bp_check
cat("\\end{document}\n")
dev.off()
sink()
```

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