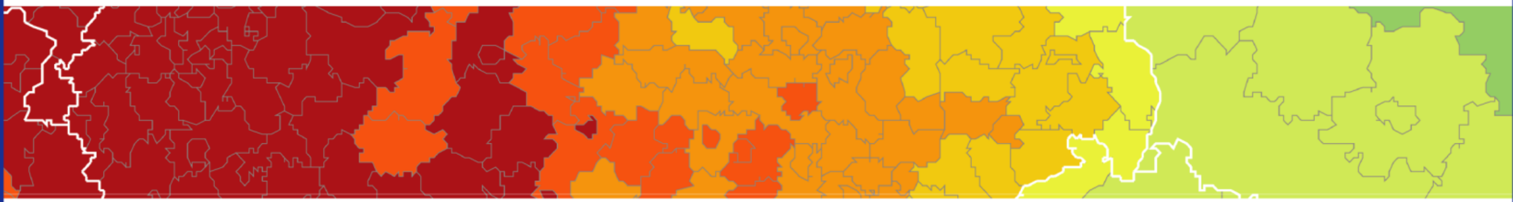


ESPON QoL – Quality of Life Measurements and Methodology

Annex 3 to the Final Report

Applied Research

Final Report

30th October 2020

Final Report

This applied research activity is conducted within the framework of the ESPON 2020 Cooperation Programme.

The ESPON EGTC is the Single Beneficiary of the ESPON 2020 Cooperation Programme. The Single Operation within the programme is implemented by the ESPON EGTC and co-financed by the European Regional Development Fund, the EU Member States and the Partner States, Iceland, Liechtenstein, Norway and Switzerland.

Project team
Carlo Sessa, Giorgia Galvini, Institute of Studies for the Integration of Systems – ISINNOVA (Italy)
Oriol Bioscal, Harold del Castillo, MCRIT (Spain)
Herta Tödtling-Schönhofer, Jasmin Haider, Metis (Austria)
Daniel Rauhut, Teemu Makkonen, University of Eastern Finland – UEF (Finland)
Maarten Kroesen, TUDelft (Netherlands)

Project Support Team
Sabine Stölb
LE GOUVERNEMENT DU GRAND-DUCHÉ DE LUXEMBOURG
Ministère de l'Énergie et de l'Aménagement du territoire
Département de l'aménagement du territoire

Janja Pečar
REPUBLIKA SLOVENIJA
URAD RS ZA MAKROEKONOMSKE ANALIZE IN RAZVOJ

Anna Lea Gestsdóttir
Byggðastofnun
Icelandic Regional Development Institute

ESPON EGTC:

Project Expert: Sandra Di Biaggio

Financial Expert: Caroline Clause

Information on ESPON and its projects can be found on www.espon.eu.

The web site provides the possibility to download and examine the most recent documents produced by finalised and ongoing ESPON projects.

Contact: info@espon.eu

Annex 3 - Latent Classes Clustering method: concept and applications

ESPON QoL – Quality of Life Measurements and Methodology

30th October 2020

Disclaimer:
This document is an Annex to the Final Report.

The information contained herein is subject to change and does not commit the ESPON EGTC and the countries participating in the ESPON 2020 Cooperation Programme.

The final version of the report will be published as soon as approved.

Table of Contents

List of Figures

List of Tables

Abbreviations

AG	Advisory Group
ARCGis	Aeronautical Reconnaissance Coverage Geographic Information System.
ART	Articulation of Territorial Networks
AT	Austria
CBC	Cross Border Cooperation
CEO	Chief Executive Officer
CO2	Cytochrome Oxidase 2
CPI	Consumer Price Index
DG	Directorate General
DFR	Draft Final Report
DHB	District Health Board
EC	European Commission
ECE	Electrical and Computer Engineering
ECHP	European Community Household Panel
EEAS	European External Action Service
EFTA	European Free Trade Association
EQLS	European Quality of Life Surveys
ES	Spain
ESPON	European Territorial Observatory Network
ESPON EGTC	ESPON European Grouping of Territorial Cooperation
EU	European Union
EU LFS	EU Labour Force Survey
EU-SILC	EU Statistics on Income and Living Conditions
FP7 ITN	Framework Programme 7 (2007-13) Initial Training Network
FI	Finland
FUA	Functional Urban Area
GDP	Gross Domestic Product
GHS	Global Human Settlements
GNI	Gross National Income
ICT	Information and Communication Technology
IPA	Instrument for Pre-accession Assistance
IT	Italy
JRC	Joint Research Centre
LAU	Local Administrative Unit
LC clustering	Latent Class clustering
LGBT	Lesbian, Gay, Bisexual, Transgender
LU	Luxembourg
MIT	Massachusetts Institute of Technology
NCEA	National Certificate Educational Achievement
NDP	National Development Plan
NEET	Not (engaged) in Education, Employment or Training
NO	Norway
NSI	National Statistical Institutes
NSO	National Statistics Office
NUTS	Nomenclature of Territorial Units for Statistics
OECD	Organization for Economic Co-operation and Development
OLAP	Online Analytical Processing
OS	Official Statistics
PM10	Particulate Matter of 10 Microns in diameter or smaller
PM2.5	Particulate Matter (less than 2.5 microns in diameter)
PST	Project Support Team
QoL	Quality of Life
QoLOBA	Quality of Life Outcomes-Based Accounting
QoP	Quality of the Place
SDG	Sustainable Development Goals
SI	Slovenia
SMEs	Small and Medium Enterprises
SPI	Social Progress Index

TED	Technology, Entertainment and Design
ToR	Terms of Reference
TQoL	Territorial Quality of Life
UK	United Kingdom
UCLG	United Cities and Local Governments
USA	United States of America
UN	United Nations
UNDP	United Nations Development Programme
UN-GGIM	United Nations Committee of Experts on Global Geospatial Information Management
UN-HABITAT	United Nations Human Settlements Programme
UN-HDI	United Nations Human Development Index
UNOPS	United Nations Office for Project Services
UNSCR	United Nations Security Council Resolutions
WBC	Western Balkans Countries

1.1 Motivation for using the latent class cluster approach

An important limitation of the composite index approach is that the composite index, while allowing for comparisons between regions, represent a *quantity* and no longer a *quality*. Hence, they only allow statements of the kind "region X performs better on the index than region Y", but the qualitative reasons underlying this statement are obscured because of the aggregated nature of the composite index. It may even be the case that two regions perform exactly the same on the index, but for very different reasons.

The heart of the Latent Class clustering approach lies in the recognition that Quality of Life cannot be defined and operationalised as a single composite index, but should be measured (revealed) as a set of qualitatively distinct patterns that are holistic in nature. Hence, instead of looking at the aggregate outcome, we argue that the focus should shift to the underlying qualitative patterns of QoL. This calls for a more contextual and region-specific approach, i.e. assessing how regions score on a range of dimensions, and thereby revealing their specific challenges and achievements in terms of relevant QoL dimensions.

To identify such communalities across regions clustering methods may be used, for example, K-means clustering or probabilistic clustering techniques like Latent Class Analysis (which has several advantages over deterministic clustering approaches). By clustering regions with similar Quality of Life patterns into (internally homogenous) groups, these methods are able to parsimoniously capture the heterogeneity in the data, while at the same time revealing the qualitatively distinct patterns. In the end, the emerging patterns can provide richer and more actionable policy insights than any single composite QoL index can provide.

The aim of this chapter is to illustrate the benefits of the latent class cluster method compared to the composite index approach. First we will compare both approaches (i.e. the composite index approach and the latent class clustering approach) in terms of their underlying assumptions. We will argue that the composite index approach makes several strong theoretical assumptions which may not hold empirically. Next, we will illustrate the benefits empirically by applying the latent class clustering approach to three cases, at the European level (NUTS 3), at the national level (The Netherlands) and at sub-national level (Barcelona). These empirical applications are driven by a conceptual basis for applying the latent class clustering approach to measure QoL of regions.

In the following we provide a methodological comparison between the latent class methodology and the composite indicator approach (section 1.2). After this we outline the conceptual thoughts behind the latent class cluster approach (1.3), after which an empirical application to the European NUTS 3 regions is presented (sections 1.4). Note that the applications of the latent class cluster approach to Barcelona and the Netherlands are presented in the respective case study reports.

1.2 The composite index vs the latent class clustering approach

In this section we explain the conceptual distinctions between the composite index approach and the cluster approach and discuss the strengths and weakness that follow from these.

Figure 1 provides the conceptualizations of the composite index approach and the cluster approach. In the composite index approach, the index (or dimension) is calculated as a weighted function of the indicators (varying weights can be used for this purpose). As a result, each indicator contributes to and thus 'causes' a part of the overall score of the index. Hence, the arrows run from the indicators to the composite score. Here, there is an important conceptual difference with the cluster approach, where the arrows run in the opposite direction. In this approach a (limited) number of distinct QoL profiles is assumed to *underlie* the used set of indicators. Conceptually, cluster membership is assumed to ‘cause’ the scores on the indicators instead of vice versa.

The second conceptual difference is that the cluster approach allows for two types of variables, namely the indicators, which are used for the actual clustering, and covariates, representing external variables. These latter variables are not actually used for the clustering, but by cross tabulating these variables with the class membership a richer profile can be obtained for each latent cluster. For these relationships, causality may be assumed to flow in either direction as reflected by the double arrows.

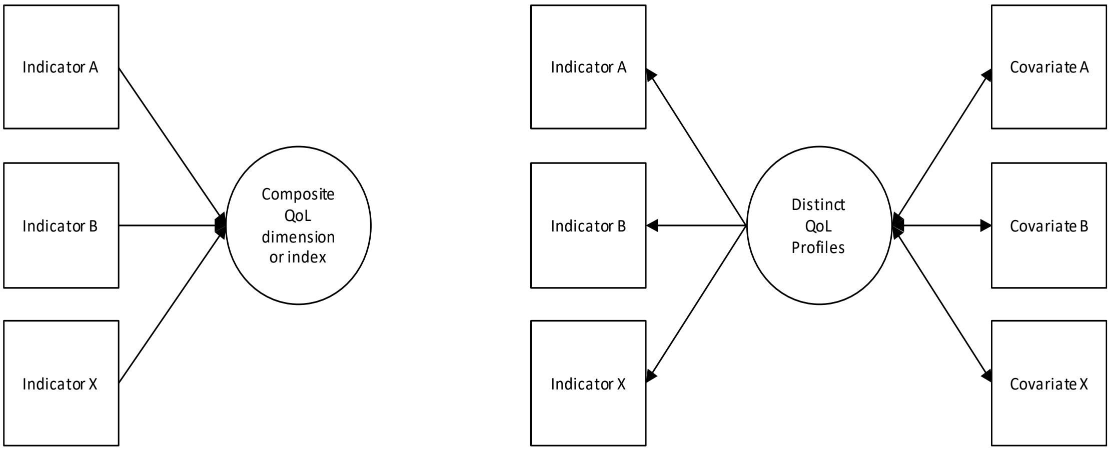


Figure 1 Conceptualization of the composite index approach (left) and cluster approach (right)

One benefit of the cluster approach compared to the composite index approach is that it provides a more contextualised and holistic understanding of quality of life patterns. The composite index approach only provides a single QoL score, which may obscure qualitatively distinct patterns that are informative from a policy viewpoint. The cluster approach, on the other hand, can reveal these underlying QoL profiles. To be able to detect and understand these underlying patterns can be relevant for policy makers.

A second benefit of the clustering approach relates to the normalisation required in the composite index approach. Because the indicators need to be merged to a single index in the composite index approach, this approach requires indicators to be normalised (or standardized) to obtain a common scale. As a result, only *relative differences* across the observations are ‘passed on’ to the final composite score and information on the *absolute values on the original scales* is lost. This is problematic in the cases where the variance of an indicator is very low (too low to be considered substantively meaningful) and/or when the lowest and highest values in the data do not correspond with commonly agreed upon levels of low or high quality of life. For example, imagine a fictional case in which life expectancy is used as the sole indicator for the dimension of health and that the value of this indicator ranges from 82 to 83 years across the regions considered in the analysis. The lowest scoring region will then get a normalised score of 0 and the highest scoring region a score of 100 on the dimension of health, grossly overrating the true absolute differences between the two regions. Moreover, all values present in the data may actually be considered as indicative of a rather high quality of life. All this information is lost in the computation of the aggregate score on the health dimension, or any overarching composite index that aggregates multiple of such dimensions.

The cluster approach effectively circumvents this problem since the indicators need not be transformed to a common scale. Instead the indicators can directly be included in the cluster model using their original scales. Note that especially latent class cluster analysis is very flexible in this regard, as it can (simultaneously) handle indicators of various scale types (continuous, ordinal and nominal). The resulting cluster profiles show how the clusters (groups of regions) perform on the used set of indicators in terms of their original scales, allowing also normative judgments to enter the interpretation of the clusters. In addition, the clustering (by definition) capitalises on those indicators with the highest (co)variance, so indicators with little variance will automatically have a low impact on the clustering process. Turning back to the life expectancy example above, should this variable be used as indicator of a cluster model (among other variables), the results would show that the resulting clusters differ little with respect to this variable and the clustering itself would not strongly be driven by the life expectancy indicator (because of the low variance in the indicator). Finally, because the original scales are kept, one can judge the (average) life expectancy of each cluster as ‘high’ by comparing the mean values with (known) thresholds and/or common standards.

A third limitation of the composite index approach is a higher score on an indicator is defined as being indicative of either increased or decreased Quality of Life. For some indicators this makes sense. For example, a higher life expectancy is generally regarded as indicative of higher quality of life, while a higher unemployment rate may be considered as indicative of lower quality of life. Yet, for other indicators the relationship between the indicator and the related value judgement may be concave. For example, a very low fertility rate may be considered undesirable from a QoL perspective, but a very high fertility rate equally so. The ideal value takes on a value somewhere ‘in the middle’. The composite index approach is not (or at least poorly) able to handle indicators of this kind. Again, the cluster approach effectively solves this problem, since it does not require making the value judgement of defining higher scores as more/less desirable upfront. Instead, the analysis will simply reveal the fertility rate in each cluster, which can then be judged as being more or less desirable.

Fourthly, objective and subjective indicators as well as input and output indicators (indicators that are under control of the policy maker or not) are typically mixed in the composite index approach. This means that the composite scores (for certain dimensions and/or the overall index) do not provide information as to whether Quality of Life is objectively or subjectively low or high in a specific region, nor on how policy makers may try to influence certain input indicators to increase quality of life in terms of certain output indicators. The latent class cluster approach provides a solution to this problem by allowing two types of variables, namely indicators and covariates. For example, a set of ‘input’ indicators may be used as indicator variables of a cluster model. Next, the resulting configurations (which are formed around the used indicators and therefore amenable by policy makers) may be linked to a set of output indicators which are included in the model as covariates. Such an analysis may then reveal which *mix of input variables* results in (overall) desirable scores on the considered output variables.

Notwithstanding the benefits of the clustering approach over the composite index approach, the latter also has several clear advantages over the clustering approach. For one, the composite QoL index can be interpreted straightforwardly and QoL maps provide a quick and clear overall picture of QoL in different regions. Interpretation in the cluster approach requires more effort from the side of the researcher and is therefore less straightforward. In addition, maps can only show class membership and thereby do not directly reveal variations in overall QoL.

Secondly, in the composite index approach, weights for the indicators can be set for different types of regions to account for regional differences in the concept of QoL. The cluster approach, on the other hand, does not use weights, so such specific adjustments are not possible.

Thirdly, the composite index approach can also be more easily implemented practically. Software packages (e.g. for factor analysis or PCA) are widely available and user friendly. The latent class clustering approach, on the other hand, requires dedicated software packages like Latent Gold or Mplus. There are freely available software packages (e.g. in R) but these are not very user friendly.

And fourthly, the composite index approach can handle a large (potentially infinite) number of indicators and be applied when there are few observations (e.g. <50), whereas the latent class clustering approach can handle a limited number of indicators (=<10) and not be applied when there are few observations (e.g. <50).

Table 1 summarises the strengths and limitations of both methods. Overall, the composite index approach is associated with several implicit assumptions and value judgments, which are opened up by the more flexible and exploratory cluster approach leading to several advantages. Nevertheless, the composite index approach also has several clear advantages over the clustering approach, most notable being more straightforward in the interpretation of the results and its practical implementation.

Table 1 Limitations of the composite index approach and benefits of the cluster approach

Composite index approach	**Cluster approach**
Weaknesses	Strengths
A single QoL index provides no information on the context of QoL in a region.	QoL profiles provide a contextualised understanding of QoL in a region
Normalization (standardization) leads to a loss of information, only information on relative differences on a common scale remains available.	Normalization (standardized) is not required, information on absolute values on the original scales is retained.
The approach assumes a convex relationship between the score on an indicator and the related value judgment in terms of QoL, which may be problematic for some indicators.	No assumption has to be made with respect to the relationship between the score on an indicator and the related value judgment in terms of QoL.
Input & output and/or objective & subjective indicators are mixed in the computation of the dimension or final composite index.	Indicators and covariates may be separately identified and can therefore be related to input & output and/or objective & subjective indicators.
Strengths	Weaknesses
The composite QoL index can be interpreted straightforwardly and QoL maps provide a quick and clear overall picture of QoL in different regions.	Interpretation takes more effort from the side of the researcher and is therefore less straightforward. Maps can only show class membership and thereby do not directly reveal variations in overall QoL.
Weights for indicators can be set for different types of regions to account for regional differences in the concept of QoL.	The approach does not use weights, so specific adjustments are not possible.
The approach is easy to implement and (free) software packages (e.g. for factor analysis) are widely available and user friendly.	The approach requires dedicated software packages like Latent Gold or Mplus. There are freely available software packages (e.g. in R) but these are not very user friendly.
The approach can handle a large (potentially infinite) number of indicators and be applied when there are few observations (e.g. <50).	The approach can handle a limited number of indicators and not be applied when there are few observations (e.g. <50).

1.3 Conceptual thoughts behind the Latent Class Cluster approach

The latent class cluster methodology is explorative in nature and (thereby) agnostic with respect to the used theoretical framework to define Quality of Life, i.e. it does not favour one theoretical framework over another. This raises the question, however, as how to proceed with the selection of indicators, a process which is usually guided by the adopted theoretical framework.

To deal with this problem, we suggest following a pragmatic and practice-oriented approach, namely to consider and select those dimensions and/or indicators which are able to reveal those QoL patterns that provide the most policy-relevant ‘actionable’ insights. For example, we can consider using the eight (aggregated) QoL dimensions of Eurostat’s QoL framework as indicators of a cluster model. Such an analysis would be able to reveal qualitatively distinct profiles representing clusters of regions that have similar performances across the life domains, thus facing similar ‘struggles’ and ‘achievements’ in terms of the different QoL dimensions. This would provide useful information for individual regions to increase QoL in their particular region. We have used this example as a ‘proof of concept’ of the proposed methodology in intermediate report.

But one can also imagine zooming in on particular Quality of Life dimensions to reveal other policy relevant patterns. In the following, we discuss two relevant patterns in particular.

The first pattern relates to the distinction between objective and subjective QoL outcome indicators. Because they complement each other’s strengths and (thereby) compensate for each other’s weaknesses, it is generally believed that any methodology that aims at measuring QoL will be more valid and reliable when both objective and subjective QoL indicators are considered. However, when integrated into a single composite index, valuable information is lost. In particular, when considering scores of objective conditions and subjective evaluations of these conditions for a particular life domain (e.g. education) four quadrants may actually be distinguished, namely ‘real hell’ and ‘real paradise’, representing states where both dimensions are aligned, and ‘fool’s paradise’ and ‘fool’s hell’ were both dimensions are misaligned (see Figure 2). The empirical application presented in the following section (1.4) is based on this patterns.

For regions seeking to improve QoL it would be highly relevant to know into which category they belong. For example, if they belong to a ‘fool’s paradise’ class they should spend efforts on enhancing objective conditions, whereas, if they belong to a ‘fool’s hell’ class, they should focus on managing expectations and aspiration levels of the people living in their respective region. The proposed methodology would be able to reveal these qualitatively distinct patterns, clustering regions with similar values of latent indicators in more homogenous clusters, and allowing to compare the profile of these indicators and the other variables within and between clusters.

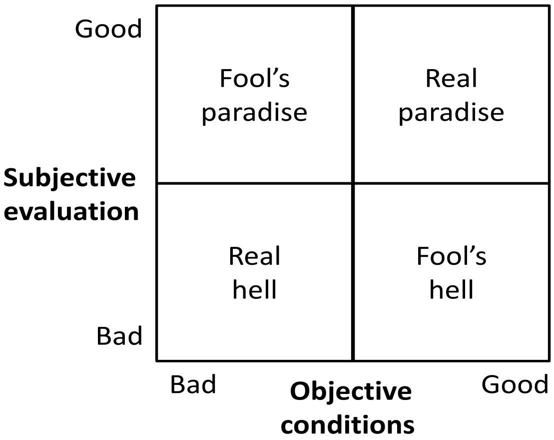


Figure 2 Four quadrants describing different combinations of objective conditions and subjective evaluations. Source: Hanell, 2018

Another policy-relevant pattern may be revealed when focusing on the distinction between quality of life enablers and the life maintenance and flourishing dimensions of the TQoL framework. For example, to measure health one may identify the number of doctors per 1,000 inhabitants (a QoL enabling indicator) or the average life expectancy (a life maintenance indicator). Here as well, the combination of these two dimensions leads to four quadrants that represent qualitatively different patterns that have policy-relevant implications (see Figure 3). In particular, consonant regions can be defined as either being in a state of poor quality of life enablers and, coherently, poor measured outcomes, or in a state of high enablers and outcomes.

On the contrary dissonant regions – where quality of life enablers and measured outcomes diverge – can be interpreted as regions with different materialism and post-materialism attitudes and lifestyles prevailing.[1] In "post-materialistic" regions low territorial endowments (QoL enablers) are compatible with high quality of life outcomes evaluation due to people prevailing preferences for a more frugal lifestyle, while in "materialistic" regions high territorial endowments could be associated with low quality of life outcomes due to the hurdles of a prevalent consumeristic lifestyle, with poor social and environmental quality of life outcomes.

[1] The ways in which individuals measure their status and success varies dramatically across countries. 70% of Chinese say they measure their success by the things they own. Only 21% of Swedes and Spaniards agree (https://www.slideshare.net/IpsosMORI/ipsos-global-trends-2017). In developed economies, and particularly among younger age cohorts, more people are starting to value experiences and access over ownership of material goods.

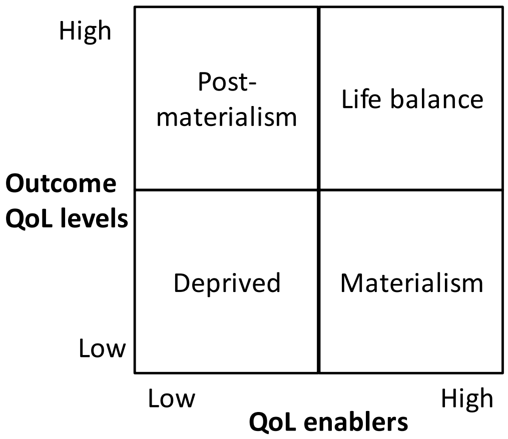


Figure 3 Four quadrants describing different combinations of QoL enablers and outcome levels

For any specific region, it would be relevant to know to which quadrant it belongs to. For example, should the region (primarily) focus on increasing the quantity or quality of the QoL enablers (more doctors) or focus on changing people's values and behaviours (e.g. dietary habits to increase life expectancy)? Or, what can be learned from post-materialistic regions, who, despite having low quantity or quality of QoL enablers, are able to achieve high outcome levels in terms of life maintenance and/or life flourishing? Again, the proposed methodology would be able to reveal these qualitatively distinct patterns and be able to show the allocation of specific regions to these patterns. The empirical application presented in the Barcelona case study report is based on this pattern.

In the following we will apply the latent class clustering approach to reveal the first pattern shown above (Figure 2). To this end, we will apply the method to data from our TQoL framework (consisting of objective dimensions) combined with a subjective measure of QoL.

1.4 Application of latent class clustering to the TQoL dimensions (NUTS 3 regions)

To illustrate the patterns in figure 2 this section will apply the latent class approach to three dimensions of our TQoL (life enablers, life maintenance and life flourishing) and a subjective QoL measure. Given that the analysis includes both objective and subjective dimensions it is able to reveal the patterns identified in Figure 2.

The subjective well-being index is constructed using 7 indicators from the 2016 edition of European Quality of Life Survey, namely life satisfaction, happiness and satisfaction with five aspects of life (education, standard of living, accommodation, family life and local area). These indicators have been measured at the European level in the European Quality of Life Survey (EQLS) that has last administrated in 2016 (N=35,947), see Eurofound (2017) for details[2]. A factor analysis (Table 2) reveals that the items converge on a single underlying factor that can

[2] Eurofound (2017), European Quality of Life Survey 2016: Quality of life, quality of public services, and quality of society. Publications Office of the European Union, Luxembourg. https://www.eurofound.europa.eu/surveys/european-quality-of-life-surveys/european-quality-of-life-survey-2016

be interpreted as composite measure of the subjective QoL. Next, the data are aggregated to the level of NUTS 3 regions.

Table 2 Descriptive statistics of the seven subjective QoL items and factor loadings (based on PCA)

	Mean	Std. Dev.	factor loading
Life satisfaction (1 very dissatisfied, 10 very satisfied)	6.75	2.21	0.79
Taking all things together on a scale of 1 to 10, how happy would you say you are?	7.06	2.09	0.79
Satisfaction with education (1 very dissatisfied, 10 very satisfied)	7.16	2.27	0.61
Satisfaction with standard of living (1 very dissatisfied, 10 very satisfied)	6.72	2.25	0.83
Satisfaction with accommodation (1 very dissatisfied, 10 very satisfied)	7.57	2.08	0.76
Satisfaction with family life (1 very dissatisfied, 10 very satisfied)	7.84	2.13	0.72
Satisfaction with local area (1 very dissatisfied, 10 very satisfied)	7.73	2.05	0.64
Valid N	35,947		

To gain some initial insights in the data, Table 3 provides the descriptive statistics of and correlations between the three dimensions of our TQoL framework (life enabling, life maintenance and life flourishing dimension) and the composite subjective QoL index. Interestingly, the life enabling and life maintenance dimensions correlate quite strongly with the subjective QoL index, while the life flourishing dimension is only weakly correlated with the subjective index. The overall TQoL index correlates most strongly with the subjective QoL index (0.427), providing a form of cross-validation. However, the correlation is far from perfect, suggesting that there are indeed clusters that reside in the off-diagonal quadrants.

Table 3 Descriptive statistics of and correlations between the three dimensions of our TQoL framework and the composite subjective well-being index

Descriptive Statistics (NUTS 3 regions 2015-2019)				**Correlations**			
	N	Mean	Std. Dev.	Main-tenance	Flouris-hing	Subj. QoL	TQoL
Life enabling (0-1)	1309	0.53	0.09	0.621**	0,008	0.386**	0.794**
Life maintenance (0-1)	1351	0.60	0.14		0.079**	0.419**	0.887**
Life flourishing (0-1)	1220	0.48	0.07			0.098*	0.389**
Subjective QoL index (1-10)	732	7.37	0.75				0.427**
TQoL (0-1)	1308	0.53	0.08				

** Correlation is significant at the 0.01 level (2-tailed).

Using the three dimensions and the subjective QoL index as indicators of the LC model the model with 6 classes provided the optimal fit to the data. Table 4 shows the profiles of the six classes and Figure 4 maps the class membership. Overall, the patterns are quite intuitive. In general, higher scores on the dimensions are associated with higher scores on the subjective QoL index. In addition, while the life enabling and maintenance dimensions are consistently aligned, this is not the case for the flourishing dimension. For example, cluster 3 scores relatively low on the life enabling and maintenance dimension, but high on the flourishing one, while this pattern is exactly opposite in cluster 4. Also the last two patterns (class 5 and 6) are quite interesting. Whereas class 5 scores lowest on the three (objective TQoL) dimensions, it still has a higher score on the subjective QoL index than the sixth class. So it seems that the subjective QoL in the sixth class is somewhat underrated compared to the objective conditions (representing a fool's hell). Below, we provide a more detailed interpretation of each class.

Table 4 Class profiles of NUTS 3 regions

NUTS 3 regions (2015-2019)	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6	**Sample**
Cluster Size (%)	30.8	30.8	14.5	8.9	8.5	6.6	
Indicators (means)							
Life enabling (0-1)	0.53	0.61	0.46	0.53	0.40	0.41	0.53
Maintenance (0-1)	0.65	0.71	0.46	0.59	0.34	0.51	0.60
Flourishing (0-1)	0.52	0.47	0.56	0.40	0.38	0.47	0.48
Subjective QoL index (1-10)	7.80	7.68	7.02	7.24	6.91	6.68	7.37
TQoL (0-1)	0.57	0.60	0.48	0.51	0.36	0.46	0.53
Country							Total
Albania	12	0	0	0	0	0	12
Austria	8	26	0	1	0	0	35
Belgium	7	7	0	29	1	0	44
Bulgaria	0	0	0	0	18	10	28
Croatia	0	0	20	1	0	0	21
Cyprus	0	0	0	1	0	0	1
Czech Republic	0	1	8	5	0	0	14
Denmark	10	1	0	0	0	0	11
Estonia	0	0	0	5	0	0	5
Finland	18	1	0	0	0	0	19
France	44	16	1	37	0	3	101
Germany	54	338	0	9	0	0	401
Greece	4	0	48	0	0	0	52
Hungary	0	0	0	2	18	0	20
Iceland	2	0	0	0	0	0	2
Ireland	5	0	0	0	0	3	8
Italy	33	2	2	2	12	59	110
Latvia	0	0	0	1	5	0	6
Liechtenstein	1	0	0	0	0	0	1
Lithuania	0	0	1	3	6	0	10
Luxembourg	1	0	0	0	0	0	1
Malta	2	0	0	0	0	0	2
Montenegro	1	0	0	0	0	0	1
Netherlands	33	7	0	0	0	0	40
North Macedonia	8	0	0	0	0	0	8
Norway	0	18	0	1	0	0	19
Poland	1	0	66	1	1	4	73
Portugal	5	0	7	0	3	10	25
Romania	0	0	0	2	40	0	42
Serbia	25	0	0	0	0	0	25
Slovakia	0	0	5	2	1	0	8
Slovenia	6	3	0	3	0	0	12
Spain	15	2	41	0	0	1	59
Sweden	11	10	0	0	0	0	21
Switzerland	26	0	0	0	0	0	26

United Kingdom	155	18	6	0	0	0	179
Total	487	450	205	105	105	90	1442

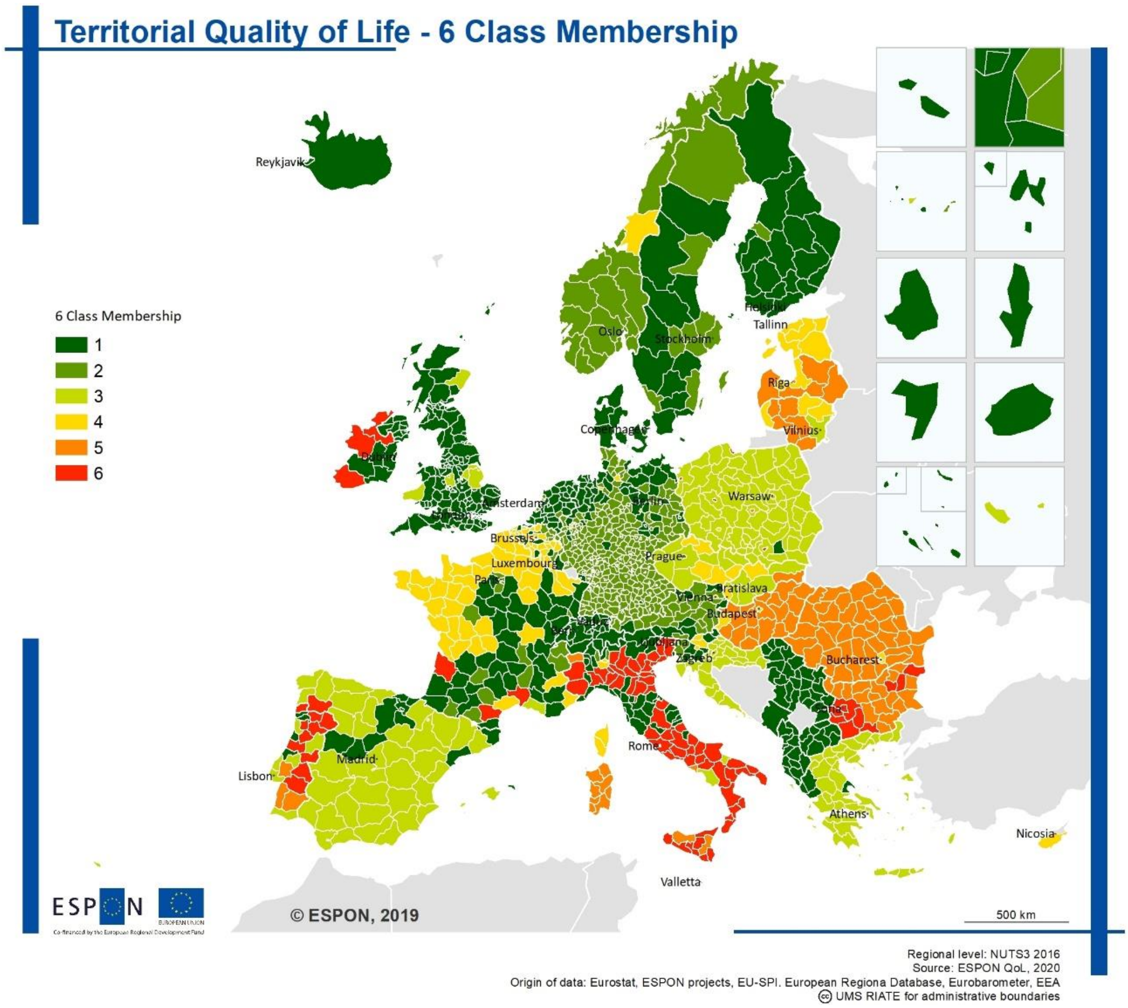


Figure 4 Class membership of European NUTS 3 regions

The first class (30.8% of the sample) performs average on the life enabling dimension and above average on life maintenance and life flourishing dimension. While this cluster does not have the highest objective scores, it does score highest on the subjective QoL dimension. Relatively many regions of the UK, the Netherlands and Serbia belong to this cluster.

The second class (again consisting of 30.8% of the sample) show exactly the opposite pattern, scoring particularly high on the life enabling and maintenance dimension, while lower than average on the life flourishing one. Overall, this cluster has the highest TQoL. The subjective QoL index is also high, but lower than in the first cluster. Relatively many regions of Austria, Germany, Norway and Sweden belong to this cluster.

The pattern of the first two classes indicates that there seems to be a trade-off between the life enabling dimension and the life flourishing one, i.e. there is a (local) negative correlation. Apparently, reaching a high QoL on all dimensions is difficult to achieve in practice.

The third class (14.5% of the sample) scores highest on the life flourishing dimension, but below average on the life enabling and life maintenance dimension and the subjective QoL index.

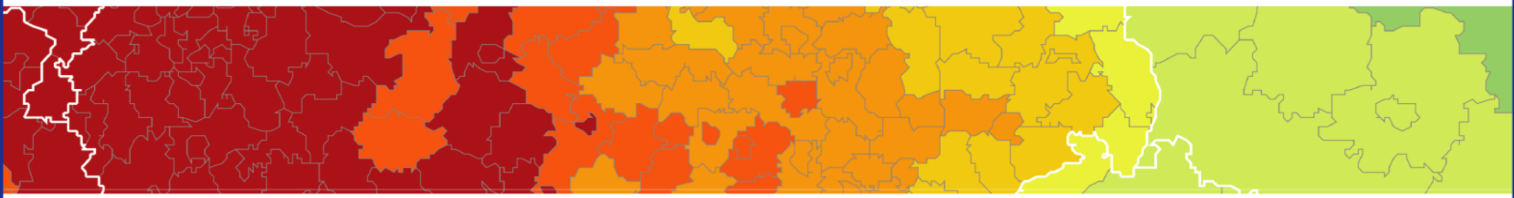
Apparently, the higher order needs are best served in these regions, but life enabling, and maintenance dimensions require attention. The regions belonging to this cluster are mostly located in the Croatia, Greece, Poland and Spain.

The pattern of the fourth class (8.9% of the sample) is opposite from the pattern of the third class. The regions belonging to this class score average on the life enabling and life maintenance dimensions and below average on the life flourishing one. Still, the subjective QoL is somewhat higher than in class 3, indicating that the life enabling, and life maintenance dimensions are more important determinants of subjective QoL. Relatively many Belgium and France regions belong to this cluster.

Class 5 (8.5% of the sample) scores poorest on all dimensions, but interestingly does not have the lowest subjective QoL score. In fact, the subjective QoL is still substantially higher than the lowest score (the sixth class). Regions from Eastern European countries are strongly represented in this class, in particular from Bulgaria, Hungary and Romania.

Finally, class 6 (6.6%), while not performing particularly poor on the TQoL dimensions (for example, it has an average score on the life flourishing dimension), still has the lowest subjective QoL score. Hence, as noted above, these patterns can be identified as one of a fool's hell. The regions belonging to this cluster are mostly located in Italy and Portugal.

Overall, in line with the main aim of the clustering approach it can be concluded that the clusters provide more detailed/contextualised information as to what patterns underlie the composite QoL scores. These patterns are substantively meaningfully, and also providing actionable insights to policy makers. In this particular case, the patterns reveal which dimension should be the focus of policy if the aim is to improve overall QoL. In addition, the analysis shows that for some regions the objective conditions are under-evaluated, suggesting that policy makers should focus on managing expectations and aspiration levels of the people living in these respective regions. On the other hand, there are regions that objectively perform poorly, but still have a relatively high score in terms of subjective QoL (class 5). Here, the focus should be on improving objective conditions.



ESPON 2020 – More information

ESPON EGTC
4 rue Erasme, L-1468 Luxembourg - Grand Duchy of Luxembourg
Phone: +352 20 600 280
Email: **info@espon.eu**
www.espon.eu, **Twitter**, **LinkedIn**, **YouTube**

The ESPON EGTC is the Single Beneficiary of the ESPON 2020 Cooperation Programme. The Single Operation within the programme is implemented by the ESPON EGTC and co-financed by the European Regional Development Fund, the EU Member States and the Partner States, Iceland, Liechtenstein, Norway and Switzerland.