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Segmenting citizens according to their self-sufficiency: A tool for local government

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ABSTRACT

Identifying subgroups of citizens with varying levels of self-sufficiency in a large local or regional population provides local government with essential input for providing matching services and well-grounded spending of health and well-being expenditures. This paper identifies self-sufficiency levels of citizens by segmenting a broad adult population. We used data from a citizen survey based on a randomly selected response group containing questions on a wide range of topics, including finances, health and living conditions, and complemented these data with registration data, including information on housing type and household composition. We conducted a latent class cluster analysis using six indicators: *perception of making ends meet*, *perceived health*, *quality of life*, *self-efficacy*, *access to social support* and *social network*. High scores on the indicators translate to high levels of self-sufficiency. We used a biased-adjusted, three-step approach to characterise the segments. Six meaningful segments were identified and labelled as 'highly self-sufficient,' 'self-sufficient – medium access to social support,' 'self-sufficient – medium self-efficacy,' 'moderately self-sufficient – low self-efficacy & high social network,' 'moderately self-sufficient – low access to social support/social network & high perceived health' and 'not self-sufficient.' At a macro level, *perception of making ends meet* and *quality of life* have discriminating value in assessing self-sufficiency. For a more detailed differentiation between groups with similar levels of self-sufficiency, *perceived health*, *self-efficacy*, *access to social support,* and *social network* are valuable indicators. Overall, this study introduces a comprehensive tool to assess self-sufficiency in larger groups of citizens by using a parsimonious number of indicators. Local and regional governments can apply this tool to effectively assess the self-sufficiency levels of their population and signal potentially vulnerable groups. In this way, the tool makes the identification of self-sufficiency levels of larger populations more feasible and more efficient and can be widely adopted in different contexts.

1. Introduction

Increasing healthcare expenditures and health disparities are challenges for countries all over the world (Mackenbach et al., 2016; Marmot and Bell, 2009). In many countries, governments focus on preventive measures (World Health Organization, 2022) and on creating healthy cities to stimulate healthy ageing (Barton and Grant, 2013). Despite many efforts in health promotion, health disparities are still persistent (Mackenbach et al., 2018; OECD, 2019). There is a growing consensus amongst scholars and practitioners that social inequalities create health disparities (Braveman and Gottlieb, 2014; Carey and Crammond, 2015) and that these should be addressed (Marmot et al., 2012; Weiss et al., 2016). Addressing health disparities requires understanding the needs of individuals and communities and strengthening the individual's own capabilities across multiple domains of life (Chinchilla et al., 2022). Thereby aiming to achieve high levels of self-sufficiency is often seen as the ultimate goal to reduce health disparities among citizens (Lauriks et al., 2014). In this study, we adopt the following definition of self-sufficiency: *'achieving an acceptable level of functioning in the essential domains of daily life, if necessary by organising appropriate support when your level of functioning threatens to decline or has declined in a way that you cannot avoid or rectify yourself'* (Lauriks et al., 2017, p. 3). Comparing self-sufficiency to the literature on control beliefs (self-perception on one's control over their competence to bring about desired outcomes)

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(see Ajzen, 1991; Lachman, 2006), self-sufficiency specifically relates to an individual's (self) assessment of functioning across multiple and specific aspects in life, including finances, health, and social network (Bannink et al., 2015; Cummings and Brown, 2019). As such, self-sufficiency can be considered an outcome variable as it refers to how an individual actually functions in daily life. This outcome is derived from an individual's cumulative score on their functioning across several life domains, and this combined score determines the level of self-sufficiency (Cummings and Brown, 2019; Fassaert et al., 2014).

To increase self-sufficiency, governments focus on healthy ageing and prevention policies, projects and activities on the national level and encourage local governments to design healthy city approaches (Barton and Grant, 2013) and tailor local prevention policies focused on health promotion (Ministry of Health, Welfare and Sport, 2019). Local governments face several challenges when tailoring services for their citizens, including high healthcare expenditures, access to services, integration of services, and efficiency issues (Axelsson and Axelsson, 2006; Stange, 2009).

Knowing individuals' self-sufficiency levels can be difficult and costly (Fassaert et al., 2014). A tool capturing signals of self-sufficiency issues would aid local governments to identify cumulative needs at a district or local level for support on specific domains. Such a tool could serve as a valuable mechanism for identifying and analysing indicators and patterns that indicate areas of potential concern, thereby enabling governments to proactively address emerging self-sufficiency issues. This will help avoid unnecessary spending on services and ensure fair provision where needed, ultimately reducing healthcare expenditures and allocating resources more efficiently (Brewster et al., 2018; Levesque et al., 2013; Obrist et al., 2007; Santana et al., 2018).

While segmentation studies have proven effective in identifying distinct needs and characteristics among specific subgroups, such as chronically ill patients (Smeets et al., 2020) and veterans (Vaughan Sarrazin et al., 2018), as well as demographic groups like adolescents (Bannink et al., 2015) and older people (Eissens van der Laan et al., 2014; Looman et al., 2018), there remains a critical gap in knowing the self-sufficiency levels of an entire adult population at the local and district levels. This paper aims to bridge this gap, providing local governments with a tool to identify different self-sufficiency levels in the entire adult population. This will help signal needs among specific citizen groups, allowing more effective resource allocation and service tailoring.

This paper presents a comprehensive self-sufficiency tool with a limited number of indicators to identify subgroups of citizens with different levels of self-sufficiency in a large local or regional population. This tool enables efficient classification of citizens according to self-sufficiency levels and can predict key determinants for differentiating between groups' self-sufficiency. This research presents the results of the tool's application using data collected from a randomly selected sample of citizens from a medium-sized city in the Netherlands. The application of this tool identified *perception of making ends meet* and *quality of life* as key determinants of self-sufficiency for segmenting the investigated population. Additionally, *perceived health*, *self-efficacy*, *access to social support* and *social network* proved useful for further understanding fine-grained differences within similar self-sufficiency groups. While the outcomes are context-dependent and likely to differ across various populations, the proposed tool remains universally deployable for local governments to monitor self-sufficiency levels and make informed decisions on budgeting, service allocation, and resource pooling.

2. Methods

2.1. Data source and study population

We analysed data from two sources from a medium-sized city in the Netherlands with an average population of 200.000 with an age distribution of 26.4% young adults (18–26 years old), 46.5% adults (27–64 years old) and 12.7% older adults (65+). First, we used survey data collected in 2018 from a randomly selected sample of citizens. The data were collected through an online survey and a sample of residents was called to answer questions over the phone. This dataset contains subjective information on citizens' daily activities, finances, health, and living arrangements. Second, the team of researchers from the municipality matched this with data from the Personal Records Database (registration data), which includes objective information on housing type and household composition. Data were weighted to match the gender and age distribution of the total population and the response threshold of 250 persons per district (a total of 33 districts were included) was met. A total of 7751 complete responses are included in this study.

2.2. Selection of indicators

The literature on self-sufficiency discusses several domains and aspects related to self-sufficiency, such as income, financial satisfaction, work, health, and quality of life (see Table 1, columns 1 and 2) (Bannink et al., 2015; Cummings and Brown, 2019; Lauriks et al., 2014; Tosun et al., 2019). Two researchers independently matched each domain to the available data. This resulted in an identical data-domain matching outcome and the identification of 18 indicators for nine salient self-sufficiency domains (see Table 1, column 3).

We have divided the indicators into two categories those used to predict the segments and those used to describe the segments at a later stage. Indicators rooted in self-evaluation, i.e., respondents' self-assessment of their own functioning, closely align with both the definition of self-sufficiency adopted in this study and the indicators that are commonly employed in the literature to measure self-sufficiency (Cummings and Brown, 2019; Fassaert et al., 2014; Lauriks et al., 2014). As a result, we chose to focus on self-evaluation-based indicators for predicting class membership or the segments. We have initially selected the following indicators as predictive elements due to their self-evaluation nature: *perception of making ends meet* (finance), *quality of life* (health), *perceived happiness* (health), *own perception of ability to change things* (self-efficacy), *self-efficacy own ability to do things* (self--efficacy), *support - lack–of engagement* (access to social support), *support – help* (access to social support), *satisfaction social network* (social network), *participation in society* (community participation). This choice not only supports conceptual clarity by aligning with the definition of self-sufficiency and its measurement indicators found in the literature, but also enhances generalizability as self-evaluation-based indicators are less context-specific and therefore comparable across different contexts. For instance, a "*persons' own perception of the extent to which they are able to make ends meet*" – a self-evaluation-based indicator of the finance domain – measures a perception that remains independent from region-specific cost-of-living variables, thus aligning more closely with the self-assessment of a person's own financial situation. As a result, it proves more generalizable compared to an indicator like monthly net household income, a non-self-evaluation indicator of self-sufficiency in terms of the finance domain. The latter is less generalizable due to its dependency on the cost of living in a specific region. Context-specific non-self-evaluation indicators-*income, work, education, subsidised housing, home ownership* and *living conditions* (size and type of household), *experienced difficulties with physical/mental health* and *received help* – have been included to describe the predicted segments in subsequent stages.

To predict the segments, we ran a series of latent class analyses employing diverse combinations of predictive indicators for domains characterized by more than one indicator, namely health, self-efficacy, and access to social support. The analyses showed that a model with a limited number of indicators demonstrated superior performance, evidenced by improved model fit (classification errors, goodness-of-fit tests) and enhanced interpretability of the segments. This result aligned with our goal of developing a parsimonious tool to assess self-sufficiency for larger adult populations. Therefore, we chose the best-

Table 1
Overview of self-sufficiency domains and corresponding indicators.

Domain	Based on	Indicators	Description indicators	LC[a] analysis	Profiling segments (3-step)
Finances	Bannink et al. (2015); Cummings and Brown (2019); Lauriks et al. (2014); Tosun et al. (2019)	• Perception of making ends meets	Persons' own perception of the extent to which they are able to make ends meet	x	x
		• Income	Monthly net household income		
Work & education	Cummings and Brown (2019)	• Work situation	Person indicates they work		x
		• Education	Highest level of education		x
Housing	Bannink et al. (2015); Cummings and Brown (2019); Lauriks et al. (2014); Tosun et al. (2019)	• Subsidised housing	Person lives in social housing (or not)		x
		• Home ownership	Person is a homeowner (or not)		x
Domestic relations	Bannink et al. (2015); Cummings and Brown (2019); Lauriks et al. (2014)	• Living conditions	Household information (size and type)		x
Health	Bannink et al. (2015); Cummings and Brown (2019); Lauriks et al., 2014)	• Quality of life	Persons' perception of quality of life	x	x
		• Perceived health	Persons' perception of health status	x	x
		• Perceived happiness	*Persons' perception of happiness (Excluded)*		
		• Experiences difficulties with physical/mental health	Whether or not a person has problems related to health		
		• Receives help	Whether or not a person receives help when needed		
Self-efficacy	Cummings and Brown (2019) (life skills); Lauriks et al. (2014) (life skills)	• Own perception of ability to change things	Perception that person cannot do much to change things	x	x
		• Self-efficacy – own perception of ability to do things	Perception that person can do anything they want		
Access to social support	Cummings and Brown (2019)	• Support – lack of engagement	Persons' perception that they have only a few people they can talk to Persons' perception that they know enough people to ask for help	x	x
		• Support – help			
Social network	Bannink et al. (2015); Lauriks et al. (2014)	• Satisfaction with social network	How satisfied a person is with their social network	x	
Community participation	Bannink et al. (2015); Cummings and Brown (2019); Lauriks et al. (2014)	• Participation in society	*How satisfied a person is with how they participate in society (Excluded)*		

[a] Latent class.

performing model with the fewest indicators. Within the health domain, we separately incorporated the *quality of life* and *perceived happiness* into the model to contrast their influence on class membership prediction. The results of the analysis revealed that *perceived happiness* lacked distinctiveness as an indicator for class membership due to zero variance across the segments, whereas *quality of life* demonstrated variance across the segments. Therefore, we decided to include *quality of life* as a predictive indicator. For the self-efficacy domain, we carefully examined the ways the items were measured, given that reverse items are less reliable compared to non-reverse items (Weijters and Baumgartner, 2012). The indicator *self-efficacy – perception of ability to do things* is measured with a non-reversed item (i.e., a person's perception that they can do anything they want), and so we labelled it as a predictive indicator. In contrast, the indicator *own perception of ability to change things* is measured with a reversed item (i.e., a person's perception that they cannot do much to change things), and so we considered it as an indicator to describe the segments. For the *access to social support* domain, it was not immediately clear which indicator to include as predictive based on content and independence. For this domain, the indicator *access to support – lack of engagement* is measured as a persons' perception that they have only a few people they can talk to, while *access to support – help* is measured as a persons' perception that they know enough people to ask for help. A preliminary latent class analysis showed that *access to support – lack of engagement* is a stronger differentiator between the segments compared to *access social support – help*. Therefore, we included *access to support – lack of engagement* as a predictive indicator and included *access to support – help* to describe the segments. Finally, after running the preliminary latent class analysis, we found that *participation in society* showed almost zero variance across the segments and this indicator did not improve model fit. Therefore, we removed this indicator from the analysis.

The final selection for the latent class analysis included six predictive indicators: *perception of making ends meet*, *perceived health*, *quality of life*, *self-efficacy*, *access to social support (lack of engagement)* and *social network* (see Table 1, columns 5 and 6).

2.3. Statistical analysis – latent class analysis

We conducted a latent class cluster analysis using the Latent Gold 5.1 software. Latent classes are unobservable segments, but through latent class modelling, it is possible to recover these unobservable segments based on observed (predictive) indicators from the data (Magidson et al., 2020; Oberski, 2016; Vermunt, 2008). Several latent class analyses were performed to determine the correct number of classes or segments, and each model was assessed using multiple criteria, including information criteria (BIC), goodness-of-fit tests (likelihood-ratio), and bivariate residuals (Magidson et al., 2020). Latent class modelling assumes that the observed variables are unrelated and mutually independent given class membership (Vermunt, 2008). Bivariate residuals are a local goodness-of-fit test that can be used to analyse where violations of local independence occur by testing pairs of indicators on local independence (Magidson et al., 2020).

We performed a bias-adjusted three-step approach to characterise the segments and examine the association between class (segment) membership and descriptive indicators of interest. In the three-step approach, (1) the latent class model is estimated based on a set of observable (predictable) indicators, (2) individuals are assigned to latent classes, and (3) the relationships between the classes and descriptive indicators are examined, taking into account the classification errors from step 2 (Bakk et al., 2013; Vermunt and Magidson, 2021). We performed the bias-adjusted three-step approach using the following settings: descriptive indicators included as dependent, individuals assigned to classes based on the proportional assignment and maximum likelihood bias adjustment (Vermunt, 2010; Vermunt and Magidson, 2021). We used the Wald test to assess whether there is a relationship between the descriptive indicators and the classes (Magidson and Vermunt, 2002). Also, we validated (face validity) the segments by presenting them to four governmental policymakers working in the social and health services domain.

3. Findings

Based on our model, we identified six meaningful segments. The LCA (Latent Class Analysis) model with six classes has a non-significant p-value for the likelihood-ratio goodness-of-fit tests (p-value >0.05) meaning that the estimated counts are close to the observed counts, the lowest BIC (Bayesian information criterion; the lower, the better fit), and the results of the bivariate residuals were within the acceptable range (<4) (Magidson et al., 2020) (Table 2). The entropy R-squared is 0.5, implying that 50% of the class membership can be predicted from the observed responses (see Van den Bergh et al., 2017).

To ensure that model 6 is the best performing, we used likelihood ratio tests and looked at the distribution of the segments to compare models with five, six and seven segments or classes. The results show that a model with an additional segment (model 6 compared to model 5) improves model fit (see Table 2). However, a model with more than six segments is less parsimonious and does not improve interpretation. After selecting the number of segments, we checked whether the model's predictive indicators were associated with class membership. The Wald test is significant (0.05) for all indicators implying that all predictive indicators are associated with the segments and should be included in the model.

In terms of validation, the outcomes of the model fit and segment interpretation demonstrated that the estimated model aligns well with the data and that the appropriate indicators were selected. Furthermore, to ensure interpretability, we engaged in discussions with multiple policymakers and researchers from local governments, validating the recognizability of the segments. The segments were found to be recognizable, both in terms of their classification and descriptions. Lastly, it is important to note that each segment comprises a substantial size (see Yan et al., 2018). Table 3 presents the relationships between the six segments and the self-sufficiency indicators. The probability that a response is associated with a particular segment is indicated for each segment. Table 3 proposes an overall score of self-sufficiency as the overall mean of each individual indicator score for each segment. All are three-point scales with 0 assigned to the mid value. For interpretation purposes, we assigned 1 to the highest score, 0 to the neutral score and −1 for the lowest score. Based on these means, we were able to classify whether segments scored low (mean below 0), moderate (mean between 0 and 0.5) or high (mean above 0.5) for each indicator and for the overall score of self-sufficiency, as Table 4 reports.

3.1. Differentiating between segments

A comparison between the scores for overall self-sufficiency and individual indicators (Table 4) shows that in all segments two indicators, namely perception of making ends meet and quality of life, are consistent with the overall self-sufficiency score. This suggests that the scores of these two indicators can be used at the macro level to differentiate between high, moderate, or low self-sufficient segments.

In contrast, the scores of the remaining four indicators are not consistently aligned with the overall self-sufficiency scores. Therefore, these indicators cannot be used to differentiate segments in terms of overall self-sufficiency, but they are useful for a fine-grained differentiation between groups with similar levels of self-sufficiency. Among the segments with high overall self-sufficiency, self-efficacy distinguishes segment 3 from segments 1 and 2*,* while *access to social support* distinguishes segment 2 from segments 1 and 3. In the two segments with a moderate overall self-sufficiency score, segment *4* has lower *perceived health* and *self-efficacy* compared to segment 5, while segment 5 has lower *access to social support* and *satisfaction with social network* compared to segment 4.

3.2. Characterising the segments

The three-step analysis enabled us to characterise each segment. Fig. 1 presents the results of the analysis and the characteristics of each segment.

The results show that segment 1 (28% of the sample) scores highly on all self-sufficient indicators and is thus labelled '*highly self-sufficient.'* On average, citizens in this segment are highly educated workers (65%) with a high income. In terms of living conditions, we see that individuals in this segment are often homeowners (76%), and live with a partner (35%) or partner and children (37%). Most citizens in this segment do not experience any health-related difficulties (88%).

Citizens in segment 2 *(27%)* score highly on all self-sufficiency indicators except for *access to social support*, and this segment is thus labelled 'self-sufficient – medium access to social support.' Citizens belonging to segment 2 are, on average, highly educated workers (69%) with middle to high incomes. In terms of living conditions, individuals in segment 2 are often homeowners (61%) living with their partner (38%) or partner and children (30%). Most citizens in this segment do not experience any health-related difficulties (83%).

Citizens in segment 3 score highly on all self-sufficiency indicators except for *self-efficacy,* and we label this segment as '*self-sufficient – medium self-efficacy' (21%)*. Citizens belonging to segment 3 are, on average, mid-to-highly educated workers (52%) or pensioners (28%) with mid-to-high incomes. Individuals in segment 3 are mostly homeowners (75%) living with a partner (37%) or partner and children (31%). Citizens in this segment do not experience health-related difficulties (69%) or are slightly hindered by health-related difficulties (28%).

Citizens in segment 4 score low on *self-efficacy*, moderate on *perception of making ends meet*, *quality of life*, *perceived health,* and *access*

Table 2
Model selection results and criteria.

Model	N clusters[a]	LL[b]	BIC[c]	Npar[d]	L^2[,e]	df[f]	p-value	Class. Err[g]
Model 1	1 cluster	−31802	63720	13	5162	5162	1.1e-565	0.000
Model 2	2 cluster	−30136	60452	20	1832	1832	2.70e-58	0.088
Model 3	3 cluster	−29962	60165	27	1482	1482	1.3e-26	0.161
Model 4	4 cluster	−29770	59844	34	1099	1099	0.000	0.175
Model 5	5 cluster	−29736	59840	41	1032	1032	0.011	0.254
Model 6	6 cluster	−29695	**59819**	**48**	948	948	**0.270**	0.332
Model 7	7 cluster	−29673	59838	55	905	905	0.600	0.344

[a] Number of clusters.
[b] Log likelihood.
[c] Bayesian information criterion.
[d] Number of parameters.
[e] Likelihood ratio test.
[f] Degrees of freedom.
[g] Classification errors.

Table 3
Probabilities segments (λ that response is associated with segment).

Segment size		Segment 1	Segment 2	Segment 3	Segment 4	Segment 5	Segment 6
		28%	27%	21%	11%	11%	2%
Perception of making ends meet	Difficult	0.0101	0.0247	0.0499	0.2566	0.1104	0.5686
	Reasonable	0.1572	0.2316	0.3064	0.4607	0.3983	0.3554
	Easy	0.8327	0.7437	0.6437	0.2827	0.4913	0.0760
	Mean	.82	.70	.60	0.03	.38	−.5
Quality of life	Dissatisfied	0.0000	0.0029	0.0036	0.1440	0.1196	0.6783
	Neutral	0.0094	0.0685	0.0734	0.3828	0.3643	0.2712
	Satisfied	0.9906	0.9287	0.9231	0.4733	0.5161	0.0504
	Mean	.99	.93	.92	.33	.40	−.63
Perceived health	Poor	0.0028	0.0029	0.0047	0.0722	0.0076	0.2399
	Fair	0.0250	0.0259	0.1065	0.3397	0.1330	0.4498
	Good	0.9723	0.971	0.8888	0.5881	0.8594	0.3104
	Mean	.97	.97	.88	.46	.85	.07
Self-efficacy: 'I can do anything I want'	Disagree	0.0000	0.0178	0.2337	0.3970	0,2049	0.9016
	Neutral	0.0028	0.1279	0.3308	0.3370	0.3226	0.0592
	Agree	0.9972	0.8543	0.4355	0.2660	0.4725	0.0393
	Mean	1	.84	.20	−.13	.27	−.86
Access to social support: 'I have only a few people I can talk to'	Agree	0.0001	0.2829	0.0725	0.2677	0.6068	0.7308
	Neutral	0.0045	0.1542	0.0949	0.1522	0.1488	0.1253
	Disagree	0.9954	0.5629	0.8326	0.5801	0.2444	0.1439
	Mean	1	.28	.76	.31	−.36	−.59
Satisfaction with social network	No, dissatisfied	0.0000	0.0088	0.0000	0.0069	0.2464	0.5019
	Neutral	0.0028	0.2645	0.0226	0.1903	0.5158	0.4139
	Yes, satisfied	0.9972	0.7267	0.9774	0.8028	0.2378	0.0842
	Mean	1	.72	.98	.79	−.01	−.42
Overall self-sufficiency	***Overall mean***	***0.96***	***0.74***	***0.72***	***0.31***	***0.26***	***−0.59***

Table 4
Simplified categorisation segments based on level of self-sufficiency.

	Perception of making ends meet	Quality of life	Perceived health	Self-efficacy	Access to social support	Satisfaction with social network	Overall self-sufficiency
Segment 1	High	High	High	High	High	High	**High**
Segment 2	High	High	High	High	Moderate	High	**High**
Segment 3	High	High	High	Moderate	High	High	**High**
Segment 4	Moderate	Moderate	Moderate	Low	Moderate	High	**Moderate**
Segment 5	Moderate	Moderate	High	Moderate	Low	Low	**Moderate**
Segment 6	Low	Low	Moderate	Low	Low	Low	**Low**

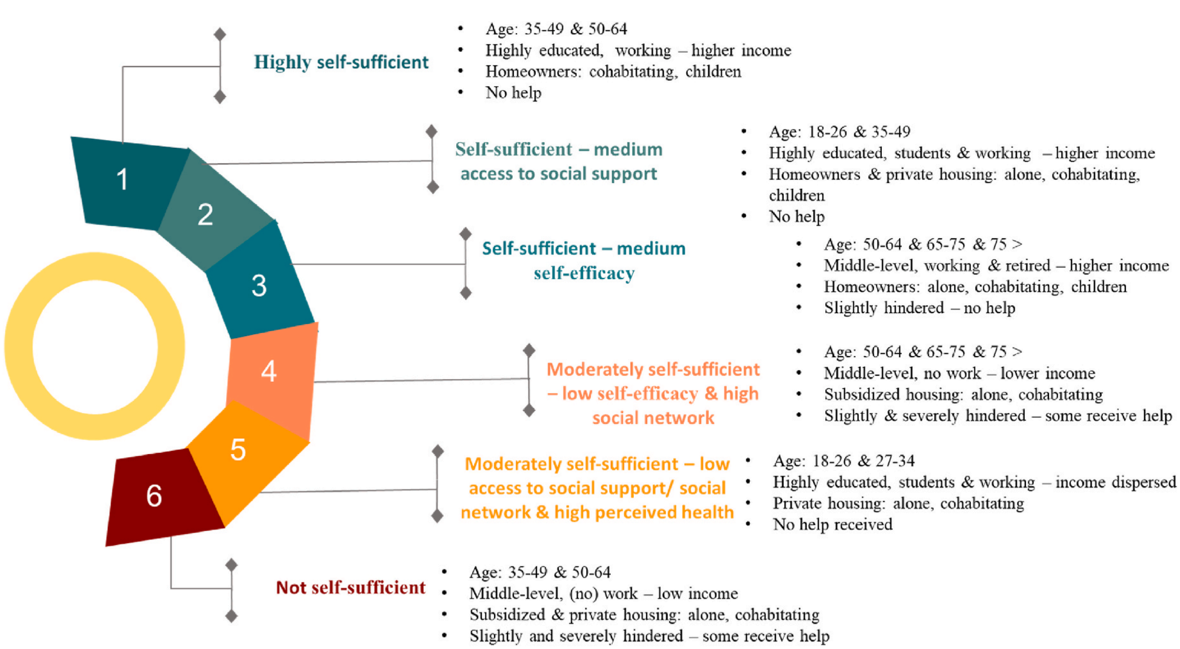

Fig. 1. Summary of main characteristics segments.

to social support, and high on *social network*. We labelled this segment as 'moderately *self-sufficient – low self-efficacy & high social network*' (11%). Citizens belonging to segment 4 are, on average, not highly educated workers (48%) or pensioners (32%) and have a low income. Only a small percentage of segment 4 is a homeowner (25%), and many live in social housing (46%), either alone (40%) or with a partner (40%). In terms of experienced difficulties related to health, most experience difficulties (80%), many are strongly hindered (30%) and indicate that they receive help because of their health condition (64%).

Segment 5 scores low on *access to social support* and *social network*, moderate on *perception of making ends meet*, *quality of life* and *self-efficacy*, and high on *perceived health*. Based on their overall score and low scores on *access to social support* and *social network* and a high score on *perceived health*, we labelled this segment as *'moderately self-sufficient – low access to social support/social network & high perceived health' (11%)*. Citizens belonging to segment 5 are, on average, mid-to-highly educated workers (65%) with low-to-middle income. Less than half are homeowners (44%), while the remaining (56%) live either in social housing (27%) or in non-owned private housing (29%), either alone (46%) or with a partner (39%). In terms of experienced difficulties related to health, some experience difficulties (43%), most are only slightly hindered (37% out of 43%), and only about half indicate that they receive help (28% out of 43%).

Segment 6 scores low for every self-sufficiency indicator except for *perceived health* (moderate) and is therefore labelled *'not self-sufficient'* (2%). Individuals in this segment experience low levels of self-sufficiency in multiple domains of life related to the *perception of making ends meet*, *quality of life*, *perceived health*, *self-efficacy*, *access to social support* and *social network*. Citizens are, on average, mid-educated workers (57%) or pensioners (23%) with a very low income. Only a small percentage are homeowners (29%), and many live in social housing (51%), either alone (49%) or with a partner (38%). In terms of experienced difficulties related to health, almost all experience difficulties (96%), a large percentage is strongly hindered (63%) and indicate that they receive help (69%).

3.3. Comparing segments with similar levels of self-sufficiency

Perception of making ends meet and *quality of life* are indicators that can be used to differentiate between high, moderate, and low self-sufficient segments. The remaining indicators *perceived health*, *self-efficacy*, *access to social support* and *social network* can aid in differentiating between segments with similar levels of self-sufficiency. Among the self-sufficient segments (1–3), *access to social support* differentiates segments 1 and 3 (high) from segment 2 (moderate). Self-efficacy differentiates segments 1 and 2 (high) from segment 3 (moderate). Therefore, both *access to social support* and *self-efficacy* can be considered decisive indicators for discriminating groups in the higher self-sufficient segments.

Looking at the descriptive indicators of the high self-sufficiency segments (1–3), the segment scoring high for each indicator of self-sufficiency (segment 1) is characterised by having the highest household income, the highest percentage of living with a partner and children, and the lowest percentage of health-related difficulties. The segment with moderate rather than high *access to social support* (segment 2) is characterised by having the youngest citizens, the highest percentage of males and students, and the lowest percentage of homeowners. In contrast, the segment with moderate rather than high self-efficacy (segment 3) is characterised by having the oldest citizens, the lowest education, and the highest percentage of health-related difficulties.

Looking at the moderately self-sufficient segments (4–5), *perceived health* and *self-efficacy* are lower in segment 4 (perceived health: moderate; self-efficacy: low) compared to 5 (perceived health: high; self-efficacy: moderate). In contrast, *access to social support* and *social network* are lower in segment 5 (access to social support: low; social network: low) compared to 4 (access to social support: moderate; social network: high). A further comparison shows that segments 4 and 5 share similar household compositions but differ in many other descriptive indicators. Segment 4, with self-sufficiency issues related to moderate *perceived health* and *low self-efficacy*, is characterised by having more pensioners, fewer people working, a higher percentage of females, lower education, a higher percentage living in social housing, and a higher percentage of health-related difficulties. Meanwhile segment 5, with self-sufficiency issues related to low *access to social support* and low *social network*, is characterised by having younger citizens, a higher percentage of males, a higher education, and a lower percentage of citizens receiving help in case of experienced health-related difficulties.

Overall, our analysis shows that in the specific case presented, the application of the proposed tool can assist in distinguishing between segments at a micro-level by looking at *perceived health, self-efficacy, access to social support, and social network* together with a combination of demographics and descriptive indicators. This enables local governments to signal needs among citizens in each segment even when the segments are classified as self-sufficient on the macro level. It is important to note that demographics and descriptive indicators need to be evaluated together rather than alone because combined they compose a profile of a group of citizens, which makes it possible to signal potential vulnerable groups.

4. Discussion

This paper identifies the self-sufficiency levels of a broad adult population and shows which indicators have discriminating value in assessing self-sufficiency. We identified six meaningful segments, three with higher levels of self-sufficiency: 1) highly self-sufficient, 2) self-sufficient – medium access to social support, and 3) self-sufficient – medium self-efficacy and three segments with lower levels of self-sufficiency: 4) moderately self-sufficient – low self-efficacy & high social network, 5) moderately self-sufficient – low access to social support/social network & high perceived health, and 6) not self-sufficient.

Our study presents a comprehensive tool for self-sufficiency assessment, coupled with its application to a context-specific case. It illustrates that a tool with few indicators is appropriate for identifying groups of citizens with different self-sufficiency levels. Unlike previous segmentation studies, we segmented an entire adult population, not just a preselected subgroup (Eissens van der Laan et al., 2014; Smeets et al., 2020; Vuik et al., 2016). Also, our research complements other segmentation studies based on self-sufficiency because it includes self-sufficient citizens in our sample and not just vulnerable groups, for example, homeless people (Cummings and Brown, 2019; Lauriks et al., 2014) and clients with mental health needs (Fassaert et al., 2014). This approach provides a more representative picture of self-sufficiency across a diverse adult population.

In contrast to prior studies (Cummings and Brown, 2019; Fassaert et al., 2014; Lauriks et al., 2014), our study adopts a parsimonious number of indicators to assess self-sufficiency, specifically, *perception of making ends meet, quality of life, perceived health, self-efficacy, access to social support* and *social network*. Importantly, our analysis shows that just two indicators (*perception of making ends meet* and *quality of life*) enable one to discriminate between groups with high (segments 1–3), moderate (segments 4–5) and low (segment 6) levels of self-sufficiency. By applying this simple tool, local government actors can monitor these two indicators to assess the self-sufficiency levels of their population at a broader macro level. These results can be coupled with corresponding geographical data to analyse self-sufficiency at the district level. The derived information can be further used to assess the allocation of services according to the segments.

Our proposed tool can be employed by local governments not only to gather a general understanding of the self-sufficiency levels of their population, but also to delve deeper into the differences between groups with similar levels of self-sufficiency. Local governments are challenged by a complex balance: providing services tailored to citizens' needs while concurrently managing health expenditure (Brewster et al., 2018; Levesque et al., 2013; Obrist et al., 2007; Santana et al., 2018). The key to managing this challenging balance lies in having a detailed understanding of the self-sufficiency levels of citizens. In our study, we show that *perceived health, self-efficacy, access to social support and social network* are helpful in differentiating between groups with similar levels of self-sufficiency. For the highly self-sufficient segments, we observe that *access to social support* differentiates segment 2 (moderate access to social support*)* from segments 1 and 3 (high access to social support). Additionally, *self-efficacy* differentiates segments 1 and 2 (high self-efficacy) from segment 3 (moderate self-efficacy). These self-sufficient segments struggle to a certain extent in one domain (access to social support*,* and self-efficacy). This is a novel finding that complements prior studies focused on vulnerable groups only. Our study confirms that vulnerable groups need the most attention when local governments are designing social and health services. In fact, vulnerable citizens in segment 6 struggle severely in each domain of self-sufficiency. However, we show that (highly) self-sufficient citizens can still suffer from specific issues. Governments must be aware that focusing just on vulnerable citizens might cause long-term social issues if the needs of self-sufficient citizens are not understood and resolved. Our findings advise to monitor the overall population and pay particular attention to *access to social support* and *self-efficacy* when designing tailored services for citizens with high self-sufficiency.

The two segments with a moderate level of self-sufficiency, segments 4 and 5, struggle to a certain extent in multiple domains, where segment 4 scores high only on *social network,* and segment 5 scores high only on *perceived health.* In fact, segment 4 scores low on *self-efficacy,* and segment 5 scores low on *access to social support* and *social network.* Our analysis shows that segments with higher (2–3) and lower (4–6) levels of self-sufficiency experience issues related to the lack of self-efficacy and access to social support. Overall, consistent with recent studies (e.g., Karimi et al., 2021), we argue that it is important that governments and health service providers offer services dedicated to resolving this lack. Thereby local governments can simultaneously increase levels of self-sufficiency for vulnerable citizens and prevent the aggravation of problems for moderately or highly self-sufficient citizens.

In addition to differentiating between the segments, our study shows that a combination of specific descriptive indicators can be used to signal vulnerable groups. Considering that not every municipality has access to data related to self-sufficiency, it is possible to use a combination of demographic and descriptive data to signal potentially vulnerable citizens. On the surface, it is not always immediately evident that indicators such as income, housing, household dimensions and 'received help on their own' can signal a potential problem. Nevertheless, putting together these items is important in signalling potentially vulnerable groups that need help. For example, segments 2 and 5 are very similar in terms of demographics, education and working conditions. They are characterised by young, highly educated citizens, mostly working or studying with a comparable income. However, they differ largely in terms of living conditions and health, where segment 2 individuals are more likely to be homeowners and live with a partner and children and are, on average, less affected by health-related difficulties. Overall, the tool we present in this paper, inclusive of the specific indicator selection and analysis, is generalizable to other contexts. However, the application and outcomes derived from our specific case are context-specific and, therefore, not generalizable.

Local governments can use this tool to periodically assess the levels of self-sufficiency amongst their citizens, providing them the ability to monitor changes of these levels over time. Local governments can use these results to signal needs of groups of citizens, shaping responsive and targeted policies. In our case, the self-sufficiency levels of the population are best described by six different segments, each demonstrating unique characteristics of self-sufficiency. The local government, therefore, obtained an in-depth understanding of the self-sufficiency profiles and their defining features. For instance, a sizable portion of young individuals in segment 5 may have shortcomings in the domain of *acces to social support,* signalling a potential area of focus. Moreover, on a district level, our tool can signal underserved citizens. With geographical data integration, local governments can analyse the distribution of the segments across the districts, juxtaposing signalled shortcomings in the specific domains of particular segments against the available services. For example, if certain districts have unmet needs despite the presence of service providers, this suggests a gap in service provision. Moreover, understanding segment distribution can guide effective allocation of limited resources, such as strategically placing social care teams based on the quantity and expertise required. It can also inform the outsourcing of services. If a significant portion of a segment scores low on *self-efficacy*, for instance, commissioning agreements can stipulate the development of services or interventions to support this aspect. Overall, we present a tool that equips local governments to signal potential needs, allocate resources efficiently, and monitor progress, facilitating informed decision-making for budgeting, service provision, and policy formation.

The ability to use a large database made conducting this study possible. However, there are limitations to using this data. First, we could not preselect self-sufficiency indicators to include in the survey and influence the ways questions were posed, which might preclude the inclusion of potentially important aspects. Second, although we were able to identify segments with lower levels of self-sufficiency, we believe that these groups are, in reality, more prominent and are not fully represented in our sample. This is related to the sampling process since citizens need access to a computer and some level of literacy to participate in the survey, and citizens who cannot respond are automatically excluded. Third, another limitation of this study is that we did not have the opportunity to externally validate the segments with exogenous information, e.g., health outcomes, healthcare expenditures (see Smeets et al., 2020), and healthcare utilization (see Eissens van der Laan et al., 2014). Our model is built on health indicators derived from survey data, and we cannot consider the health outcomes from the same data as exogenous information for comparing our segments. Additionally, we did not have access to alternative databases, e.g., owned by health insurance companies, to do so. One avenue for future research could be to enhance our model and test it against health outcomes and healthcare expenditures. For future research, it would be interesting to examine transitory behaviour across segments over a more extended period using longitudinal data (Elliott et al., 2008). Finally, besides examining transitory behaviour over time using longitudinal data, future research could seek to analyse the decisive factors contributing to lower levels of self-sufficiency.

Data availability

The data that has been used is confidential.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.socscimed.2023.116246.

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