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Social Support Typologies: Different Approaches for Reducing Social Support Data[1]

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Abstract

Social support refers to certain qualitative aspects in social contacts. Information about social support in surveys is usually collected through name generators and name interpreters. Here we use a faster way for asking questions on ego-centred social support-networks and propose a compact way for reducing this information. Our aim is to measure diversity of role relations and diversity of support content in social support networks. We take role relations, rather than individuals, as the unit of analysis for support networks (i.e. the aggregated contribution of persons with the same role relation). A random sample of 623 Belgians living in the Flemish region were asked to name the role relations they can rely on for each of five specific sorts of support. Using latent class analysis (LCA) within log-linear analysis, we focus on aggregated content diversity and aggregated role diversity. We explore whether a limited number of types of support for role relations and of role relations for items of support can be found in the sample. A large number of alternative models are found. We explore several alternative models and subsequently we evaluate the results. Our evaluation is based on the fit of the model (significance of the likelihood-ratio) and the stability of the parameters (identifiable solution). We find that in many cases the kinds of support (that a role relation gives to the respondent) can be represented by a latent variable with a limited number of classes. On the other hand, the types of relations that give a specific kind of support can hardly ever be reduced to an underlying categorical variable.

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1 Introduction

Interest in social support networks has largely been concentrated in areas concerned with (mental) health and specialised research on social networks. In large scale surveys specific questions about social support are largely absent. A possible reason for this absence might be that no short method for measuring social support in ego-centred based surveys has been developed and moreover no generally accepted representation of a support network is available.

When an ego-centred network-perspective is used in social surveys, respondents are usually asked about the availability of certain kinds of support from their social relations through name generators. These types of questions ask respondents to name *every individual* from whom they (can) receive emotional, instrumental or other kinds of support. It is customary to supplement the questionnaire with name interpreter questions, which supply additional information about the (social-demographic) characteristics of these alters and their relation to the respondent (e.g. McCallister et al., 1978; Burt, 1984). The main focus in this way of questioning is on the *size* of the social support system (number of support-givers, proportion alters with certain characteristics, mean number of types of support for each relationship, etc) (cf. Vaux, 1988; Campbell, et al., 1986; Huang et al., 1990; Marsden, 1990; Wellman et al., 1990).

However, measuring and representing social support in this way has two major disadvantages. First, it is *time-consuming* for the interviewer and *cognitive demanding* for the respondent (cf. van der Poel, 1993: 53; Kogovšek *et al.*, 2000: 3). An often used solution consists in restricting the number of names by asking the respondents to give only the five most important names (or the first five that come to the respondent's mind). However, this procedure may produce distortions in the characteristics of social support networks (cf. Burt, 1984:315; Huang et al., 1990: 202). For example, this technique is reported to be biased towards alters with strong ties (Huang et al., 1990: 203 referring to research by R. Burt).

Second, the constructed variables (size and other network properties) reveals only a *small part* of the complexity of social support networks (cf. Vaux, 1988). Often a large number of *one-dimensional* variables (e.g. the proportion of kin in a social support network) are necessary to cover more complex aspects. For social support to be included in more complex models, this necessitates more compact representations of the information.

The central aim of this paper is to overcome these shortcomings. The use of an ‘easier’ way to measure social support networks, while still taking account of the importance of role relations should make survey questions on social support more available. The first part of the paper deals with the development of these questions. In the second part, we focus on the question if the information from these questions can be presented in a more compact way by using multidimensional variables obtained through latent class analysis. This should result in variables with a limited number of types comprising much of the information.

2 Measuring social support networks

Social support basically refers to certain qualitative aspects of social contacts (House *et al.*, 1988; Antonucci *et al.*, 1997). Because the concept of social support is rather broad (cf. Vaux, 1988: 25; 28), any measurement instrument will necessarily encompass only a small part of the full complexity (Vaux, 1988: 25). As a consequence, the appropriate way of building a questionnaire depends largely on the specific aspects and dimensions of social support that one wants to capture.

It is widely accepted that social support is not uni-dimensional. Most authors make at least some distinction between emotional support, instrumental support, information, and companionship (cf. House, 1981; Wellman *et al.*, 1990; van der Poel, 1993: 55). Moreover, individuals often can rely on different significant others for different types of support. Nadel, Freeman and Ruan (1997: 99) argue that the role-relationship an individual has towards someone else dictates the limits of the concrete forms of behaviour. McCallister and Fischer (1978: 136) have described these rules as ‘a specific, cultural defined set of expectations, obligations, and rights between incumbents of two reciprocal social positions’. It should be noted that these rules may differ between groups within a society. Moreover, the implementation of these rules depends on the interpretation given by the individual (cf. van der Poel, 1993: 50). Role relationships, thus, are crucial to typify networks for specific dimensions of social support. In order for a specific support to occur within a role relationship, ego has to find it appropriate within the role relation to ask support from alter, while at the same time alter has to see it as just for him or her to offer that support given the role relation. Of course, a necessary precondition for such an evaluation is the existence of a relations with that type of role.

In this paper our interest lies in measuring the *diversity* of ego-centred social support networks, regarding the different role relations of support giving alters and the different types of social support. More specifically, our aim is to capture possible variations, with respect to both the kind of relation between ego and alter and the type of support. In order to avoid the earlier mentioned drawbacks of name generators, we use a different approach. Rather than taking every alter in a social support-network as a different case, we consider the group of individuals with a specific role relation to ego as the unit of analysis. A respondent then receives a specific kind of support from a specific role relation whenever one individual with that role relation gives that kind of support. Whether an individual has only one support-giver to rely on for a specific type of support, or whether he or she has more sources of the same support is only relevant in so far as these sources of support come from different role relations.

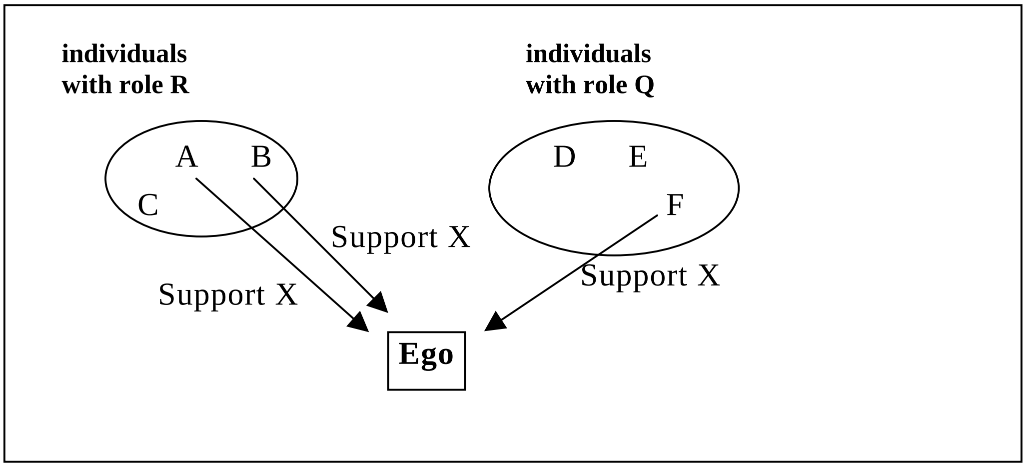

Figure 1a: Support from different role relations.

From this aggregated perspective, variation in social support networks can be interpreted in at least two different ways. First, it can refer to the *diversity of role relations* that deliver support. Second, it can refer to the *diversity of the social support contents*.

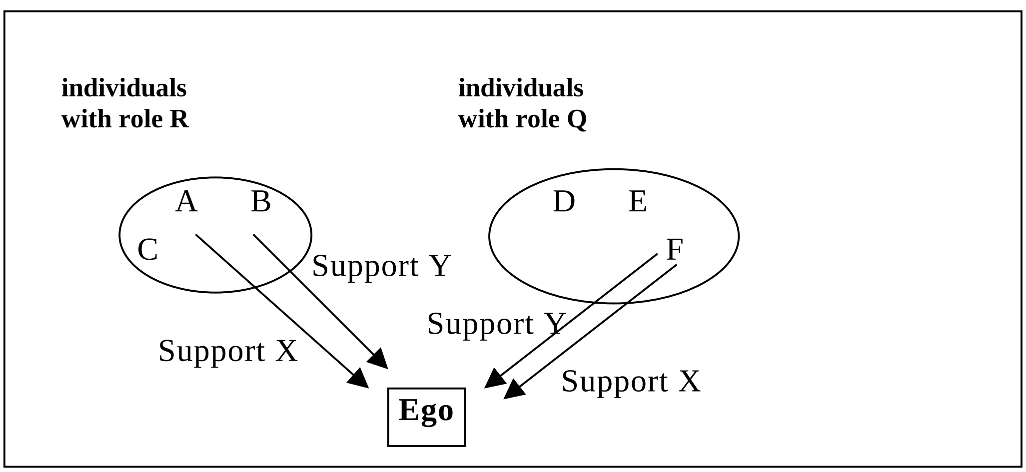

Figure 1b: Different support from a role relation.

From the perspective of social integration (for any social support contents) the different sort(s) of role relations within which support-transactions take place can be very crucial. Individuals with diverse sorts of relations to rely on for a specific type of support may be more strongly integrated and may feel more secure. Such a situation may also imply less dependence on a specific role relation (cf. range in Burt 1983). We will use ***aggregated role diversity*** of a support type to refer to the situation where different individuals with other roles to the respondent give the same support[5]. Figure 1a illustrates this. Individual A and individual B with role R may gives support X to ego and another individual F with another role Q may give the same type of support X to ego. Support of type X is both given by (at least one individual with) role relation R and (another individual with) role relation Q.

The second type of diversity refers to the variation in the types of support contents that specific *role relations* (not individuals) provide. Diverse support from one role relation may point to that type of role relation taking a more central position for that individual in situations of crisis. We are interested in whether individuals with the *same role relations* are at the same time a source for different types of support. In other words we look at which (probably) different alters with the same kind of role relationship are the source of what kinds of support. We therefore speak of ***aggregated content diversity*** of a role. In Figure 1b we give a graphical representation. Individual A with a role R gives support X, while individual B with the same role relation R is a source for support Y. Individual F with role Q gives at the same time support X and support Y. In both cases we say that role relation R, respectively Q, gives both support X and Y.

In order to be able to consider the full complexity of social support networks (including aggregated role and content diversity) while using a manageable way of data collection and analysis we use an alternative way for measuring social support networks. First of all, this implies the use of a non-conventional way of questioning. Second, we propose the use of latent class analysis to reduce the data. These two elements are elaborated in the next section. First we give information about the data.

3 Methodology

3.1 Data

The sample is a classical two-stage random sample of 623 Belgians living in the Flemish region aged between 23 and 75 years. We randomly selected 58 communities. The cluster of 10 respondents were divided over the communities relative to their population size. In these 58 communities, the clusters of 10 respondents were selected by a classical random sampling procedure. Compared to the population of Flanders, there is slight under-representation of the youngest

[5] Aggregated role diversity has some similarities with Burt's range in *the statuses of the alters* (Burt, 1983). However, status refers to socio-demographic characteristics, not roles. Moreover, the measure we want to develop is not simply an index of the number of different statuses.

age group (23-29 year) and of the lower educated group. The survey took place in February and March 1997. The interviewers were trained and supervised by the ISPO[6]. The questions used in this paper are part of a large survey, centred on value orientations and factual question about social integration. (Waege, 1997).

3.2 Questions

The conventional way of measuring social support networks concentrates on the number of alters in an individual's social support system. For this reason, questions are often used that acquire information about *all* the support-givers of a individual. Since the aim of this paper is to grasp what different kinds of support from different role relations an individual receives, we can ask whether a specific role relation (not a specific individual) provides a specific support. The diversity of a network can then be measured without respondents having to name all support-givers.

Because social support is a multidimensional concept, different dimensions of social support should be captured. To avoid differences in interpretation, the different support items should be as specific as possible (van der Poel, 1993: 51). It should be noted that depending on the selection of the types of social support possibly other dimensions of social support are touched upon, and probably other responses will emerge (Bernard, 1990: 180). Since our aim is to uncover diversity, items referring to different dimensions of social support should be used. The following five questions are used:

1. Is there someone who you can call on when you have the need to talk/discuss something, or isn't there such a individual? [TALK]
2. Is there someone who you would be able to rely on if you where sick, or isn't there such a individual? [SICK]
3. Suppose that you would like to go out for the day tomorrow and you don't want to go alone. Is there someone of who you can think that highly probable would want to go with you, or isn't there such a individual? [TRIP]
4. Suppose that someone very close to you passes away. Is there someone who you could call on immediately – without making any sort of arrangement - for comfort, or isn't there such a individual? [COMFORT]
5. Is there someone who you would be able to rely on if you had financial problems, or isn't there such a individual? [MONEY]

Question 3 mainly refers to companionship, while questions 2 and 5 refer to instrumental aid. The dimension of emotional support is captured by questions 1 and 4.

[6] Inter-university Centre of political opinion research.

Respondents were given 19 different role relations from which they could select an unlimited number of possible support-giving types:

- partner
- other close relatives (father, mother, children, brothers, sisters)
- distant relatives (e.g. cousin, niece, grandmother, grandfather)
- close friends
- colleagues at work/school
- mates/acquaintances
- priest/nun/father/monastic
- free-thinking adviser
- GP/psychologist/psychiatrist and equivalent
- strangers that I met by accident
- savants of important individuals that I happen to know a bit
- a public service, council, etc.
- OCMW (public welfare office/public welfare worker)
- other

Respondents had to decide for themselves about the hierarchical priority of (competing) relations (e.g. respondents had to choose whether to categorise a support-giver among ’colleagues’ or ’friends’, when the support-giver was both).

In order to measure the full range of potential sources of support, we asked if a respondent *could* (hypothetically, as far as they can judge) rely on someone for a specific type of support, not whether they actually *did* receive that kind of support (in a certain period of time). It has been shown that respondents asses the availability of potential support quite accurately (van der Poel, 1993: 53) and that potential supportive relationships may be as important as effective support (van der Poel, 1993: 52; referring to research by T. Wills).

Because of low frequencies for some role relations, we regrouped the role relations into the following eight categories: 1) partner, 2) close relatives, 3) distant relatives, 4) (close) friends, 5) colleagues, 6) acquaintances and/or mates, 7) GP, psychologist and/or psychiatrist, and 8) others. The frequencies of the resulting 40 combinations are presented in Table 1.

With the exception of support when in financial problems, partner is the most frequently named as source of support. Close relatives are the main source for help when a financial crisis occurs. However, close relatives are even more important for support item ‘talk’, ‘sick’, and ‘comfort’. Whatever the sort of support, distant relatives are only important for about one fourth of the respondents. Friends are about as important as close relatives for talking, making a trip, but less important for comfort, and far less important for ‘sick’ and ‘money’. Acquaintances and mates are named as a source of talk, and to a lesser extend for trip. Colleagues are also a source for support item ‘talk’. The category ‘doctor/ psychologist/ psychiatrist’ and ‘other(s)’ are only relevant for support item ‘talk’.

Table 1: Percentage of the respondents who can rely on a specific role relation for a specific type of support.

	talk	sick	trip	comfort	money
1 partner	74,6	73,7	66,1	70,8	28,0
2 close relatives/siblings	58,0	61,8	48,3	61,4	56,0
3 distant relatives	26,7	23,7	20,5	27,8	24,8
4 (close) friends	61,7	32,1	50,6	52,5	16,8
5 colleagues	22,8	4,5	7,8	6,6	1,1
6 acquaintances/mates	23,5	6,9	14,7	8,7	3,1
7 doctor/psychologist/ psychiatrist	13,0	15,6*	0,0	2,6	0,0
8 other(s)	5,9	2,4	1,0	1,9	3,3
0 none	*3,5*	*1,9*	*5,0*	*2,4*	*16,8*
N	**622**	**620**	**619**	**619**	**614**
total no. of role relations named	*1785*	*1369*	*1293*	*1438*	*819*

* This high percentage is probably caused by a misinterpretation of the question. This question was probably interpreted as referring to professional help rather than social support. This dummy was therefore excluded from the analysis

3.3 Data-reduction

Given that social support is only one factor in a complex model, the obtained information should be condensed into a limited number of variables. This necessitates a reduction of the data by building typologies. Before going into the details of the analysis we give information on the technique.

Given that we are working with nominal manifest variables we apply latent classification within the log-linear analysis (LCA). Latent class analysis tries to find a latent categorical variable X with a certain number of categories T based on the relationship among the nominal manifest variables (A,B,C,D,E) (Goodman, 1974).

LCA uses probabilities to define the relationship between manifest and latent variables. The chance of belonging to latent class t of X is given by the latent probability π_t^X . When one belongs to class t of the latent variable, one has $\pi_{i\ t}^{\bar{A}\ X}$ chance of choosing category i of manifest variable A. The same is true for variables B, C, etc. These are the conditional response probabilities (Hagenaars, 1990: 98).

The basic idea behind LCA is that answers on manifest variables are solely resulting from the position on a latent categorical variable. This implies that the relationship between manifest variables can be interpreted as the result of the relationship between X and A, respectively B, C, D, and E. Therefore, the relationship between manifest variables is supposed to be local independent

(Hagenaars, 1990: 97) within any latent class t of X the chance of answering i for A is independent of the answer given on B, C, D or E. Because of local independence it can be assumed that the chance of a respondent in class t of X choosing i, j, k, l, and m for A, B, C, D en E equals the product of the corresponding conditional response probabilities:

$$\pi^{\bar{A}\bar{B}\bar{C}\bar{D}\bar{E}X}_{ijklmt} = \pi^{\bar{A}X}_{it}\,\pi^{\bar{B}X}_{jt}\,\pi^{\bar{C}X}_{kt}\,\pi^{\bar{D}X}_{lt}\,\pi^{\bar{E}X}_{mt} \tag{1}$$

The chance of such a response pattern and belonging to latent class t can be calculated by multiplying $\pi^{\bar{A}\bar{B}\bar{C}\bar{D}\bar{E}X}_{ijklmt}$ in (1) with the probability of belonging to class t in latent variable X (Hagenaars, 1990: 97):

$$\pi^{ABCDEX}_{ijklmt} = \pi^{X}_{t}\,\pi^{\bar{A}\bar{B}\bar{C}\bar{D}\bar{E}X}_{ijklmt} \tag{2}$$

The predicted frequencies $\hat{F}$ can be calculated as:

$$\hat{F}^{ABCDE}_{ijklm} = N * \Sigma^{T}_{t=1}\,\pi^{ABCDEX}_{ijklmt} \tag{3}$$

To obtain the best fit LCA searches iteratively for the maximum likelihood estimates of the conditional response probabilities $\pi^{\bar{A}X}_{it}$, and the latent class probabilities π^{X}_{t} in order for the (log)likelihood ratio chi-squared (L^2) to be minimal (Hagenaars, 1990: 48, 103-104).

$$L^2 = 2\,\Sigma\Sigma\,(f \ln(f / \hat{F})) \tag{4}$$

These estimates are indicated by a $\hat{\pi}$. We use LEM for the model-fitting and the parameter estimation (Vermunt, 1993).

A probabilistic relationship exists between the manifest and the latent variables. For each response pattern there is a certain chance of assigning it to class t of X. As a consequence, every individual with a specific response pattern has a specific probability of belonging to latent class t. These probabilities are calculated by dividing the estimated probability for response pattern i,j,k,l,m and belonging to latent class t (2) by the relative occurrence of each of the patterns.

$$\hat{\pi}^{ABCDE\bar{X}}_{ijklmt} = \hat{\pi}^{ABCDEX}_{ijklmt} / \hat{\pi}^{ABCDE}_{ijklm} \tag{5}$$

For each person we obtain T of these probabilities in accordance with their response pattern.

In order to obtain a single latent variable the modal latent class t* is assigned to each person. The latent class $t^{*\,ABCDE}_{\;ijklm}$ for a individual with response pattern (i,j,k,l,m) is that value t from 1 to T for which the probability $\pi_{i\ j\ k\ l\ m\ t}^{A\ B\ C\ D\ E\ \bar{X}}$ has the highest value (with specific values: i,j,k,l,m). However, this predicted score $\tilde{X}$ (Hagenaars, 1990: 113) may not always result in an adequate representation of the data.

Obtaining an adequate fit is sometimes problematical with LCA. We now turn to the problems we encountered and give information about the solution we used. First, the algorithm may not always reach the best possible solution. Depending on the choice of starting values, the iterative procedure may converge at a local, rather than a global maximum (Vermunt, 1997: 68). When rerunning the same model with other starting values the solution with the highest likelihood (probably) indicates that the global maximum is reached and should therefore be preferred (Vermunt, 1997: 68). Because ℓEM randomly assigns starting values (Vermunt, 1993) we rerun every model at least five times (with each time different starting values). When these reruns result in different values for the likelihood-ratio, we then try to obtain five times the model with the lowest value. This procedure is followed in order to be (quite) confident that no lower solution for L^2 can be achieved. However as Vermunt (1997: 68) points out, we can never be completely confident that the global maximum solution is reached.

Even when the global maximum is reached, there is not always a unique solution for the latent and the conditional response probabilities. This refers to a problem of identifiability (Goodman, 1974: 219; Hagenaars, 1990: 111). In order to check whether all of the parameters of an LCA-model are identifiable, the model has to be rerun with different starting values (Hagenaars, 1990: 112). When the reruns generate the same parameter-values (with the lowest value for the likelihood ratio) we can be quite confident that the model is identifiable (Hagenaars, 1990: 112). In order to control for this, we rerun every model at least five times, only counting those reruns that generated the lowest likelihood ratio. However, in the case where the (presumed) global maximum is rarely reached, checking the identifiability of a model is practically not possible.

A specific problem emerges when one or more ‘estimated cell frequencies’ takes on a zero value. This situation can arise with sparse tables. If that is the case a sensitivity analysis is recommended (Agresti, 1990; 250). This means that for every model the results of the parameters should be compared when a small constant (0.001, 0.01 and 0.1) is added to every observed cell frequency in the table. If as a result of these slight changes to the frequency table no substantial change in the parameter estimations takes place, these parameter estimations may be used.

In what follows we present the results of this procedure on our data. Because many different inputs response patterns can be used as input we first present the basis on which our selection took place.

4 Building typologies: Choice of input and output variables

In the first step of the data-management we re-coded the answers (role relations) for the five support items into binary variables (dummies). More specifically we create a dummy for each role relation within each type of support. These dummies then indicate whether there is at least one individual with a specific role relationship who provides a specific type of support. We subsequently combine these binary variables, resulting in 'response patterns'. In creating the response patterns, we are faced with the following crucial decisions:

1. how should we arrange the data in order to be able to find the earlier specified constructs of social support,
2. which dummies should we include in the analysis,
3. and how many classes should the latent variable have?

The general guidelines for constructing our response patterns are first outlined. Thereafter, these rules are further clarified on the basis of an example. The procedure consists of three steps, each of which is a response to one the questions.

First, to rearrange the data, two possible ways (each resulting in another construct of social support) are available:

1. For each social support content we can build a categorical variable representing the major types of combinations of role relations. As a result, we obtain a typology of role-diversity for any specific support-type (**aggregated role diversity**).
2. Another type of categorical variable is built by considering the different kinds of support that people with the same role relation provide. The result of this reduction is a typology of social support contents for any given role relation (**aggregated content diversity**).

Second, problems for LCA can emerge with sparse frequency tables. When many expected frequencies have a low value, the L^2 and (Pearson-)χ^2 will not approximate the theoretical χ^2 distribution (Hagenaars, 1990: 87). For these reasons, when selecting the components to build typologies (with this sample) at most five dummies should be selected. For a solution to be identifiable it is also necessary for a model to have a positive value for the degrees of freedom. For a model without parameter restrictions to have positive degrees of freedom at least four dummies should be included. In practice this means that at least four and at most five dummies should be selected.

In addition, any dummy included should, therefore, have sufficient variation. In order to maximise this variation we considered taking together role-categories (which were not often named) that could on theoretical grounds be considered to be (almost) equivalent. Merging role relations 'partner' and 'close relatives' to one category is one possibility. Other possible merges considered are between 'distant relatives' and 'acquaintances/mates', and between 'colleagues' and 'distant relatives'. Within these margins some freedom exists on which dummies to include and which to leave out.

Finally, it should be decided, how many classes the latent variable should have. In LCA the number of categories (classes) of the latent variables has to be specified. Because of the exploratory nature of this analysis all possible numbers of latent classes are taken into consideration.

The following example illustrates this procedure. For the aggregated content diversity of the role 'friends' three different response patterns are considered. The group of models for which the code starts with 'A9' include all five items (where 'A' refers to the fact that it is first of different combinations considered, and '9' is the code for the role relation 'friends'). This specific combination gives the possibility to consider a model with 2, 3, 4 or 5 latent classes (respectively models A9<u>2</u>, A9<u>3</u>, A9<u>4</u> and A9<u>5</u>). Given that only 17% of the respondents (Table 1) named friends for the support item 'money', it is questionable whether this item should be included in the reduction. Models coded 'B9' only include those support items related to 'comfort', 'trip', 'sick' and 'talk'. Given that the response pattern then only consists of 4 dummies, only those models with two and three latent classes where retained (respectively model B92, and model B93). A third alternative model C9 was considered, where support item 'sick' was included, but 'money' (32%) was left out.

5 Results

In what follows we will first evaluate the different models. We subsequently go into more detail about the meaning of the resulting latent classes.

A total of 66 different models were fitted. In order for a models to be acceptable it must satisfy a number of criteria:

1. Only those models should considered where the likelihood ratio was not significant at a 0.05 level.[7]
2. However, in order for the significance of the L^2-value to be used, the L^2 should approach the (theoretical) χ^2-distribution (Hagenaars, 1990: 88). In practice this means that the values for the χ^2 and the L^2 should not differ significantly.
3. Given that the L^2-value was found to be insignificant, the identifiability of the model is a further precondition.

[7] The degree of freedom used for testing the significance can be calculated as: the number of cells in the frequency-table minus the number of parameters estimated, where the value is not bigger than 0.9995 or lower than 0.0005 (see: Goodman, 1974).

Table 2a: Parameters for the different ’aggregated role diversity’ models.

P–partner,
R–close relative,
D-distant relative,
F-close friend,
C-colleagues,
M-mates acquaintances,
O-doctor/psych,others.

Code	χ^2	L^2	Df+Bd	sign	ID	P R D F C M O
Talk						E E D C B A
A12	**29.136**	**30.077**	**20**+0	**0.069***	**S**	
A13	-	16.618	14+1	0.342*	U	
A14	**3.909**	**5.148**	**8**+3	**0.953***	**S**	
A15	2.866	3.265	2+8	0.975*	Z	
Talk						E E D C B D A=doctor+other
B12	37.975	43.154	20+0	0.002	S	
B13	**14.941**	**17.467**	**14**+2	**0.423***	**S**	
B14	7.971	9.749	8+3	0.638*	Z	
B15	-	3.811	2+**6**	0.874*	U[A,B]	
Sick						E D C B A A
A22	-	76.776	20+1	0.000	U	
A23	-	53.762	14+2	0.000	U	
A24	-	33.864	8+6	0.002	U	
A25	18.010	20.305	2+8	0.041	Z[B]	
Sick						D C B A - -
B22	35.308	34.163	6+1	0.000	S	
B23	15.861	15.136	1+3	0.010	S	
Sick						D C B A - B
C22	30.406	33.241	6+1	0.000	S	
C23	15.857	14.855	1+4	0.011	S	
Trip						D D C B - A
A32	27.174	28.426	6+0	0.000	S	
A33	**9.843**	**10.205**	**1**+3	**0.070***	**S**	
Trip						D C B A - B
B32	27.681	29.472	6+1	0.000	S	
B33	-	12.501	1+2	0.006	U	
Trip						D C B A - -
C32	20.958	21.889	6+1	0.003	S	
C33	6.140	6.553	1+**1**	0.038	Z	
Trip						E D C B A A
E32	68.687	74.145	20+3	0.000	S	
E33	41.717	43.661	14+3	0.001	Z	
E34	26.735	32.351	8+5	0.002	S	
E35	18.832	23.828	2+**6**	0.002	Z	
Comfort						D C B A - B
A42	26.570	30.162	6+0	0.000	S	
A43	12.064	12.348	1+**3**	0.015	S	
Comfort						D D C B - A
B42	15.605	15.693	6+2	0.047	S	
B43	8.159	9.063	1+5	0.170*	Z	

Comfort						**D C B A - -**
D42	-	26.438	6+1	0.000	U	
D43	-	11.590	1+4	0.041	U	
Comfort						**E D C B A A**
E42	74.857	87.383	20+2	0.000	S	
E43	57.2749	59.952	14+6	0.000	S	
E44	39.218	39.442	8+6*	0.000	Z^B	
E45	22.385	24.452	2+8*	0.011	S^B	
Money						**D C B A - B**
A52	22.773	22.381	6+1	0.002	S	
A53	-	1.224	1+1	0.747*	U	
Money B						**D C B A - -**
B52	23.956	23.719	6+1	0.001	S	
B53	-	1.543	1+1	0.672*	U	

(See footnote in Table 2b)

a) Support-specific: aggregated role diversity

Table 2a presents the model code, the χ^2 and L^2 statistic, and the significance of the L^2-value for the 40 different models referring to aggregated role diversity. On the basis of the L^2-statistic we find that quite a limited number of the models give an acceptable reduction. However only part of them are identifiable. For the support item 'talk' models **A12**, **A14** and **B13** are acceptable typologies of role diversity. These findings indicate that for 'talking' there exist a limited number of different types of role relations that fit most of the sample. (The parameters for these models can be found in Table 3a.) No feasible models for the item 'sick' were found. For the support type 'trip' only model **A33** delivers an acceptable result. It is unclear whether model **B43** for support 'comfort' is identifiable. A three-class solution is acceptable for the support type 'money' (A53, and B53), but not identifiable. In total as little as four acceptable models were found.

Model A12 in Table 3a makes a distinction between one class where no one or only relatives are contacted when in need for a talk, while a second class consists of individuals who can contact close relations and others, when in need of a talk. A second solution on the basis of the same response patterns is a variable with four categories (A14). On the one hand, we can distinguish those who only name relatives, from those who only name close relations, those who name colleagues and relatives, and finally those who name close relations and colleagues as supportive when in need of a conversation. An alternative solution is bases on another kind of response pattern. One type consists of individuals who can have a discussion with all role relations, except ‘doctor/psychologist/psychiatrist’ or ‘others’, a second type can have a thorough conversation with all, except ‘colleagues’, while a third type only can talks to ‘close relatives’ when needed. The only other acceptable model (A33) makes a distinction between three types of responses for making a trip. A distinction is made between individuals who only name ‘close relatives’, a group that only names ‘close relations’, and finally a group that names ‘relatives’ and ‘friends’.

Table 2b: Parameters for the different 'aggregated content diversity' models.

Code	χ^2	L^2	Df+Bd	sign(Df+Bd)	ID	talk	sick	trip	comfort	money
Partner						**D**	**C**	**B**	**A**	-
B62	32.893	29.964	6+0	0.000	S					
B63	**0.338**	**0.346**	**1**+2	**0.951***	**S**					
Partner						-	**D**	**C**	**B**	**A**
C62	29.781	34.304	6+0	0.000	S					
C63	**2.109**	**2.558**	**1**+2	**0.465***	**S**					
Close relatives						**D**	**C**	**B**	**A**	-
A72	15.729	15.364	6+0	0.018	S					
A73	-	1.011	1+0	0.315*	U					
Close relatives						**E**	**D**	**C**	**B**	**A**
B72	70.313	65.781	20+0	0.000	S					
B73	-	21.424	14+1	0.124*	U					
B74	**15.036**	**14.764**	**8**+6	**0.395***	**S**					
B75	**5.684**	**5.911**	**2+7**	**0.749***	**S**					
Distant relatives						**E**	**D**	**C**	**B**	**A**
A82	37.633	36.449	20+0	0.014	S					
A83	**10.508**	**10.456**	**14**+2	**0.842***	**S**					
A84	**4.433**	**4.461**	**8**+4	**0.974***	**S**					
A85	2.858	2.887	2+9	0.992*	Z					
Friends						**E**	**D**	**C**	**B**	**A**
A92	44.017	45.099	20+0	0.001	S					
A93	**10.182**	**11.039**	**14**+0	**0.683***	**S**					
A94	**6.116**	**7.316**	**8**+5	**0.885***	**S**					
A95	-	3.135	2+**7**	0.959*	U[A]					
Friends						**D**	**C**	**B**	**A**	-
B92	14.091	14.354	6+0	0.026	S					
B93	-	0.122	1+0	0.727*	U					
Friends						**D**	-	**C**	**B**	**A**
C92	13.519	15.641	6+0	0.016	S					
C93	-	3.353	1+**0**	0.067*	U					
Colleagues						**D**	**C**	**B**	**A**	-
A102	**3.221**	**3.885**	**6**+0	**0.692***	**S**					
A103	1.266	1.534	1+3	0.821*	Z					
Acquaintances/mates						**D**	**C**	**B**	**A**	-
B112	13.633	13.535	6+0	0.035	S					
B113	**3.627**	**3.631**	**1**+2	**0.304***	**S**					

Df: degrees of freedom
Bd: number of conditional response probability with value approaching 0 or 1
***sign(Df+Bd)*:** significance when number of conditional response probabilities with value approaching 0 or 1 are taken into account
ID: We used 'S' under the heading ID to indicate that the parameters for the five runs of the model were took on the same value, or did not differ more than 0.0001 (identifiable). If the parameters of a model have no single best value we marked the model as 'U'. In cases where rarely the lowest L^2- solution was reaching, this was indicated by the letter 'Z'.
***** not significant at a 0.05 level
[A] zero value for at least one expected frequency (0.01 added to each cell in observed frequency table)
[B] zero margin(s) fitted

Table 3a: Latent class models for aggregated role diversity.

model	*latent probabilities*	conditional response probabilities					description
code		doctor	acquaint.	colleagues	friends	close+distant relatives	
talk (*E* = 0.151 *lambda* = 0.499)							
A12 X_1	*0.699*	0.170	0.313	0.306	0.791	0.786	cl. rel.+others
X_2	*0.301*	0.037	0.053	0.049	0.213	0.456	relatives
talk (*E* = 0.244 *lambda* = 0.578)							
A14 X_1	*0.043*	0.175	0.505	0.999	0.000*	0.621	coll+ relatives
X_2	*0.264*	0.322	0.439	0.000*	0.813	0.848	close relations
X_3	*0.270*	0.074	0.240	0.622	1.000*	0.805	coll+ cl.rel.
X_4	*0.423*	0.042	0.076	0.041	0.313	0.516	relatives

model	*latent probabilities*	conditional response probabilities					description
code		others doctor	colleagues	friends	distant rel.	close relatives acquaint/mates	
talk (*E* = 0.129 *lambda* = 0.750)							
B13 X_1	*0.229*	0.141	0.995	0.761	0.549	0.958	all
X_2	*0.486*	0.070	0.000*	0.449	0.194	0.828	close relations
X_3	*0.285*	0.410	0.000*	0.789	0.784	0.905	all, except colleagues

model	*latent probabilities*	conditional response probabilities				description
code		acquaintances	friends	distant rel.	close relatives partner	
trip (*E* = 0.211 *lambda* = 0.616)						
A33 X_1	*0.449*	0.263	0.739	0.101	0.658	close relations
X_2	*0.172*	0.000*	1.000*	0.515	1.000*	relatives+friends
X_3	*0.379*	0.077	0.005	0.189	0.881	close relatives

b) Types of relations: aggregated content diversity

The other proposed measure of diversity tries to reduce support-types for the different types of relations. Table 2b presents the models for this aggregated content diversity. In total 26 reductions of support type were proposed. For each of the important role relations at least one acceptable reduction could be found, indicating that a simple typology of kinds of social support for each relation-type exists.

Two acceptable models were found for the role relation ‘partner’ (**B63**, **C63**), one for ‘close relatives’ (**B74**), two for ‘distant relatives’ (**A83**, **A84**), another two for ‘friends’ (**A93**, **A94**), and one for ‘colleagues (**A102**), and ‘acquaintances/mates’ (**B113**). It is unclear whether model **A103** is identifiable. The latent class probabilities and the conditional response probabilities for those models are found in Table 3b.

Table 3b: Latent class models for aggregated content diversity.

model code		*latent probabilities*	money	comfort	trip	sick	talk	description of latent class
partner (*E*= 0.141 *lambda*= 0.748)								
B63	X_1	*0.363*	-	0.756	0.603	0.797	0.826	emot.
	X_2	*0.442*	-	0.980	1.000*	0.986	0.993	always
	X_3	*0.196*	-	0.000*	0.008	0.069	0.039	never
partner (*E*= 0.163 *lambda*= 0.960)								
C63	X_1	*0.475*	0.533	1.000*	0.950	0.981	-	always
	X_2	*0.330*	0.082	0.695	0.640	0.794	-	emot.
	X_3	*0.195*	0.006	0.021	0.000*	0.060	-	never
close relatives (*E*= 0.156 *lambda*= 0.762)								
B74	X_1	*0.220*	0.114	0.000*	0.042	0.051	0.000*	never
	X_2	*0.136*	0.411	0.455	0.362	0.000*	0.527	emot.
	X_3	*0.344*	0.855	1.000*	0.812	0.904	1.000*	always
	X_4	*0.300*	0.622	0.688	0.489	1.000*	0.552	emot./instr.
close relatives (*E*= 0.112 *lambda*= 0.801)								
B75	X_1	*0.250*	0.130	0.020	0.000*	0.066	0.054	never
	X_2	*0.436*	0.831	1.000*	0.866	0.912	0.892	always
	X_3	*0.064*	0.000*	0.385	1.000*	0.366	0.362	comp.
	X_4	*0.184*	0.545	0.793	0.000*	0.732	0.665	instr./emot.
	X_5	*0.066*	1.000*	0.000*	0.646	0.743	0.497	instr.
distant relatives (*E*= 0.073 *lambda*= 0.772)								
A83	X_1	*0.193*	0.576	0.635	0.496	0.498	0.497	emot./comp.
	X_2	*0.681*	0.065	0.044	0.011	0.023	0.078	never
	X_3	*0.126*	0.742	1.000*	0.805	1.000*	0.963	always
distant relatives (*E*= 0.098 *lambda*= 0.701)								
A84	X_1	*0.133*	0.326	0.500	0.434	0.494	0.554	emot./comp.
	X_2	*0.070*	1.000*	0.838	0.590	0.522	0.360	instr.
	X_3	*0.123*	0.731	1.000*	0.804	1.000*	1.000*	always
	X_4	*0.674*	0.068	0.045	0.010	0.018	0.072	never
friends (*E*= 0.169 *lambda*= 0.735)								
A93	X_1	*0.362*	0.406	0.972	0.856	0.670	0.967	emot./comp.
	X_2	*0.327*	0.047	0.539	0.525	0.233	0.754	comp.
	X_3	*0.311*	0.020	0.008	0.083	0.022	0.067	never
friends (*E*= 0.170 *lambda*= 0.728)								
A94	X_1	*0.262*	0.017	0.007	0.054	0.012	0.000*	never
	X_2	*0.313*	0.043	0.348	0.455	0.195	0.677	comp.
	X_3	*0.050*	0.810	0.891	1.000*	1.000*	1.000*	always
	X_4	*0.375*	0.294	1.000*	0.802	0.564	0.947	emot./comp.
colleagues (*E*= 0.028 *lambda*= 0.784)								
A102	X_1	*0.873*	-	0.005	0.018	0.001	0.124	never
	X_2	*0.127*	-	0.489	0.489	0.347	0.941	comp.
acquaintances/mates (*E*= 0.113 *lambda*= 0.515)								
B113	X_1	*0.205*	-	0.244	0.387	0.204	0.662	comp.
	X_2	*0.766*	-	0.010	0.055	0.000*	0.106	never
	X_3	*0.029*	-	1.000*	0.857	0.940	0.922	emot.

instr.:instrumental support
emot.: emotional support
comp.: companionship

Models (B63 and C63) for role ‘partner’ both make a distinction between a category of respondents who probably have no partner, a second group who mainly has an affective relation with their partner, and the largest proportion who name their partner for all considered support items. Both model with four latent classes (B74) and five latent classes (B75) distinguish between a group that never names close relatives, a second group that names this role relation for emotional and instrumental support, and a group that names close relatives for all five items. With the four-latent class model only emotional support make up a further group, while for the five-latent class model the two extra groups are individuals who only name close relatives for instrumental aid, respectively companionship. For the latent class solution with three categories for the role relation ‘distant relatives’ (A83) the category ‘never’ is the largest, while individuals naming them for the five items make up a second group, and emotional support and companionship a third. The fourth group added for a model with four classes (A84) only receives instrumental aid from distant relatives. The latent classes for friends are ‘never’, ‘companionship’, and ‘companionship and emotional support’ in the case of a model with three classes, and an extra class ‘always’ for a model with four latent classes. Colleagues are either never asked for support, or only for companionship (A102). Acquaintances and mates are for some important for emotional support, for others for companionship. In most cases however they are never named.

6 Discussion

With regard to the fit and identifiability of the models, the contrasts between the models for aggregated role diversity and models for aggregated content diversity could hardly be any sharper. With the exception of the support item 'talk', no acceptable reduction of the response patterns of role relations for support items are found. The fit of these models shows that the role relations that respondents name as sources of support for 'sick', 'trip', 'comfort' and 'money' can hardly ever be reduced with these models. This leads to the conclusion that there are no simple rules governing the choice of role relations for specific support items. Two reasons may lie behind this finding. Either the rules that govern the choice of role relations are very various in our sample, making it impossible to capture this diversity of response patterns with these limited typologies. Or the rules may be applicable, but the availability of these role relations are dependent on the situation. In reality both may be true.

In contrast to the aggregated role diversity, the types of support from specific role relations can be captured by a number of typologies. Although differences exist, LCA is able to capture these differences by a limited number of classes (types). This implies that, in general people may have very different choices of relation-types for specific support, but when specific role relations are selected for one type of support, this has probably also important implications for other types. Different kinds of support given by the role relations 'partner', 'close relatives', 'distant relatives', 'friends', 'colleagues' and 'acquaintances/mates' all were reducible to a typology of support in a satisfactory way. Clearly this illustrates that these kinds of support refer (partly) to one underlying dimension. These findings may be explained by the fact that other criteria than the rules governing the selection of role relation type themselves are central in ’selecting’ possible support-givers. In fact the availability of these role relations may be very crucial. Another explanation may be that dissimilar rules apply in the many different parts of the population, but that the rules governing one role relation, ’corresponds’ with the rules governing other role relations.

The research-result make clear that this approach for measuring social support networks can be used in the case of aggregated content diversity, but less for aggregated role diversity. But, in the first case there are competing models. This fact leaves us with a further problem. Which of these competing models should we use for further analyses? To evaluate these competing models we will go through a number of criteria.

One general criterion that should be considered is the parsimony principle (Hagenaars, 1990: 61). Since we want to use these latent variables in further analyses, selecting the models with the minimal number of classes is in some cases preferable. When ascribing the modal latent class to each response pattern, this principle may be very important for technical reasons. It may be preferable to avoid a situation whereby one or more latent classes count only a small number of cases. More specific, if one or more latent classes have very low frequencies, this is problematic for further analyses (since this may lead to partitioning in further analyses, and by consequence to sparse tables).

However giving too much attention to parsimony, may result in a latent classification that has a vague meaning. There should be a balance between parsimony and differentiating as many possible types. The equilibrium should result from the meaning of the latent classes (i.e. the concept within the model). This meaning of different typologies may depend on the relevance within a general theoretical construct.

Assigning the modal latent class to the different response patterns is in itself an approximation of the probabilistic model. Therefore, a further concern is how well the modal latent class is an acceptable approach for the probabilities. Another evaluation can be founded on the ability to differentiate the different responses patterns with the model. Both indexes *E* and *lambda* are measures centred awround the ascription of the modal latent class to each combination. The two indices E and Lambda tells us how well the classification differentiates between the latent classes.[8]These are only some of the criteria that can be used to select between competing models.

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[8] Since we assign the latent class with the largest conditional probability $\pi^{A\,B\,C\,D\,E\,\bar{X}}_{i\,j\,k\,l\,m\,t*}$ to every individual according to their response pattern some misclassification will take place (Hagenaars, 1990: 114). The probability of ‘misclassifying’ a individual with a certain pattern is given by the complement of the conditional probability (for the modal latent class of that combination): $\varepsilon^{ABCDE}_{ijklm} = 1 - \pi^{ABCDE\bar{X}}_{ijklmt*}$. An overall measure of misclassifications is given by the mean probability of misclassification over all individuals. This index *E* takes the sum of the complement of the modal latent class probability for every individual divided by the sample size N. The index *E* gives us an

Our research has some limitations that should be noticed. The choice of the support items included in our survey was primarily guided by the objective of capturing different dimensions of social support. There are no clear cut reason why these specific support items should be used. The use of other questions could possibly result in other classifications. Some of the included support questions are, moreover, formulated very generally. The use of more specific questions then also could possibly result in other classifications.

A related consideration refers to the situation of multiple roles. Whenever one individual has more than one role relation to ego, from the aggregated perspective two alternative visions can be developed. On the one hand, one can follow the reasoning of this paper and state that ego can best define what the most important role is to each alter. An alternative possibility would be to take all the different roles into account, thereby assigning that individual to more than one category of role relation.

Asking questions about role relations, however, might in itself provide less accurate information than when name generators and name interpreters are used. An alternative approach would be to measure networks with name generators and name interpreters and subsequently use LCA. Computer assisted interviewing could then be used to ease the problem that name generators and name interpreters are time consuming for respondents.

In this paper we surveyed only one of both sorts of diversities at a time. It may be possible to incorporate the whole information (cf. Table 1) in one latent variable. We did not use such models because of possible problems with sparse tables. For more complex, hence more compact LCA-models, a larger sample is needed. We, moreover, only consider diversity in types of support and role relations, thereby ignoring other possibly relevant elements of diversity, such as the intensity of relations, the number of support givers in a specific role relation, and characteristics of network members.

As with most findings in the social sciences, our results are influenced by culturally specific factors. The results found here refer to the specific Flemish situation. Although cross-cultural generalisations cannot be made on the basis of this research, there are reasons to believe that differences between (Western) societies on social support and role relations are not that extensive (Freeman et al., 1997).

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idea of how well the assignment of the modal class is compared with the probabilistic model. *E* is lowest when each latent class (X_1,X_2,...) identifies exactly the ascription to every of the manifest variables (A,B,...). In other words when every conditional probability is either 0 or 1. If *E* takes a large value the relationship between the manifest variables (response patterns) and the assigned modal latent class variable (predicted score) $X^{\sim}$ differs from the relationship between the same manifest variables and the probabilistic latent variable X. The second index *Lambda* adjusts the index E for the values of the overall latent probabilities. (see: Hagenaars, 1990: 115).

7 Conclusion

The central aim of this paper is to demonstrate the usefulness of Latent Class Analysis for summarising complex social support network information into a single categorical variable by using typologies. We, furthermore, use an alternative way for measuring diversity in type of support and role relations rather than resorting to name generators and name interpreters. The proposed technique should make it possible to include 'social support' into more complex modelling, making this concept more widely available to a large range of research areas.

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