Multilevel analysis of personal networks as dependent variables

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Abstract

In this paper, it is shown that multilevel methods are particularly well-suited for the analysis of relations in personal networks and the changes in these relations. Justice is done to the hierarchical nested structure of the data and the resulting dependence between observations ''within egos''. Multilevel techniques can also give more specific insight on why personal networks change: they allow to distinguish between the influence of individual and of tie characteristics on the stability of personal networks as a whole and of specific ties within a personal network. This is illustrated by an application to changes in networks of four Dutch samples experiencing different life events. © 1999 Elsevier Science B.V. All rights reserved.

1. Introduction

This paper proposes the use of multilevel analysis for the analysis of (changes in) ego-centered networks. Multilevel analysis or hierarchical linear modelling (HLM) can be viewed as a modified version of multiple linear regression designed to deal with data with a *hierarchical* clustering structure. This nested structure is common to many sample designs and implies that the data cannot be assumed to consist of independent observations. Introductory texts are in the works of Bryk and Raudenbush (1992), Goldstein (1995) (a mathematically more demanding book), and Snijders and Bosker (1999).

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A classical example of a multilevel structure is provided by educational data where pupils are nested within schools, a two-level structure. The assumption that pupils from the same school do not ''resemble'' each other more than pupils attending different schools, implied by the assumption of independent observations, is not tenable. Longitudinal data are another example of a hierarchical structure, with measurement occasions nested within individuals. In multilevel terminology, the pupils or measurement occasions constitute the first or lowest level, the schools or individuals the second or highest level. Extensions to three levels (adding classrooms between pupils and schools) or even higher levels (regions) are feasible. For ease of exposition and in view of the application to the analysis of personal networks, this paper is restricted to two-level models.

In network research, there is a growing awareness of the advantages of multilevel analysis and the necessity to use it. When personal networks are studied, the data have a hierarchical structure: ties are nested within networks. The use of multilevel analysis for personal networks was proposed by Snijders et al. (1995). Other examples were given in the works of Völker and Flap (1997) and Van Tilburg (1998). Snijders and Kenny (1999) propose multilevel models for a very different network design, viz., multiple entire networks (with continuous relational variables).

The aim of this paper is to expand on these publications and to give an illustration of the usefulness of multilevel modelling for ego-centered networks. The hierarchical linear model is appropriate for the analysis of personal network data if some characteristic of the tie (e.g., transactions between ego and alter, change over time in tie strength, etc.) is the dependent variable. The ties, or ego–alter pairs, therefore are the ''cases'' in the statistical analysis, and the data collection design implies that the ties, or alters, are nested within the egos, or respondents. Thus, the data have a two-level hierarchical structure. In multilevel terminology, ties are level-one units and egos are level-two units.

The assumption of independent observations is violated in this case: relations of one individual have more in common than relations of different individuals, and it is likely that this is reflected in statistical dependence. Ordinary regression analysis (OLS), treating the data as if all observations are independent, produces unreliable standard errors and hypothesis tests because of model misspecification. Other approaches such as aggregation (analyzing egos as cases, where the dependent variable is, e.g., the mean tie strength of all ego's relations) or disaggregation (separate analyses of the observations for each higher level unit, i.e., one analysis of relations for each respondent) deal with the problem of model misspecification but do not use all information available and do not always answer the research questions as fully as desired. In Section 5, we will show how aggregation and disaggregation may affect the analysis.

Multilevel or hierarchical linear models explicitly take into account the nested data and the related dependency structure by allowing unexplained variability between ties (i.e., at level-one) and also between egos (at level-two). This means that random residuals are postulated for both levels, so that there is a variance parameter *within* egos, i.e., between ties, and another variance parameter *between* egos (there may be more than one variance parameter at level-two; this is the case in random slope models, discussed below). Two ties of the same respondent are correlated because they share the same ego-dependent residual (or residuals). These multiple variance parameters are interesting in themselves since they represent conceptually distinct sources of variability present in

the data. Thus, it is possible to study research questions at the level of the relation (e.g., tie strength, change over time), looking for explanations both at the relation level (e.g., tie content, duration, alter's characteristics) and at the respondent's level (e.g., marital status, age).

As an illustration and further explanation of multilevel analysis, detailed results of a three-wave field study by Van Busschbach (1996) are presented. Respondents were interviewed repeatedly about the members of their personal network. By comparing what the same respondents reported at different moments, the changes that occurred in the networks as a whole and the changes in each specific tie were documented. Using multilevel analysis, it could both be found why some personal networks as a whole are more stable over time than others and which characteristics explain the differences in the stability of the specific ties within a personal network.

In Section 2, the study and the data are presented in more detail. In Section 3, the multilevel model is introduced, including procedures for hypothesis testing and model selection. The multilevel analysis of the data is presented in Section 4 followed by a detailed interpretation of the results. In Section 5, the results are compared with results from other studies, some of which were reported in a special issue of Social Networks on change in personal networks (1997, 1). The use of multilevel modelling for the analysis of personal network data is further illustrated by comparing the results with findings from aggregated and disaggregated analyses.

2. Application: changes in ego-centered networks over a period of 4 years

The data used for this multilevel analysis of personal networks come from a three-wave study by Van Busschbach (1996), following Van Sonderen (1991) and Van Sonderen and Ormel (1991). The study included not only changes in the personal communities of respondents from a random sample of the Dutch population ($N = 46$) but also those in three special populations selected on the bases of the occurrence of different life events: a sample of men (38) leaving work because of retirement, a sample of women (58) expecting their first baby and a sample of people (53) who had recently moved to a different city (Table 1). The random sample (from a phone directory) was selected on the basis of age and gender. For the selection of the other subsamples,

Table 1
Characteristics of the four subsamples

	Young mothers	Moved	Retired	Random group
Sample size	58	53	38	46
Men	0	62%	100%	60%
Women	100%	38%	0	40%
Age (SD)	29 (4.1)	46 (17.0)	61 (2.1)	41 (16.4)
Married/cohabiting	93%	57%	96%	60%
With partner	6%	9%	0%	12%
Formerly married	0%	23%	2	12%
Single/never married	1%	11%	2	16%

people were approached through midwives, personnel managers, and register offices of a few cities and villages, respectively. Of all people contacted, 51% was willing to participate in the study. After 4 years, 6% of the people who participated in the first interview could not be interviewed because they had died or could not be traced, 17% refused to be interviewed for the third time. There are no significant differences in age, gender, or size of network at the beginning of the study between sample members and dropouts.

The interviews, 2–3 h each, were held at the home of the respondent. Information was gathered concerning health, supportive interactions, feelings of being supported, life events, work, and other activities. As name elicitors to delineate the network, the exchange-approach was used (McCallister and Fischer, 1978), which is based on the idea that the network is defined by the day-to-day interactions between individuals. The names of the persons with whom the subject had a personal relation were established using a structured 21-item questionnaire on support given and received. The questions focused on a relative broad definition of membership which includes relatives, friends, neighbors and co-workers, and were thus not restricted to ties that were deemed 'strong' in some respect: some networks with more than 70 ties were found (the average network contained 20 ties). Information on frequency of contact and other characteristics of the relations were also gathered. For practical reasons, these additional questions were only asked for the 20 to 30 most important relations of the subject. In the second and third interviews, subjects were asked to state whether they were still in contact with the persons mentioned in the first interview. In case relations had dissolved, the respondents were questioned about the reasons why.

In line with Suitor et al. (1997), it was found that after 1 year, two-thirds of the associates named at the first interview were named again. After 4 years, 75% of the ties still existed. The average total size of the network did not change significantly over time. This suggests a 'natural' circulation in which one out of every four relations was replaced over a period of 4 years without it influencing the total size of the network. Morgan et al. (1997) and Van Tilburg (1998) emphasize the possible influence of the unreliability of the delineation procedure. The data collection of this study was aimed at minimizing the chances that change would be recorded in cases where the respondent just forgot to mention some one named before. Several questions were asked about each tie mentioned in the first interview, including why the contact was lost if this was the case. In research exclusively focused on changes in the network as a whole (Belsky and Rovine, 1984; Rands, 1988), the amount of turnover in each tie is missed and results can be easily distorted by unreliable answering.

In the analyses presented here, data on a total of 2928 ties are used. The data set has a *nested* structure: for each respondent, the set of information contains information on individual characteristics at the higher level and information on each of the different relations of the respondent at the lower level. For each respondent, information is available not only on age, gender, educational level, marital status but also on behavioral constraints like restrictions on free time, money, physical mobility and personal skills. On the relational level, information was gathered on appreciation, amount of time necessary to travel from one to another, and the amount of similarity in the relation. Also available is information on the duration of the relation in months and on the

balance between support given and received in the past. The type of support exchanged was recorded for every relation, distinguishing instrumental support, emotional support and companionship. The strength of a tie is measured by the frequency of contact, taking into account visits, telephone calls, and letters. Thus, an impression of 'cost' and 'benefits' in the relation and the amount of investments made by ego and alter was obtained.

The aim of the study was to test some general hypotheses that explain why some relations with friends and family members remain stable over time while others dissolve, guided by the following research questions:

- What aspects of the relationship and which characteristics of the persons involved influence differences in stability and change in the strength of relations in a personal network?
- Do the same principles apply to changes that occur in everyday life and to changes after special life events?

We tested two kinds of hypotheses. First, hypotheses on the influence of relational characteristics on the variations in stability between relationships and second, hypotheses on the influence of differences between individuals in the way they are able to maintain their relationships. This means, we sought to predict which ties will and which ties will not be affected and to explain both the stability and instability of the network as a whole.

The hypotheses were postulated in line with the work of Rusbult (1980a,b, 1983, 1987) on the ''investment model''. She suggests that the degree of stability of a relation depends not only on costs and benefits at present but also on investments made in the past and the degree to which support was given and received over time. The idea that people invest in one another is also one of the basic assumptions in social capital theory (Coleman, 1988, 1991; De Graaf and Flap, 1988; Völker and Flap, 1997; Flap, 1999). It is assumed that people invest in each other to gain future access to different resources (Bourdieu, 1980; Lin, 1982). Because the (expected future) value of investments in relationships is not stable over time, relationships are always subject to change (Völker, 1995).

Integrating both views, we came to a set of hypotheses about the decision to invest guided by eight different considerations. These are considerations at the level of the relationship: the direct costs and benefits, previous investments, the expected benefits in the future and the length of the shared future. There are also considerations at the individual level of the respondent: behavioral restrictions (time budget, physical mobility, personal characteristics) and the availability of alternative relations. These considerations affect the network as a whole. In this paper, we will not expand further on the details of all our hypotheses but concentrate on the analyses and results as an example of how multilevel analysis can be used. See Van Busschbach (1996) for an elaborate treatment of the hypotheses.

3. The multilevel model

The multilevel or hierarchical model will be introduced in this section to the extent that is necessary for the analysis of personal network data presented here. General

textbooks on multilevel modelling are by Bryk and Raudenbush (1992), Goldstein (1995), and Snijders and Bosker (1999).

A ''general'' multilevel model is formulated for the dependent variable Y_{ij}, e.g. (change in) strength of relation i of respondent j with one explanatory variable at the first level, x_{ij}, e.g., type of relation, and one at the second level, z_j, e.g., respondent's marital status. The regression equation at the first level is:

$$Y_{ij} = \beta_{0j} + \beta_{1j}x_{ij} + R_{ij}, \tag{1}$$

where regression coefficients β_{0j} and β_{1j} vary over respondents, and are referred to as the *random intercept* and the *random slope*, respectively. R_{ij} is the level-one error term with expected value 0 and variance σ^2.

At the second level, two regression equations are formulated for the random intercept and for the random slope:

$$\beta_{0j} = \gamma_{00} + \gamma_{01}z_j + U_{0j} \tag{2}$$

and

$$\beta_{1j} = \gamma_{10} + \gamma_{11}z_j + U_{1j}. \tag{3}$$

The regression coefficients γ_{00}, γ_{01}, γ_{10}, γ_{11} are called the *fixed* effects. They do not vary across respondents and can be viewed as the average effects over the whole population of individuals. In this multilevel model, the random intercept and random slope are partly explained by the level-two variable. The random error terms (or random effects) U_{0j} and U_{1j} represent the unexplained variation that remains among the individuals. This is analogous to the residual R_{ij} which expresses unexplained variation between relations within individuals. It is assumed that the random effects follow a bivariate normal distribution with expected value 0 and a covariance matrix with elements $\mathrm{var}(U_{0j}) = \tau_0^2$, $\mathrm{var}(U_{1j}) = \tau_1^2$, and $\mathrm{cov}(U_{0j}, U_{1j}) = \tau_{01}$.

The multilevel model is obtained by substituting Eqs. (2) and (3) in Eq. (1):

$$Y_{ij} = \gamma_{00} + \gamma_{01}z_j + \gamma_{10}x_{ij} + \gamma_{11}z_j x_{ij} + U_{0j} + U_{1j}x_{ij} + R_{ij}, \tag{4}$$

containing the fixed effects in the first part and the random effects in the second part. A fixed *cross-level interaction* term is obtained as the product of the level-one and level-two variables z_j and x_{ij}. The strength of this effect is reflected by the regression coefficient γ_{11}. A ''random interaction'' term is given as $U_{1j}x_{ij}$. The strength of this effect is reflected by parameter τ_1^2, the variance of U_{1j}. As a consequence, the variance of Y_{ij} depends on the value of x_{ij}, implying that the assumption of homogeneous variances (common in analysis of variance) is not made. This multilevel model can easily be expanded with more explanatory variables. It is not necessary to assume random slopes for all explanatory variables at the relation level (1). The existence of a random slope (i.e., unexplained variability between egos in the effect of some variable x_{ij}) can be tested as will be shown below.

The significance of the fixed effects (the γ values) can be tested with the well-known *t*-test, based on the ratio of parameter estimate to standard error. If the sample contains a sufficiently large number of respondents, the *t*-distribution can be approximated by a standard normal distribution. This test is not appropriate for the random effects. Instead,

a likelihood ratio or deviance test is used comparing the relative goodness-of-fit of two nested models. By definition, the deviance (minus twice the loglikelihood value) of the model with the most parameters is equal or smaller than the deviance of the model containing less parameters. The difference in deviance of these two models can be used as a test statistic with an approximate χ^2 distribution with the number of different parameters as the degrees of freedom. Thus, testing the hypothesis of a random slope which is equivalent to $H_0: \tau_1^2 = \tau_{01} = 0$ can be tested by comparing the deviances of the model in which these two parameters are included and of the model with identical parameters except that τ_1^2 and τ_{01} are excluded. Under the null hypothesis, the difference in deviance has a χ^2 distribution with $df = 2$.

These tests are used as measures in the model selection process. In most cases, a forward selection process is judicious, which should — as in all statistical analyses — be guided by theoretical insights and considerations. The model building process for our data is presented in Section 4.

4. Results of the multilevel analysis

The dependent variable in the study on network change after important life events is the change in contact frequency (visits and telephone calls) between the first measurement and the third (after 4 years). Frequency of contact was measured on a scale varying from 1 (less than once a year) to 8 (daily); at the second and third measurement, the value 0 (no contact) was added to the answer categories. The difference between first and third measurement ranges from -8 to 6. The data set contains a vast amount of explanatory variables at both levels. First, we discuss the relevant variables at level-one.

The first four variables are measured at all time points. *Appreciation* was used as an indication for the benefits of the relation and measured on a scale from 1 (very negative) to 5 (very positive). The logarithm of the travel time ((*log*) *Travel Time*) in minutes was used as an indication of costs. The logarithm of the duration of the relation in months ((*log*) *Duration*) was used to measure former investments. *Homogeneity* in the relation was measured on a four-point scale as the sum of 0/1 values for homogeneity in age (less than 10 years apart), gender, living situation (unmarried, married, with/without family) and working situation (with or without a job).

The next four variables were measured at the first interview. For attachment (referred to as *Kin / Non-kin*), four categories are distinguished, ranging from member of the nuclear family (4), via kin (3), friend (2) to colleague, neighbor, and other acquaintance (1). The level of education of the network member (*Education Nominee*) ranges from 1 (primary education, i.e., no completed high school education) to 8 (university). *Companionship* and *Emotional Support* are dummy variables indicating the type of support that is exchanged in the relation.

At level-two, the level of the respondent, information was available on age, gender (*Man* = 1, *Woman* = 0), marital status (*Married* = 1, *Unmarried* = 0), level of education, working situation, the change that the respondents experienced during the research period (dummy variables *Young Mother*, *Recently Moved*, and *Retired Man*), and a dummy variable *Moved After First Interview* for all respondents.

The number of alternative relations was measured by the size of the total network at the first interview. Free time was calculated taking into account working hours, hours necessary to care for (young) children, and household duties. As an indication of financial means, people were asked to state how much money they could afford to spend per month per person in the household apart from housing, taxes and other obligatory payments.

Where applicable, the explanatory variables are defined as the change between the first and third measurement. On the basis of theoretical considerations, a number of interactions (within either level and cross-level) are investigated as well.

In order to get a more or less straight way through the jungle of possible models, we distinguish four model selection steps after the null or empty model. The null model is "empty" because it does not contain any explanatory variables, but only the intercept (grand mean) and the two error terms for both levels. This model is often used as starting model and gives a clear idea of the variation at both levels.

The four steps are:

1. Adding fixed level-one explanatory variables (including interaction terms between them),
2. Adding fixed level-two explanatory variables (including interaction terms between them),
3. Adding random slopes and cross-level interaction terms,
4. Adding covariances between the random slopes.

Although the first two steps are illustrative for multilevel analysis, the third step is even more substantial since it gives the opportunity of investigating whether and how much the found effects vary over persons. Level-two explanatory variables are used to try to "explain" this variation (which amounts to cross-level interaction terms, see (3)). The fourth step investigates how much dependence is found among the random slopes.

In Table 2, the estimates for the null model are given. The intercept indicates a mean decrease in contact frequency of 1.31 points on the eight-point scale. The level-one variance is almost 10 times as large as the level-two variance, leading to an intraclass ($=$ intra-respondent) correlation of 11% ($= 0.59/(0.59 + 4.55)$). This indicates that, as is to be expected, much more variation is present at the relation level than at the respondent level.

Table 2
Null model (no explanatory variables)

	Estimate	(S.E.)
Fixed effects		
Intercept	-1.31	(0.59)
Random effects		
Level-2 variance τ_0^2	0.59	(0.09)
Level-1 variance σ^2	4.55	(0.12)
Deviance	12951.5	

In the first step, 34 level-one explanatory variables and within-level-one interactions are added, leading to a model deviance of 12088.0, a significant improvement of the null model (with deviance 12951.5) beyond doubt. Leaving out all variables with insignificant coefficients (on the basis of a *t*-test) except for the variable *Companionship*, because of level-one interactions, results in a model with 17 explanatory variables and a deviance of 12098.7. The deterioration of fit due to leaving out the non-significant variables of 8.7 is not significant on 17 degrees of freedom ($p = 0.95$). We observe a decrease in the two residual variances, implying that the variables explain variability at both levels. The fact that adding level-one variables to the model decreases the residual variance not only at level-one but also at level-two is caused by the presence also of between-ego variability on these variables, i.e., the means per respondent of the level-one variables vary more than is expected by chance. The model is presented in Table 3.

The intercept, that is the overall mean change in contact frequency if all explanatory variables are 0, is estimated as -7.28 implying that in the — impossible — situation that all other variables are zero, frequency of contact has decreased by more than seven

Table 3
Model with fixed level-1 variables added

	Estimate	(S.E.)
Fixed effects		
Intercept	−7.28	(0.58)
Level-1 (alter) variables		
Kin/Non-kin	2.16	(0.18)
(log) Duration	0.69	(0.12)
Level of Education Nominee	0.12	(0.04)
Change in Appreciation	0.50	(0.18)
Change in (log) Travel Time	−0.18	(0.07)
Change in Homogeneity	0.23	(0.06)
Companionship	−0.13	(0.54)
Emotional Support	−0.94	(0.34)
Level-1 interaction variables		
Kin/Non-kin × (log) Duration	−0.28	(0.03)
Kin/Non-kin × Change in appreciation	0.12	(0.04)
Kin/Non-kin × Change in (log) Travel Time	−0.08	(0.03)
Kin/Non-kin × Companionship	−0.29	(0.10)
(log) Duration × Change in appreciation	−0.10	(0.04)
(log) Duration × Companionship	0.32	(0.11)
(log) Duration × Emotional Support	0.17	(0.07)
Change in Homogeneity × Companionship	0.10	(0.04)
Level of Education Nominee × Companionship	−0.13	(0.04)
Random effects		
Level-2 variance τ_0^2	0.41	(0.07)
Level-1 variance σ^2	3.41	(0.09)
Deviance	12098.7	

points. This degree of decrease in frequency is not found in the majority of ties because of significant positive effects that compensate for this decrease and make frequency of contact more stable over time.

Strong effects were found for characteristics of the relationship. As could be expected (Dykstra, 1990; Morgan et al., 1997; Wellman et al., 1997), we found that especially relations with kin remain more stable over time than relations with non-kin ($\hat{\gamma} = 2.16$, S.E. = 0.18). Contrary to common belief and for instance research findings by Suitor and Keeton (1997), this study shows that relationships in which emotional support is given are less stable ($\hat{\gamma} = -0.94$, S.E. = 0.34). Other things being equal, these relations decrease almost one point more than relations of which emotional support is not the most important characteristic (i.e., companionship or instrumental support).

In line with Rusbult (1983), Sprecher (1988), and Broese van Groenou (1991), the results indicate that investments made in the past also have a stabilizing effect, represented by the positive effect ($\hat{\gamma} = 0.69$, S.E. = 0.12) of *(log) Duration*: the longer the respondent knows the nominee, the smaller the decrease in contact frequency.

A fourth, but far less important stabilizing factor, is the level of education of alter: a higher educational level of alter slightly increases the contact frequency ($\hat{\gamma} = 0.12$, S.E. = 0.04). This points to the presumed possible importance of ties with people with valuable resources because of their higher education. This influence of one's social position on investments is one of the main notions in social capital research aimed at the labour market (De Graaf and Flap, 1988; Boxman et al., 1991) and was also found by Lin (1982) in his research on instrumental action and social networks.

As an example, the expected change in contact frequency of a respondent with a new neighbor without a high school education (*Kin* = 1, *(log) Duration* = 1, *Education Nominee* = 1), giving mainly instrumental support is: $-7.28 + 1 \times 2.26 + \log(1) \times 0.69 + 1 \times 0.12 = -5.0$. A similar calculation shows results in an expected change in contact frequency of 0.36 with an old friend from college (*Kin* = 2, *(log) Duration* = 120, *Education Nominee* = 8) from whom emotional support is obtained. In this case, the relationship with the old friend is expected to be more stable than the relationship with a new neighbor.

For changes that affect the content or context of the relation, the amount of decrease can be calculated in the same way. Changes in costs and benefits have a marked influence on the frequency of visits and telephone calls. Decrease of appreciation, i.e., a negative value for *Change in Appreciation*, results in a decrease in frequency of visits and phone calls and greater appreciation makes subjects tend to visit their friends and family members more often ($\hat{\gamma} = 0.50$, S.E. = 0.18). An increase in travel time leads to less frequent visits and less frequent calls (on a log scale: $\hat{\gamma} = -0.18$, S.E. = 0.07). Homogeneity is known to influence the choice and development of friendship (Verbrugge, 1977; Wellman et al., 1997; Van de Bunt, 1999). In this study, it was also possible to show the effect of increasing or decreasing homogeneity over time. Overall, increasing homogeneity in terms of age, gender, marital status or working status makes a tie more stable over time ($\hat{\gamma} = 0.23$, S.E. = 0.06).

These changes do not have the same consequences for each tie however. Nine interaction effects were found, giving more insight in the joint effect of the level-one variables.

There are negative interaction effects for kinship with *(log) Duration* ($\hat{\gamma} = -0.28$, S.E. = 0.03), with change in (log) *Travel Time* ($\hat{\gamma} = -0.08$, S.E. = 0.03), and with companionship ($\hat{\gamma} = -0.29$, S.E. = 0.10): this means that non-kin catch up with kin if the relationship has lasted longer, and that the strong positive effect of kinship is somewhat lowered when the nominee has moved away, and when the basis of the tie is companionship.

The positive sign of the interaction variable of kinship with appreciation ($\hat{\gamma} = 0.12$, S.E. = .04) implies that appreciation is more important for kin than for non-kin. As an example, we can calculate the influence of a conflict on the relationship with an aunt (*Kin / Non-kin*, score 3) as compared to the relationship with a neighbor (score 1). Let us presume that the appreciation score for both ties was the same to start with (a positive score of 4) and was equally bad at the time of the third interview (a very negative score of 1), i.e., a change of -3. Other variables are assumed to be equal. The difference in change of contact with the aunt and the contact with the neighbor due to the conflict would be estimated as $(0.12 \times 3 \times -3) - (0.12 \times 1 \times -3) = -0.72$, implying a negative effect of almost one point more for the relationship with the aunt. Because of the strong effect of *Kin / Non-kin*, however, the overall difference in change of contact is still positive: $(2.16 \times 3 + 0.12 \times 3 \times -3) - (2.16 \times 1 + 0.12 \times 1 \times -3) = 5.40 - 1.80 = 3.60$.

The negative interaction effect of *(log) Duration* with *Change in Appreciation* ($\hat{\gamma} = -0.10$, S.E. = 0.04) indicates that the effect of change in appreciation is smaller in ties in which friends have known each other for a long time. Relationships which are mostly based on shared activities (companionship) differ in two other ways from other relations. The effect of a change in homogeneity has a stronger effect in these relations (($\hat{\gamma} = 0.10$, S.E. = 0.04) and in these relations, alters with a higher education are not as much preferred (($\hat{\gamma} = -0.13$, S.E. = 0.04). So, to give an example, a relationship between football buddies is more stable over time when people share the same life style and put an equal interest in the relationship.

For companionship, two other interaction effects were found, indicating that the effect of shared activities is stronger when the relationship has a longer history ($\hat{\gamma} = 0.32$, S.E. = 0.11), and decreases for relationships with alters with a high level of education ($\hat{\gamma} = -0.13$, S.E. = 0.04). Two other interaction effects point to the meaning of long-term relationships for support given. The longer one knows the other, the more stabilizing is the effect of both companionship (($\hat{\gamma} = 0.32$, S.E. = 0.11) and of emotional support (($\hat{\gamma} = 0.17$, S.E. = 0.07) on the relation.

All in all, the interaction effects tell us that differences between kin and non-kin are not as large as a superficial analysis suggests. Over time, ties with non-kin grow to resemble kin relations in their degree of stability. Moreover, investments in kin relations are, contrary to what could be expected, not only influenced by norms but also by considerations as travel distance and appreciation.

In step 2, 22 level-two explanatory variables and within level-two interactions are added, resulting in a model deviance of 12 046.8, a significant improvement. Among these are five average scores per respondent (on *Companionship*, *Homogeneity*, *(log) Duration*, *Education Nominee* and *Kin / Non-kin*) to investigate whether differences in network composition *between* respondents as represented by those five variables have

effects by themselves, next to the effect *within* respondents, i.e., at the relation level (differences between within-unit and between-unit regressions are discussed in the work of Snijders and Bosker, 1999, Section 4.5).

A total of 13 effects are removed for reasons of non-significance. The ''control'' variables, (gender, age, marital status, and life event group), although insignificant except for *Recently Moved* and *Retired Man*, are retained in view of the need to control for the non-random selection of the research subjects and the specific way our subjects vary in age and gender (i.e., older men and younger women). Two effects that were significant in this model (mean companionship and education respondent) were not significant in later steps and are not included in Model 2, presented in Table 4. The deviance is 12 080.3. The difference in deviance with Model 1 is 12 098.7 − 12 072.1 = 26.6 which is significant on $df = 7$ ($p = 0.0004$). The estimates of the coefficients of level-one variables hardly change.

Table 4 shows which social characteristics of ego are important. The four different subsamples with subjects experiencing different life events, allowed us to compare the influence of these events on the network. Surprisingly, after 4 years, there was statistically no difference in the amount of turn-over for two of the four samples. Other things being equal, respondents from the random sample experienced the same amount of change as the women who gave birth to their first child and the subjects who had moved just before the first interview. In most studies on network change, researchers focused on the (short-term) changes after major life events, but it seems as if in the long run all networks are in a constant state of change (e.g., Shulman, 1975; De Jong-Gierveld and Dykstra, 1993; Starker et al., 1993).

There was, however, a negative effect of *Retired Man* ($\hat{\gamma} = -0.64$, S.E. = 0.24), i.e., pensioners experience on average more loss than others in their relations. This confirms what Fischer and Oliker (1983) found in their cross-sectional data. They commented on the loss of friends and other contacts after retirement by pointing out that men who were occupied by a job most of their lives, lack the skills and experience to develop and maintain relationships outside the workplace.

Two other main effects were found for moving house, both for the life event group ($\hat{\gamma} = -0.37$, S.E. = 0.16) and for the respondents in the other groups who happened to move house in the research period ($\hat{\gamma} = 0.53$, S.E. = 0.12). Note that the overall effect of moving house for the life event group is equal to $0.53 - 0.37 = 0.16$. Somewhat surprisingly, the effect of moving house is slightly positive. Note, however, that moving will have an effect on travel time and that the effect of moving house is controlled for travel time. Most likely, this positive effect is lowered by the change in travel time for most relations. The influence of other respondent characteristics on a change in contact were not significant. No support was found for the influence of age, gender, or marital status on stability and change. Time restrictions, or limitations in physical mobility or financial means, had no distinct influence on changes in the frequency of contact, nor had the number of alternative relations. We did not include any significant level-two interaction terms, although there was an ''almost significant'' positive effect of *Moved After First Interview* with *Man / woman*.

Note that especially the level-two variance τ_0^2 is reduced in this step where level-two variables have been added.

Table 4
Model with fixed level-2 variables added

	Estimate	(S.E.)
Fixed effects		
Intercept	−7.45	(0.62)
Level-1 (alter) variables		
Kin/Non-kin	2.19	(0.18)
(log) Duration	0.70	(0.12)
Level of Education Nominee	0.12	(0.04)
Change in Appreciation	0.50	(0.18)
Change in (log) Travel Time	−0.18	(0.07)
Change in Homogeneity	0.25	(0.06)
Companionship	−0.09	(0.54)
Emotional Support	−0.95	(0.34)
Level-1 interaction variables		
Kin/Non-kin × (log) Duration	−0.28	(0.03)
Kin/Non-kin × Change in Appreciation	0.12	(0.04)
Kin/Non-kin × Change in (log) Travel Time	−0.07	(0.03)
Kin/Non-kin × Companionship	−0.28	(0.10)
(log) Duration × Change in Appreciation	−0.10	(0.04)
(log) Duration × Companionship	0.31	(0.11)
(log) Duration × Emotional Support	0.17	(0.07)
Change in Homogeneity × Companionship	0.10	(0.05)
Level of Education Nominee × Companionship	−0.13	(0.04)
Level-2 (ego) variables		
Young Mother	−0.17	(0.18)
Recently Moved	−0.37	(0.16)
Retired Man	−0.64	(0.24)
Man/Woman	−0.04	(0.16)
Age	0.003	(0.005)
Married	−0.08	(0.07)
Moved After First Interview	0.53	(0.12)
Random effects		
Level-2 variance τ_0^2	0.33	(0.06)
Level-1 variance σ^2	3.41	(0.09)
Deviance	12 072.1	

In step 3, random slopes are tested for relevant — level-two — variables. Recall that a random slope for variable X, a characteristic of alter, means that the effect of X on the change in contact frequency varies between egos. This is done by first adding random slopes and the covariance with the intercept of the variables to the model and then adding selected cross-level interaction terms. This leads to the model presented in Table 5. Six significant random slopes are found and one significant cross-level interaction term. The deviance is improved by 210.8 points ($df = 13$, $p < 0.00001$). The standard errors of the fixed effects are somewhat different than those in Model 2. This is

Table 5
Model 3 with random slopes and cross-level interactions added

	Estimate	(S.E.)
Fixed effects		
Intercept	−7.58	(0.72)
Level-1 (alter) variables		
Kin/Non-kin	2.09	(0.20)
(log) Duration	0.79	(0.13)
Level of Education Nominee	0.11	(0.04)
Change in Appreciation	0.44	(0.20)
(log) Travel Time	−0.16	(0.09)
Homogeneity	0.23	(0.05)
Companionship	0.26	(0.59)
Emotional Support	−0.73	(0.35)
Level-1 interaction variables		
Kin/Non-kin×(log) Duration	−0.27	(0.03)
Kin/Non-kin×Appreciation	0.12	(0.05)
Kin/Non-kin×(log) Travel Time	−0.07	(0.03)
Kin/Non-kin×Companionship	−0.22	(0.10)
(log) Duration×Appreciation	−0.10	(0.05)
(log) Duration×Companionship	0.28	(0.11)
(log) Duration×Emotional Support	0.13	(0.07)
Change in Homogeneity×Companionship	0.11	(0.04)
Level of Education Nominee×Companionship	−0.10	(0.05)
Level-2 (ego) variables		
Young Mother	−0.09	(0.16)
Recently Moved	0.61	(0.53)
Retired Man	−0.50	(0.21)
Man/Woman	0.12	(0.14)
Age	0.002	(0.005)
Married	−0.10	(0.06)
Moved After First Interview	0.37	(0.11)
Cross-level interaction variables		
Recently Moved×(log) Duration	−0.18	(0.10)
Random effects		
Level-2 variance τ_0^2	0.31	(0.06)
Level-1 variance σ^2	2.69	(0.08)
Random slopes		
Kin/Non-kin	0.19	(0.04)
(log) Duration	0.10	(0.04)
Change in Appreciation	0.21	(0.06)
(log) Travel Time	0.08	(0.03)
Companionship	0.78	(0.26)
Emotional Support	0.45	(0.14)

Table 5 (continued)

	Estimate	(S.E.)
Covariances × intercept		
Kin/Non-kin	− 0.13	(0.04)
(log) Duration	− 0.06	(0.03)
Appreciation	− 0.03	(0.04)
(log) Travel Time	− 0.01	(0.03)
Companionship	− 0.13	(0.08)
Emotional Support	− 0.16	(0.06)
Deviance	11 861.3	

because the covariance structure of the data is represented differently, and better, in Model 3. The consequence is that the tests of fixed effects based on Models 1 and 2 are less reliable than those based on Model 3.

The random effects show us that the different characteristics of a tie carry a different weight for different subjects. There are significant random effects for the effect of appreciation (variance of 0.21, S.E. = 0.06), travel time (variance of 0.08, S.E. = 0.03), of kinship (variance of 0.19, S.E. = 0.04) and of duration of the relation (variance of 0.10, S.E. = 0.04). This means, for instance, that some people are more tolerant about changes in appreciation and that some people are better than others in overcoming distances. Also, it shows that there are big individual differences in the way people handle their kinship ties and long-term friends. Even more relevant are the random effects for companionship (variance of 0.78, S.E. = 0.26) and emotional support (variance of 0.45, S.E. = 0.14). The main effect for companionship is relatively small and not significantly different from zero. For this type of support, the parameter estimates mean that whereas over all individuals there is no average effect, for a part of the subjects the effect of companionship is positive and for others negative (using the mean plus or minus twice the standard deviation as an approximate 95% interval, the effect varies between $0.26 − 2\sqrt{0.78}$ = -1.51 and $0.26 + 2\sqrt{0.78}$ = 2.03). Calculating such intervals shows that *Kin / Non-kin* and *(log) Duration* are the only variables with random slopes for which the effect is homogeneously positive.

By adding cros-level interactions, we hoped to find some explanations for this variance between the subjects. Only one cross-level interaction proved significant: a negative interaction between whether subjects moved after the first interview and duration of the tie. Moving houses reduces the effect of *(log) Duration*, although some individual differences remain. Similarly, *(log) Duration* reduces the effect of moving houses. Including this cross-level interaction altered the estimate of the main effect of the corresponding life event group *Recently Moved* to the non-significant positive value of 0.61. This cross-level interaction effect is not very convincing, however, as it is the only nominally significant effect among a large number of interaction effects.

In step 4, we added covariances between the random slopes. In two cases, this led to a significant better model and a decrease in deviance of 18.5 ($df = 2$, $p < 0.0001$). The covariance between the random slopes for appreciation and kinship ($− 0.12$, S.E. = 0.04,

Table 6
Final model

	Estimate	(S.E.)
Fixed effects		
Intercept	−7.67	(0.70)
Level-1 (alter) variables		
Kin/Non-kin	2.10	(0.20)
(log) Duration	0.80	(0.13)
Level of Education Nominee	0.11	(0.04)
Change in Appreciation	0.42	(0.20)
(log) Travel Time	−0.17	(0.08)
Homogeneity	0.22	(0.05)
Companionship	−0.32	(0.58)
Emotional Support	−0.72	(0.35)
Level-1 interaction variables		
Kin/Non-kin × (log) Duration	−0.28	(0.03)
Kin/Non-kin × Appreciation	0.12	(0.05)
Kin/Non-kin × (log) Travel Time	−0.06	(0.03)
Kin/Non-kin × Companionship	−0.21	(0.10)
(log) Duration × Appreciation	−0.09	(0.05)
(log) Duration × Companionship	0.28	(0.11)
(log) Duration × Emotional Support	0.13	(0.07)
Change in Homogeneity × Companionship	0.10	(0.04)
Level of Education Nominee × Companionship	−0.10	(0.05)
Level-2 (ego) variables		
Young Mother	−0.08	(0.16)
Recently Moved	0.66	(0.52)
Retired Man	−0.52	(0.21)
Man/Woman	0.12	(0.14)
Age	0.003	(0.005)
Married	−0.10	(0.06)
Moved After First Interview	0.37	(0.11)
Cross-level interaction variables		
Recently Moved × (log) Duration	−0.18	(0.10)
Random effects		
Level-2 variance τ_0^2	0.27	(0.05)
Level-1 variance σ^2	2.67	(0.08)
Random slopes		
Kin/Non-kin	0.22	(0.04)
(log) Duration	0.11	(0.04)
Change in Appreciation	0.23	(0.06)
(log) Travel Time	0.08	(0.03)
Companionship	0.71	(0.25)
Emotional Support	0.58	(0.16)

Table 6 (continued)

	Estimate	(S.E.)
Covariances × intercept		
Kin/Non-kin	−0.10	(0.04)
(log) Duration	−0.07	(0.03)
Change in Appreciation	−0.33	(0.11)
(log) Travel Time	−0.01	(0.03)
Companionship	−0.12	(0.08)
Emotional Support	−0.43	(0.18)
Other covariances		
Kin/Non-kin × Change in Appreciation	−0.12	(0.04)
Kin/Non-kin × Emotional Support	−0.20	(0.06)
Deviance	11 842.8	

i.e., a correlation of −0.53) was added as well as the covariance between the random slope for emotional support and kinship (−0.20, S.E. = 0.06, i.e., a correlation of −0.57). Both are negative covariances, which means that when, for some respondent, kinship has an effect 'above average' (in comparison with its fixed effect), then appreciation and emotional support tend to have for this respondent a 'below average' effect and vice versa. Maybe this stands for a difference in attitude and norms (kin-oriented vs. individualistic) between respondents, but as we did not include questions on, for instance, moral values or religion, we cannot give a better explanation. We consider this our final model and present it in Table 6.

5. Discussion

Now that we have shown how multilevel modelling can be used in the analysis of longitudinal data of personal networks, two questions come to mind. The first one is related to the results shown in our example. In what way are the results found in our study comparable to those found before? Special attention is paid to studies presented in the special issue of Social Networks (1997, 1). Are extra insights found using the multilevel model? The second question addresses the difference between the multilevel modelling technique and other common methods ignoring the nested structure of the data. We compare the results with what could have been found with other regression models. We complete the discussion with some concluding remarks.

5.1. More on the results found in the multilevel analysis

Our first research question is directed at the characteristics of the ties and the characteristics of ego. As for the influence of the ties, the results are in line with most research done in this area. We also found that networks are comprised of a persistent

core of ties that is maintained across time and a periphery of ties that is unstable over time (Kahn and Antonucci, 1980; Zeggelink, 1993; Morgan et al., 1997). Keeping the nested structure of the data intact, we found that the variance in stability between ties is far greater (10 times as large) than the variance between networks as a whole. Because there was no need to aggregate the information on each of the separate ties, we know what the characteristics are of the ties in the core of the network in answer to the question 'why do some ties persist more than others' (Suitor et al., 1997, p. 4).

Closeness in terms of kinship, appreciation, and having known each other for a long time is, in this study as in others, the main predictor of the stability of a tie, when looking at the effect size of these variables. Subjects with resources obtained by education are in the long-term more able to maintain their relations. The marked influence of change in travel distance is interesting in this era of technology facilitating communication and mobility. Wellman and Tindall (1990) concluded in their study that face-to-face contact is still important and not substituted by contact by telephone. They found that people use the telephone not to replace face-to-face contact but to facilitate it.

One of our hypotheses drawn from social capital theory was that a high social status of the other person has a positive influence on the decision to invest in relations. Changes in homogeneity of the relation were also assumed to influence investments. These hypotheses were corroborated by the multilevel analysis, which supports the assumptions held in social capital theory. They may also explain why in most studies larger networks are found for people with a higher education (Fischer, 1982) and relatively large changes in networks after life events are important for the homogeneity of the tie, like divorce (Broese van Groenou, 1991), widowhood (Morgan, 1989; Stevens, 1989) and change in employment status (De Jong-Gierveld and Dykstra, 1993; Wellman et al., 1997) or the changes due to re-entering college (Suitor et al., 1997).

Unfortunately, except for the clear evidence that there are big individual differences in the mean stability of the ties comprising the network, the question as to 'which social characteristics of egos affect turnover in networks' (Suitor et al., 1997, p. 4) is still not answered adequately as no support was found for the direct influence of age, gender, and financial or physical restrictions on stability and change. The fact that we did not find an effect for age is not without a precedent. Van Tilburg (1998) did not find an effect of age when using a multilevel model to analyze changes in the networks of elderly people. The suggestion of the importance of age to explain differences in the stability of ties comes from cross-sectional research (e.g., Fischer and Oliker, 1983; Wellman et al., 1997). The explanation offered is that young people are confronted with more status transitions in their own lives as well as in the lives of their friends on other network members and therefore have relatively less stable relationships. And indeed, this explanation is not invalidated by our findings nor by the findings of Van Tilburg (1998): by controlling for differences in the characteristics of the ties and for the differences in life events, the age factor disappeared. The suggestion that women are more capable to maintain their relationships over time (Fischer and Oliker, 1983) was not supported by our data.

Keeping the nested structure of the data intact, however, made two things clear. Independent of its size and context, a personal network changes over time. This is what Wellman calls the 'inherent instability of the system'. Secondly, apart from individual

differences in the amount of change, there is significant variation in the importance of kinship, friendliness or emotional support as a base for a stable relationship.

In the second research question, attention is drawn to the possibility of generalization of the results over different life events. In most studies, only one type of life event and its after-effect are studied. In this study, it was possible to compare the changes after three different life events and the change that occurred in a random sample. Multilevel analyses were useful to show that, in general, the content of change is comparable for different life events. Two events proved to have a significant impact by itself: retirement and moving house. Wellman et al. (1997) did not find an effect of moving which may attributed to the small sample.

The small negative effect of *Married* is on the boundary of significance ($p = 0.054$). Wellman et al. (1997) found that networks change when changes in marital status occur, whether it is marriage or divorce. Therefore, he concludes that ''it is the change in marital status itself that is important and not its direction'' (p. 42). The negative effect in our analysis suggests that it is both the status change and the direction that account for the instability of the network.

Our main conclusion is that the idea of the investment considerations (see Section 2) provides a good framework for the explanation of the (in)stability of relations over time. In some cases, the weight of these considerations is dependent on the support exchanged in the relation: investments are of extra importance in emotional relations, expected value of the relation (as expressed by a change in homogeneity) is of extra importance where companionship is the main goal. The general investment model, however, cannot explain individual differences: we found a lot of variation between people in the way they handle investment considerations. Where some people are guided by the benefits of the relation (as expressed by appreciation), others are guided by a secure future value of their investments and prefer to remain investing in kin despite changes in appreciation. The random effects seem to be of great importance and more theoretical work is needed to come up with testable hypotheses to explain the corresponding interpersonal differences.

5.2. What could multilevel analysis have added to the studies presented in the special issue?

Ignoring the nested structure of the data can lead to two kinds of analysis. First, ignoring the nesting completely by treating the data as independent observations. Second, eliminating the dependency by averaging over the lowest level. The first method is statistically incorrect because the model assumptions are violated. This will result in biased estimates, underestimation of standard errors, and possibly in false conclusions. The second method is statistically correct, but suffers from loss of information.

5.2.1. A disaggregated analysis: ordinary least squares regression analysis on the same data

A straightforward regression model was fitted to the data set as a simple alternative, but incorrect, method of analysis. For comparison with the first multilevel model

reported in Table 3, a model was estimated in which only relation variables are used as explanatory (or independent) variables. Obviously, just one variance parameter is estimated. A value of 3.80 was found, which is approximately equal to the sum of the two multilevel variance estimates $(0.41 + 3.41)$. All other parameters had slightly different estimates, with absolute differences not larger than 0.03. Two parameter estimates showed a larger although not very important difference. The first was the intercept, which is now -7.98 (with S.E. = 0.59), i.e., 0.30 lower than in the multilevel analysis. The second variable is Companionship, which is now -0.015 (with S.E. = 0.56). This estimate was not significantly different from 0 in the multilevel analysis either.

Next, a regression model was estimated in which respondent characteristics are included, similar to the multilevel model reported in Table 4. The estimates for the explanatory relation variables were again roughly the same. The estimates for the explanatory respondent variables were also more or less the same. The most striking difference in this analysis was found in the standard errors of the regression estimates, which were reduced by approximately 50%. By ignoring the nested structure, the sample of respondents is 'inflated', and therefore the standard errors are underestimated. This leads to overestimation of the significance of effects, but in this analysis, none of the previously non-significant level-two variables became significant.

As a final model, the ''cross-level'' interaction variable *Recently Moved* × *(log) Duration* was added to the previous model. Larger differences with the models reported in Tables 5 and 6 were found, although the model is actually not comparable to these models because the variance structure is so completely different. Failing to model the variance structure does affect the regression estimates considerably. Because of the incorrect standard estimates, especially the *t*-tests, are invalid in this analysis.

Also performed were analyses in SPSS to ''automatically'' select the most important (i.e., significant) variables. We will not give an exact comparison but will sketch the rough differences and similarities. In a backward selection procedure, the same level-one variables were found, except for *Companionship* (which is not surprising) and *(log) Travel Time*. In the multilevel analysis, the effect of *(log) Travel Time* was not so strong, but the interaction with *Kin / Non-kin* was. Apart from these variables, SPSS selected the interaction *(log) Duration* × *(log) Travel Time* and a variable indicating whether the network member has a paid job. These variables were also found in a forward selection procedure, whereas the interaction of *(log) Duration* × *Emotional Support* was not found. Two other interactions with emotional support were selected instead.

In the search procedures including respondent variables, we expected to find more significant effects. Controlling for life event group, gender and marital status, the variables indicating respondent's financial means, education, and interaction of *Moved After First Interview* with education and with gender, became significant. In the multilevel analysis, these effects were too weak to be included in the models. This supports the earlier conclusion that simple-level analysis that does not take into account the nesting of alters within ego leads to downward biases of standard errors, and therefore, the risk of non-replicable results.

5.2.2. An aggregated analysis: a regression model for the mean difference in contact frequency

For this analysis, we computed the means of all relation variables per respondent. This means that the sample size was now 95 instead of 2928. Of course, the variance was reduced considerably: 0.98 in an empty model (which is larger than the between-respondent variance of 0.59 reported in Table 2, because it also contained the within-respondent sampling variance of the mean). Next, a model comparable to the model reported in Table 3 was estimated. The results were quite different. This is due to the changed range of the variables, which makes comparison difficult. Only *Kin / Non-kin* and *Homogeneity × Companionship* were significant in this analysis. In the automatic search procedures, not many more variables were found.

Our conclusion here is that modelling the mean change in contact frequency per respondent (and thus ignoring differences between relationships of the same respondent) is really different from modelling the change per relationship and can lead to different outcomes and conclusions. The fact that there seems so much less to be found is due to the fact that approximately 90% of the variation is removed by aggregation. The aggregated analysis is statistically correct, however, so it depends on the research question which approach is to be preferred. The aggregated analysis answers the question ''on what does it depend whether persons (egos) lose many or few contacts?'', while the multilevel analysis answers the question ''on what does the stability of individual contacts depend?''.

What does this mean for the analysis of social network data which are commonly not analyzed with multilevel models but with ordinary least squares regression models, like, e.g., Suitor and Keeton (1997) and Wellman et al. (1997)? Apart from possibly wrong conclusions, as demonstrated above, multilevel analysis provides the possibility to investigate the importance of other covariates than just the role position or role in the network (cf. Morgan et al., 1997). As shown in Section 4, the importance can be expressed both in terms of fixed (or overall effects) and random (or varying over respondents) effects. The random effects give insight into (as yet unexplained) differences between egos, and can be used as a guide for developing further hypotheses (e.g., about cross-level interactions).

A multilevel model is easily extended to more levels, as is the case in the work of Morgan et al. (1997), where multiple measurements have been made. The measurement becomes the lowest level (1), the relationship the second, and the respondent the highest (level 3). An extra advantage of multilevel modelling here is that it is not necessary to have complete data on all ties on all measurements. All available data, however, are taken into account (See also Snijders, 1996 for the use of multilevel methods for longitudinal data). Another possible extension is with a higher level, e.g., geographical units such as neighborhoods or counties which may be associated with differences in network structures. Multilevel models are also available for binary data (Völker, 1995; Völker and Flap, 1997; Snijders and Bosker, 1999, Chap. 14).

5.3. Concluding remarks

Suitor et al. (1997) believe that in the future, the study of change in networks will include different types of data, different types of change and different types of network.

Our opinion is that network analysis can benefit from recent achievements in the field of statistics which will lead to more encompassing and better founded results. Improved insight is not always found by broadening the theoretical scope of the research but can sometimes be obtained by studying the same data in a more adequate way doing justice to their complexity.

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