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Résumé

Considérations d'ordre conceptuel et analytique relatives à la recherche multiniveaux en promotion de la santé

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La recherche en promotion de la santé fait souvent appel à un modèle socio-écologique pour élaborer ses concepts. Celui-ci produit des données ou des variables associées à plusieurs niveaux, tels que le niveau individuel, le niveau correspondant au milieu de vie et le niveau provincial. Ces données sont ensuite regroupées par niches ou par grappes. En d'autres termes, la recherche multiniveaux en promotion de la santé se fonde sur l'idée que le milieu influe sur la santé, transcendant les caractéristiques et comportements individuels. On peut faire une analyse rigoureuse de ces effets de contexte à l'aide de la modélisation multiniveaux, dans le but de déterminer s'ils découlent véritablement du milieu ou sont le produit du profil social des résidants. Cette méthode facilite également l'analyse des effets de l'interaction transversale. Les auteurs abordent les questions conceptuelles et méthodologiques soulevées par la recherche multiniveaux. Bien que les modèles conceptuels permettent de proposer des trajectoires multiniveaux vers des résultats de santé, les analyses techniques ne révélant que des effets globaux moyens ne permettent pas de mettre en évidence les autres facteurs influençant les comportements de santé.

Mots clés : modélisation multiniveaux, effets de contexte, contexte

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Multilevel Health Promotion Research: Conceptual and Analytical Considerations

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Health promotion research is often conceptualized through the use of socio-ecological frameworks. This results in data or variables associated with multiple levels such as individual, community, and provincial. These data are nested, or clustered. In other words, multilevel health promotion research is based on the idea that community influences health, above and beyond one's individual characteristics or behaviours. These contextual effects can be analyzed rigorously using multilevel modelling (MLM), thus determining whether contextual effects are truly derived from context or are the result of residents' social profile. MLM also facilitates examination of cross-level interaction effects. The authors discuss conceptual and methodological issues related to multilevel research. While multilevel pathways to health outcomes have been suggested at the conceptual level, analytical techniques that produce only average overall effects fail to reveal the various other influences on health behaviour.

Keywords: multilevel modelling, hierarchical multilevel modelling, contextual effects, public health research, context

Various conceptual frameworks for explaining the production of health in populations have included explicit consideration of the role of context (i.e., factors beyond personal characteristics) in determining the health of individuals (Evans & Stoddart, 1990; Hancock 1986; Stokols, 1996). For example, while an individual's health may be influenced by his own employment status, it may also be influenced by the level of employment in the community in which he lives, independent of his own employment status. These frameworks reflect the fact that individuals are not independent of their communities but are influenced by them. This consideration has extended the range of health determinants to include contexts (e.g., families, workplaces, residential communities) and specific variables or characteristics of those contexts (e.g., environment, employment levels and types, socio-economic status) and the associations among them.

A parallel approach has been the development of empirical models to estimate the direction and size of these complex relationships underlying the production of health. Hierarchical multilevel modelling, for example, is a statistical technique that handles data with a specific structure — units that are nested into groups or clusters, like individuals within families and families within communities. Many health promotion strategies exhibit this type of structure since they include community-level policies as an approach to influencing individual health or health-related behaviours.

The purpose of this paper is to discuss conceptual and methodological issues related to multilevel research problems and explain how multilevel models can be used to help identify separate individual and contextual influences on health and the interactions among these influences. Traditional analytical techniques such as simple regression modelling produce average effects that can mask the ways in which health or health-related behaviour is influenced. In particular, observed poor health of a community might arise from particular characteristics of the community (e.g., level of air pollution), the composition of the community (e.g., clustering of heavy smokers), or the interaction among people and contextual characteristics (e.g., the level of air pollution exacerbates the harmful health effects of smoking) (Jones, Moon, & Clegg, 1991). Only through the use of appropriate techniques can each of these influences be detected.

The first section of the paper highlights conceptual issues associated with multilevel research problems. In keeping with much of the literature, we use the terms "context" and "community" in reference to geographic areas, although the notion of context is not confined to geographical considerations but can apply to any factor beyond the personal circumstances and characteristics of the individual. The second section deals with technical approaches to analyzing multilevel data. Our exploration of multilevel research issues leads us to conclude that multilevel modelling (or MLM) is the most robust method by which to treat the levels of data. MLM supports the incorporation of various levels of data (e.g., individual, family, workplace) as well as particular variables measured at each level (e.g., individual education, family income, workplace smoking policies) to provide estimates of the relationships *within* each level (e.g., what are the associations between individual education and individual health and family income?) and *among* levels (how does smoking policy at the workplace affect the association between individual smoking and individual health?). From a conceptual standpoint, MLM more closely resembles the multiple and interacting pathways influencing health than does a single-level regression model.

Researchers have used the MLM technique to examine the determinants of a range of health-related factors (see Table 1). These include health status (Beland, Birch, & Stoddart, 2002; Duncan, Jones, & Moon, 1996; Humphreys & Carr-Hill, 1991; Mitchell, Gleave, Bartley, Wiggins, & Joshi, 2000), risk factors for disease (Diez-Roux, Link, & Northridge, 2000; Diez-Roux et al., 1997), health-related behaviours such as smoking

Table 1 *Some Multilevel Health Studies*

Study	Independent Variables		Dependent Variables	Findings
	Contextual level	**Individual level**		
Beland et al., 2002	Clusters: – level of unemployment – gender distribution – age-group distribution – education – proportion of population that consists of immigrants – family structure – income – employment status – occupational status	– employment status – sources of stress – socio-economic status – social support – psychological factors	– perceived health status	– level of unemployment and health relationship did not vary among contexts – stress and health relationship did vary among contexts, and this relationshp was influenced by area-level economic well-being
Carr-Hill et al., 1996	Ward: – housing tenure – social class – unemployment status – permanent sickness – student status – car ownership – single-career households – dependent children – elderly living alone – overcrowding – education – longstanding illness – rural/urban – access to health care	– change in employment status – health status – sociodemographic	– consultation rates in general practice	– small contextual effect found – individual effects stronger

Table 1 (cont'd)

Study	Independent Variables		Dependent Variables	Findings
	Contextual level	Individual level		
Diez-Roux et al., 1997	Census-block groups: – education – income – house value – occupation	– social class	– prevalence and risk factors for coronary heart disease	– small neighbourhood effects, sometimes not significant but consistent across various dependent variables – interaction effect demonstrated only for one neighbourhood (men only)
Diez-Roux et al., 2000	State level: – three indices of income inequality	– income	– cardiovascular disease risk factors: BMI, hypertension, sedentarism, smoking	– contextual income inequality associated with three of four dependent variables, especially at low levels of individual income – the remaining variable, smoking, demonstrated an association with income inequality at higher levels of individual income – significant effect found only in women
Duncan et al., 1999	Region Ward	– demographic – socio-economic	– smoking behaviour – alcohol consumption	– very small effects for smoking, a little higher for drinking – contextual effects were mostly compositional

Duncan et al., 1996	Ward Individual	– demographic – social class	– smoking status – smoking behaviour (consumption rates)	– most variation in consumption due to individuals – after considering composition, smoking status varied by ward – wards with high number of smokers also demonstrated high levels of average consumption
Duncan et al., 1999	Region Electoral ward: – index of deprivation	– demographic – social class – housing tenure – employment status – education status – marital status	– smoking status – smoking behaviour (consumption rates)	– ward deprivation had an independent effect on individual smoking status and behaviour; model suggested a uniform effect across all regions – variation among wards could not be fully accounted for by ward-level deprivation or composition
Ecob & Macintyre, 2000	Postal code sector: – area deprivation	– good exercise habits – bad exercise habits – good diet habits – bad diet habits – occupational / social class – education – household material deprivation – marital status – moved in last five years	– smoking status – smoking behaviour (consumption rates) – drinking status – drinking behaviour	– bad diet demonstrated variations by area, even after controlling for area deprivation – good and bad diet demonstrated independent relationship with area deprivation – bad exercise habits demonstrated independent relationship with area deprivation – smoking status demonstrated independent relationship with area deprivation – many cross-level interaction effects identified

Table 1 (cont'd)

Study	Independent Variables		Dependent Variables	Findings
	Contextual level	**Individual level**		
Humphreys & Carr-Hill, 1991	Five clusters derived from ward-level information to differentiate rich from poor areas	– socio-economic – health-related behaviours	– self-assessment of health – reporting of long-standing illness – score from a symptom list – respiratory function	– contextual effect demonstrated, but most of the effect due to individual characteristics – composition effects not examined
Jones & Moon, 1999	General medical practices	– previous death of an infant – smoking mother – housing tenure – stability of family – employment status – mother's age	– childhood immunization	– results demonstrated differences in the ranking of practice rates of immunization when using MLM versus using crude aggregate rates – ranking of practice rates of immunization changed for some practices when patient composition was taken into account
Jones et al., 1991	General medical practices: - type of practice	– previous infant death in family – smoking mother – tenure – stability of parental relations – employment sector – mother's age	– childhood immunization	– most variation in the outcome attributed to individual-level variables – a small amount of variation attributed to type of practice

Jones & Duncan, 1995	Ward: – deprivation index – urban/rural Constituency: – household weekly income	– demographic – socio-economic – health behaviour	– self-assessment of health – reported symptoms of heart disease, hypertension and stroke – forced expiratory volume	– after controlling for individual-level factors, places with high deprivation were associated with poorer health outcomes – after controlling for individual-level factors, places with low income were associated with poorer health outcomes
Kleinschmidt et al., 1995	Ward: – deprivation index	– demographic	– smoking behaviour	– strong significant association between smoking deprivation of ward – cross-level interaction relationships not detected
Mitchell et al., 2000	Ward: – level of deindustrialization	– demographic – social class – work status – attitude to the community	– index of health derived from perceived symptoms	– deindustrialization had an independent effect on health – attitude to community had an independent effect on health – no interaction between the two
Soobader & Leclere, 1999	Census county: – income inequality – median household income – percentage in poverty Census tract: – income inequality – median household income – percentage in poverty	– income-to-needs ratio – education – occupation	– perceived health	– when county level was used as the level of aggregation, contextual effect found – reduced effect found when tract level was used as the level of aggregation (individual level was dominant)

(Diez-Roux et al., 2000; Diez-Roux et al., 1997; Duncan, Jones, & Moon, 1993, 1999; Kleinschmidt, Hills, & Elliott, 1995) and alcohol consumption (Duncan et al., 1993; Ecob & Macintyre, 2000), disease-prevention practices such as immunization (Jones & Moon, 1999; Jones et al., 1991), and health service utilization (Carr-Hill, Rice, & Roland, 1996).

Conceptual Issues Associated with Multilevel Research Problems

Contextual Effects Versus Contextual Variations

When faced with data showing strong regional patterns in individual health, one is tempted to immediately explain these in terms of contextual variables. For example, we might explain observed differences in health among individuals in rural and urban communities in terms of rural-urban differences in access to health care, industrial pollution, and so forth. However, this search for contextual explanations can be misleading since observation of regional patterns in health does not mean that contextual factors are at play. Researchers using MLM often set out to first establish that regional patterns are not explained by different types of individuals in the different regions (Birch, Stoddart, & Beland, 1998; Diehr et al., 1993; Hayward, Pienta, & McLaughlin, 1997). For example, Diehr et al. first determined whether there were significant differences in average levels of health behaviours between communities, and then continued to analyze community-level differences in health after allowing for this between-community difference in behaviours.

This highlights the difference between *variations* by community and *effects of* the community. The presence of contextual variations per se does not in itself establish the presence of contextual effects. Variations in outcomes among communities might depend less on the nature of a given community and more on the concentration of people in that community.

The Issue of Composition

An analysis may initially reveal an association between contextual characteristics and the outcome under study. This association, however, could be due to different communities being composed of different types of individual rather than an independent effect derived from the community itself. Compositional effects, as they are known, are related to individuals, and if not considered may artificially inflate or deflate the importance of contextual characteristics.

Often, studies fail to consider composition, in some cases because available data are restricted to the level of community (Kleinschmidt et al., 1995; Turner, 1995). Robert (1998) sought to determine whether community socio-economic status influenced three health measures, after controlling for individual and family socio-economic status. Various combinations of the three health measures (chronic conditions, self-rated health, functional limitations) and the four measures of community socio-economic status demonstrated an association with each other. These effects were small, however, and might still have been due to the social profile of community members, as only age, sex, and race were included in the analysis. Other determinants could have been marital status, residence type (urban or rural), or a lifestyle variable such as proportion of smokers. Similarly, Diehr et al. (1993) took account of the communities' social profile explicitly when estimating community influences on health behaviours. Although the researchers detected significant community effects after adjusting for individual characteristics, most of the observed community variation was attributed to variations in composition. Other studies also found small associations between contextual variables and outcomes after considering composition (Brooks-Gunn, Duncan, Klebanove, & Sealand, 1993; Fox, Jones, & Goldblatt, 1984; LeClere, Rogers, & Peters, 1997; Sloggert & Joshi, 1994).

Compositional effects might be considered a nuisance in multilevel research, as they require additional consideration in the analysis. Failure to take composition into account can inflate or deflate the relationship between community-based effects and outcomes.

From a policy perspective, however, the detection of compositional effects is just as important as the detection of effects due to contextual characteristics. Such information might be helpful for decision-makers having to allocate resources between individuals and communities. When resources are allocated among communities, the influence of composition may actually hide need, or performance. For example, Jones and Moon (1999) compared crude aggregate rates of immunization uptake by general practices with those following adjustment for composition using MLM. They displayed their results by ranking the various practices, thereby demonstrating that the type of people in the catchment area of a practice influences immunization rates. They argue that many practices might be performing well, given their catchment area, despite their seemingly low levels of achievement as shown by the crude rates. Thus, by adjusting for differences due to populations, MLM offers a more comparable measure of performance.

Detecting Contextual and Individual-Level Effects

When a contextual effect is identified, the next challenge is to determine what specific community characteristics explain the effect. Waitzman and Smith (1998) used the income status of the area (poverty versus non-poverty) as a community variable. However, this implies that the nature of the community effect being explored is confined to the extreme end of the area income scale, as opposed to being a more general effect associated with differences in area levels of income (Haan, Kaplan, & Camacho, 1987; Sloggert & Joshi, 1994). Ecob and Macintyre (2000) investigated whether extreme ends of measures produced different results; they analyzed diet as *good* or *bad* and physical activity as *good* or *bad* when examining area deprivation and health behaviours. Using MLM, they demonstrated that significant results in terms of overall relationships and area variations differed according to the measure being used. For example, *bad* exercise patterns, but not *good* exercise patterns, were related to area deprivation.

Often, attempts to determine the effects of context are driven by data availability rather than by theoretical considerations, leading to the testing of numerous variables, often without any discussion of implications for Type I errors or the false conclusion that associations exist (Brooks-Gunn et al., 1993; Colby, Linksy, & Straus, 1994). Excessive data manipulation with minimal regard for theory may uncover artefactual associations between variables due simply to large sample sizes.

Analytical Approaches to Multilevel Research Problems

In addition to providing a more comprehensive understanding of a research problem, MLM offers significant technical advantages for inference-making based on the study findings.

These advantages include guarding against the "ecological fallacy" (associations observed in studies performed at the contextual, or ecological, level are interpreted as representing relationships at the individual level) and the "atomistic fallacy" (associations observed in studies performed at the individual level are interpreted as representing relationships at the contextual level) (Jones & Duncan, 1995). Such approaches ignore the effect of individual characteristics on context by assuming homogeneity among individuals (i.e., only contextual variables vary) (Sloggert & Joshi, 1994), or ignore the effect of contextual characteristics on individuals by assuming homogeneity among contexts (i.e., only individual-level variables vary) (Diez-Roux, 1998).

In addition to the empirical issue of misinterpreting observed associations, it has been argued that measurement at the individual level is conceptually different from that at the aggregate level (Firebaugh, 1978). The researcher can avoid committing these fallacies by incorporating multiple levels of data in the study. The advantages and disadvantages of various approaches to analyzing multilevel data will now be discussed.

Stratification of Data

Stratification of data has been used to explore multilevel relationships (Birch, Jerret, & Eyles, 2000; Blaxter, 1990; Hayward et al., 1997). In this method, the researcher conducts separate analyses (e.g., individual-level regression models) for each community and then compares results across communities. It can be used as a preliminary technique for understanding one's data set and as a way of establishing variations by context. Handling the levels of data in this way helps guard against committing the ecological and atomistic fallacies.

Blaxter (1990), for example, used a national survey to compare standardized ratios of various health conditions (i.e., illness, psychosocial health, fitness, disease/disability) for different groups of social classes across Britain. She found that those in lower social classes experienced poorer health. In addition, Blaxter took a contextual approach to understanding health by comparing the ratios across standard regions and electoral wards. She found that healthy lifestyle made less difference to health in some geographic areas than in others.

Context can be defined on the basis of natural geographical boundaries. However, this approach can miss heterogeneities associated with people (e.g., composition), context, and health. Blaxter's study was criticized because it did not take into account the social composition of the regions. Furthermore, to achieve reliable cell sizes, she analyzed the data using (large) standard reporting regions. To maximize sensitivity using stratification techniques, researchers need to redefine context to represent types of context (e.g., upper class racially mixed area versus upper class racially homogeneous area). Fox et al. (1984) were interested in the influence of socio-economic characteristics of areas as well as individual characteristics on mortality. They derived 36 clusters of wards based on 40 socio-economic indicators such as age of settlement and number of rooming houses. Because it included more meaningful contextual areas, their stratification provided a more detailed description of contextual differences and mortality.

As a rule, the stratification approach is feasible only when there is a manageable number of communities so that they can be compared one by one (it would be difficult to compare findings from, say, 50 different communities). This approach can detect differences among contexts, and then the significance of these differences can be tested empirically. The stratification approach does not reveal whether an effect *due* to context is present. It also ignores the hierarchical nature of the data.

Despite these problems, establishing variations by context is a useful first step in analyzing multilevel data. It can provide the impetus for the researcher to seek explanations for any observed variations in outcomes.

Also, it offers some insight regarding the appropriate specification of level of context. For example, individual smoking patterns that differ by province may not be as important as those that differ by community. Context may be acting on health, but poor outcomes might be seemingly negated when aggregated to broader contextual levels.

Single-Level Regression Models

Single-level empirical approaches in the form of regression models are the most common technique for analyzing multilevel data. The researcher runs a series of models and compares the results. Usually the first model considers individual-level variables; some are included as controls (e.g., age, sex), others as variables of interest. Subsequent models may include dummy variables to represent various communities (Diehr et al., 1993), or may include variables that measure specific features of the community.

The Alameda County study (Haan et al., 1987) was one of the earliest studies to incorporate data from individual and contextual levels. The researchers examined effects on mortality after considering age, sex, race, physical health status, socio-economic factors, health practices, social networks, and psychological factors. The contextual variable was a dichotomous measure reflecting whether the area qualified as a "poverty area residence." Poverty areas were identified based on federal criteria, which included social and environmental characteristics. Hann et al. ruled out possible confounding or misspecified effects arising from individual-level factors after comparing results among different regression models (e.g., those with and without the individual-level factors). They found a higher risk of mortality associated with living in a poverty area than living in a non-poverty area.

Researchers may also seek to determine whether contextual variables modify the influence of individual-level variables on outcomes (interaction effects) using single-level regression models (Brooks-Gunn et al., 1993; Turner, 1995). One might ask, for example, whether the relationship between level of physical activity and age is dependent on the community's socio-economic status. Turner did so when studying the effects of employment status, education, and community level of unemployment on depression and physical health. He found evidence of interaction effects between level of area unemployment and personal employment status on health outcomes.

A limitation of the single-level regression model with multilevel data is the clustering effect. Residents of a given community are more likely than their counterparts in another community to demonstrate similar outcomes. This clustering effect results in a loss of independence among measurements, thereby violating an assumption of regression modelling. If ignored, variance calculations can be underestimated, possibly leading to a Type I error (incorrectly rejecting the null hypothesis) when the regression results are examined.

Some researchers using single-level regression models address the clustering problem explicitly (Anderson, Sorlie, Backlund, Johnson, & Kaplan, 1996; O'Campo et al., 1995). Researchers have used statistical programs like SUDAAN to adjust for clustering in their data (Robert, 1998; Soobader & LeClere, 1999). Such programs estimate the amount of correlation within each community and adjust the variances accordingly. Another way to address the clustering issue is to examine the (intraclass) correlation post-hoc (Kleinschmidt et al., 1995); the extent of within-cluster homogeneity or similarity, and its possible effect on the results, can then be assessed.

O'Campo et al. (1995) used both a standard logistic regression model and a model based on the generalized estimating equation to examine the determinants of male-initiated domestic violence. Use of the latter model was intended to compensate for clustering. Differences between the two models lend further support to the use of a more robust technique.

In addition to clustering, combining contextual and individual-level information in a single regression model can lead to multicollinearity among variables, resulting in inflated variances. The researcher can avoid this problem by using an index (e.g., a social deprivation index) based on a combination of deprivation indicators (e.g., low income, poor accommodation, poor access to cultural facilities) to measure deprivation at the contextual level (Haan et al., 1987; Sloggert & Joshi, 1994; Waitzman & Smith, 1998). However, estimated relationships are then less easily translated into policy recommendations since it is difficult to isolate the effect of specific mechanisms on outcomes.

Two-Level Regression Models

Other researchers have used two-step regression models to examine individual- and community-level data (O'Campo, Xue, Wang, & O'Brien Caughy, 1997). In the first step an individual-level model for each context is produced, and in the second step the intercepts and coefficients from this step are regressed on contextual variables. This technique allows the researcher to determine the overall significance of the two levels and to consider individual and contextual characteristics in the analysis.

For example, O'Campo et al. (1997) studied the influence of individual and community factors on low birthweight. They found that all of the observed relationships between individual-level variables and low birth weight varied between communities (e.g., cross-level interactions). In this type of situation, the benefits of individually focused interventions might be overstated unless communities are taken into account. For instance, the association between nutrition and birthweight might matter more in some communities than in others.

With this approach the assumptions required for the first analytical step are invalid (Hox & Kreft, 1994). The estimated coefficients are considered fixed, which means that inferences can be made only for the communities included in each analysis. In the second step, however, the same coefficients are considered to be random variables. This means that the communities form a sample from the population of communities and inferences are made for this population. The assumption in each step is different, theoretically leading to different error structures in each case. Consequently, results from significance testing based on these standard errors can be upwardly biased (Hox & Kreft).

Hierarchical Multilevel Modelling

Hierarchical MLM offers several features with which to investigate grouped data. This approach is an extension of regression modelling, in which two or more levels of data are modelled simultaneously but separately. In this way the health influences at both levels — individual and contextual — can be compared. In addition, making inferences using a multilevel model avoids the ecological and atomistic fallacies.

The treatment of the residuals, or error terms, in MLM provides researchers with additional information. MLM supports detailed analysis of the heterogeneity or variation among contexts, while traditional regression techniques rely for information on an average measure of the remaining variation. For example, MLM allows one to ask if the relationship between age and level of physical activity differs significantly among communities. MLM is similar to the two-step regression technique described above. Computationally, however, it is statistically more efficient in determining regression coefficients. Details about the derivation of MLM equations can be found elsewhere (Goldstein et al., 1998).

The majority of published MLM studies employ two-level models — individuals at level one and the contexts or communities to which they belong at level two. Some explore three levels, whereby individuals belong to communities that are nested into larger regions (Duncan et al., 1993, 1996, 1999; Jones & Duncan, 1995). The literature also includes more complex designs such as cross-classified designs (in which individuals belong to more than one context, such as school and place of worship, and the contexts are not nested), but their empirical application is less common.

To begin, one might ask whether MLM is required for all cases of clustered data. Kleinschmidt et al. (1995) compared the results of smoking behaviour obtained using a single-level regression model and two-level hierarchical MLM. The results were similar for the two models. They concluded that the single-level model was acceptable for their analysis, which employed census tracts. Smaller geographic areas may feature greater homogeneity, however, thus necessitating the use of MLM due to clustering effects.

MLM allows for the modelling of separate and joint effects of individual and contextual pathways. Although the latest software was developed to address multilevel problems (Goldstein et al., 1998), its capabilities have also advanced the conceptualization of the problem. Variations in outcomes using traditional analyses suggest that the effects of context differ according to population, but MLM also allows the researcher to determine whether contextual effects are different *within* a population in terms of health outcomes. For example, in a rich community do the very wealthy have a health advantage over the less affluent? Do opportunities and resource use differ within a given community? In turn, these questions encourage discussion about appropriate policy goals and interventions. The elimination of regional differences might be achieved at a cost — for example, within a region only some members might benefit.

MLM researchers have given some attention to measurement of the dependent variable. Specifically, they have explored whether behaviours measured in a dichotomous fashion — present or absent — demonstrate different empirical relationships from those measured in terms of a continuous variable representing intensity or exposure. MLM allows for the use of these two effects separately. To illustrate, Duncan et al. (1996) labelled individuals as either smokers (1) or non-smokers (0) and then assigned each smoker a continuous measure of number of cigarettes per week. Thus, intensity was nested within the presence or absence of a behaviour. After controlling for individual characteristics, they found variation within the community with respect to behaviour but not with respect to intensity. Ecob and Macintyre (2000) found similar results in the relationship between smoking and area deprivation. On the other hand, they found no area variation or relationship with deprivation in either alcohol consumption or amount of consumption. These studies demonstrate that MLM facilitates the modelling of different *dimensions* of behaviour.

MLM software (Mln) is in a state of active development. Consequently, readers of the literature may need to determine whether results of studies are comparable or generalizable on technical grounds. For example, improved estimation procedures for multilevel logistic models became available as part of the standard software around 1995. Even at that point, some researchers hesitated to identify particular communities as "high" or "low" because it was demonstrated that higher-level random terms could be seriously underestimated (e.g., see Duncan et al., 1999);

they preferred to confirm between-context variability without naming the most successful or problematic community. Updated versions of the software have been released periodically and estimation procedures have become more precise and more stable. The most recent versions of MLWin (the Windows version of Mln) incorporate bootstrapping approaches to deal with large variance estimates.

Some Limitations of Multilevel Data Analysis

MLM software has recently become available due to the increased processing capabilities of modern personal computers. Thus, studies published over the last 10 years can be considered initial attempts to match research problems involving multilevel data with the advantages of MLM software. Interestingly, the availability of the software has also advanced our understanding of the nature of the problem. In particular, the idea that interactions between variables might occur at one contextual level (e.g., a joint effect between a municipal by-law and a media campaign on smoking behaviour) is receiving more attention, as is the idea that interactions might occur across levels (e.g., a joint effect between the municipal by-law and family attitude to smoking behaviour).

One limitation of most MLM studies is the use of convenient geographical boundaries based on national surveys or databases. Such boundaries are not theoretically defined — there is little reason to expect that contextual influences on health will derive from census divisions, for example. Another limitation is that most empirical works and discussions about the role of context tend to concentrate on one mechanism: from the community to the individual. Individuals can also shape communities, by setting social norms, supporting particular political structures, or establishing resources. While researchers have started to understand the ways in which health can be influenced by community-level factors, they have paid little attention to the ways in which individuals interpret or give meaning to local structures and norms.

Although the studies presented in Table 1 vary in terms of subject matter, they offer tentative generalizations about the effects of context on health behaviour. These generalizations are based on studies using hierarchical MLM techniques, which offer significant advances over traditional approaches. This set of studies demonstrates that most contextual effects can be explained by the social profile of individuals. In cases where significant contextual effects remained after considering composition, these were small in magnitude (i.e., accounting for less than approximately 10% of the total variation in the dependent variable).

MLM can provide a detailed description of the influences on health. Unlike most other quantitative techniques, it is capable of generating information about the heterogeneity of empirical relationships among and within contexts. MLM remains a descriptive technique, however, which means that other methods must still be used to obtain *explanations* for social behaviours and structures.

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