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Review article

Using a dyadic logistic multilevel model to analyze couple data

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Abstract

There is growing recognition within the sexual and reproductive health field of the importance of incorporating both partners' perspectives when examining sexual and reproductive health behaviors. Yet, the analytical approaches to address couple data have not been readily integrated and utilized within the demographic and public health literature. This paper seeks to provide readers unfamiliar with analytical approaches to couple data an applied example of the use of dyadic logistic multilevel modeling, a useful approach to analyzing couple data to assess the individual, partner and couple characteristics that are related to individuals' reproductively relevant beliefs, attitudes and behaviors. The use of multilevel models in reproductive health research can help researchers develop a more comprehensive picture of the way in which individuals' reproductive health outcomes are situated in a larger relationship and cultural context.

Keywords: Couples; Reproductive health; Multilevel modeling; Methods

1. Introduction

There is increasing recognition of the importance of incorporating both partners' perspectives when examining sexual and reproductive health behaviors. The integration of both partners' perspectives allows us to better predict sexual and reproductive health behaviors, facilitates the development of more appropriate and effective couple-level interventions and provides critical insights into the powerful influences beyond the individual that also affect reproductive outcomes, such as those attributable to gender inequity and power differentials in relationships [1,2]. Despite the notable benefits of couple or dyadic data, however, analytic approaches have not been well integrated and utilized within the demographic and reproductive health literature.

Dyadic data are typically derived from surveys that elicit information from both members of a partnership pair (e.g., husband and wife) and, as such, offer a more holistic view of sexual and reproductive behaviors. Partners' beliefs, attitudes and behaviors can have separate, and even interactive, effects on relationship functioning [3] and on sexual and reproductive outcomes [4–6]. The benefits of dyadic data, however, are coupled with additional considerations and potential complications. For example, partners' reports may be discrepant, requiring a decision regarding how these reports should be handled. In some cases, discrepant couple reports may be discarded, yet this strategy reduces statistical power for detecting effects and also prevents further exploration of why partner reports are discrepant. For example, these differences may reflect disparate perceptions of the relationship and/or differences in information available to each partner, as well as how that information may be processed and internalized given prevailing gender norms and roles [7].

In addition, partners' reports are often dependent on each other, as partners are likely to influence one another and to share a similar context. In addition to the conceptual issues, this dependency is statistically problematic because it creates a situation in which partners' error terms may be correlated,

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violating the assumption of independent errors in general linear models [11]. Thus, researchers must utilize a strategy that accounts for this dependency, while simultaneously incorporating the unique reports of partners within the relationship.

Dyadic multilevel modeling provides a useful approach to analyzing couple data to assess the individual, partner and couple characteristics that are related to beliefs, attitudes and behaviors. This article is intended to give reproductive health researchers unfamiliar with multilevel modeling techniques an initial introduction from which to build their understanding and use of the approach. An applied example of the use of dyadic logistic multilevel modeling is provided, demonstrating the potential of dyadic logistic modeling and its utility in developing a more comprehensive picture of the way in which individuals' reproductive health outcomes are situated in a larger relationship and cultural context.

2. Dyadic logistic multilevel modeling

Multilevel modeling is a statistical technique for the analysis of nested or clustered data, that is, individual observations within the same organizing unit. Since observations from within the same cluster may be more similar to each other than randomly paired individual observations, the multilevel model includes an error structure that accounts for the dependence of the errors of observations from within the same cluster.

In the dyadic logistic multilevel model, there are two levels of analysis: the individual level, including both partners' individual observations (Level 1; identified by subscript *i*), and the couple level (Level 2; identified by subscript *j*). At Level 1, individual respondents' outcomes and predictors are included in a single-level logistic regression equation specific to each couple. The logistic equation is used in cases in which the outcome is binary (0 = no outcome, 1 = outcome), transforming the binary outcome to the log odds of the outcome; this allows the formerly binary outcome to be analyzed using a linear regression model. Similar to logistic regression, predictors can be categorical or continuous and include main effects and interactions.

Level 1

$$\log\left[\frac{P}{1-P}\right]_{ij} = b_{0j} + b_{1j}X1_{ij} + b_{2j}X2_{ij} \tag{1}$$

As an example, let us say the outcome in Eq. (1) represents the log odds of an individual respondent (i) in a particular couple (j) reporting that they make the decision to use family planning jointly with their partner (1: joint decision, 0: not joint decision). Predictor $X1_{ij}$ is the respondent's age. Predictor $X2_{ij}$ is the respondent's partner's age.[4]

The b_{1j} coefficient is the expected increase in the log odds of reporting a joint decision for every one unit increase in respondent's age, over and above the effect of partner age. The b_{2j} coefficient is the expected increase in the log odds of reporting a joint decision for every one unit increase in partner age, over and above the effect of respondent age. At Level 1, the multilevel model is analogous to a logistic regression model performed for each couple.

As it is impossible to run this logistic regression model within each couple with only two observations, the multilevel model instead characterizes the distribution of such coefficients across couples. Two different types of parameters are thus estimated at Level 2 of the model: fixed effects (gammas or γs) estimate the "average" Level 1 coefficients across couples, and variance components estimate the degree to which coefficients differ across couples. Specifically, each of the b coefficients at Level 1 are modeled as outcome variables at the couple level (Level 2) by an overall effect and, for the intercept only, a couple-specific error term. This couple-specific error term is known as a *random effect* because it allows the introduction of a random term (i.e., *error term*) at the couple level.

Level 2

$$b_{0j} = \gamma_{00} + u_{0j} \qquad \operatorname{var}(u_{0j}) = \tau_{00} \qquad u_{0j} \sim N(0, \tau) \tag{2}$$

$$b_{1j} = \gamma_{10} \tag{3}$$

$$b_{2j} = \gamma_{20} \tag{4}$$

The equations at Level 2 demonstrate how the b coefficients at Level 1 are modeled. In Eq. (2), the expected log odds of reporting a joint decision for a given observation in which both partner and respondent age are 0 in couple j (b_{0j}) is modeled as a function of the overall log odds of reporting a joint decision at 0 for both respondent and partner age (γ_{00}) and an adjustment for each couple's deviation from the overall effect (u_{0j}). The variance of the one Level 2 random effect (u_{0j}) is referred to as τ_{00}. This represents the amount of variance by which individual couples' intercepts deviate from the overall intercept (γ_{00}).[5] Because individuals in the same couple share the same error term, the inclusion of the error also appropriately models within-couple similarity.

In Eqs. (3) and (4), the effects of respondent age in couple j and partner age in couple j, respectively, are modeled as an overall fixed effect across couples with no corresponding random effect. In multilevel models with larger group sizes, more than one effect can be allowed to vary randomly at Level 2. However, the group size of the dyadic logistic multilevel model only allows for the estimation of one

[4] Respondent and partner ages are entered in their natural metric. Consequently, b_{0j} is the expected log odds of reporting a joint decision for a respondent in couple j at 0 ("birth"). It may be more useful to center respondent and partner ages at the average age of the sample. For more information on centering, see Ref. [8].

[5] This allows the model to capture the degree to which relationship partners' responses are similar to each other. However, it does not allow for situations in which partners' responses are dissimilar. For an alternate parameterization of the Level 2 variance term, see Ref. [8], Chapter 4.