Using multilevel regression and poststratification to estimate physical activity levels from health surveys

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ABSTRACT

Background: Large-scale health surveys often consider sociodemographic characteristics and several health indicators influencing physical activity that often vary across units (regions or states). Data in a survey for some small units are often not representative of the larger population. This study developed a relatively simple multilevel regression and poststratification (MRP) model to estimate the proportion of leisure-time physical activity across Brazilian state capitals, based on the Brazilian cross-sectional national survey VIGITEL (2018).

Methods: We used various approaches to evaluate whether the MRP approach outperforms single-level aggregated estimates, with various subsample proportions tested.

Results: The mean absolute errors were consistently smaller for the MRP estimates than single-level regression estimates, particularly with smaller sample sizes. MRP consistently had predictions closer to the estimation target than single-level aggregated estimations. MRP presented substantially smaller uncertainty estimates compared to aggregated estimates.

Conclusions: Our results confirm that MRP is a promising strategy to derive disaggregated data for health-related outcomes and, in particular, physical activity indicators from aggregated-level surveys. Overall, the MRP is superior to single-level aggregated estimates and disaggregation, yielding smaller errors and more accurate estimates. MRP significantly expands the scope of issues for which researchers can better address participation bias and interpret interactions to estimate descriptive population quantities. The observations present in this study highlight the need for further research, potentially incorporating more information in the models to better interpret interactions and types of activities across target populations.

INTRODUCTION

Leisure-time physical activity has beneficial health effects ¹. It is an essential asset to encourage physical activity in population-based programs ². National Health surveys are an indispensable resource for developing health promotion programs, including promoting physical activity practices. Hence, data about health-related behavior considering the amount of physical activity and life quality is valuable ³.

Sociodemographic characteristics and environmental and contextual variation are essential determinants of physical activity ⁴. Furthermore, the differences in sociodemographic factors on leisure-time physical activity may promote and successfully implement healthy practices and lifestyles. Sociodemographic characteristics have been necessary to understand the current health scenario ⁵.

National health surveys often include information about sociodemographic characteristics and several health indicators that often vary across communities, regions, or states. The common problem is that subsamples of respondents in a survey for some units at the community, region- or state-level are too small and often not representative of the larger population. This represents a necessary methodological hurdle for research on health and physical activity to make valid inferences from a collected survey sample to the larger (underlying) population or sub-

populations ⁶.

To deal with this limitation in extensive surveys, researchers have used disaggregation, i.e., the no-pooling approach, where the outcome information is used solely from the survey respondents' subsamples. The no-pooling approach assumes that each subsample provides no information about any other subsample ⁷. Disaggregation from even extensive surveys often produces small subsamples and noisy outcome estimates ⁸.

On the other hand, inferences from health-related survey data, particularly considering physical activity outcomes, have generally used single-level aggregated models to combine relevant information from individual and contextual characteristics ⁹⁻¹⁶. An aggregated model, i.e., a complete pooling approach, assumes that the subsamples are invariant, the same as estimating a standard parameter for all subsamples ⁷. Furthermore, with imbalanced sampling common in surveys, when some individuals, locations, or times are sampled more than others, over-sampled clusters likely dominate the inference ⁷.

Alternatively, multilevel regression and poststratification (MRP) has become a standard modeling approach to estimate sub-national or subsamples outcomes in large-scale surveys ⁶. MRP was developed ^{17,18} and has been mainly used in political sciences ^{6,8,19-21}. In this context, MRP has been noted to outperform disaggregated empirical means ^{19,21}. Recently, MRP has been applied to health science data ²²⁻²⁶. The approach initially uses multilevel regression to model individual outcomes of interest as a function of individuals and/or contextual and geographical predictors to estimate a target sub-population ²⁷. Lastly, the outcome estimates for each individual-contextual subgroup are weighted by each subgroup's proportions in the actual population to derive an overall population-level estimate ^{19,21,23}.

Brazil offers a particular case study. It is one of the world's most populated countries, with extensive demographic, socioeconomic, and cultural contrasts. Also, there have been several national health surveys implemented to support the country's health surveillance system. The surveys include at least three primary large-scale national health surveys, the National Health Survey (PNS) ²⁸, the National Adolescent School-based Health Survey (PeNSE) ²⁹, and the "Surveillance of Risk Factors and Protection Against Chronic Diseases by Telephone Inquiry" (VIGITEL) ³⁰. These surveys have provided an essential resource of information to support the development of health promotion programs at national-, state- and community-levels, including promoting physical activity practices. Nevertheless, interpretations have been mostly based on single-level aggregated models ³¹⁻³⁴.

In this study, we developed a relatively simple MRP model to estimate the proportion of individuals with at least 150 minutes per week of leisure-time physical activity across Brazilian state capitals, considering age groups and gender as demographic characteristics. Based on VIGITEL data, we compared competing model estimates of leisure-time physical activity across Brazilian state capitals to evaluate whether the MRP approach outperforms single-level aggregated estimates. Lastly, we estimated and interpreted the proportion of individuals with at least 150 minutes per week of leisure-time physical activity estimated using MRP across sub-populations, female and male individuals in each Brazilian state capital and age group.

METHOD

Data

We used the responses from the annual national survey VIGITEL conducted in 2018 in all 27 capitals of the Brazilian states (available at <http://svs.aids.gov.br/download/Vigitel/>), and the demographic data from the Brazilian census of 2010 of the Brazilian Geography and Statistics Institute (IBGE) (available at <https://www.ibge.gov.br/estatisticas/sociais/populacao/9662-censo-demografico-2010.html?edicao=9673&t=downloads>). In this study, the VIGITEL survey sample considered included responders with at least 20 years old and with the outcome response (physical activity practice in leisure time) comprised 47,121 individuals. The outcome variable, the physical activity level in leisure time, was categorized into inactive (none) and active (≥ 150 min/week). We considered gender (two levels: male and female), age group (six levels: 20 to 29, 30 to 39, 40 to 49, 50 to 59, 60 to 69, and more than 70 years old), from all 27 states capitals in Brazil. The VIGITEL survey was approved by the National Committee of Ethics in Research with Human Beings of the Ministry of Health ^{30,35}.

Data Analysis

Multilevel and poststratification. The approach initially uses multilevel regression to model individuals' responses as a function of both demographic (gender and age group) and geographic (state capital) predictors, partially pooling the outcome variable (amount of physical activity per week). We use a multilevel logistic regression model. We labeled the survey response y_i as 0 for physically inactive individuals (physical activity below 150 min/week), and as 1 for physically active individuals (physical activity above 150 min/week). Each individual's outcome was estimated as a function of the individual's characteristics, i.e., age group, gender, and state capital (for individual i , with indexes j , k , and l for age group, gender, and state capital, respectively):

$$Pr(y_i = 1) \sim \text{logit}^{-1}(\beta^0 + \alpha_{j[i]}^{gender} + \alpha_{k[i]}^{age\ group} + \alpha_{l[i]}^{state\ capital})$$

$$\alpha_{j[i]}^{gender} \sim N(0, \sigma_{gender}^2), \text{ for } j = 1, 2$$

$$\alpha_{k[i]}^{age\ group} \sim N(0, \sigma_{age\ group}^2), \text{ for } k = 1, \dots, 7$$

$$\alpha_{l[i]}^{state\ capital} \sim N(0, \sigma_{state\ capital}^2), \text{ for } l = 1, \dots, 27$$

The poststratification allows us to estimate the physical activity level attained per week for any set of individual demographic and geographic values, cell c , based on the multilevel regression estimates. Hence, the model estimates for each individual's demographic and geographic group are weighted by each group's percentages in the actual population, obtained

from the most recent Brazilian census in 2010, to produce the MRP preference estimate. The poststratification table comprises two gender levels, seven age-group levels, and twenty-seven state capital levels, encompassing 378 cells (2 x 7 x 27), including the sample size and respective proportion in each group. The prediction in each cell, θ_c , is weighted by these population frequencies of that cell. For each state capital, the average response is calculated over each cell c in state capitals:

$$y_{state\ capital}^{MRP} = \frac{\sum_{c \in S} N_c \theta_c}{\sum_{c \in S} N_c}$$

Hence, it represents our estimations of the proportion of physically active individuals in states.

We used a Bayesian perspective to estimate and interpret the multilevel model fits³⁶. The models estimates were regularized by using normal prior (0,10) for population-level effect (intercept) and exponential prior (1) for group-level effects. We run three chains in parallel for 500 iterations with 250 warmup iterations. The models were obtained using the “brms” package (Bürkner, 2017), which call Stan³⁷, allowing to fit a fully Bayesian model using Hamiltonian Monte Carlo sampling using R³⁸.

Comparing MRP and single-level aggregated models. Single-level aggregated models are often used to analyze health-related outcomes, such as physical activity, cross-sectional observations, and large surveys, despite the theoretical and analytical concerns^{39,40}. We fitted a single level-aggregated model., i.e., a single logistic regression model to estimate defined as

$$Pr(y_i = 1) \sim \text{logit}^{-1}(\beta^0 + \beta^{gender} + \beta^{age\ group} + \beta^{state\ capital})$$

To compare MRP and single-level aggregated estimates’ relative performance, we used cross-validation based on a split-sample validation approach^{19,21}. The VIGITEL dataset used in this study was randomly split, using half of the sample to define the baseline or “true” proportion of physically active individuals in each state capital. We consider disaggregation means of the baseline sample as the estimation target.

We then use proportions of the remaining sample to generate estimates of proportions of physically active individuals employing MRP and single-level aggregated models. We draw such random samples 300 times for four sample sizes. The approximate sample sizes are 23,500 for the baseline sample, 600 for the 2.5% sample, 2,400 for the 10% sample, 5,900 for the 25% sample, and 12,000 for the 50% sample. We intend that the smaller sample sizes echo typical sizes in small cross-sectional studies and smaller-scaled surveys.

Predictive success, i.e., how close each set of estimates is to the baseline sample’s target measure, was assessed by calculating the mean absolute error. In each run of a simulation q , let $y_{q,s}^{baseline}$, be the proportion of physically active individuals in state capitals in the baseline data,

$y_{q,s}^{aggregated}$ be the aggregated estimated proportion in state capital s on the sampled data, and $y_{q,s}^{MRP}$ be the MRP estimate proportion in state capital s on the sampled data. For each of the five sample sizes, calculated the errors produced by each method in each state capital in each simulation, the most straightforward measure being the absolute difference between the estimates and the baseline measure:

$$e_{q,s}^{aggregated} = |y_{q,s}^{aggregated} - y_{q,s}^{baseline}|, e_{q,s}^{MRP} = |y_{q,s}^{MRP} - y_{q,s}^{baseline}|$$

That forms two matrices of absolute errors, of size 100 (simulations) x 27 state capitals. For state capital s , we calculated the mean absolute error for each method across simulations:

$$\bar{e}_{q,s}^{aggregated} = \frac{\sum_q e_{q,s}^{aggregated}}{100}, \bar{e}_{q,s}^{MRP} = \frac{\sum_q e_{q,s}^{MRP}}{100}$$

Lastly, we calculated the mean absolute error over both state capitals and simulations, collapsing the means-by-state capital into a simple number for each sample size and method:

$$\bar{e}_{q,s}^{aggregated} = \frac{\sum_q e_{q,s}^{aggregated}}{100 \cdot 27}, \bar{e}_{q,s}^{MRP} = \frac{\sum_q e_{q,s}^{MRP}}{100 \cdot 27}$$

Results

The VIGITEL sample considered for analysis comprised 47,121, reflecting those who answered the questions about physical activity practice in leisure time older than 20 years. Distribution by gender, age, and state capitals according to the attainment of recommendation for leisure-time physical activity are summarized in Table 1.

Figure 1 presents a visual overview of the mean absolute errors of MRP and single-level aggregated models with different sample sizes. Also, corresponding MRP and single-level aggregated model estimates with the target estimation with different sample sizes are presented in Supplementary figure 1. The mean absolute errors were consistently smaller for the MRP estimates. Particularly with smaller sample sizes, MRP consistently had predictions closer to the estimation target than single-level aggregated estimations

Table 1. Characteristics of the VIGITEL sample.

Variable	Total sample n = 51,015	Insufficient time in PA n = 31,917	Sufficient time in PA n = 19,098
Gender			
Male	15,500 (36.3)	10,243 (32.1)	8,257 (43.2)
Female	32,515 (63.7)	21,674 (67.9)	10,841 (56.8)
Age, years			
20 to 29	5,999 (11.8)	2,989 (9.3)	3,010 (15.5)
30 to 39	6,710 (13.1)	3,773 (11.7)	2,937 (15.1)
40 to 49	7,767 (15.2)	4,680 (15.5)	3,087 (15.9)
50 to 59	9,974 (19.5)	6,140 (19.0)	3,834 (19.7)
60 to 69	10,589 (20.8)	6,853 (21.3)	3,736 (19.2)
≥ 70	10,673 (20.9)	7,807 (24.2)	3,529 (14.7)
State			
Acre	1,731 (3.4)	1,006 (3.2)	725 (3.8)
Alagoas	1,996 (3.9)	1,294 (4.1)	702 (3.7)
Amapá	1,340 (2.6)	771 (2.4)	569 (3.0)
Amazonas	1,577 (3.1)	1,009 (3.2)	568 (3.0)
Bahia	1,969 (3.9)	1,347 (4.2)	622 (3.3)
Ceará	1,949 (3.8)	1,253 (3.9)	696 (3.6)
Distrito Federal	1,857 (3.6)	900 (2.8)	957 (5.0)
Espírito Santo	1,998 (3.9)	1,218 (3.8)	780 (4.1)
Goiás	1,981 (3.9)	1,264 (4.0)	717 (3.8)
Maranhão	1,951 (3.8)	1,190 (3.7)	760 (4.0)
Mato Grosso	1,970 (3.9)	1,210 (3.8)	761 (4.0)
Mato Grosso do Sul	1,985 (3.9)	1,297 (4.1)	688 (3.6)
Minas Gerais	1,934 (3.8)	1,209 (3.8)	725 (3.8)
Paraíba	1,982 (3.9)	1,284 (4.0)	698 (6.7)
Paraná	2,022 (4.0)	1,286 (4.0)	736 (3.9)
Pará	1,986 (3.6)	1,334 (4.2)	733 (3.8)
Pernambuco	1,983 (3.9)	1,334 (4.2)	649 (3.4)
Piauí	1,935 (3.8)	1,199 (3.8)	736 (3.9)
Rio Grande no Norte	1,957 (3.8)	1,219 (3.8)	738 (3.9)
Rio Grande do Sul	2,025 (4.0)	1,370 (4.3)	655 (3.4)
Rio de Janeiro	1,981 (3.9)	1,363 (4.3)	618 (3.2)
Rondônia	1,752 (3.4)	1,008 (3.2)	744 (3.9)
Roraima	1,557 (3.1)	922 (2.9)	635 (3.3)
Santa Catarina	1,918 (3.8)	1,200 (3.8)	718 (3.8)
Sergipe	1,945 (3.8)	1,167 (3.7)	778 (4.1)
São Paulo	1,951 (3.8)	1,190 (3.7)	534 (2.8)
Tocantins	1,941 (3.8)	1,401 (4.4)	856 (4.5)

Figure 2 displays scatter plots of estimation target (“true value”) against MRP and single-level aggregated. The aggregated estimates did not shrink enough to the reference line for perfect correlation, particularly with smaller sample sizes. MRP estimations are clustered around this line in all sample sizes.

Figure 1. Cross-validation - mean absolute errors by state capital and sample size.

Figure 2. Plotted MRP and aggregated estimates against estimation target (“true value”) by sample size.

Figure 3 presents an overview of how MRP estimates compare with the VIGITEL survey disaggregated means and single-level aggregated estimates. The MRP estimations showed substantially higher proportions of active individuals across state capitals than the survey disaggregated means. On the other hand, MRP presented substantially smaller uncertainty estimates compared to aggregated estimates.

Figure 3. Estimations of the proportion of physically active individuals by state capitals.

MRP estimations of the proportions of female and male individuals attaining 150 min per week in leisure time across capital states and age group are displayed in Figure 4 and Figure 5, respectively. Regardless of state capital or age group, the MRP estimations indicate that males are substantially more physically active than females. In eleven state capitals, 50% or more of the males are physically active, in which Brasília attended the highest value. By age group, the MRP estimations indicate that only males aged 20 to 29 years show a proportion of physically active individuals above 50%. For females, after 30 years, the proportion of physically active individuals is below 40%, and decreasing substantially as age groups are older. A similar trend is present for males, but only in the age group of 70 years or older, the proportion of physically active individuals is lower than 40%.

Figure 4. Estimations of the proportion of physically active individuals by gender and state capitals based on MRP

Figure 5. Estimations of the proportion of physically active individuals by gender and age group based on MRP.

Discussion

In this study, based on national health survey data, we compare approaches to estimate leisure-time physical activity across Brazilian state capitals and evaluated whether the MRP approach outperforms single-level aggregated estimates. We considered a relatively simple MRP model to estimate the proportion of individuals with at least 150 minutes per week of leisure-time physical activity across Brazilian state capitals and considering demographic characteristics (age groups and gender). Overall, the results strongly suggested the plausibility of using MRP to estimate health-related outcomes from large-scale surveys. Our simulations showed that MRP estimates outperformed single-level aggregated estimates, mainly when sample sizes were smaller. MRP also showed substantially smaller uncertainty estimates than single-level aggregated modeling (i.e., complete pooling) and disaggregated empirical means (i.e., no-pooling). The MRP estimations aggregated by state capital showed, except for one state capital (Brasilia), that the proportion of inactive individuals was substantially larger than active individuals. However, sub-population estimates by gender across the state capitals showed that inactivity was more prevalent in females, and in several state capitals, there were higher proportions of physically active than inactive in male individuals. The MRP estimations showed that only males between 20 and 29 years had a higher proportion of physically active individuals, and males were more active across all age groups than females.

It has been extensively shown in political sciences research that MRP outperforms survey disaggregation (disaggregated means)^{17,19,21,41,42}. We focused on comparing MRP against single-level aggregated model-based estimations, a common approach when dealing with physical activity outcomes in cross-sectional surveys. Our results are consistent with observations showing that that MRP outperformed aggregated estimates¹⁷. MRP notably outperformed aggregated estimates in the examinations with small sample sizes. Physical activity surveys often physical activity cross- comprise Sample sizes in physical activity surveys are often similar to the range of samples considered in this study^{10-16,43,44}. Our estimations showed that MRP had smaller mean absolute errors against a “true value” and less uncertainty in the outcome of interest than aggregated estimates.

The key to the superiority of MRP is in the multilevel model used that allows for more efficient use of the data. The multilevel model allows for partial pooling by incorporating group-level effects (also referred to as random effects). These may be understood as a weighted average between the total sample estimate and a group or unit estimate, where the specific weights are based on the entire variation of the sample and the group or unit variation²⁷. In particular, the partial pooling will be more substantial for smaller units with fewer observations⁴². Moreover, it has been highlighted that the careful inclusion of contextual or geographical variables (higher hierarchical variables) can improve the prediction precision of MRP^{21,23,42}. In the context of physical activity surveys, the inclusion of simple demographic information may suffice for MRP, as noted in other fields^{19,21}, but the addition of demographic information and increase of model complexities to improve estimations merits further study.

Even with a considerable sample data size and data collection process, the VIGITEL survey has some limitations in its methodology. The decision to use the only landline, which coverage varies across the capitals of North and Northeast ⁴⁵, and data collection only the state capitals cities. This information did not detract from the VIGITEL survey's quality, and notably its yearly data collection, but limits its representativeness of the population. Brazil has another national survey, which happens in all cities across the country, giving more national representation, the PNS survey. However, it happens less frequently, every five years ⁴⁶. It has been noted in a national health surveillance system data that estimates of behavioral risk factors obtained from MRP are valid and could be used to characterize local geographic variations in population health indicators when accurate local survey data are not available ²⁶. Considering the present study results, MRP is a valuable approach to reduce the estimation bias and produce reliable data interpretations in surveys with limited representative samples.

Regarding the empirical findings, it is relevant to discuss the difference between the inferences, in which the MRP shows significantly higher proportions of compliance with the recommendations of physical activity. Based on our observations, interpretations based on single-level aggregated estimations need to be considered with caution. The potential pitfalls of single-level estimates-based interpretations may be more severe when small sample sizes are available. Considering national health-related surveys, potentially biased inferences may influence the main actions' progress or programs arising from it.

Environmental factors can explain variation in physical activity in leisure-time across the state capitals. The Brazilian state capitals present a similarly high Human Development Index ⁴⁷. Particularly in Brazil, some government actions are offered to promote physical activity in the health system ⁴⁸. Differences between state capitals in a country with enormous social, cultural, economic, and geographic contrasts Brazil can be attributed to several factors such as the heat and humidity, air pollution, cultural differences, public spaces, attitudes toward nature, range of travel modes, and specific cultural contexts ⁴⁹.

The predicted proportion of physically active individuals in the population across the Brazilian state capitals was higher in the male. Also, males had higher proportions of physically active individuals than females across all age ranges. These observations are consistent with South America data 5,50, and can be explained in parts by biopsychosocial factors ⁵⁰. The results may be explained, for instance, by access to sports involvement is highly uneven with a male predominance ⁵¹. Another explanation is the physical activity practice in different domains by females, as in the household ⁵. However, females' leisure domain is fewer than for males because of the double journey, particularly in developing countries ⁵⁰. Highlighting leisure, physical activities in time reserved for a voluntary choice of activities, combining a feeling of satisfaction, wellbeing, and fun can provide health promotion for physical and mental aspects.

Male and female were active in leisure-time physical activity reduced as the age group increases. Leisure is a domain-independent of other attributes as age, exists according to unique opportunities, and performed voluntarily over short periods with enough recovery time ¹. Therefore, advancing age is attached to making working commitments. Even with more time after the retirement process, the routine during life reflects the functional capacity and consequences of health outcomes ⁵². It follows that the older had lower levels of physical activities when compared with the youngest ones.

Conclusion

Our results confirm that MRP is a promising strategy to derive disaggregated data for health-related outcomes and, in particular, physical activity indicators from aggregated-level surveys. Overall, the MRP is superior to single-level aggregated estimates and disaggregation, yielding smaller errors and more accurate estimates. Hence, caution in interpreting single-level aggregated estimations of physical activity outcomes, particularly with smaller sample sizes, is warranted. Additionally, our models allow for more accurate estimations of target populations. In the present data, younger males and from a particular state capital in Brazil were likely to have a minimum amount of time in physical activities for a healthier lifestyle. MRP significantly expands the scope of issues for which researchers can better address participation bias and interpret interactions to estimate descriptive population quantities. The observations present in this study highlight the need for further research, potentially incorporating more information in the models to better interpret interactions and types of activities across target populations.

Contributions

MC contributed to designing the study, curated the data, and helped to draft the manuscript; TRBB contributed to designing the study and helped to draft the manuscript; FGM curated the data and helped to draft the manuscript; HMC contributed to designing the study, performed the statistical analysis and drafted the manuscript. All authors helped draft and have read the manuscript, approved the final version of the manuscript, and agree with the order of presentation of the authors.

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Data and Supplementary Material Accessibility

Data and code for the models and figures are available at <https://osf.io/fy93a/>.

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