Bayesian multilevel modeling and its application in comparative journalism studies

Abstract

Comparative approaches are frequently used in communication research, especially journalism studies. The purpose of this paper is to argue that Bayesian multilevel regression is the most justifiable option for analyzing comparative data. We argue that it is the only approach that can simultaneously account for non-atomicity (nested nature) and non-stochasticity (non-random sampling) of comparative data. Using the openly available *Worlds of Journalism Study* and *useNews* datasets, we demonstrate how to apply the Bayesian approach for the analysis of comparative data. We address the common challenges when using the Bayesian approach and highlight the advantages of posterior predictive checks for modeling checking.

Keywords: Bayesian inference, multilevel model, comparative communication research, ecological effect

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Comparative approaches are frequently used in communication research, especially in journalism studies. Journalism studies are using the comparative approach (Hanusch & Vos, 2019) to model journalistic culture (e.g. Esser & Umbricht, 2013), news value (e.g. Burggraaff & Trilling, 2017; Wilke, Heimprecht, & Cohen, 2012), news flow (e.g. Wu, 2000; Grasland, 2019), among others. Around 40% of recent comparative studies in journalism research are comparative content analysis (Hanusch & Vos, 2019), which include news articles from various outlets and usually also from various countries. Then the included news articles are coded either manually or automatically. Another 10% of recent comparative studies in journalism research are surveys such as the Worlds of Journalism Study (WJS) (Hanusch & Hanitzsch, 2017). Although this article uses examples from journalism studies, the comparative approach is not bound to journalism studies and has been widely deployed in various subfields of communication. Comparative communication research is not exclusive to comparison across countries. Based on De Vreese (2017)'s classification, one can do comparisons across times, media, and other units (e.g. language regions within a multilingual country, see Vogler & Udris, 2021). In social media studies, for instance, it is common to compare content across sources (e.g. Zhao & Zhan, 2019). The methodological issues discussed in this paper apply also to those cases.

Although some comparative studies are purely descriptive, most of these studies are aimed to study how contextual conditions such as characteristics of media outlets (e.g. political orientation, online versus offline) or their countries (e.g. post-communist country) influence the behaviors of journalists or the content of news articles. For example, some hypotheses are "the coverage of foreign countries by the news is primarily determined by geographical proximity and the status of the covered country" (Wilke et al., 2012, p. 306) and "the degree of opinion-orientation will be highest in newspapers from Polarized Mediterranean systems and lowest in those from Anglo-American systems." (Esser &

Umbricht, 2013) Employing the language from epidemiology (Susser, 1994), the effect on media content and journalistic behaviors in these hypotheses is assumed to be ecological. It assumes a macro contextual factor (e.g., newspapers from Polarized Mediterranean systems) is associated with an outcome at the micro-level (e.g., degree of opinion-orientation), namely, the journalist-level or article-level.

This study of ecological effects on individual behaviors has a long tradition in communication research. There are hypothesis-generating and hypothesis- testing comparative studies. An example of hypothesis-generating comparative research is AUTHOR1 , in which the sentiment profiles of terrorism coverage from Muslim- and Christian-majority countries were visualized. Hypothesis-generating comparative study, however, is rare. As we see from the example hypotheses above, most of these studies propose hypotheses to test for ecological effects. In this context usually traditional (frequentist) hypothesis testing approaches were used: Esser and Umbricht (2013) lumped multiple outlets from the same country together and then used univariate analysis of variance to test for the differences in the proportion of opinion-orienting articles across countries. In Wu (2000), multiple stepwise regression was used. These approaches violate the underlying independence of observations assumption of linear regression (See non-atomicity below). It highlights the fact that comparative research introduces a feature that researchers usually overlook: media contents are clustered in a multilevel structure. A news article is nested within its media outlet and its media outlet is in turn nested within its country. Such data structure brings two problems: non-atomicity and non-stochasticity. And specifically, we propose two solutions: multilevel modeling and Bayesian approach.

The goal of this paper is twofold. We use examples from journalism studies as the most critical cases in communication science to highlight the strength of multilevel models and the advantages of Bayesian models. In our paper, we first discuss these two issues and then suggest Bayesian multilevel regression as the most defensible option. Using the openly available WJS and *useNews* datasets, we then demonstrate how to apply a Bayesian approach for the analysis of comparative data.

Multilevel models and non-atomicity

In comparative research, it is easy to assume that macro-level independent variables (e.g. Anglo-American systems) could be analyzed at the same level as the micro-level dependent variable (e.g. the degree of opinion-orientation). The manifestation of this assumption is to enter macro-level variables as independent variables in multiple regression analysis and regress them against a micro-level dependent variable. Suppose one wants to study how the democratic performance of a country affects journalists' perceived professional autonomy using the WJS data (Wave 1: Reich & Hanitzsch, 2013; Wave 2: Hamada, 2021). The relationship can be expressed in the following regression equation: let y_i be the dependent variable at the micro-level (journalist-level: perceived professional autonomy) and x_i be the independent variable at the macro-level (country-level: democratic performance). Suppose there are m journalists where $i = 1, 2, \ldots, m$.

$$y_i = \beta_0 + \beta_1 x_i + \epsilon_i \tag{1}$$

This method is the so-called "disaggregation approach". From an epistemic standpoint, searching for ecological effect by studying the value of slope (β_1) leads to the so-called atomistic fallacy (Hox, Moerbeek, & Van de Schoot, 2017). From a statistical standpoint, this approach violates the underlying independence assumption. Almost all frequentist statistical tests assume that the observations are independent of each other: y_i given x_i are independently identically distributed (i.i.d.). Journalists from the same country are hardly i.i.d.: they are subjected to being governed by the same government and exposed to the same journalistic culture. Also, the way communication researchers survey the journalists resembles (nonrandom) cluster sampling rather than pure random sampling: one usually starts from a specific country and then surveys journalists from it. The choice of countries is almost always not randomly selected. This sampling approach makes the independence assumption even more fragile. Previous simulation studies have shown that ignoring this dependence can lead to false-positive associations (e.g. Clarke, 2008; Chen, 2012).

There are two solutions to this.[1] The first solution is to aggregate the micro-level dependent variable across a macro-level independent variable. Suppose there are n countries in the above example. One can aggregate the average level of x as z_k for the k-th country, where $k = i, \ldots, n$. Then, we can do a regression with a regression equation like so:

$$z_k = \beta_0 + \beta_1 x_k + \epsilon_k \tag{2}$$

Using this aggregation method, the unit of analysis effectively switches from journalist to country. This method is useful when x is the only independent variable. It is not technically committing the atomistic fallacy, when one uses the value of slope as the evidence for an ecological effect. However, this method still has important drawbacks. First, it cannot be used for data with more than two levels. In those cases, the lower-level predictors were lumped together and in effect, assumed to be homogeneous and discarded. Second, this method discards a massive amount of information. It is useful only for analysis of a dependent micro-level variable with a reasonable aggregation function (e.g. counting a binary variable). For numerical variables, aggregation functions such as taking a mean or median cannot capture the spread of the micro-level variable (Bryk & Raudenbush, 1988). Also, the effective sample size is reduced from the number of journalists (m) to the number of countries (n). Third, if one specifies hypotheses at the

[1] In general, the non-atomicity alone only influences the inference (e.g. p-values, confidence intervals) by increasing the chance of Type I errors. The magnitude of the regression coefficient should still be consistent. Another approach, which we are not going to discuss in detail, is to use the clustered-robust standard error. For a survey of the technique, see Wooldridge (2003). The technique can only address the non-atomicity issue alone, but not non-stochasticity.

journalist-level but bases one's conclusion on the aggregated analysis, this is a risk of interpreting the macro-level association wrongly at the micro-level, otherwise known as ecological fallacy. Nonetheless, this aggregation method, although inflexible, is still useful when the number of groups (e.g. n) is large. It is also useful to collapse micro-levels (e.g. article-level) that are not useful in answering one's research questions.

Another solution is to use the multilevel model (linear mixed model, or hierarchical model). In a multilevel model, the effect on the micro-level dependent variable (y) is modeled with equations at different levels. Using the above example, y_{ik} denotes the perceived professional autonomy of the i-th journalist in the j-th country; x_k denotes the democratic performance of the k-th country.

$$y_{ik} = \beta_0 + \epsilon_{ik} \tag{3}$$

$$\beta_0 = \gamma_{00} + \gamma_{01} x_k + \mu_{0k} \tag{4}$$

In these equations, γ_{00} is the average slope, while μ_{0k} is group-dependent deviations of the slope from the average. It is usually set as having a normal distribution with a variance τ_{00}, i.e. $\mu_{0k} \sim \mathcal{N}(0, \tau_{00})$. Instead of a single value, the regression coefficient γ_{00} is assumed to be a distribution of values depending on a macro-level group.[2] It addresses the problem of clustering of articles by macro-level variables. This model is called the varying-intercept model and is used frequently in social science research. We can then study the magnitude of γ_{01} to determine the ecological effect.

The advantage of using multilevel modeling lies in its flexibility in handling

[2] One can also think about this in terms of pooling: how the data from different groups are pooled together. Complete pooling (the disaggregation approach, one slope for all groups), no pooling (each group is modelled individually and each group has a different slope), and partial pooling (each group has a unique slope. But the distribution of all slopes follows a distribution) are three scenarios. Multilevel modeling uses partial pooling.

multi-level data. Suppose we also want to consider the clustering of journalists around o different media organizations in the above example and j-th media media organization of the i-th journalist, where $j = 1, \ldots, o$ and if such data were available.[3] The multilevel regression equations are rewritten as:

$$y_{ijk} = \pi_0 + \epsilon_{ijk} \tag{5}$$

$$\pi_0 = \beta_{00} + \mu_{0j} \tag{6}$$

$$\beta_{00} = \gamma_{000} + \mu_{00k} + \gamma_{001} x_k \tag{7}$$

This flexibility is demonstrated in the study by Rinke (2016). He studied the likelihood of opinion justification in 1559 utterances nested in 329 news items, which were in turn nested in 101 news broadcasts. Multilevel logistic regression was used to model the natural three-level hierarchy of his data.

Another way to look at the flexibility of multilevel modeling is the ability to vary other parameters in the regression equation as well. Suppose in another situation, a researcher is interested in analyzing the relationship between experience (XP) and perceived professional autonomy. Instead of assuming the effect to be uniform across countries, like in the following equation:

$$y_i = \beta_0 + \beta_1 XP_i + \epsilon_i \tag{8}$$

One can also assume the slope (β_1) to be a distribution that is governed by countries, i.e.

[3] The data on media organizations are not available in the 2nd wave of the WJS dataset.

$$y_{ik} = \beta_0 + \beta_1 XP_{ik} + \epsilon_{ik} \tag{9}$$

$$\beta_1 = \gamma_{10} + \mu_{1k} \tag{10}$$

This model is called the varying slope model and is useful to establish robust estimation of effect (in this case γ_{10}) across all countries. In this paper, we will not go into detail of this kind of model. For an example of its application in comparative communication research, see Barnidge, Huber, de Zúñiga, and Liu (2018).

In sum, multilevel modeling is more justifiable for analyzing non-atomic data from comparative research. For surveys using probabilistic sampling, the conventional frequentist approach (maximum likelihood estimation, MLE) might still be valid and is available in most statistical packages (see an SPSS tutorial for communication researchers by Hayes, 2006).

Bayesian models and non-stochasticity

"If Czech history ***could*** *be repeated, we should of course find it desirable to test the other possibility each time and compare the results. Without such an experiment, all considerations of this kind remain a game of hypotheses."* (Kundera, 1984, emphasis added)

Stegmueller (2013) demonstrates that MLE for multilevel modeling is associated with shrinkage (reduction of standard error, i.e. more false positives) and the shrinkage is more severe when the number of macro-level units (e.g. countries) is small. Stegmueller (2013) proposes to use Bayesian analysis as a robust alternative (see counterarguments from Elff, Heisig, Schaeffer, & Shikano, 2020). Although less restrictive methods such as restricted maximum likelihood (REML) have been demonstrated to remediate the shrinkage issue of MLE (Elff et al., 2020), we still agree with Stegmueller's proposal for theoretical reasons (Western & Jackman, 1994).

Before diving into our theoretical reasoning, it is important to revisit what frequentist inference is. Under the frequentist framework, each experiment is assumed to be one of infinite independent, **repeatable** experiments on randomly drawn samples from a population. Random experiments are assumed to be repeated arbitrarily often. Based on this assumption and with just one experiment from the current study, we make an estimation about the population. The discrepancy between the estimation from that one experiment and the actual value of the population is due to sampling error alone, i.e. which subjects were randomly sampled from the population. Randomized surveys, for example, are assumed to be repeatable through repeated random sampling of the population. Suppose we replicated the same survey 100 times and we would obtain a slightly different sample every time. We then calculated the 90% confidence interval of the mean for each of these 100 surveys. We should anticipate that roughly 90 out of these 100 confidence intervals would include the true mean of the population. We cannot say for sure exactly 90 out of these 100 confidence intervals would include the true mean of the population because repeated random sampling is indeed random and the process is **stochastic**. However, we can say 90 is more probable than 0 or 100.

Most of the comparative content analytic studies, for example, often collect all available content data from a bunch of selected media outlets. In contrast to cluster sampling where media outlets are sampled randomly from a sampling frame of all media outlets, these studies are collecting the entire population of observations from some nonprobailistically selected media outlets. In these census-like situations, there is no way to get more data unless the scope of these studies is changed (Berk, Western, & Weiss, 1995). It is especially true for modern large-N studies using automated content analytic techniques. Burggraaff and Trilling (2017), for instance, “collected **all** available news items from **a selection of major Dutch news outlets**, both online and print” (p. 6, emphasis added) and that amounted to 762,095 articles from 9 outlets in the period of 2014–2015. In that study, one could only get more data by including more media outlets or widening the time window.[4] Unlike a (theoretically) repeatable survey like WJS, one can randomly select more journalists from the sampling frame of all journalists in the respective country.

Therefore, these modern comparative content analytic studies are often not repeatable and thus they generate non-stochastic data. It could be argued that data from these comparative content analytic studies with a census-like approach are fundamentally irrelevant for frequentist inference (Western & Jackman, 1994). Confidence intervals generated do not have the same meaning as those from repeatable studies. According to Western and Jackman (1994, p. 413), these values from non-stochastic data "lack meaning even as abstract propositions".[5]

A common counterargument to this is the classic one from Deming and Stephan (1941, p. 45), who suggested that "[a]s a basis for scientific generalizations and decisions for action, a census is only a sample." This notion assumes a census of a population can be used to make inference on a theoretical device called *superpopulation* which "theoretically could exist, may have existed, or may exist in the future" (Gibbs, Shafer, & Miles, 2015, p. 3). In other words, a finite census-as-a-sample census is assumed to be a "representative sample" of an infinite superpopulation. This counterargument could be useful but unlike a regular random sample (cluster sample included), whose representativeness can be assessed, we can never assess the representativeness of the census-like data with respect to the theoretical superpopulation. Echoing the quote at the beginning of this paragraph, there is

[4] Comparative content analytic studies can also be performed without this census-like approach. The traditional approach of making probabilistic sample from all units can also be used (Krippendorff, 2018). As there is an explicit sampling frame of all units, the population of content about which the sample is making inference from is known in this case. Any further inference made beyond the population is speculative.

[5] In this article, we will not go into detail of the null hypothesis statistical testing (NHST) and p-values, except in the Online Appendix. Researchers are usually not only interested in whether there is or isn't an effect. Instead, we are interested in how large the magnitude and in what direction the effect is. Therefore, we will focus only on the point and interval estimations from various regression models.

no way to tell if the current Czech history is representative of all possible Czech histories in the multiple parallel universes.

Instead of invoking the theoretical device of superpopulation, we follow the arguments from Western and Jackman (1994) and Stegmueller (2013) for comparative studies: Bayesian inference should be used for analyzing data from comparative research in our field. Choosing a Bayesian approach also solves the problem of misinterpretation of confidence intervals (Rinke & Schneider, 2018). Unlike the frequentist confidence intervals, Bayesian "credible intervals support an interpretation of probability in terms of plausibility" (Morey, Hoekstra, Rouder, Lee, & Wagenmakers, 2015, p. 120).

Before we move on to the next section, it is important to point out that **non-stochastic data is not an essential condition for applying the Bayesian approach**. The same approach is equally applicable to both non-stochastic and stochastic comparative datasets.

Bayesian analysis as alternative

What is the probability for this paper being accepted by *IJOC*? Under the frequentist framework (and if *IJOC* were accepting papers stochastically), we could only find this out by repeatedly submitting this paper to *IJOC*, say for 100 times, and then count the frequency of acceptance in these repeated submissions. It is indeed impractical as well as inhumane to the editorial team of *IJOC*. Instead, we assert before submission that this paper has a probability of 24% for being accepted. That is the published acceptance rate of a similar journal. After this paper is submitted and is not desk rejected, the probability might be around 24% to 30%. After months of waiting and our confidence is shaken a little, the probability might decrease to 10% to 20%. After the paper is mixed reviewed by three reviewers and an R&R is invited, the probability might increase to 40% to 60%. If you see this paper on *IJOC*'s website, then the probability is beyond doubt

100%. If we (or other researchers) "repeat the experiment" and resubmit the same paper again to *IJOC*, the probability of the resubmitted paper for being accepted is 0%.

Without repeated experiment, these probabilities quantify our certainty on how plausible the paper is being accepted, given the current available data. We revise our old beliefs (or **prior**, $p(\theta)$) with the new data (X) and form our revised belief (or **posterior**, $p(\theta|X)$). This can be summarized in the following equation (Gelman, Vehtari, et al., 2020):

$$P(\theta|X) \propto P(\theta)P(X|\theta) \tag{11}$$

The $P(X|\theta)$ part is called likelihood function. In the *IJOC* example, the likelihood function is based on rough rules from our experience and thus is not systematic. In actual analysis, we need to derive such a likelihood function based on the available data using methods such as Markov Chain Monte Carlo (MCMC).[6] Nonetheless, the above equation indicates that there are only three ingredients in any Bayesian analysis: 1) data (X), which require no elaboration, 2) a method to derive the likelihood function $P(X|\theta)$ from the data, and 3) prior, $P(\theta)$.

R interfaces to Stan (the probabilistic programming language for conducting MCMC), such as *brms* (Bürkner, 2017), can enable the derivation of the likelihood function (Part 2). But still, it is important to be mindful that Bayesian analysis is much more computational intensive than methods such as MLE. Our benchmark suggests that Bayesian analysis needs at least 100 times more running time than MLE.

Part 3 (Prior) is arguably the most controversial part of Bayesian analysis. In the

[6] How concretely MCMC can faciliate the estimation of likelihood function, given the data and prior, is too technical to be included in this paper. Readers can get an intuition of how it works in Chapter 8 of McElreath (2020). For how the method works in regression models, Chapters 9, 10, and 12 of McElreath (2020). For a comparative perspective between Bayesian and frequentist approaches, please refer to Samaniego (2010).

IJOC example, we can select a reasonable prior (or **informative** prior) of 24% from published information. Finding previous studies for an informative prior is the logical first thing to do. Keating and Totzkay (2019) show that one in every seven communication research papers published in major communication journals was a form of replication attempt. For these one seventh of communication research, there should be previous studies available to base one's informative prior non-controversially. For the other six sevenths, one might not have any information to set an informative prior. One option is to consult experts or to make an educated guess. Expert elicitation is a way to probe how the experts in the field think about the hypotheses. A standardized protocol for expert elicitation is available (Hanea et al., 2017) and there are many software tools available to facilitate the process.[7] But one person's expert opinion could be another person's wishful thinking. And this perceived subjectivity of specifying priors by experts' judgment attracts wide-spread criticism from both statisticians (e.g. Efron, 1986) and social scientists (e.g. Elff et al., 2020).

Undoubtedly, setting prior is consequential to the analysis. But the influence from priors is greatly weakened, when the data is getting bigger. Other than expert elicitation, another non-controversial way to specify priors — at least in our opinion — is to use a weakly informative prior (Lemoine, 2019). In this way, one specifies only the possible range of the posterior. Some so-called "default weakly informative priors", e.g. $t(1, 0, 0.25)$, have been suggested for typical regression models (Gelman, Jakulin, Pittau, & Su, 2008).

Bayesian communication research

Bayesian analysis is still a minority statistical method in social sciences. As far as we know, the only available comparative communication research that Bayesian multilevel regression was used for studying ecological effect are de Leeuw, Azrout, Rekker, and Van

[7] Some examples are the web-based MATCH Uncertainty Elicitation Tool (http://optics.eee.nottingham.ac.uk/match/uncertainty.php) and the R package SHELF.

Spanje (2020) and Heidenreich, Eberl, Lind, and Boomgaarden (2022). As argued in the two previous sections, comparative communication research fits the use case of Bayesian multilevel regression analysis. This paper demonstrates how to do the analysis using the R package *brms* (Bürkner, 2017) (see the source code in the Online Appendix https://osf.io/2h4w8/?view_only=be14dc637b8e4fd1a26ac5c64682b6d9). As the interface of *brms* is almost the same as *lme4* (Bates, Mächler, Bolker, & Walker, 2015, another R package for fitting multilevel models using MLE), *lme4* users might find *brms* extremely familiar.

The two examples below show how the Bayesian multilevel regression analysis can be deployed to the common archetypes of comparative journalism studies. The first example is an analysis of a comparative, stochastic survey dataset (WJS). This example was chosen to highlight the multilevel (non-atomicity) aspect and represent the situation of replication studies. The second example is an analysis of a comparative, non-stochastic content analytic dataset. This example was chosen to highlight the necessity of using the Bayesian approach to analyze non-stochastic comparative data and represent the situation of studies where noninformative priors were needed.

Example 1: The Worlds of Journalism study

In this example, the Bayesian approach is applied to a stochastic dataset from a survey in which some randomization is involved. The starting point of this example is the recent study by Hamada (2021). Using the second wave data from WJS (2012-2016), the study seeks to study this hypothesis (the H2a in the paper): *The greater the level of democracy in a country, the more perceived professional autonomy journalists enjoy.* To rephrase this, the level of democracy in a country has an ecological effect on the journalists' perceived professional autonomy.

It is important to point out that the study is a replication. The same hypothesis has been studied in the earlier study by Reich and Hanitzsch (2013), which uses the first wave data from WJS and has a remarkably similar title to that of Hamada (2021). The earlier study has studied this hypothesis (the H4): *Journalists' perceived professional autonomy is positively associated with democratic performance and press freedom, and it is negatively related to political parallelism and state intervention.* The operationalizations of both professional autonomy (based on two questions in WJS) and level of democracy (based on the Economist Intelligence Unit's Index of Democracy) are the same in the two studies. It is important to recite the operationalization of professional autonomy here. The two questions in the survey are: (1) "Thinking of your work overall, how much freedom do you personally have in selecting news stories you work on?" (2) "How much freedom do you personally have in deciding which aspects of a story should be emphasized?" The possible answers ranged from 5 = "complete freedom" to 1 = "no freedom at all". The two answers were averaged.

Interestingly, the analytical approaches are also similar in the two studies. The study by Reich and Hanitzsch (2013) contains multiple regression models on how journalist-level characters predict perceived professional autonomy. However, for country-level predictors such as Index of Democracy, Reich and Hanitzsch (2013) apply an aggregated approach due to "methodological considerations" of "includ[ing] substantive country-level predictors in an OLS regression" (p. 146). Effectively, the analysis boils down to aggregating the perceived professional autonomy of all journalists into mean values according to baskets of Index of Democracy and then comparing those mean values by ANOVA. The subsequent study by Hamada (2021) applies the same aggregated approach by studying the bivariate correlation between the mean perceived professional autonomy of all journalists in a country and the Index of Democracy of a country.

Bayesian multilevel analysis of WJS

Let's assume we were in the shoes of Hamada (2021) and wanted to replicate the study by Reich and Hanitzsch (2013) with the second wave WJS data. Bayesian multilevel regression provides several advantages over the aggregated approach.

First, it can take advantage of the hierarchical structure of the data and estimate the contextual effect of democratic performance on the journalist-level perceived professional autonomy. It allows for adjustment of other journalist-level predictors that are known to influence perceived professional autonomy, e.g. rank ($RANK$), experience (XP), gender (GEN), & having a university degree ($UNIV$). It also makes it possible to adjust for the possible confounding effects of other country-level variables. For example, GDP per capita (according to the World Bank) is moderately correlated with the Index of Democracy (r = 0.53). The correlation between Index of Democracy ($DEMO$) and perceived professional autonomy (PPA) found by Reich and Hanitzsch (2013) could be spurious and the GDP per capita were the actual determinant of perceived professional autonomy. We can adjust for the effect of GDP per capita by entering it also as an independent variable. The data can also provide such variance because there are countries with high GDP per capita but with low democracy (e.g. UAE and Qatar) and vice versa (e.g. Botswana and India).

Priors

The idea of choosing priors is to select a probable probability distribution for each of unknown parameters in a model. Usually, the first step for choosing priors is to review previous studies and look for possible values to be used as our informative priors. Incorporating of prior information from Reich and Hanitzsch (2013) in this Bayesian analysis makes the intention to replicate clearer.

Reich and Hanitzsch (2013) suggest that the relationship between Index of Democracy and perceived professional autonomy is in “J shape”, with the average perceived professional autonomy of journalists in authoritarian regimes (the lowest end of democratic performance) being higher than those in hybrid regimes (3.92 vs 3.65). We can incorporate this prior information into our model by modeling a cubic relationship between Index of Democracy and perceived professional autonomy. Like the general procedure of conducting polynomial regression, we also create a parsimonious model assuming only a linear relationship to study whether the cubic regression improves the model fit. In other words, whether the relationship is really in “J shape” is studied . It’s important to spell out all the equations so that we can have an idea of all the estimands. For the parsimonious model, the regression equations are:

$$PPA_{ik} = \beta_0 + \beta_1 XP_i + \beta_2 RANK_i + \beta_3 GEN_i + \beta_4 UNIV_i + \epsilon_{ik} \tag{12}$$

$$\beta_0 = \gamma_{00} + \gamma_{01} DEMO_k + \gamma_{02} \log GDP_k + \mu_{0k} \tag{13}$$

For the cubic model, the regression equations are:

$$PPA_{ik} = \beta_0 + \beta_1 XP_i + \beta_2 RANK_i + \beta_3 GEN_i + \beta_4 UNIV_i + \epsilon_{ik} \tag{14}$$

$$\beta_0 = \gamma_{00} + \gamma_{010} DEMO_k + \gamma_{011} DEMO_k^2 + \gamma_{012} DEMO_k^3 + \gamma_{02} \log GDP_k + \mu_{0k} \tag{15}$$

From the model 4 in Reich and Hanitzsch (2013), we know that the standardized beta coefficients for the variables rank (β_1) and professional experience (β_2) are .15 and .07 respectively. Unfortunately, the associated standard errors (or standard deviations) were not reported but only asterisks representing statistical significance ($p < 0.001$ for rank, $p < 0.01$ for professional experience). We estimated the maximum standard deviation based on the significance level. For example, the standard deviation of the standardized regression coefficient ($\sigma_{\beta_1'}$) of rank can be estimated by solving :

$$Pr(\frac{\beta'_1}{\sigma_{\beta'_1}}) = \frac{0.001}{2} \sim \mathcal{N}(0,1) \tag{16}$$

$$\frac{\beta'_1}{\sigma_{\beta'_1}} = 3.29 \tag{17}$$

$$\frac{0.15}{\sigma_{\beta'_1}} = 3.29 \tag{18}$$

$$\sigma_{\beta'_1} = 0.045 \tag{19}$$

The above information can be used as an informative prior of the current analysis. Unfortunately, the ANOVA result in relation to γ_{01} from Reich and Hanitzsch (2013) cannot be used as the prior and we need to use weakly informative priors suggested by Lemoine (2019). For regression coefficients, e.g. γ_{01}, we used a normal distribution of $\mathcal{N}(0,1)$. For variance terms, e.g. μ_{0k}, a student t-distribution of $t(3,0,2.5)$ was used. All, except the prior for regression coefficients, are default priors suggested by *brms*. In practice, we suggest pre-registering the priors before the data collection. As this is a secondary data analysis, we cannot do that.

In order to make the result from this replication comparable to that of Reich and Hanitzsch (2013), we also calculate the standardized regression coefficients, i.e. all variables are transformed to Z-scores.

Other parameters. Other parameters such as *adapt_delta* control how the MCMC should be performed. It is in general safe to use the default values unless MCMC shows evidence of nonconvergence. We provide a short guide on how to diagnose convergence (online appendix).

Modeling

For this analysis, we tried 3 different approaches: 1) Disaggregation approach (ignoring the multilevel structure); 2) Multilevel regression using MLE; and 3) Bayesian multilevel regression. In the disaggregation case, the multilevel structure is ignored and the regression equations become:

$$
\begin{aligned}
PPA_{ik} &= \beta_0 + \beta_1 XP_i + \beta_2 RANK_i + \beta_3 GEN_i \\
+\beta_4 UNIV_i + \beta_5 DEMO_k \\
+\beta_6 GDP_k + \epsilon_i \\
PPA_{ik} &= \beta_0 + \beta_1 XP_i + \beta_2 RANK_i + \beta_3 GEN_i \\
+\beta_4 UNIV_i + \beta_5 DEMO_k \\
+\beta_6 GDP_k + \beta_7 DEMO_k^2 \\
+\beta_8 DEMO_k^3 + \epsilon_i
\end{aligned}
$$

It is important to remind our readers that the results from the three are likely to be similar, but it is not evidence for the disaggregation approach and the MLE approach is a replacement of the Bayesian approach (Morey et al., 2015). The interval estimates have different meanings and can't be directly compared. Comparing the three approaches, the disaggregation approach is the least useful because it violates the underlying independence assumption.

Results

The Bayesian multilevel regression gave the *posterior distribution*, $P(\theta|X)$, of the regression coefficients. It is a distribution and therefore we need ways to display both the central tendency and spread of the distribution. By default, *brms* displays the mean and the 95% High Density Interval (HDI). These two values represent the point and interval estimates of the regression coefficient.

Table 1

Point and interval estimates from WJS analysis using three different analytic strategies: Bayesian multilevel modeling, multilevel modeling using MLE, and Disaggregation approach

term	Bayesian	MLE	Disaggregation
(Intercept)	0.02 (-0.06, 0.11)	0.03 (-0.06, 0.11)	0.01 (0, 0.02)
Experience	0.08 (0.07, 0.09)	0.08 (0.07, 0.09)	0.09 (0.08, 0.1)
Rank	0.15 (0.14, 0.16)	0.16 (0.15, 0.17)	0.16 (0.15, 0.17)
Gender (Female)	-0.06 (-0.07, -0.05)	-0.06 (-0.07, -0.05)	-0.04 (-0.05, -0.03)
University Degree	-0.01 (-0.03, 0)	-0.01 (-0.02, 0)	-0.04 (-0.05, -0.02)
Index of Democracy	0.24 (0.13, 0.34)	0.24 (0.14, 0.34)	0.24 (0.22, 0.25)
GDP per capita	-0.05 (-0.15, 0.05)	-0.04 (-0.14, 0.05)	-0.06 (-0.07, -0.04)

By looking at the regression coefficient and the 95% HDI of the parsimonious model (Table 1), the standardized regression coefficient for Index of Democracy is 0.24 (95% HDI: 0.13 to 0.34). The Index of Democracy is the strongest predictor among all other predictors (Rank: 0.15, Experience: 0.08, gender: -0.06, university degree: -0.01). The standardized regression coefficient for GDP per capita is not large (-0.05). It supports Hamada (2021)'s h2a, even after adjusting for the possible confounding effect of GDP per capita.

By comparing the point and interval estimates using different approaches, point estimates are remarkably similar. Bayesian multilevel regression gave a wider 95% HDI than confidence intervals from frequentist methods. It is like previous studies (Elff et al., 2020; Stegmueller, 2013). While the frequentist confidence intervals and the Bayesian credible interval seem to be similar, they are from a philosophical point of view totally different and lead to different forms of inference. The Bayesian approach allows us to say that *given the observed data, the true value of the standardized regression coefficient has*

95% probability of falling within 0.13 and 0.34. In contrast, the frequentist confidence interval only allows us to say that *when computing a confidence interval from the same type of data in repeated studies (if possible), 95% of the confidence intervals will include the true value of the standardized regression coefficient*. One of the misconceptions of frequentist confidence intervals is that they can be interpreted in a Bayesian way as described above (Morey et al., 2015). This example illustrates that a Bayesian approach allows us to interpret the results in a more intuitive way.

J Shape. By looking at the conditional effects plot of the cubic model (Figure 1), it suggests that the relationship is not "J shape."[8]

Posterior predictive checks. One unique feature of the Bayesian approach is posterior predictive checks (PPC) for studying how our model works. Bayesian analysts have a strong culture of model checking (e.g. Mimno, Blei, & Engelhardt, 2015; Gelman, 2007), while many analyses – not only in communication research – end with regression tables and inferences.

A useful model for theory testing should pin down the data-generating process in the real world, not just whether the model fits the data. Therefore, a model should be able to generate simulated data that are like the observed data (Gelman, 2007). The gist of posterior predictive check is to use the fitted model to generate some simulated data (y_{rep}) and compare them with the original observed data (y). If the model is useful, the model should display a similar probability distribution of y_{rep} and y. (Figure 2).

As one can see in Figure 2, the fitted model can get the range and the peak of the original data about right. But the model can only give simulated data y_{rep} with a gaussian distribution whilst the shape of the original data y is not gaussian at all. In the online appendix, we model the finger-like shape of the data with another technique.

[8] Another way to evaluate the model fit is to use leave-one-out cross validation. See the online appendix for the analysis.

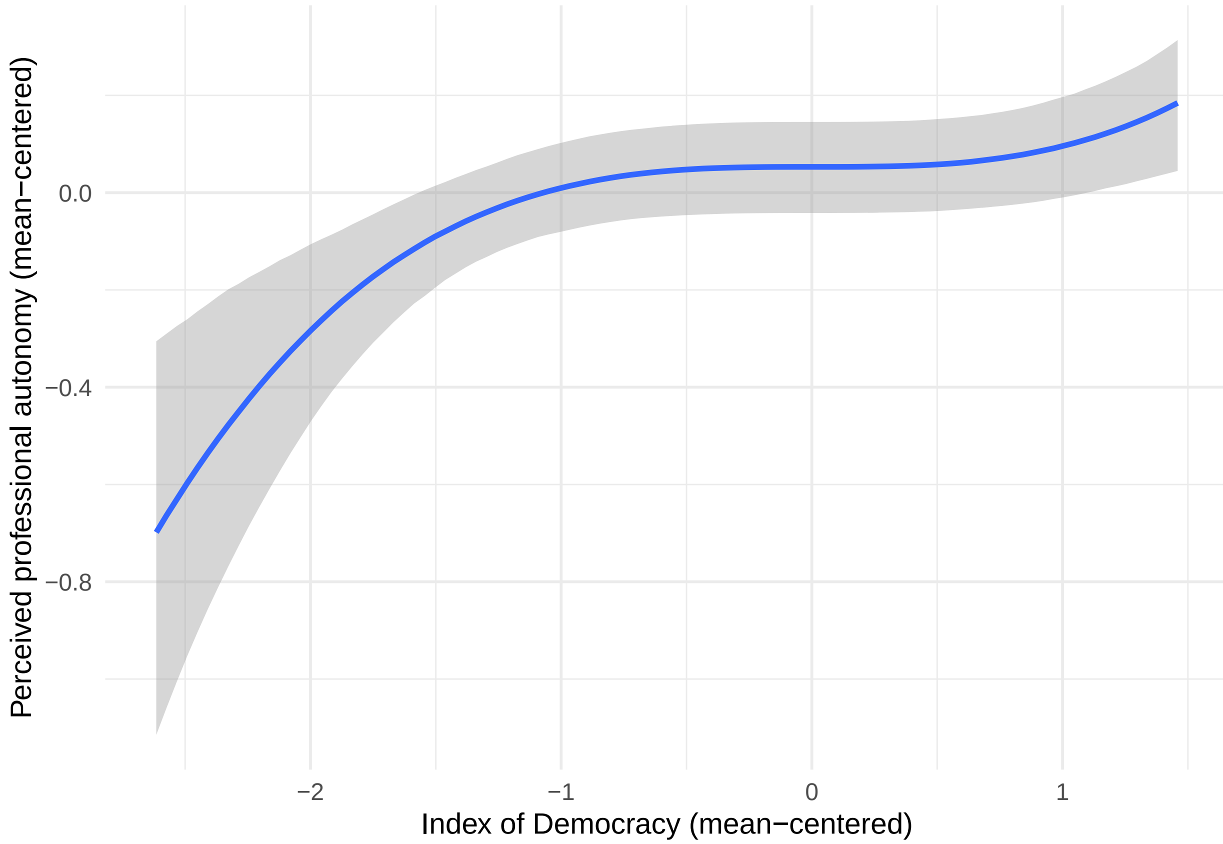

Figure 1. Conditional effects plot showing no "J shape" relationship between perceived professional autonomy and Index of Democracy.

Summary of Example 1

In this example, the Bayesian multilevel regression approach allows the study of ecological effect hypotheses of a macro-level variable (e.g. Democracy) on a micro-level variable with a comparative, semi-randomized dataset. The inference of the model is at the level specified in the hypotheses (micro-level, i.e. journalists) and allows adjustment for other confounding variables (e.g. GDP per capita). Visualizations such as conditional effects plot and posterior predictive checks assist model checking.

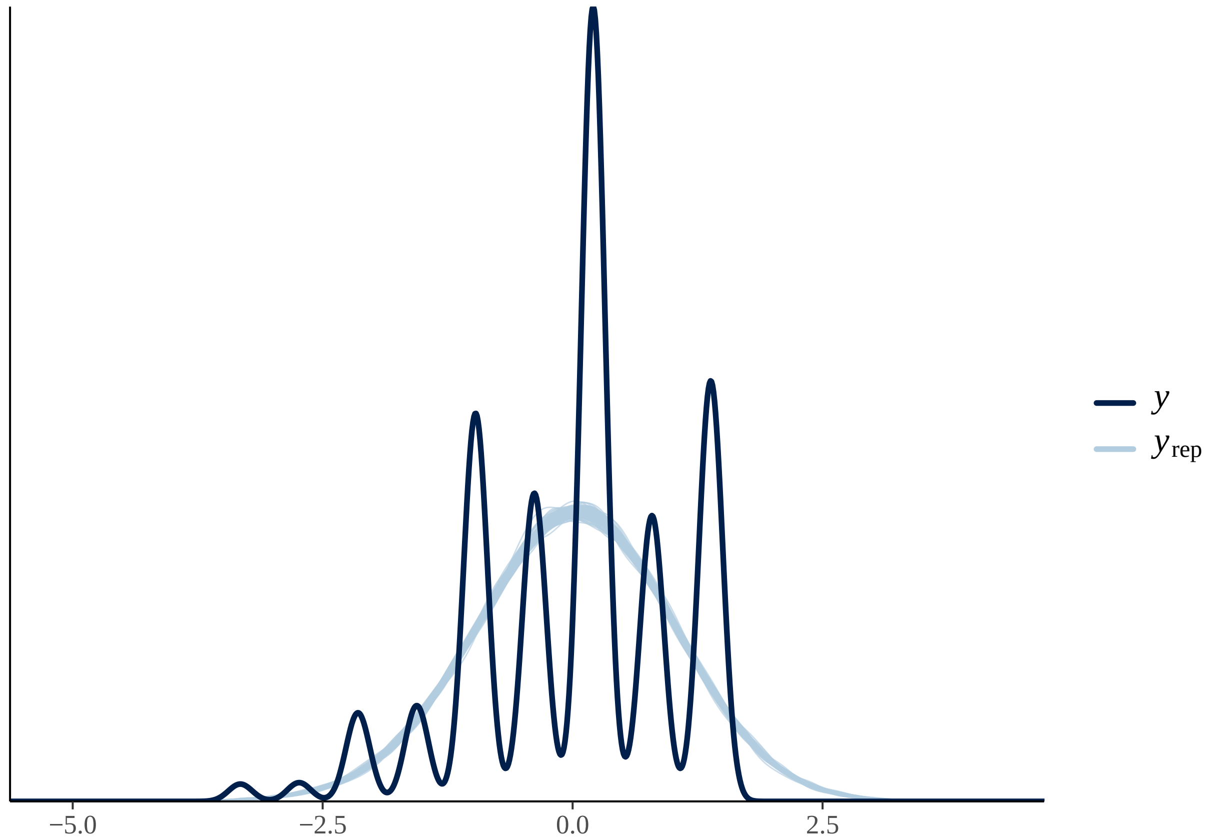

Figure 2. Posterior predictive checks with 100 sets of simulated data based on the parsimonious model

Example 2: useNews

We used the useNews dataset (Puschmann & Haim, 2020) to demonstrate how to perform a Bayesian multilevel regression analysis on a nonstochastic comparative dataset. The analysis was guided by a classic question in news value research: Does the distance between China and the host country of a media outlet increase the frequency of China coverage? In other words, we hypothesized that there is an ecological effect between a closer distance to China and an increased frequency of China coverage. Several distance measures were used to formulate our pre-registered hypotheses. Due to limited space, only the analysis of trade volume between two countries is displayed here. For other analyses, please refer to the online appendix.

For demonstrative purposes, our analysis was separated into two levels: outlet-level analysis (here) and article-level analysis (in the Online Appendix). The outlet-level analysis is an aggregated version of article-level analysis. It is used to demonstrate the flexibility of Bayesian analysis to handle two-level data with a very small data size. The article-level analysis is used to demonstrate the analysis of a massive three-level dataset.

Data

The useNews is an openly available dataset (Puschmann & Haim, 2020) that includes 2019 to 2020 media content data from an array of worldwide media outlets. The media content data was collected from the MediaCloud and made available as document-term matrices.

We used only the data from 2019 as the baseline and excluded media outlets that contributed <1,000 articles in that year. This threshold allowed us to retain media outlets that the frequency of China coverage can be reliably estimated. In total, 61 media outlets contributed 1,525,871 articles.

In the outlet-level analysis, the data has 61 rows and each row represents a media outlet. The data contains a count of articles covering China (z), total number of articles (n), country of the outlet(k), and distance measures (x).

Coverage of China

A dictionary-based approach was used. The seed English and German dictionaries from the R package newsmap (Watanabe, 2017) were used as the basis. The seed dictionaries contain words about Chinese, China, Beijing and Shanghai. We developed further the Spanish, Romanian, Korean, Portuguese, Norwegian, and Dutch dictionaries.[9] The dictionaries were applied to the 61 document-term matrices (format of the provided

[9] The validation of the dictionary is available in the online appendix.

dataset) of all included media outlets. An article is classified as China coverage when at least one dictionary match is detected.

Distance measure: Trade volume

The volumes of import to and export from China with the host country of a media outlet was extracted from the 2019 edition of China Statistical Yearbook (http://www.stats.gov.cn/tjsj/ndsj/2019/indexeh.htm). This measure was log-transformed, because previous studies showed the relationship between news coverage and these distance measures is not linear (Grasland, 2019; Wu, 2000).

Outlet-level analysis. We used negative binomial regression for this analysis.[10] Applying the same notation under the introduction section, the multilevel regression equations are:

$$\log z_{jk} = \gamma_{00} + \mu_{0k} + \gamma_{01} \log x_k + \log n_j + \epsilon_{jk} \tag{20}$$

$$\log z_{jk} - \log n_j = \gamma_{00} + \mu_{0k} + \gamma_{01} \log x_k + \epsilon_{jk} \tag{21}$$

$$\log \frac{z_{jk}}{n_j} = \gamma_{00} + \mu_{0k} + \gamma_{01} \log x_k + \epsilon_{jk} \tag{22}$$

Media outlets are nested in countries. Thus, a country-based variance is added (μ_{0k}). We also added $\log n_j$ as an offset value. An offset value is a term that does not have the associated regression coefficient at the right-hand side of the regression equation. Effectively, we modeled the *rate* of China coverage.

The estimand of interest, γ_{01}, is interpreted as the average unit change in the log rate of China coverage, $\log \frac{z_{jk}}{n_j}$, for each unit change in the log distance measure of the outlet k with China.

[10] We propose four extensions: hypothesis testing, investigating cross-level interaction, establishing informative prior, and testing for temporal changes (online appendix).

Table 2

Point and interval estimates from outlet-level analysis using three different analytic strategies: Bayesian multilevel modeling, multilevel modeling using MLE, and Disaggregation approach

term	Bayesian	MLE	Disaggregation
(Intercept)	-6.69 (-8.01, -5.24)	-6.77 (-7.89, -5.66)	-6.77 (-7.88, -5.66)
Log (Trade Volume)	0.25 (0.15, 0.34)	0.25 (0.18, 0.33)	0.25 (0.18, 0.33)

Priors

There are four unknown parameters to be estimated: γ_{00}, μ_{0k}, γ_{01} and the negative binomial shape parameter ϕ. Although Wu (2000) is a possible reference point, we select not to use this as priors because China was not studied. In this analysis, we used weakly informative priors suggested by Lemoine (2019). The priors were the same as the ones used in Example 1. An additional gamma distribution of $\mathcal{Gamma}(0.01, 0.01)$ was used for the shape parameter ϕ.

Regression results

Table 2 shows a summary of all models from the outlet-level analysis using three different ways of modeling. Similar to Example 1, three methods give a similar point estimate but a wider interval estimate from the Bayesian model.

Posterior predictive checks. Similar to the previous example, we conducted the posterior predictive check (Figure 3). Our model can capture both the range, peak and shape of the original data. But there are many variations in the simulated data, probably due to the fact that the Bayesian model is based on just 61 data points and one single predictor.

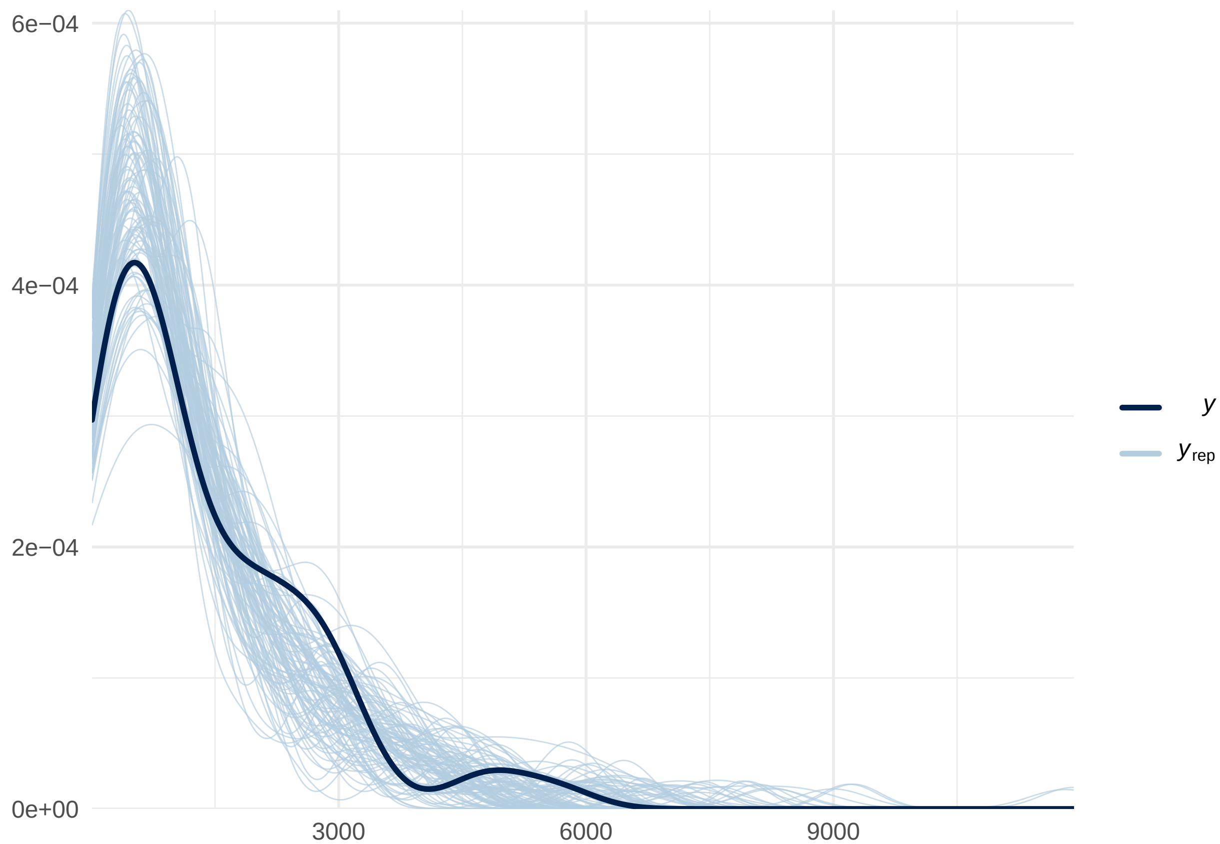

Figure 3. Posterior predictive checks with 100 sets of simulated data

Summary of Example 2

In this example, the Bayesian multilevel regression approach allows the study of ecological effect hypotheses in a nonrandom, comparative dataset. Various extensions we demonstrated in the online appendix show the flexibility of the approach.

Conclusion

In this paper, we argue the case for using Bayesian multilevel regression analysis to analyze data from comparative communication research. We demonstrate using the openly available WJS and useNews datasets that Bayesian analysis provides valid inference of ecological effects and can be done easily with the R package *brms*. We mainly used the WJS dataset to illustrate the strength of multilevel models, whereas the useNews dataset was selected as an example where Bayesian models are conceptually the most defensible option. However, both multilevel models and Bayesian analysis are connected approaches.

First of all, the hierarchical data structure in both examples warrants the multilevel modeling approach. The question then is why we should use a Bayesian approach as these models can also be estimated with a frequentist approach. As the useNews dataset represents a census-like situation, we argue a Bayesian approach is more appropriate. Of course, as the argument about the theoretical superpopulation shows, one could always justify a frequentist approach. However, there are also several practical reasons why a Bayesian approach is more suitable than a frequetist approach.

First, the Bayesian interpretation of CIs is far more intuitive than the frequentist interpretation (Morey et al., 2015). Secondly, while all the models reported here can also be estimated within a frequentist framework, using a Bayesian framework and, more specifically, *brms* allows estimating them all with the same package. This also makes it easier to compare different competing models, as we have illustrated in our analysis. Third, comparing models and checking the data-generating quality of the models is an essential part of a Bayesian framework. Of course, frequentist models can also be compared based on information criteria such as the BIC. However, PPCs that give by far the most detailed information about models and indicate in which area they potentially fail are only possible by using a Bayesian approach. Finally, while we discussed the question about priors as a potential challenge of Bayesian models, they are instead a strength of Bayesian models. Researchers must define priors to run a Bayesian regression analysis. As we could show, this limitation does not pose a controversial challenge as weakly informative priors can be chosen, and in most cases, enough data is available. Thus, the priors have almost no influence on the posterior distribution of the parameters. Moreover, if we have prior knowledge, it allows us to create even more useful models, as the first example has shown.

Using a Bayesian approach still has several limitations. First, it takes more time to get the results of a Bayesian regression analysis. Estimating a Bayesian regression model is a computationally demanding task. It took four days on a regular computer to get the results of the Bayesian regression model with 1,525,871 articles (Example 2, article-level analysis). Still, eventually, it worked, and typical studies in comparative journalism research , e.g. 27,567 journalists in Example 1 can be estimated within a reasonable time frame. Secondly, if sampling procedures are used for a typical experimental design that could be replicated, using a frequentist approach is probably the less complicated approach. In any other scenario, we believe the benefits of the Bayesian approach outweigh the potential limitations.

Coda: An education reform proposal

Unlike what it was several years ago, software and educational materials for doing Bayesian analysis have been tremendously improved. We see the availability of the R package *brms* (Bürkner, 2017) and approachable textbooks such as *Regression and Other Stories* (Gelman et al., 2020) and *Statistical Rethinking* (McElreath, 2020) as watershed moments in the (re)mainstreamization of the Bayesian approach. These development coincides with Rinke and Schneider (2018)'s recommendation of a different teaching of statistics for communication research. In their opinion, the teaching of frequentist hypothesis testing would be less central. "Instead, more substantive concerns, replication, effect sizes, and better ways of drawing statistical inferences, including Bayesian methods, would take center stage." (Rinke & Schneider, 2018, p. 18) We concur with their proposal. The frequentist approach should be taught only in the context of analyzing data with explicit randomization, such as randomized experiments and simple random surveys. We hope that this paper can convince the educators of our field to teach Bayesian methods, especially for multilevel regression analysis. We should also teach the issues concerning the non-atomicity and non-stochasticity of real-world data, as well as the necessity of model checking with procedures such as posterior predictive checks.

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