

Incorporating Qualitative Distinctions in Within-Person Effect Analyses

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Within-person effects are getting increasing interest in social and behavioral sciences. Differences in within-person effects are recognized as a key element for understanding between-person differences. Research has examined factors that could explain heterogeneity in within-person effects. The original-score approach estimates person-specific effects at the within-person level and use their original scores to conduct between-person regression analyses. The absolute-score approach focuses on the magnitude differences of person-specific effects and use their absolute values to explore potential correlates.

However, within-person effects are not only quantitatively different but also *qualitatively* different. Individuals may exhibit positive, null, or negative effects, each reflecting a different underlying mechanism. For example, individuals with positive predictive effects of stressors on distress (stress-reactive) are qualitatively different from those with near-zero predictive effects (stress-nonreactive) and those with negative predictive effects (stress-reactive but in the reverse direction). Pooling these heterogeneous groups without accounting for their qualitative differences can lead to erroneous conclusions when identifying predictive factors of within-person effects.

Therefore, this study aimed to improve between-person analysis of within-person effects by incorporating qualitative distinctions between individuals. We proposed a Bayesian multilevel model to better explain heterogeneity in within-person effects. At the within-person level, we considered a linear regression model with random intercepts and random slopes. The population was then divided into distinct groups based on the sign and strength of within-person effects. At the between-person level, we constructed log-linear regression models for random intercepts and slopes that accounted for these distinct groups.

We conducted a simulation study to preliminarily test the performance of the proposed approach. Focusing on the regression effects of the between-person factor on random slopes, we set a moderate regression effect (0.3) for the positive-effect group, and no regression effect for the null-effect group. In the reference condition ($N_i \approx 300$, $T_i \approx 30$), the proposed approach showed acceptable model convergence (86%), and low bias, small RMSE, high power, and a low Type I error rate of regression coefficients (Table 1). Model convergence and parameter estimation accuracy decreased when N or T was smaller. The results supported the effectiveness of the proposed approach in identifying different predictive patterns across qualitatively different groups.

We further compared existing approaches and the proposed approach in an empirical example. 355 participants completed the Ruminative Responses Scale (Nolen-Hoeksema & Morrow, 1991), and five momentary assessments on stressors and psychological distress per day for seven days. Existing approaches (Figure 1a,b) suggested that rumination exacerbated individuals' psychological reactivity to stressors. However, as illustrated in Figure 1c, rumination *only* magnified the detrimental effect of stressors on psychological distress in the stress-reactive group, not in the stress-nonreactive group. This finding highlights the necessity of incorporating qualitative differences in within-person effects for a nuanced understanding of their between-person correlates, helping to identify at-risk individuals and design personalized interventions.

In conclusion, recognizing qualitative distinctions in within-person effects is crucial for examining their heterogeneity and explanatory factors. We hope that the proposed Bayesian multilevel model can help improve the between-person analyses of within-person effects.

Table 1. Simulation results of the regression coefficients for the positive-effect and the null-effect groups in three conditions.

Simulation conditions	Positive-effect group			Null-effect group			
	Bias	RMSE	Power	Bias	RMSE	Type I error	Model convergence
$N_{i,j} \frac{1}{2} 300, T_{i,j} \frac{1}{2} 30$	0.008	0.108	91.86%	-0.011	0.153	8.14%	86%
$N_{i,j} \frac{1}{2} 150, T_{i,j} \frac{1}{2} 30$	0.040	0.122	72.13%	-0.010	0.240	3.28%	61%
$N_{i,j} \frac{1}{2} 300, T_{i,j} \frac{1}{2} 15$	0.038	0.135	77.08%	0.062	0.329	12.50%	48%

Note: The simulation was replicated for 100 times.

Figure 1. Between-person analysis results from (a) the original-score approach, (b) the absolute-score approach, and (c) the proposed approach.

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Reference

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