Additional Analysis Example for a General Approach to Modeling Latent Variable Interactions and Nonlinear Effects

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Accommodating Latent × *Discrete Interaction*

One of the great strengths of factored regression's framework is that it readily accommodates a range of manifest predictor variables. As previously noted, Blimp supports binary, ordinal, multicategorical, skewed continuous, and normal predictors. The model specification is largely the same across variable types. For discrete predictors, one defines the variable type using the `ORDINAL` or `NOMINAL` command. The manifest by latent interaction is then specified in the same manner as a latent by latent interaction. To illustrate, I created a binary version of the organizational constraints variable by performing a median split on the simulated latent variable scores. The structural regression equation is now given by the following equation.

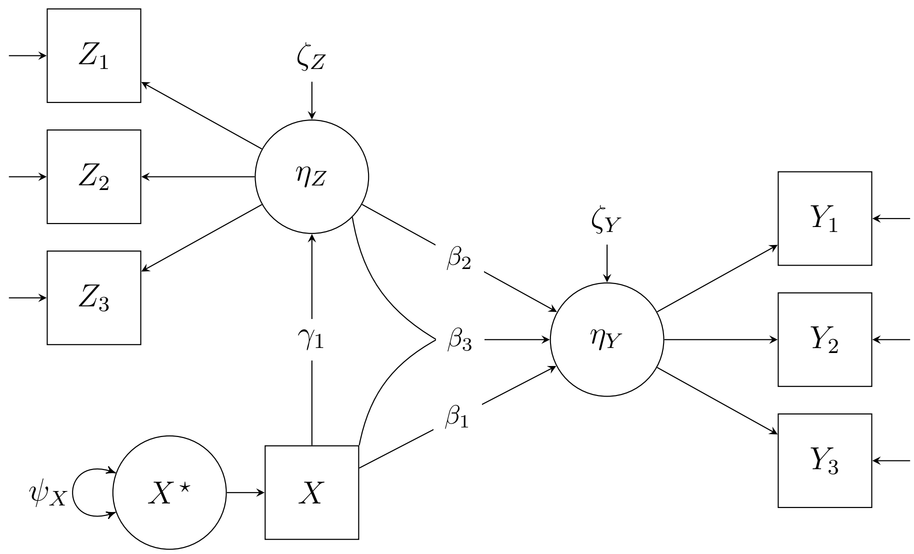
$$\texttt{cwb}_i = \beta_0 + \beta_1(\texttt{consci}_i) + \beta_2(\texttt{bin\_org}_i) + \beta_3(\texttt{consci}_i \times \texttt{bin\_org}_i) + \zeta_i \qquad (1)$$

Equation (1) illustrates that I must include the interaction between the latent variable and manifest binary variable, `consci` and `bin_org`. In Blimp's syntax, I explicitly specify the interaction within the regression model. The modified `MODEL` excerpt is as follows.

Returning to the path diagram in Figure 1, the manifest by latent interaction requires two modeling changes. First, the observed binary organizational constraints (`bin_org`) would need a model to accommodate any potential missing data. Second, in Figure 1, the predictors link via a regression equation rather than a covariance. The moderated regression itself is left unchanged. The key changes to the Blimp script are shown in the follow-

Figure 1

Path Diagram for Latent × Binary Interaction Model



Note: The mean structure is not illustrated in the diagram. The conjoined arrow for the β_3 path represents the product between X and η_Z. For identification, ψ_X is generally fixed to one.

ing syntax excerpt, and the full script is available at `https://github.com/blimp-stats/Latent-Interactions`.

```
ORDINAL: bin_org;    # Define binary variable
LATENT:  cwb consci; # Define latent variables

## Begin Modeling Syntax
MODEL:
  bin_org ~ 1;
  consci ~ bin_org;
  cwb ~ consci bin_org consci*bin_org;
  # Specify cwb and consci measurement models here

## Simple effects for binary orgcon
SIMPLE: consci | bin_org;
```

Listing `bin_org` on the `ORDINAL` line invokes a probit formulation for the first regression after the MODEL command. Alternatively, listing bin_org after the NOMINAL command would invoke a logistic regression. The second regression after the MODEL command is the aforementioned directed pathway between consci and bin_org. In this example, the SIMPLE command produces conditional effects for each level of the discrete moderator (i.e., the effect of conscientiousness on counterproductive work behavior in the low and high organizational constraint groups).

The parameter interpretations parallel any standard multiple regression model with an interaction between a binary and continuous predictor. Returning to Figure 1, the γ coefficient would represent the group mean difference on latent consci between the low and high organizational constraint groups. The lower-order effects have familiar interpretations. For example, the β_1 slope is the counterproductive work behavior group mean difference at the average latent consci. The β_2 slope would convey the conditional effect of latent consci on latent cwb in the low organizational constraints group. Finally, the interaction coefficient (β_3) would represent the consci slope difference for the high organizational constraints group.

Next, suppose that organizational constraints is a multicategorical variable (cat_org) with low, medium, and high groups coded 1, 2, and 3. The structural model would now include two dummy codes representing the difference relative to a reference category. Each dummy code (D_2 and D_3) would then interact with the latent conscientiousness factor. The regression equation is as follows.

$$\begin{aligned} \texttt{cwb}_i = {} & \beta_0 + \beta_1(\texttt{consci}_i) + \beta_2(D_{2i}) + \beta_3(D_{3i}) \\ & + \beta_4(\texttt{consci}_i \times D_{2i}) + \beta_5(\texttt{consci}_i \times D_{3i}) + \zeta_i \end{aligned} \tag{2}$$

The Blimp syntax excerpt below lists cat_org on the NOMINAL line, but it is otherwise identical to the binary model.

```
NOMINAL: cat_org;    # Define nominal variables
LATENT:  cwb consci; # Define latent variables

## Begin Modeling Syntax
MODEL:
  cat_org ~ 1;
  consci ~ cat_org;
  cwb ~ consci cat_org consci*cat_org;
  # Specify cwb and consci measurement models here

## Simple effects for categorical orgcon
SIMPLE: consci | cat_org;
```

In this case, Blimp invokes a multinomial logistic model for `cat_org`. In both models where it is a predictor, Blimp automatically creates a pair of dummy codes, treating the lowest numeric code as the reference group. The following syntax excerpt is an equivalent specification of the focal structural model that makes the automatic dummy coding more explicit.

```
## Begin Modeling Syntax
MODEL:
  cwb ~ consci cat_org.2 cat_org.3
        consci*cat_org.2 consci*cat_org.3;
```

Above, adding a period followed by the category's numeric code references the dummy code for that category. For example, `cat_org.2` is equivalent to D_2 in Equation (2). The substantive interpretations parallel any multiple regression with an interaction between multicategorical and continuous predictors. Where the dummy codes represent the differences between the reference group and the category. Finally, alternative or custom coding schemes are possible by embedding logical statements as predictors in a regression equation (see Chapter 2 in the Blimp User Guide for details; Keller & Enders, 2022).

References

Keller, B. T., & Enders, C. K. (2022). *Blimp user's guide (version 3.0)*. Los Angeles, CA.