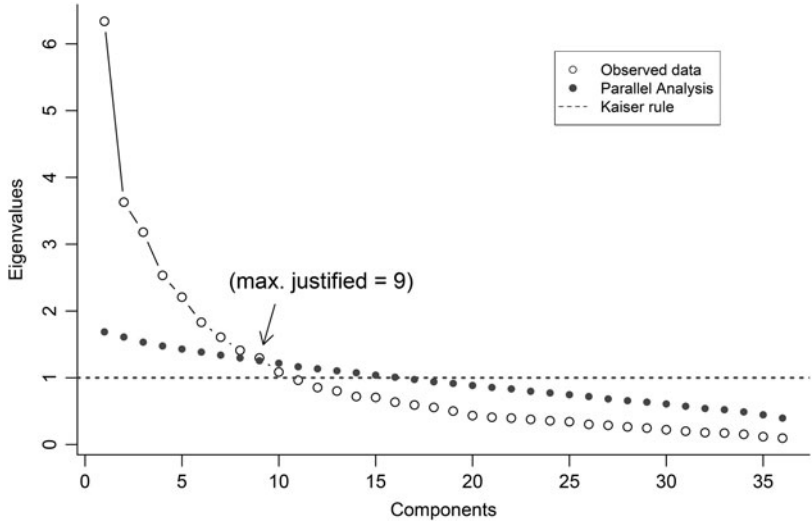

FIGURE C.1. Scree plot showing eigenvalues calculated from the correlation matrix of the observed survey data, which comprised responses to 36 survey items from each participant, and the simulated eigenvalues from parallel analysis. The arrow indicates the maximum number of factors justified jointly by the Kaiser rule and parallel analysis.

Factor analysis is a powerful dimension reduction routine; however, it requires the researcher to determine *a priori* how many dimensions of variability (factors) the model should locate. If this decision process is not guided by principled criteria, one danger is that the researcher could end up selecting a model that returns a factor structure that confirms or that is most easily interpretable with respect to initial hypotheses about the primary dimensions of variability in the data, rather than the model with the greatest explanatory power (for related discussion, we recommend Harrell, 2001; Simmons et al., 2011).

For the present analysis, rather than explore various different decision criteria, thereby risking inflated type I error rates, we selected two principled and broadly accepted approaches advocated in the statistical literature, parallel analysis and the Kaiser rule (see Bandalos & Boehm-Kaufman, 2008), and used their common denominator as the number of factors to be located. Parallel analysis is a simulation procedure using randomly generated data to estimate the number of components for a dataset of a given size (here, 277 participants × 36 survey items) that have greater-than-chance variability. For the parallel analysis, 100 Monte Carlo simulations were performed, each time generating a random dataset with dimensions 277×36 and then calculating the corresponding correlation matrix and eigenvalues (i.e., the scaling factors used in a linear transformation of a correlation matrix). The eigenvalues averaged across these simulations were then compared to the observed eigenvalues, as shown in the Scree plot in Figure C.1, which displays the variance associated with each component in the dataset. When the eigenvalues for components in the observed data are greater than the eigenvalues from the simulated data, the variability in these components is larger than expected due to random

noise. Parallel analysis suggested a nine-factor model (see Franklin, Gibson, Robertson, Pohlmann, & Fralish, 1995, for discussion of parallel analysis being resistant to overextracting factors). The second technique is the Kaiser rule, which is to set the number of factors for a given analysis equal to the number of eigenvalues >1.0 in the correlation matrix of observed values. The Kaiser rule suggested a 10-factor model. The model reported above is a nine-factor model as this was the maximum number of factors suggested by all decision criteria. The model was defined to perform a varimax rotation, which locates orthogonal (uncorrelated) latent variables, and to calculate Thompson regression scores for each participant. Thompson regression scores are the observed values for the items in that factor, standardized across subjects, and weighted by loading values (DiStefano, Zhu, & Mîndrila, 2009).