## 5.5 Conclusion

Today the enterprise known as structural equation modeling is increasingly under fire. The founding fathers have retired, their teachings are forgotten, and practitioners, teachers, and researchers currently find the methodology they inherited difficult to either defend or supplant. Modern SEM textbooks are preoccupied with parameter estimation and rarely explicate the role that those parameters play in causal explanations or in policy analysis; examples dealing with the effects of interventions are conspicuously absent, for instance. Research in SEM now focuses almost exclusively on model fitting, while issues pertaining to the meaning and usage of SEM's models are subjects of confusion and controversy.

I am thoroughly convinced that the contemporary crisis in SEM originates in the lack of a mathematical language for handling the causal information embedded in structural equations. Graphical models have provided such a language. They have thus helped us answer many of the unsettled questions that drive the current crisis:

1. Under what conditions can we give causal interpretation to structural coefficients?
2. What are the causal assumptions underlying a given structural equation model?
3. What are the statistical implications of any given structural equation model?
4. What is the operational meaning of a given structural coefficient?
5. What are the policy-making claims of any given structural equation model?
6. When is an equation not structural?

This chapter has described the conceptual developments that now resolve such foundational questions. In addition, we have presented several tools to be used in answering questions of practical importance:

1. When are two structural equation models observationally indistinguishable?
2. When do regression coefficients represent path coefficients?
3. When would the addition of a regressor introduce bias?

4. How can we tell, prior to collecting any data, which path coefficients can be identified?

5. When can we dispose of the linearity-normality assumption and still extract causal information from the data?

I remain hopeful that researchers will recognize the benefits of these concepts and tools and use them to revitalize causal analysis in the social and behavioral sciences.

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