from the training sample as priors, construct a posterior predictive distribution for the unobserved time point given that individual's growth curve up to that point. The result of all this will be an analysis in which the data help make the necessary exchangeability judgments adaptively, and in which the posterior predictive variability captures all three sources of uncertainty above—structural, estimation and prediction.

I am grateful to Professor Rao for having written a paper that provoked a great deal of thought in me, and I look forward to comparing the results of this propagation of uncertainty analysis with those from his prediction methods and from other approaches to prediction in growth curve models.

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In preparing these remarks I have had the benefit of comments from James Hodges and John Rolph.

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Comment

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1. INTRODUCTION

It gives me great pleasure to comment on this paper by Professor Rao. The central issues raised here are choice of a prediction model and assessment of associated prediction errors for growth curve data. Professor Rao has given us a number of different approaches to these problems. I offer a few general comments and some specific comments, mention alternative directions in growth curve modeling and prediction and also make some comments on the mice data used in this paper.

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2. SOME GENERAL COMMENTS

For a statistician, context should always play a role in the modeling process. Too often, data are analyzed without regard to the original purpose of their collection. This can be especially true when modeling a growth process where biological reasoning may help in the modeling and subsequent interpretation of results. The first thing I noticed about this paper is that there is no clear description of the three data sets used as illustrations or why they are even interesting for prediction purposes. (Does anyone understand what