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On choosing a model for estimating individual differences in latent growth trajectories◊

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A B S T R A C T

Studies on the speed at which tasks of varying difficulties are processed frequently meet methodological obstacles, such as the difficulty to achieve reliable individual differences in parameters that describe response time growth with increasing task difficulty and the lack of stable correlations between growth parameters and external variables. In this computer simulation study, we demonstrate that instability and the systematic underestimation of correlations between growth parameters and external variables can be due to the choice of an inappropriate model to describe individual growth trajectories. Furthermore, the failure to choose a sufficiently flexible function for modeling can prevent the identification of individual differences in a shape of growth. Although we discuss our results and conclusions within the context of processing speed research, they are true for any studies that involve the modeling of latent change curves.

Keywords: latent growth modeling, computer simulation study, individual differences, speed of information processing, cognitive ability

A novel research approach developed by early chronometric researchers in the mid-1970s aimed to bring cognitive models developed within experimental psychology to the field of research on individual differences. Obtaining individual-level response times on tasks similar to those constructed in the experimental paradigm and explicitly evaluating parameters of a theoretical model for each individual participant, researchers hoped to be able to analyze individual differences in theoretically tractable meaningful indexes. Estimating correlations between these indexes and conventional psychometric measures, primarily with intelligence, would allow researchers to go beyond the limits of descriptive correlation studies and gain an understanding of the nature of individual differences in cognitive ability.

One of the most obvious examples of this research logic involves studies on individual differences in the rate of increase in choice reaction time with an increase in the number of alternative stimuli (a comprehensive review of this research paradigm can be found in (Jensen, 1987a, 1998a, 2006)). These studies originated from experimental psychology and adopted a theoretical model of information processing (Hick, 1952; Hyman, 1953), which was based on Shennon's (1948) formula of information and implied a very restricted hypothesis of a precise (logarithmic) relationship between response time and the number of stimuli (we will come back to this model later on in this paper). Other examples of the same approach are studies on individual differences in visual scanning and Sternberg's (1966) memory scanning tasks (e.g., Jensen, 1987b; Neubauer et al., 1997), and studies by Hunt on individual differences in visual search, visual matching, span of apprehension (e.g., Palmer, MacLeod, Hunt, Davidson, 1985), and sentence verification (e.g., see (Hunt, MacLeod, 1978) for a discussion that also points out important methodological issues that arise when the cognitive approach is brought to the field of individual differences).

These early chronometric studies were quite time-consuming, as they required estimating certain parameters from individual-level data and were obviously limited in what estimates of quality of model fit could be obtained and how the parameters were computed. The development of structural equation modeling, and primarily of the latent growth modeling approach (Duncan & Duncan, 1995; McArdle & Epstein, 1987; Meredith & Tisak, 1990), gave new life to chronometric studies on

◊ The English version of the paper is slightly shorter than the version published in Russian. Our simulation studies are fully described in both versions. However, several basic introductory notes and concluding remarks were omitted, as they were viewed as unimportant for an English-speaking reader.

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individual differences. Interestingly, one of the first papers on latent growth modeling (Meredith & Tisak, 1990) explicitly mentioned this new analytical technique's applicability to the evaluation of latent change in psychological variables that occur not only with time, but also with "age, grade, trial number, degree of arousal, experimental condition, test form or stimulus intensity" (p.107). However, this type of analysis, although it has become extensively common in longitudinal research, was beyond the attention of chronometric studies for a surprisingly long time. One of the first authors who started using structural equation modeling to analyze trajectories of response time change over conditions of a cognitive task was Schweizer (2006a, 2006b). Note, however, that his version of modeling is not the latent growth modeling in the classical sense, as it works only with covariance matrices and does not include the analysis of mean structure. The advantages of conventional latent growth modeling and its recent developments for the analysis of individual differences in response times on tasks of varying difficulty were discussed in detail by Dodonov and Dodonova (2012).

However, although the availability of sophisticated analytical techniques was able to substantially enrich studies on individual differences in trajectories of response time change over conditions of cognitive tasks, several methodological problems that accompany this research approach still remain unresolved, which has caused some researchers to be skeptical about this paradigm's future (e.g., Lohman, 1994). Again, a good example of theory-based expectations that have not been fully justified and gave rise to methodological controversies can be found in the field of studies on individual differences in choice reaction times obtained by Hick's task. Recall that the processing of this task was commonly interpreted in terms of information theory, which implied that obtained response times should be described by a logarithmic function $f(x) = a \cdot log_2(x+1) + b$, where b is the parameter of the baseline level (intercept) regarded as the speed of sensory-motor processes and a is the response time growth rate with an increase in the number of alternative stimuli, which is meant to represent the speed of information processing in a cognitive system. When this model was brought to the area of individual differences, an obvious expectation (first formulated by Roth (1964)) was that this growth parameter is related to cognitive ability. In other words, lower-ability participants were expected to be slower in information processing and thus have steeper trajectories of response time growth with increasing amount of information. However, empirical results that have actually been obtained in the field are contradictory. Several studies have failed to find a significant association between the growth parameter of Hick's task and cognitive ability (e.g., Beauducel and Brocke, 1993), while others have reported moderate statistically significant correlations (e.g., Neubauer et al., 1997; Rammsayer & Brandler, 2007). In addition, at least some studies have reported that correlations between the intercept of the Hick's function and ability level are higher than those obtained between the slope and cognitive ability (Jensen, 1987a, 1998a).

Commenting on these contradictory results, Jensen (1998b) claimed that this is primarily a methodological problem: "The frequent failure of the slope parameter (b) of the Hick function to support its theoretically predicted relationship to IQ is a bum rap.... This fact, however, is not a failure of the theoretical prediction, but rather the effect of inherent statistical artifacts that suppress the theoretically expected correlation." (p. 43). For example, Jensen mentioned that the growth parameter is always less reliable than the intercept. At the same time, the growth and baseline parameters share the same measurement errors, which are negatively correlated with each other. This means that a baseline-level parameter acts as a suppressor variable when the association between the growth parameter and any external variable is analyzed. (A detailed discussion on this can be found, for example, in Jensen, 1998b).

At the same time, there is another methodological point that has rarely been mentioned when problems in evaluating individual differences in response time growth parameters are discussed. Data obtained within Hick's paradigm have always been modeled by the logarithmic function, as this is the only shape of growth that can be hypothesized if the processing of this task is interpreted in terms of information theory. A discussion on whether the results obtained within an experimental approach confirm the functional relationship between the choice reaction time and the amount of information lies far beyond the scope of this paper (e.g., see Kornblum (1969) for a hypothesis that this is probability of non-repetition of stimuli rather than the amount of information that is a true independent variable in such studies). However, a question of obvious importance for studies on individual differences is whether the logarithmic function is able to provide reasonably good fit to individual-level data obtained in empirical research.

To our knowledge, Arthur Jensen, one of the most prominent researchers on individual differences in choice reaction times, never mentioned the failure of a logarithmic function (or, in Jensen's terms, a linear function in semi-log scales) to fit empirical results. However, one study by Neubauer (1991) that involved a modified Hick's paradigm reported that the results of about 20% of participants did not correspond with the theoretically expected relationship. Besides, it is worth remembering that the sole index indicating correspondence between the model and the data within this paradigm was R^2 (percent of explained variance), for which no formal estimate of statistical significance is available.

Consider, for example, a value of R = .971 reported in a study by Jensen (1987b) for data averaged over all participants. The respective R^2 is .943. Leaving aside the question of what values of R^2 were actually obtained for individual-level data in this dataset, we provide two examples of sets of four dots that could be fitted by a logarithmic function with R^2 = .943 (Figure 1A and 1B). A graph of the logarithmic function $f(x) = a \cdot log_2(x+1) + b$ with parameters optimally describing the respective dataset is shown in blue. Although the shape of growth is obviously different in these two examples, the logarithmic function is not flexible enough to adequately describe growth trajectories. To illustrate this, we fitted the same sets of dots with a more flexible function $f(x) = a/(x+k) + b$ wherein the shape of growth is described by two parameters instead of a single growth parameter of the logarithmic function (see Figure 1C and 1D). This function fitted the data much better; the R^2 increased to .998 in both cases.

The most important point is, however, that the two models in this example differed not only in how well they

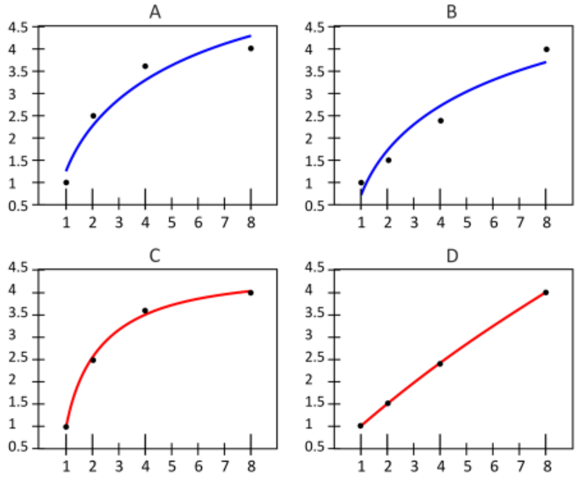

Figure 1. Examples of datasets that could be approximated by a logarithmic function with $R^2 = .943$ (A and B) and their approximation by a more flexible function (C and D).

fitted the data, but also in how well the parameters of these functions captured the differences in the shape of growth. For the two virtual participants in the above example, estimates of the parameter *a* (which is the only growth parameter within the logarithmic model) were almost equal: *a* = 1.01 and *a* = .99, respectively. At the same time, the more flexible function allowed the differences between these virtual participants to be identified in both parameters describing growth: *a* = - 4.84 and *k* = .33 for the graph in Figure 1C and *a* = 848 and *k* = 40.16 for the graph in Figure 1D. In other words, in our illustrative example, insufficient flexibility of a function was a factor that did not allow individual differences in growth parameters to be revealed.

However, although the failure to reliably identify growth parameter variance is a common problem for such studies, a model's possible inadequacy and the consequences of choosing an improper model have rarely been discussed as a plausible cause of this methodological problem. The two studies described below aimed, to some extent, to compensate for this deficiency. Using computer simulations, we analyzed how the improper choice of a function in growth modeling can affect estimates of individual differences in growth parameters, and subsequently, the associations between these parameters and external variables.

Study 1: Choice of a latent growth model and its effect on the significance of individual growth parameter variance

The above example illustrated how the specific function chosen determined whether there were differences in growth parameters for two individual datasets similar to those that can be obtained with Hick's task. In this study, the same problem was formulated in a more appropriate context for contemporary statistics, namely in terms of the significance of estimates of the variance of latent growth components obtained within a structural equation modeling framework. We thus analyzed how the improper choice of a model to describe an increasing trend observed in the data can affect the variance of latent growth components and its possible interpretation as statistically significant or non-significant.

Methods

All analyses described in this paper were performed in R (R Core Team, 2012). Package lavaan (Rosseel, 2012) was used for latent growth modeling. An R code used to generate and model data can be found at http://dodonovs.com/R/101-r.htm.

As stated above, the first study aimed to analyze how the choice of a more or less flexible function can affect the significance of estimates of variances of latent components representing baseline level and latent change in modeling. We generated data that could be plausibly described by either a most simple linear function, wherein growth is described by a single slope parameter, or by a non-linear quadratic function, wherein growth is described by two parameters: linear and quadratic.

In each step, a generated dataset included 500 rows (500 virtual participants) with each row representing nine levels of a manifest variable (for example, nine difficulty levels in a hypothetical task of varying difficulty). For each virtual participant, data were sampled from a quadratic relation with some noise added. At the same time, average data in the dataset increased almost linearly (see Figure 1). Generated numbers were such that they mimicked plausible values of response times in chronometric studies, which merely served an illustrative purpose, as this simulation arose in the context of evaluating individual differences in processing speed when completing tasks of varying difficulty.

Two alternative models, linear and quadratic, were fitted to the data (Figures 2B and 2C, respectively). In both models, a latent component representing baseline level

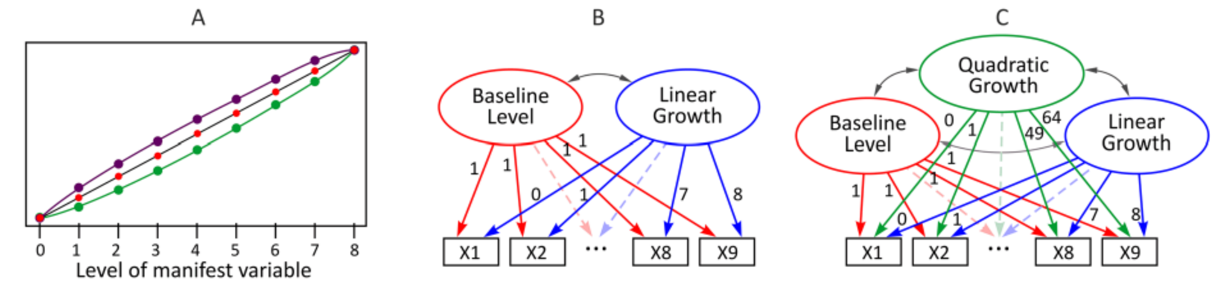

Figure 2. **A**. Examples of individual-level data generated from quadratic relations (green and purple graphs) and a linear trend for average data (red graph). **B** and **C**. Models representing linear and quadratic growth.

was specified by fixing its loadings to manifest variables at 1. To specify a linear growth component in each of the models, its loadings were fixed by linearly increasing numbers: 0, 1, 2, 3, 4, 5, 6, 7, and 8. Finally, loadings on a quadratic growth component of the quadratic model were fixed at 0, 1, 4, 9, 16, 25, 36, 49, and 64. All elements in a variance-covariance matrix of latent components were freely estimated in each model. Parameters of interest for this study were the variances of latent components (primarily of the growth components) and their associated standard errors and significance levels. Because magnitudes of variance are not informative by themselves, we focused on their estimates of significance (p-levels computed based on standard errors).

The standardized root mean square residual (SRMR; Jöreskog & Sörbom, 1981) was used as an index of model fit. Incremental indexes were not considered because their computation would require appropriate re-specification of a null model (Widaman & Thompson, 2003), which would not add any valuable information while costing additional time to simulate.

The entire procedure of generating data and fitting the two alternative models was repeated 500 times. As a result, distributions of SRMR values and p-values associated with estimated variances of latent components were obtained for each linear and quadratic model.

Results

Distributions of SRMR obtained for linear (black graph) and quadratic (green graph) models are shown in Figure 3A. When the two models are compared, the quadratic model looks preferable (which is expectable because the data were generated from the quadratic function). At the same time, the SRMR values of the linear model are also acceptable; in the absence of the “true” quadratic model for comparison, the linear model could be regarded as well-fitted to the data. However, for about 30% of generations, an optimal solution for the linear model was found at negative estimates of the variance of the latent growth component; these results were withdrawn from the analysis reported below. For the quadratic model, estimates of the variance of the linear growth component were negative in .8% of generations; estimates of the quadratic growth component’s variance were negative in .6% of generations. These generations were also withdrawn.

The variance of the latent baseline component was significant ($p < .001$) in both linear and quadratic models. However, as mentioned above, the variances of growth components were of primary interest for this study. Distribution of standard-errors-based p-levels associated with the variance of the growth component in the linear model is shown in Figure 3B. Even with a liberal criterion of $p = .05$, the variance could be interpreted as significantly different from zero only in 6.4% of generations. In other words, even when the variance was positively estimated within the non-flexible linear model, it was still statistically non-distinguishable from zero.

Figure 3C shows the distributions of the p-level values obtained for the variances of the linear (blue graph) and quadratic (green graph) growth components of the “true” quadratic model. With the same criterion $p = .05$ for the same generated datasets, the variance of the linear growth component was significant in 76.4% of generations, and that of the quadratic growth component was significant in 82.2% of generations.

Discussion

Generating data for this study, we mimicked a plausible situation in which a researcher would assume a linear shape of growth based on the preliminary analysis of average data (e.g., linear increase in response times with increasing task difficulty). Fit indexes would indicate good overall fit of the linear model. However, based on parameter estimates of the linear model, a researcher would conclude that the variance of the latent growth component was insignificant. To continue our example of modeling response times in a task with increasing difficulty, no individual differences in the rate of increase in response time would be found. Moreover, the growth component’s insignificant variance would ban further evaluation of the association of individual response time growth rates with external variables (e.g., with cognitive ability).

However, the problem was that the real shape of the growth in the data was nonlinear. For the same data, the “true” quadratic model allowed the identification of two latent growth components with significant estimated variances. However, information about individual differences in the growth trajectories was lost when an insufficiently flexible linear function was used for modeling.

The above by no means indicates that insignificant variance of the latent growth component is always an artifact of choosing an inappropriate model. Rather, the correct choice of a model is necessary, but not sufficient to

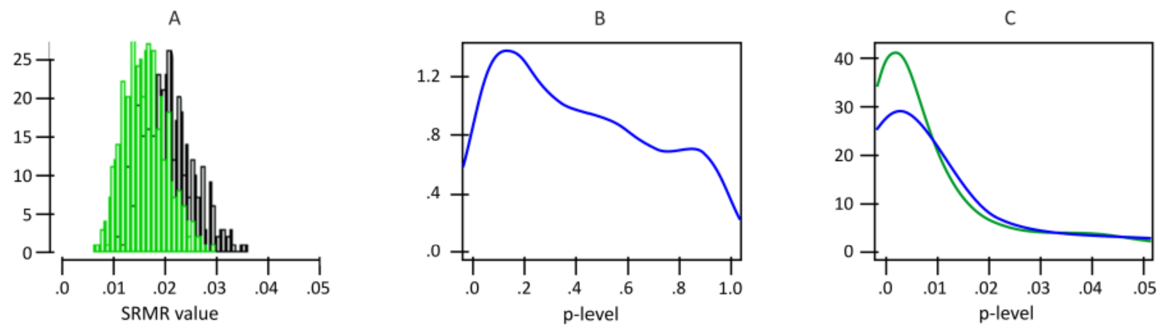

Figure 3. **A**. SRMR values for the linear (black graph) and quadratic (green graph) models. **B**. p-values associated with variance of the linear growth component in the linear model. **C**. p-values associated with variance of the linear (blue graph) and quadratic (green graph) growth components in the quadratic model.

adequately identify latent growth components and their sample variances. A correctly chosen model does not by itself guarantee significant variance; however, whenever individual differences in growth trajectories are found to be negligible, it seems reasonable to question whether a preferred model was sufficiently flexible to reveal theoretically expected differences.

Study 2: Choice of a latent growth model and its effect on the estimates of correlations between growth parameters and external variables

The previous study was concerned with the flexibility of functions chosen to model individual growth trajectories as a possible source of misidentification of the variances of growth components. It is obvious, however, that the other side of the coin is that nine data points from the above example would be perfectly fitted by an eighth-order polynomial, which does not mean that it makes any sense to use this function in modeling. There is always a kind of balance between the quality of fit a model provides for the data and the number of parameters involved in model construction.

At the same time, even functions with the same number of parameters can differ in how well they describe increasing data, which in turn can affect estimates of associations between growth parameters and external variables. The question of whether a choice of a model (among equally flexible models) can significantly affect correlations between growth parameters and external variables was analyzed in the following study. Unlike the previous study, these computer simulations involved applying two models with the same number of parameters, with a single parameter to describe growth, although the shape of growth trajectories modeled by these functions was slightly different.

Methods

Similarly to the previous study, a dataset consisting of 500 rows (500 virtual participants) was generated, with each row including nine manifest variables (e.g., representing nine difficulty levels of a cognitive task). For each virtual participant, data were generated from the power function $f(x) = a \cdot \sqrt{x} + b$ with some noise added. In addition, one more variable was generated so that its correlation with a latent growth component was moderately positive (in our example of a chronometric study, this external variable could represent, for instance, a measure of cognitive ability).

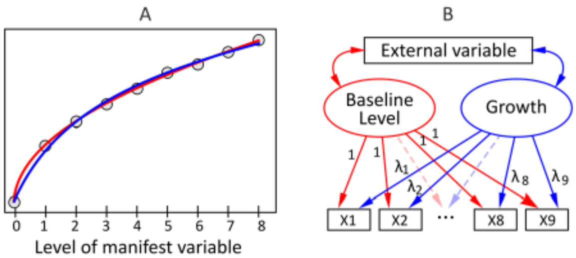

Figure 4. **A**. Example of individual-level data and the two functions with optimally-fitted parameters: the true power function (red graph) and the alternative logarithmic function (blue graph). **B**. A model with an external variable (values used to fix $\lambda_1 \ldots \lambda_9$ can be found in the text).

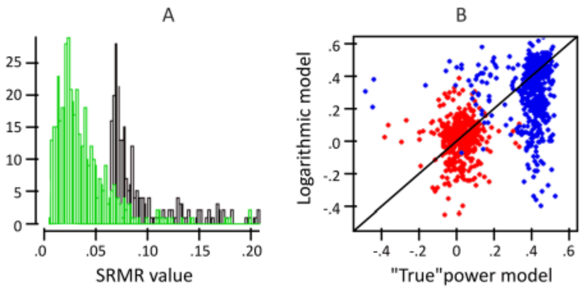

Figure 5. **A**. SRMR values for the logarithmic (black graph) and power (green graph) models. **B**. Correlation coefficients obtained within the power and logarithmic models for the latent growth (blue graph) and baseline (red graph) components.

Two models were fitted to the data: the true power model with loadings of the latent growth component fixed at 0, 1, 1.414, 1.732, 2, 2.236, 2.449, 2.646, and 2.828 and a logarithmic model $f(x) = log_2(x + 1) + b$. In the latter model, the loadings of the growth component were fixed at 0, 1, 1.585, 2, 2.322, 2.585, 2.807, 3, and 3.170. Correlations between both the baseline and growth latent components and the external variable were explicitly estimated within the model. Figure 4A shows an example of a dataset generated for one virtual participant and the shape of the two functions fitted to it. Figure 4B shows a general model under consideration. Note that the power and logarithmic models differed only in the numbers used to fix the loadings of the latent growth component.

All steps were repeated 500 times. In each step, SRMR values were recorded to evaluate the overall fit of each of the two models. Correlations between the latent baseline and growth components and the external variable were of major interest in further analysis.

Results

Figure 5A shows the distributions of SRMR obtained for the power (green graph) and the logarithmic (black graph) models. Naturally, the true model generally fitted the data better than the alternative. However, the fit of the alternative logarithmic model was also acceptable; the model could be regarded as well-fitted, especially in the absence of the true model as a comparison model.

Figure 5B shows estimated correlations between each of the two latent components and the external variable. Blue dots represent the results obtained for the latent growth component, and red dots show the results obtained for the latent baseline component. For each point on the graph, the x-coordinate represents the magnitude of the correlation between the respective component and the external variable obtained within the true power model; the y-coordinate is the similar value obtained within the “wrong” (although still acceptable) logarithmic model. In an ideal case of absolute insensitivity of the latent component’s correlation with external variable to the choice of a model, all dots in Figure 5B would lie on a straight line with a slope of 45° (this line is shown on the graph for clarity).

However, as shown in Figure 5B, this is far from being true. Even though the shapes of the two functions under consideration were close, the model choice largely affected estimates of the correlations between latent components and the external variable. The latent growth component’s correlations with the external variable lied in a narrow interval from approximately .35 to .55 when estimated within the true model. At the same time, when an inappropriate model was applied to the same data, the estimated correlations between the growth component and the external variable had a great deal of variation, with the main body of coefficients lying between -.20 to .60. Importantly, the dots in the blue graph are mostly well below the diagonal, meaning that correlations between the latent growth component and the external variable generally tended to be underestimated within the inappropriate model, compared to the true model.

Correlations between the latent baseline component and the external variable were close to zero in this study, and the results shown in the red graph in Figure 5B are thus not very informative. However, what still can be concluded is that even in this case, the choice of a model was obviously not irrelevant and largely affected the magnitudes of correlations between the baseline component and external variables.

Discussion

The results of this computer simulation study clearly demonstrated the potential costs of choosing the wrong function in studies aiming to analyze latent level associations between individual growth rates and external variables. For the same generated data, the application of a true model allowed moderate positive correlations between the latent growth component and the external variable to be accurately identified, while the respective correlations estimated within the inappropriate (although still acceptable) model varied significantly from weekly negative to moderately positive and generally tended to be underestimated. To continue our example of the relationship between cognitive ability and individual rates of response time growth with increasing task difficulty, a researcher would likely mistakenly conclude that the association was statistically insignificant, which would be an artifact caused by the model's failure to adequately describe the data.

General discussion

Discussing the problem of selecting an adequate model to describe empirical data, we intentionally considered only its very specific methodological aspects, namely the potential consequences that the improper choice of a model can have for studies on individual differences. Certainly, the question of how to construct a model that would adequately represent empirical data goes far beyond these limits and lies in the area of epistemology and ontology. Can an ability of one model to describe empirical facts better than other models be a sufficient reason to accept it as representing reality? Can any model at all truly represent reality, not just save the appearances? These questions go back at least to the conflict between Galileo Galilei and the Catholic Church and have remained relevant since the famous letter by Cardinal Bellarmine (Blackwell, 1991).

The aim of this paper was by no means to discuss to what extent and under what conditions a model fitted to properly collected experimental data can be considered a correct and adequate representation of reality. We only aimed to emphasize the potential costs of applying an improper model developed within an experimental approach to studies on individual differences. Indeed, the idea of applying theory-based, experimentally verified models to the evaluation of individual differences in performance was an advantageous step of early chronometric studies. Modern statistical methods improved the power of such studies and allowed both general trends and individual differences in parameters to be analyzed within the same models, as well as a posteriori evaluations of the overall fit of a model to empirical data. However, applying sophisticated statistical methods does not by itself necessarily help to resolve methodological problems, including those related to the identification of reliable individual differences in parameters that describe individual trajectories of response time change over conditions of a cognitive task and their associations with other variables. This study demonstrated that the improper choice of a model to describe growth trajectories can be a cause (or one of causes) of these problems. This issue is particularly important because it is fully under researchers' control, as they explicitly specify the hypothetical shape of a growth function.

Certainly, it would be inaccurate to state any direct correspondence between the results of our computer simulation studies and, for example, empirical data obtained within the Hick's paradigm. However, it is worth recalling some of the controversies in studies on individual differences in choice reaction time: contrary to theoretical expectations, correlations between cognitive ability and the parameter of response time growth with increasing numbers of alternative stimuli are relatively low and not replicable in all studies, varying in absolute values from moderate to non-distinguishable from zero, and accompanied by low reliability and low variance of the growth parameter. There certainly are a number of possible causes of the systematic underestimation of variances and the instability of correlations with external variables, and it is generally impossible to say which causes applied to those studies not analyzing empirical data. However, our simulation results clearly demonstrate that one of the methodological problems in studies within Hick's paradigm could be the improper choice of a model to describe individual-level data. This is especially plausible, as these studies are somewhat unique in that no model other that the logarithmic one has ever been applied to the data, even when there were enough reasons to conclude that the logarithmic function did not fit empirical results.

In conclusion, it is important to emphasize that although this study discussed issues related to individual differences in the processing of cognitive tasks of varying difficulty, models that describe growth at a latent level have extremely wide applicability in psychological studies. Regardless of whether, for example, longitudinal changes, effects of training or forgetting are studied, researchers hope to identify reliable individual differences in parameters that describe growth and stable associations between these parameters and external variables of interest. As such, this study's conclusions on the choice of the model describing growth and its crucial role for evaluating individual differences in growth trajectories are equally true for any study that involves modeling of latent level changes in psychological variables.

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