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On the Use of Growth Models to Study Normal Cognitive Aging

Abstract

Growth models (GM) of the mixed-effects and latent curve varieties have become popular methodological tools in lifespan research. One of the major advantages of GM is their flexibility in studying individual differences in change. We scrutinized the change functions of GM used in five years of publications on cognitive aging. Of the 162 publications that we identified, 88% test linear or quadratic polynomials, and fewer than 5% apply functions that are nonlinear in their parameters, such as exponential decline. This apparent bias in favor of polynomial decomposition calls for exploring what conclusions about individual differences in change are likely to be drawn if one applies linear or quadratic GMs to data simulated under a conceptually and empirically plausible model of exponential cognitive decline from adulthood to old age. Hence, we set up a simulation that manipulated the rate of exponential decline, measurement reliability, number of occasions, interval width, and sample size. True rate of decline and interval width influenced results strongly, number of occasions and measurement reliability exerted a moderate effect, and the effects of sample size appeared relatively minor. Critically, our results show that fit statistics generally do not differentiate misspecified linear or quadratic models from the true exponential model. Moreover, power to detect variance in change for the linear and quadratic GMs is low, and estimates of individual differences in level and change can be highly biased by model misspecification. We encourage researchers to also consider plausible nonlinear change functions when studying behavioral development across the lifespan.

Abstract: 249 words

Running Head: Growth Models in Normal Cognitive Aging

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On the Use of Growth Models to Study Normal Cognitive Aging

The last 25 years have seen major advances in statistical models for characterizing developmental change (e.g., Hertzog & Nesselroade, 2003; Little, 2013; Singer & Willett, 2003). One popular method is the growth model (GM), implemented as a linear mixed-effects model (LMEM; Bryk & Raudenbush, 1987; Laird & Ware, 1982) or a latent curve model (McArdle, 1988; Meredith & Tisak, 1990). The critical feature of the GM is that it models change by specifying an intercept and a slope component describing the overall level and change across time, respectively. For both components, one can estimate the mean parameter and variance parameter reflecting individual deviations around the mean. Given individual differences in level and/or in change, the GM can be readily expanded to test antecedents and/or correlates of such individual differences.

The Growth Model

The *linear* GM specifies a variable Y_{ij} for an individual j at time i $(i=0,1,\ldots,T-1)$ in terms of a level π_{0j} and a linear rate of growth π_{1j} multiplied by age a_{ij} (often centered around its mean) at time i for each individual j, plus a residual E_{ij}:

$$\begin{aligned} Y_{ij} &= \pi_{0j} + \pi_{1j} a_{ij} + E_{ij} \\ \pi_{0j} &= \beta_0 + U_{0j} \\ \pi_{1j} &= \beta_1 + U_{1j} \end{aligned} \qquad (1)$$

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The linear GM predicts all individual growth trajectories to be straight lines. The level corresponds to the intercept (prediction when a_{ij}=0) and the rate of growth to the linear slope (predicted change in Y for one unit change in a). Both level and change have a mean value of β_0 and β_1 and a subject-specific deviation from the mean of U_{0j} and U_{1j}, respectively (Bryk & Raudenbush, 1987; Laird & Ware, 1982). β_0 and β_1 are fixed effects and U_{0j} and U_{1j} are random effects, assumed to be normally distributed around zero (with variances σ^2_L and σ^2_C) and to possibly covary (σ_{LC}). The errors E_{ij} are typically assumed independently and normally distributed with time-invariant error variance σ^2_E.

Another popular specification of the GM is the *quadratic GM* of Equation (2) that allows the predicted trajectories to have a single change in direction. This model augments the linear GM by adding a second (quadratic) change component that linearly relates age squared to Y_{ij}:

$$\begin{aligned} Y_{ij} &= \pi_{0j} + \pi_{1j} a_{ij} + \beta_2 a_{ij}^2 + E_{ij} \\ \pi_{0j} &= \beta_0 + U_{0j} \\ \pi_{1j} &= \beta_1 + U_{1j} \end{aligned} \qquad (2)$$

Compared to the linear model, the quadratic additionally estimates one additional parameter, β_2, which allows the predicted trajectories to follow a quadratic polynomial. Although the quadratic change component could also be specified with random effects, their estimation is typically not included in extant applications (in our literature review, of the 40 records that tested a quadratic model, only nine declared having tested random effects of the quadratic slope, and of those only three found positive evidence).

Linear and quadratic GMs are often contrasted with a simpler *no growth* or *level model* that postulates no change whatsoever, with individuals maintaining the same level score over time (Equation (3); Widaman & Thompson, 2003):

$$\begin{aligned} Y_{ij} &= \pi_{0j} + E_{ij} \\ \pi_{0j} &= \beta_0 + U_{0j} \end{aligned}, \qquad (3)$$

to test the hypothesis that Y_{ij} changes over time.

The Growth Model as a Nonlinear Mixed-Effects Model

So far, the specified GMs represent change as a linear combination of level, change(s), and errors, and are thus linear in their parameters (Davidian & Giltinan, 1995). The linearity of the parameters is not to be confused with the linearity of the shape of specified change (Cudeck & Harring, 2007). In particular, the quadratic GM specifies a nonlinear trajectory of change, despite being a LMEM.

LMEMs can be generalized to allow for nonlinear relations between Y_{ij} and the parameters of the growth components (Davidian & Giltinan, 1995), generating nonlinear mixed-effects models (NLMEMs). These models have been successfully applied in various disciplines (e.g., pharmacokinetics, biology, demography, finance), to capture underlying change processes that are inherently nonlinear (e.g., drug effects and population growth often follow a logistic function, accumulation of financial interests is often exponential). One can argue that many psychological constructs change nonlinearly over time. For instance, effects of accumulating age-related insults to an adult's central nervous system could be modeled by exponential decline. Indeed, nonlinear GM have occasionally been applied to study adult cognitive change, both normal (e.g., McArdle, Ferrer-Caja, Hamagami, & Woodcock, 2002; Grimm, McArdle, & Hamagami, 2007) and pathological (e.g., Driscoll, Resnick, Troncoso, An, O'Brien, & Zonderman, 2006).

One variant of the (nonlinear) exponential model, as employed by several authors (e.g., McArdle et al., 2002; Grimm et al., 2007) is:

$$\begin{aligned} Y_{ij} &= \pi_{0j} + \pi_{1j}\, e^{\gamma a_{ij}} + E_{ij} \\ \pi_{0j} &= \beta_0 + U_{0j} \\ \pi_{1j} &= \beta_1 + U_{1j} \end{aligned} \qquad (4)$$

This nonlinear mixed-effects GM specifies an exponential functional form of change, so that as age increases successive gains or losses are not constant but proportional to the current value. Compared to the linear GM, this model estimates one additional parameter, the exponential rate of change γ. Typically, random effects for γ are not estimated in extant applications. However, because of random effects of π_{1j}, which are estimated as the variance of change σ^2_C, individuals are allowed to differ in the amount of exponential decline, ~~but not~~ rather than in its rate.

The Present Study

We start by reviewing five years of scientific literature on applications of the GM to study normal cognitive aging. This review established that the linear and quadratic GMs are very often applied by substantive researchers in this field, whereas nonlinear mixed-effects GMs, on the other hand, are very rarely used.

Justified by this pattern, we evaluated what happens if longitudinal data, created by an underlying exponential model, are analyzed with a linear or quadratic GM. We investigate how well the linear and quadratic GMs preserve or distort individual differences in level and change in such instances. If the individual differences specified by the underlying generating model are largely concordant with those estimated by the misspecified GMs, one would be justified to claim that LMEM GMs are practically useful despite their misspecification. That is, the models would be of the "wrong but useful" kind (cf. Box & Draper, 1987). If, however, the two sets of results lead to discordant inferences about individual differences in change, we would conclude that the misspecified GMs are misleading.

Method

Literature Review

We computed a detailed literature search to study how longitudinal data are commonly analyzed within GMs to study normal cognitive aging. By covering five years of literature we initially obtained 1253 records, which reduced to 162 relevant records for full analysis. The detailed search and screening procedure are described in supplementary material (Appendices 1-2, Table 1, and Figure 1).

Simulation Design

Population model. The exponential population model of Equation (4) was used to generate the data for the Monte Carlo simulation (McArdle, et al., 2002). We specified the existence of individual differences in both level and change, but not in decline rate, γ. This choice was guided by the facts that (a) in our empirical illustration (see below) estimating random effects for the exponential rate failed, (b) extant applications of the exponential model usually exclude random effects for γ, and, more importantly, (c) estimating multiple random effects in both linear and especially NLMEMs requires data denser than those of standard longitudinal panels.

Simulation factors. We based our simulation study on parameter estimates from an exponential model fitted to data from the Betula Project (Nilsson, Bäckman, Erngrund, Nyberg, Adolfsson, Bucht, Karlsson et al., 1997), a well-known study of aging, memory, and dementia. We analyzed the episodic recall scores of 1000 Betula participants assessed four times, at five-year intervals, as a function of age (final range: 35-95 years). We tested the level, linear, quadratic, and exponential GMs and found that the exponential best described the data. We used the estimated population parameters as the basis for the simulation experiment (for full results, see supplementary Table 2 and supplementary Figure 2).

The constant factors were the level mean (β_0 = 20.603), change mean (β_1 = -4.007), level variance (σ^2_L = 30.980), change variance (σ^2_C = 5.041), and level-change covariance (σ_{LC} = -3.163, corresponding to a correlation of -.253). The varying factors were the rate of exponential decline (γ= 0.066, corresponding to the illustration, and γ= 0.033, for a gentler decline) and the Growth Curve Reliability (GCR = .500, .681 - cf. illustration -, or .900, corresponding to σ^2_E = 30.980, 14.541 - cf. illustration -, and 3.442, respectively), defined as the proportion of level variance over total variance at time=0 (age 65; GCR=σ^2_L / (σ^2_L + σ^2_E); McArdle, 1988).

We generated data under six conditions, 2 (γ) by 3 (GCR), to obtain continuous trajectories spanning over a maximum of 71 time points (i.e., from 35 to 105 years). Figure 1 presents 50 random individual trajectories simulated under the six different conditions.

INSERT FIGURE 1 ABOUT HERE

Design factors. In practice, longitudinal studies of long-term change processes often adopt a longitudinal sequence design, which begins with a cross-sectional age-heterogeneous sample of persons and then follows them longitudinally over time. This sampling design generates multiple parallel subsamples differing in initial age, each providing longitudinal data on different segments of the targeted overall age range, with coverage increasing as the number of measurement occasions increases or as the measurement interval widens (Baltes, Reese, & Nesselroade, 1988). We included 10 longitudinal subsamples with 50, 100, or 200 units each, yielding a total sample size of N = 500, 1000, or 2000. Each subsample contained observations representing individuals of initial age 35, 40, 45, etc. to 80 years, observed repeatedly either T = 3 or T = 6 times. Furthermore, we varied Δ, the interval width between adjacent occasions of measurement, going from Δ = 1 to Δ = 5 years in steps of 1 year.

This designs mimics a study where the youngest subsample observed the least (T = 3) at the shortest interval (Δ = 1) would be assessed at ages 35, 36, and 37 years, the next subsample at ages 40, 41, and 42, etc. and the oldest subsample at ages 80, 81, and 82 years. The youngest subsample observed the most (T = 6) at the shortest interval (Δ = 1) would be assessed at ages 35, 36, 37, 38, 39, and 40 years, thus overlapping with the next subsample (ages 40, 41, 42, 43, 44, and 45). The oldest subsample observed the most (T = 6) at the shortest interval (Δ = 1) would have ages 80, 81, 82, 83, 84, and 85, while if Δ increases to 5, the ages would be 80, 85, 90, 95, 100, and 105 years, ultimately covering the entire adult life span. Crossing low numbers of repeated observations (T = 3 or 6) with very short to relatively long intervals within repeated observations (Δ = 1 to 5) more closely mimics existing longitudinal studies than assuming that all units have been observed during the full length of the study and at all occasions (e.g., Schaie & Hofer, 2001). Our illustration from the Betula study counts 10 subsamples, each of 100 individuals (hence N = 1000), of initial age 35, 40, 45, 50, 55, 60, 65, 70, 75, or 80 years, assessed on 4 occasions (T=4), with an interval between adjacent occasions of $\Delta = 5$ years.

Summary. In total, we fully crossed the varying simulation factors and design features to obtain 180 conditions: 2 (γ) by 3 (GCR) by 2 (T) by 5 (Δ) by 3 (N) (see Supplementary Table 3 for a full description of the simulation design). For each condition we generated 100 data sets, for a total of 18000 data sets.

Procedure

Growth model analyses. For each generated data set we estimated a series of GMs. We first applied the exponential decline GM. By doing so we tested whether the estimation procedure recovered the values of the generating function despite sampling limitations on number of occasions and varying interval lengths, and also provided a basis for comparing results obtained from the alternative GMs. We subsequently implemented the level, linear, and quadratic GMs. For the level GM we estimated 3 parameters (β_0, σ^2_L, and σ^2_E; cf. Equation (3)); for the linear GM, 6 parameters (β_0, β_1, σ^2_L, σ^2_C, σ_{LC}, and σ^2_E; cf. Equation (1)); and for the quadratic GM, 7 parameters (β_0, β_1, β_2, σ^2_L, σ^2_C, σ_{LC}, and σ^2_E; cf. Equation (2)); finally, for the exponential decline GM, we estimated 7 parameters (β_0, β_1, γ, σ^2_L, σ^2_C, σ_{LC}, and σ^2_E; cf. Equation (4)).

In all GM analyses we centered the time predictor a_{ij} (age) around its grand (sample) mean, to reduce estimation bias in the level-change covariance (σ_{LC}), and in the level variance (σ^2_L; Mehta & West, 2000; Rovine & Molenaar, 1998; Wainer, 2000).

The level, linear, and quadratic GMs are LMEMs, for which the marginal likelihood can be expressed and estimated without approximation. However, because the exponential model is a NLMEM, we had to apply an approximation method (Davidian & Giltinan, 1995). To rule out that the estimation procedure acted as a generator of divergent results we applied the same estimation procedure to all models. We used PROC NLMIXED in SAS (v. 9.3) to estimate all GMs with the adaptive Gaussian quadrature approximation, which produces the same estimates as maximum likelihood in linear models (Littell, Milliken, Stroup, & Wolfinger, 1996).

Acceptable solutions. We deemed a solution acceptable only if (a) the estimation converged to a solution and (b) the solution contained parameter estimates that were statistically viable. In particular, the estimated variance of change (σ^2_C) had to be non-negative.

Goodness of fit. From each analysis we saved the Schwarz Bayesian Information Criterion (BIC), defined as

$$BIC = 2 \cdot f\left(\hat{\theta}\right) + p \cdot \ln\left(N\right),$$

where f is the negative of the marginal log-likelihood function, $\hat{\theta}$ is the vector of parameter estimates, p is the number of estimated parameters, ln is the natural logarithm, and N is the number of subjects (Schwarz, 1978). This index is not normed, but allows comparing alternative models tested on the same data. A difference in BIC values of more than 10 between competing models can be interpreted as strong evidence in favor of the model with the lower BIC value (Kass & Raftery, 1995).

Power to detect individual differences in change. We estimated the power to detect interindividual differences in change by comparing each GM to a nested GM where the variance in change (σ^2_C) and the level-change covariance (σ_{LC}) were fixed at zero. We then compared each fully specified GM to its nested counterpart, and computed a likelihood ratio test ($\alpha = 5\%$).

Concordance in individual differences. We evaluated the validity of individual difference estimates from each model by inspecting the concordance of individual differences in growth components between the generated data and the results obtained from the GM analyses. To generate the data according to the exponential decline model of Equation (4) we first generated random effects in level and change scores (i.e., U_{0j} and U_{1j} of Equation (4)) in accordance to the constant simulation factors (cf. Supplementary Table 3). We then combined these random growth scores according to Equation (4) and added the randomly generated time-specific error component (E_{ij}), to obtain the individual repeated observations (Y_{ij}).

We analyzed each simulated data set of individual repeated observations with the four GMs and each time saved the empirical Bayes estimates of the random effects of the level and the change component. To inspect the concordance of the individual differences in growth components, we correlated the random level and change scores used to generate the data with the empirical Bayes estimates of the random effects in level and change obtained from the GM analyses.

Results

Literature Review

The literature search produced 1253 records, and after exclusion of duplicate and irrelevant records, we fully analyzed 162 records (see Supplementary Table 1). Of the 162, 102 records (63%) tested only a linear function of change, whereas 40 (25%) tested also a quadratic function, and one a cubic function. Thirteen (8%) records tested a broken-stick function (a.k.a. single-node spline; ten of which compared it to a linear or quadratic function). Of the remaining records, five (3%) tested an exponential function, two (1%) estimated the change function from the data (within a latent curve model), one used a multiple-node spline approach, and one did not specify the change function. See Supplementary Appendix 3 for detailed results.

Overall, then, 142 (88%) of the 162 records either used the linear or the quadratic function, whereas eight (less than 5%) used a function that is nonlinear in its parameters.

Simulation Results

Number of acceptable solutions. Generally, the greater the sample, the number of repeated measurements, the interval of measurements, the variable's reliability, and the rate of exponential decline, the higher the number of acceptable solutions (AS). The percentages of AS across models were: 100, 93.53, 85.57, and 97.74 for the level (which does not estimate σ^2_C), linear, quadratic and exponential model, respectively. Supplementary Figure 3 displays the average number of AS as a function of the design features.

To aid understanding of these effects, we used logistic regression to predict the probability of obtaining an AS as a function of the simulation factors. Model type most strongly influenced the probability of an AS ($\sim R^2$ = 13%-25%), GCR, T, and Δ have low effects ($\sim R^2$ = 3%-8%), and sample size was the least influential factor ($\sim R^2 < 1\%$). See supplementary Appendix 4 for detailed results.

Goodness of ~~F~~fit. We differenced BIC values of the level, linear, and quadratic GMs to against the exponential GM's BIC and compared this index of evidence favoring the exponential as a function of simulation condition and design features. The rejection rates based on BIC differences for the level, linear, and quadratic GMs were, respectively, 100%, 99.955%, and 96.295% for $\gamma = 0.066$ and 99.884%, 69.625%, and 47.191% for $\gamma = 0.033$. Thus, for a shallow declining process, the quadratic model would be judged to fit the data as well as the exponential more than half the time. Supplementary Figure 4 displays this information in detail.

We computed a logistic regression predicting the odds that the linear and quadratic GMs be rejected in favor of the exponential model as a function of GCR, T, Δ, and N, for $\gamma = 0.033$ (and not for $\gamma = 0.066$ or the level GM, because of the extremely high rejection rates). The number of occasions (T), and interval width (Δ) were the most influential factors ($\sim R^2$ = 13%-25%), GCR had a low effect ($\sim R^2$ = 8%-16%), and N was rather unimportant ($\sim R^2$ = 3%-12%). See supplementary Appendix 5 for detailed results.

Power to ~~D~~detect ~~I~~individual ~~D~~differences in ~~C~~change. Supplementary Figure 5 shows the average proportions of times the nested analogous model with $\sigma^2_C = \sigma_{LC} = 0$ was rejected compared to the fully specified linear, quadratic, and exponential model, only for $\gamma = 0.033$. For $\gamma = 0.066$ these rejection curves are virtually at 1 across all other conditions. Generally, the rejection curve of each model (hence estimated power) increased monotonically as Δ increases, with greater values at GCR = .900, $T = 6$, and Δ greater than 3. As GCR decreased, the rejection curves needed wider Δ to achieve high values, especially when $T = 3$. With the lowest GCR, the quadratic model had the least power to detect variance in change, especially when $T = 3$ and with small Δ. The most flagrant disparity between the quadratic model and the others was visible when $T = 3$, $N = 2000$, GCR = .500, and $\Delta = 1$: the power estimated for the quadratic GM in that cell is .105, while for the linear and exponential models it was .625 and .612, respectively.

To understand further the effects influencing detection of change variance we computed a logistic regression for each GM predicting the probability of a significant likelihood ratio test as a function of GCR, T, Δ, and N, for $\gamma = 0.033$. For all models the strongest factor was again Δ (~R^2 = 10%-20%), followed by T for the linear and quadratic models (~R^2 = 7%-14%), and by N for the exponential (~R^2 = 8%-13%). In the linear and exponential models, GCR influenced power the least (~R^2 = 2%-8%), while in the quadratic it was N (~R^2 = 3%-5%). See supplementary Appendix 6 for detailed results.

Concordance in ~~I~~individual ~~D~~differences in ~~L~~level. We computed analyses of variance (ANOVAs) predicting correlations between the level scores used to generate the data and the Bayes estimates of levels from each GM (in all ANOVAs the residuals were normally distributed, centered on zero, and homoscedastic). A first ANOVA testing only main effects obtained that they were significant, although their sizes were moderate to strong for type of model (partial eta squared $\eta_p^2 = .536$), γ ($\eta_p^2 = .464$), Δ ($\eta_p^2 = .112$), GCR ($\eta_p^2 = .159$), but virtually nil for *T* and *N* (both η_p^2 <.001). All two-way interactions about *N* were irrelevant (all η_p^2 = .0001). However, some two-way interactions about *T* were associated to small, yet nonzero, effect sizes. In the end, we display the results graphically with respect to all effects but *N*.

Figure 2a displays the average level correlations for γ= 0.033, by $\varDelta$ (abscissa), *T* (rows) and GCR (columns). In general, all indices are around .8. There appeared to be little effect of the model and of $\varDelta$ when GCR = .500 and *T* = 3, but when both *T* and GCR increased, the level model produces lower concordance rates, especially as $\varDelta$ increased. The correlations of the linear and quadratic models were hardly distinguishable, and they both diminished as $\varDelta$ increased (especially when *T* = 6). For the exponential model the concordance rates remain stable or even rise as $\varDelta$ increased. An ANOVA for the γ= 0.033 condition obtained the following effect size estimates (η_p^2): .308, .097, and .333 for type of model, $\varDelta$, and GCR, and less than .002 for *T* and *N*.

INSERT FIGURE 2a ABOUT HERE

The disparities in concordance rates across the models increased dramatically when γ= 0.066 (cf. Figure 2b). Already when *T* = 3 and GCR = .500, the exponential model produced the highest level correlations. As $\varDelta$ increases the correlations diminished for all models except for the exponential, for which they remained stable or grow even further, approaching 1.0, whereas for the level, linear, and quadratic they dropped at, respectively, .2, .6, and .6-.7. An ANOVA for the γ= 0.066 condition obtained the following effect size estimates (η_p^2): .821, .273, and .244 for type of GM, $\varDelta$, and GCR, and less than .001 for *T* and *N*.

INSERT FIGURE 2b ABOUT HERE

Concordance in ~~I~~individual ~~D~~differences in ~~C~~change. We repeated the same ANOVAs with respect to individual differences in change information. An ANOVA with main effects only obtained moderate to strong effects for all factors but sample size (for type of GM, γ, $\varDelta$, GCR, and T, the η_p^2 estimates were .195, .568, .527, .281, and .472, respectively; for N, η_p^2 = .002). N was also irrelevant with respect to all two-way interactions (all η_p^2 <.001). We again graphically display all effects but sample size, in Figure 3a for γ= 0.033 and 3b for γ= 0.066, respectively.

With γ= 0.033, concordance indices started very low (around .2) also for the exponential model, and only increased considerably as a function of wider $\varDelta$ when GCR increased. The three models obtain similar correlations, except with GCR = .900 and T = 6, where the linear model performed slight worse than the quadratic and exponential models. An ANOVA for the condition γ= 0.033 obtained the following effect size estimates (η_p^2): .014, .599, .389, and .569 for type of GM, $\varDelta$, GCR, and T and less than .005 for N.

INSERT FIGURE 3a ABOUT HERE

When γ= 0.066, in general the lowest correlations started around .4 and increased with wider $\varDelta$. When T = 3, the quadratic and exponential models are again hardly discernable, while the linear model obtains lower correlations. With T = 6, however, starting at $\varDelta$ = 5, 4, and 3, for GCR = .500, .681, and .900, respectively, the exponential model clearly obtained stronger concordance indices about change than the quadratic model (reaching .9 vs. .6). An ANOVA for the condition γ= 0.066 obtained the following effect size estimates (η_p^2): .509, .570, .275, and .487 for type of GM, $\varDelta$, GCR, and T and less than .002 for N.

INSERT FIGURE 3b ABOUT HERE

Prediction Quality in the Betula Project

To evaluate one possible implication of the application of the various GMs considered here, we assessed the quality of the linear, quadratic, and exponential GMs applied to analyze the Betula Project data used in the illustration and that informed our simulation study. For each participant we combined, according to Equations (1), (2), and (4) the estimated level and change scores and their age of assessment to predict their episodic recall scores. We then calculated the mean squared errors (MSE) between the observed and predicted scores under each GM for each participant.

We obtained MSE of11.40, 10.25, and 9.94, respectively, for the linear, quadratic, and exponential GM. Thus, the exponential GM, which adjusted best to the data in terms of BIC (cf. supplementary Table 2), also produced predictions that were closest to the data, thereby showing the highest internal validity.

Survival Prediction in the Betula Project

In terms of predictive validity, we compared the three GMs in terms of the terminal decline hypothesis in the Betula Project data. This hypothesis states that many individuals during the final phase of life manifest accelerated decrements in functional capacities (Gerstorf & Ram, 2013). We used Bayesian factor score estimates of each person's level and change scores on the basis of the linear, quadratic, and exponential GMs to predict survival in the 1000 Betula participants considered here, 529 of whom were deceased by the study's most recent mortality update.

The Cox proportional hazard model predicted survival and the age of either death (for the deceased) or the last assessment (for the right-censored participants). The exponential level and change estimated scores predicted best survival, with a BIC of 5681, whereas the quadratic and linear obtained worse adjustments (BIC values of 5685 and 5691, respectively). The estimated level and change scores from the exponential GM lowered the fit of the survival the most (drop in χ^2 statistic of 32.33 for two degrees of freedom, compared to 28.69 and 22.29 for the quadratic and linear, respectively – all *p*'s < .01).

Discussion

As expected, our literature review found that the vast majority (86%) of GMs applied to study normal cognitive aging implemented a linear or a quadratic function of change, whereas very few (less than 5%) considered a truly nonlinear function of change.

Hypothesized Consequences for Data Analysts

We explored what conclusions are likely to be reached when data generated under an exponential GM are analyzed with a linear or quadratic GM.

First, the exponential model can be implemented without great difficulty, despite its complexity~~, at least for fitting a population where exponential decline characterizes the dependent variable~~. Exponential models using adaptive Gaussian quadrature failed to converge in less than 3% of the 18000 data sets we generated. In contrast, the quadratic model failed to converge 14.43% of the cases. Thus, within the constraints present in our simulation study, the exponential model is a practicable alternative model to the linear and quadratic GMs.

Second, we found that in many conditions of our simulation study, it is not possible to tease apart the quadratic and the exponential model ~~apart~~ based on the commonly used BIC goodness of fit index. Thus, the chances of retaining the quadratic over the exponential model are high. ~~Of course,~~Most analysts typically testing linear and quadratic models will not consider other functions; nevertheless,~~. But~~ those scientists evaluating ~~trying out~~ an exponential model using comparative fit may end up discarding it for the more familiar and equally well-fitting quadratic model.

Third, we evaluated possible consequences of ~~does~~ retaining the misspecified ~~model, as would be the case for accepting the~~ quadratic model in our simulation study. Would doing so~~,~~ necessarily lead to inaccurate substantive conclusions about the change process analyzed? We addressed this question by considering two aspects: the power to detect individual differences in change, and the concordance between the level and change scores used to generate the data and the analogous scores predicted from the growth models. With respect to power, the quadratic GM clearly performed worst (across all conditions at 72.22%), whereas the linear and exponential fared similarly and in a range deemed by many to be satisfactory (82.21% and 81.26%, respectively). This gap increases in many conditions commonly encountered in empirical research. Thus, based on the quadratic model, we ~~may~~would often conclude that the individuals in the sample cannot be discriminated with respect to amount of change, whereas the exponential model may detect that important source of heterogeneity.

In contrast, the characterization of individual differences in growth components is often seriously compromised in quality if we rely on too simple a GM, especially when the decline rate is substantial. Concordance rates ~~a~~were generally higher for the level than for the change component. This ~~is~~ was expected, as level information is more easily estimated than change information. Whereas~~ile for the exponential model~~ the level correlations either remain stable or increase as testing intervals widen for the exponential model, for the level, linear, and quadratic models the concordance rates decrease monotonically. This effect is influenced by measurement reliability (the higher the GCR, the stronger the discordance; this effect would become even more pernicious with multiple indicator latent curve models), but not by number of occasions or by sample size. For change, concordance rates increase with more occasions of measurement and wider intervals, but not considerably with greater sample sizes. The exponential model clearly outperforms both the linear and quadratic model, and is the only model obtaining high concordance rates.

In sum then, under the empirically-based simulation conditions studied here, if a change process is exponential in nature but is~~we~~ analyzed~~ it~~ with a quadratic model, we may not pick up that individuals differ in amount of change. If we do detect variance in change, then we are very likely to obtain biased estimates of individuals' change scores. Hence, not only is the detection of change compromised; even when change is detected, it isn't well characterized by derived individual indices of change.

Finally, in terms of the empirical illustration on the Betula Project data, we found that the exponential model (a) fit the data best, (b), implied the expected individual cognitive scores that were closest to the observed scores, and (c) predicted mortality better than the linear and quadratic models. We deduce that in this sample the exponential GM likely provides the representation that best captures cognitive aging processes relative to its two competitors. We further hypothesize that the advantage of the exponential over both the linear and quadratic models would increase with greater intervals of testing ($\Delta > 5$ years), more reliable variables (GCR >.681), more occasions ($T > 4$), and a greater sample size ($N > 1000$).

Recommendations for Data Analysts

In light of these results, what should one do when analyzing real long-term change data? First, rather than continuing the common practice of solely testing the linear and the quadratic GMs, one might consider alternative, possibly nonlinear functions, which allow for substantive interpretations of their parameters. The exponential model is one such function that has proven useful in many disciplines, but other functions deserve to be considered as well (e.g., Grimm et al., 2007). Omitting nonlinear functions may cloud our understanding of the phenomena under investigation.

Second, when planning a longitudinal study, one should try to use reliable instruments (e.g., Little, Lindenberger, & Nesselroade, 1999) and assess the instruments repeatedly at carefully planned intervals (Hertzog & Nesselroade, 2003; Willett, 1989). What our results show is that even under ideal conditions, such as those of our simulation experiment (e.g., no unwanted retest effects, no longitudinal dropout, and group homogeneity), the discovery of change-related information often requires many widely spaced assessments. One practical implication is the need for patience in longitudinal sampling. A lack of change-related evidence at the second or third wave of a longitudinal study of long-term change does not preclude the sought-after effect manifesting itself after additional data collection (especially when waves are separated by wide time intervals).

Third, we found that overall the effect of sample size was rather minor, compared to the other effects of our simulation experiment. Although~~While in~~ psychologists~~y we~~ have become extremely conscious of the overall importance of sample size, the design features related to density and span of change assessments appear to be more important in enabling accurate characterization of individual differences in change ~~re are other equally, if not more, important design features that need to be considered as well~~ (Brandmaier, von Oertzen, Ghisletta, Lindenberger, & Hertzog, 2018).

In conclusion, much progress has been made in estimating nonlinear growth models and in showing their relevance in lifespan developmental psychology. We argue that the time is right for ending exclusive reliance on linear GMs for describing change. Embracing conceptual, statistical, and computational advances embedded in nonlinear GMs may deepen our understanding of psychological change phenomena.

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Figure 1. Simulated trajectories generated under the exponential decline model.

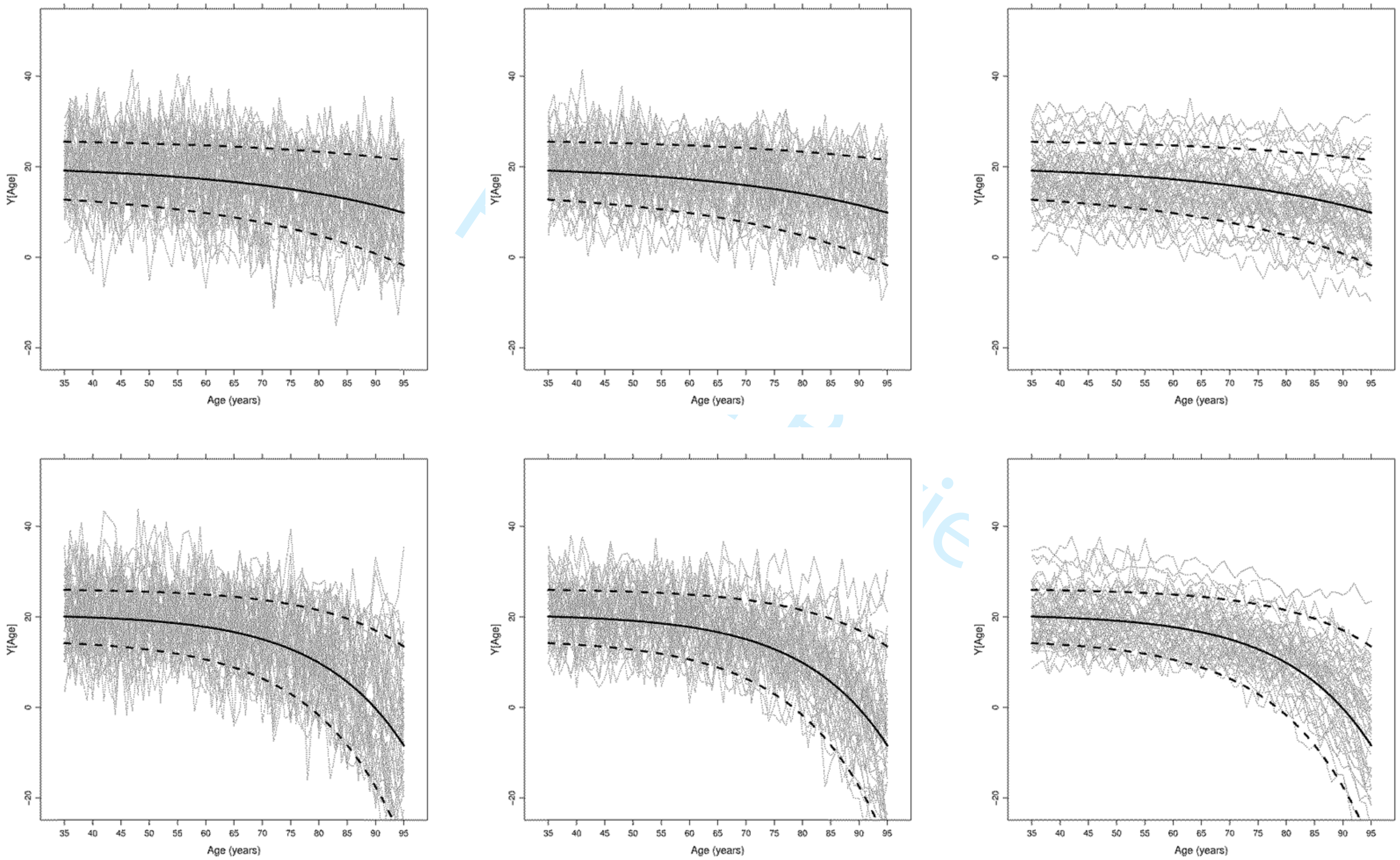
Figure 2a. Concordance in levels by interval width and model, for $\gamma = 0.033$.

Figure 2b. Concordance in levels by interval width and model, for $\gamma = 0.066$.

Figure 3a. Concordance in changes by interval width and model, for $\gamma = 0.033$.

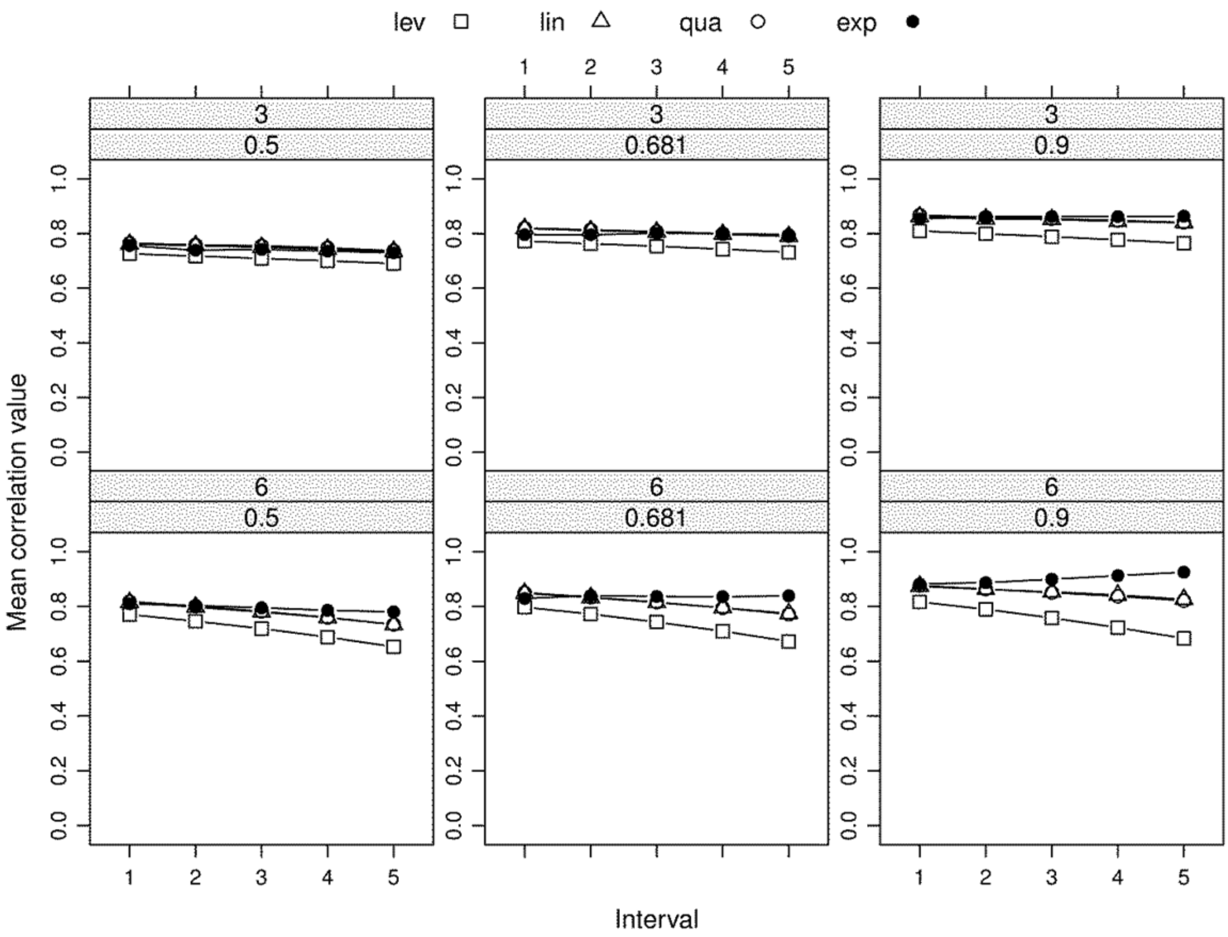
Figure 3b. Concordance in changes by interval width and model, for $\gamma = 0.066$.

Figure 1: Simulated Trajectories Generated under the Exponential Decline Model



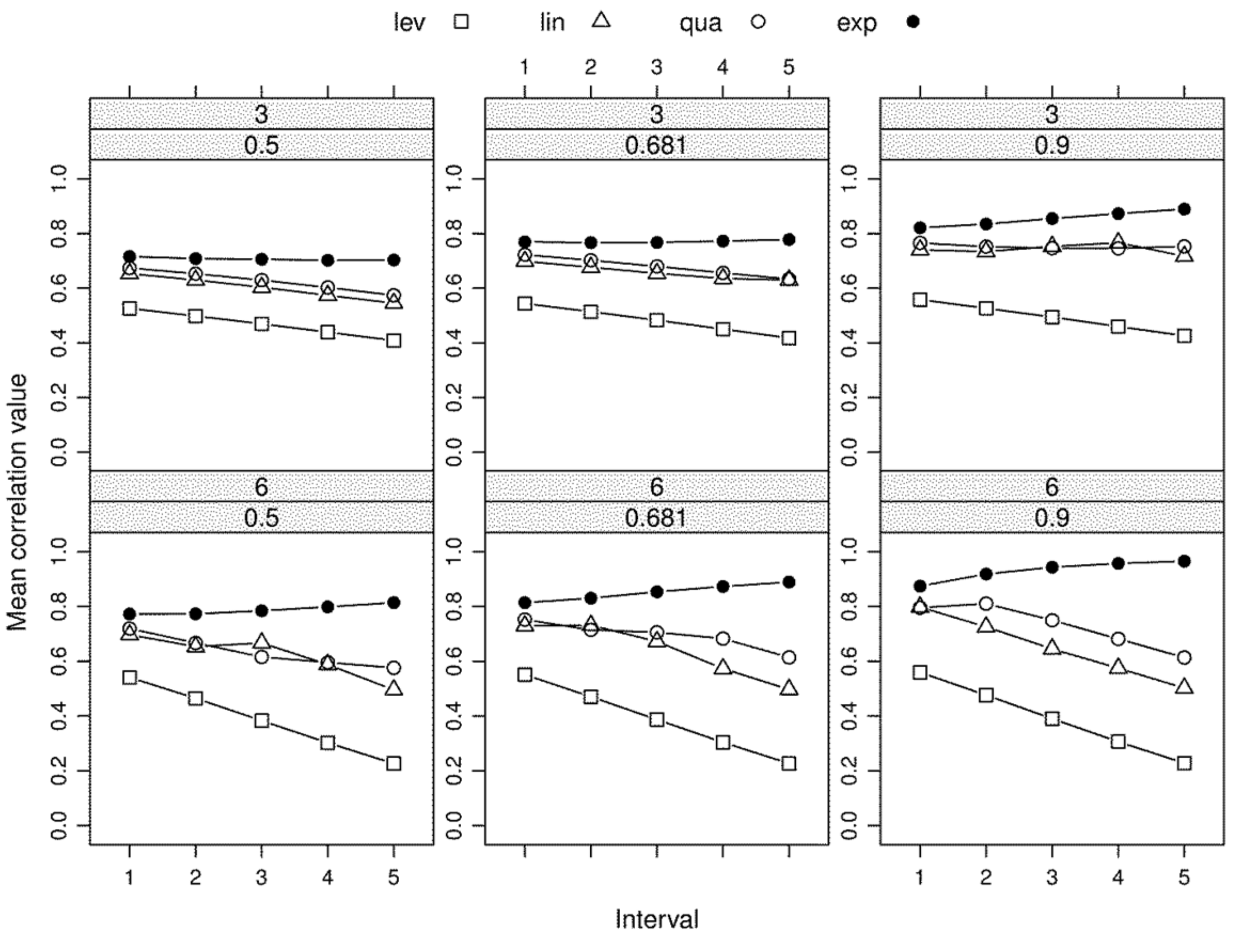
Note. Row 1: γ= 0.033, row 2: γ= 0.066; Column 1: GCR = .500, column 2: GCR = .681, column 3: GCR = .900; Thick continuous line is sample average without residuals, thick dashed lines are 1 SD above/below the mean; Thin continuous lines are 50 simulated individual trajectories.

Figure 2a: Concordance in Levels by Interval Width and Model, for γ= 0.033



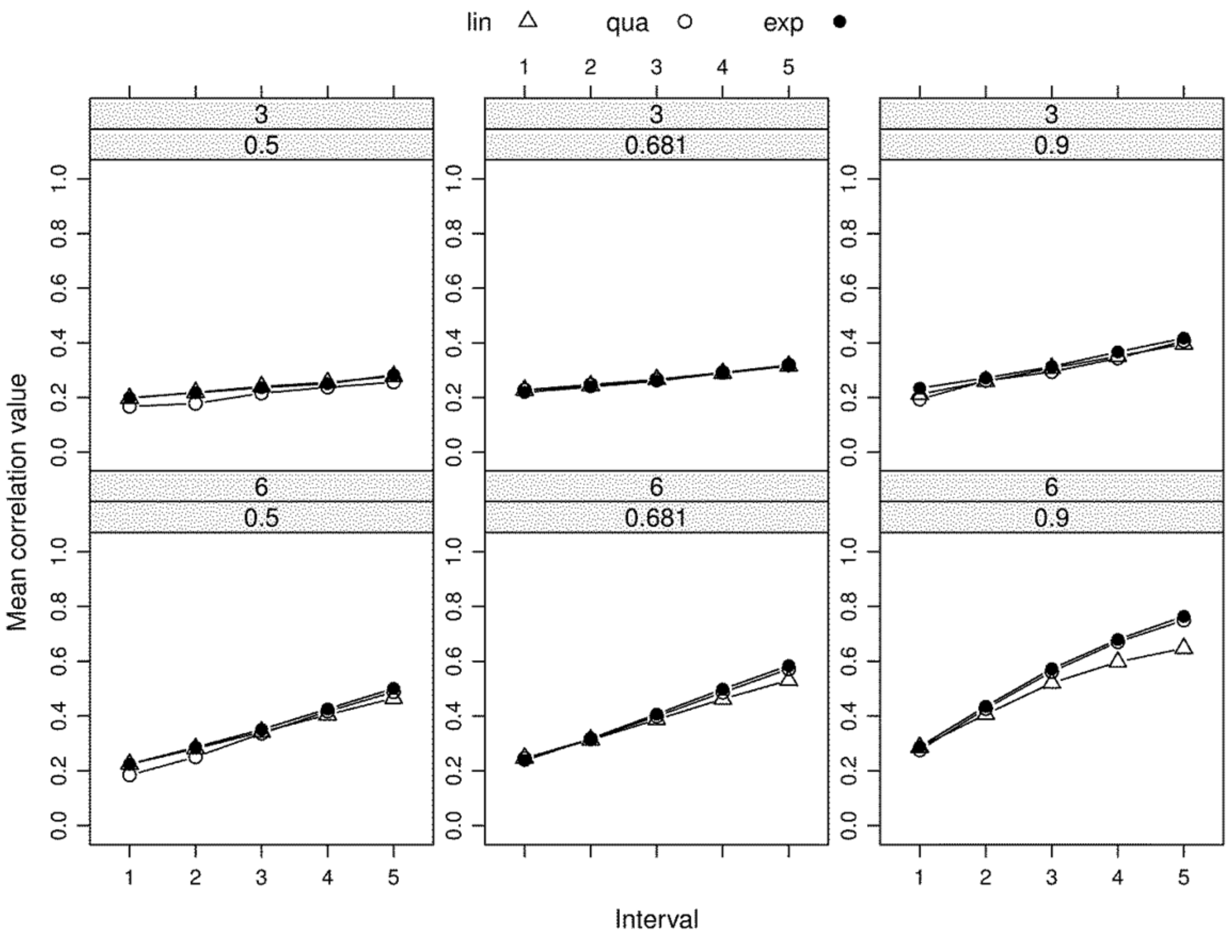
Note. Row 1: T = 3, row 2: T = 6; Column 1: GCR = .500, column 2: GCR = .681, column 3: GCR = .900.

Figure 2b: Concordance in Levels by Interval Width and Model, for γ= 0.066



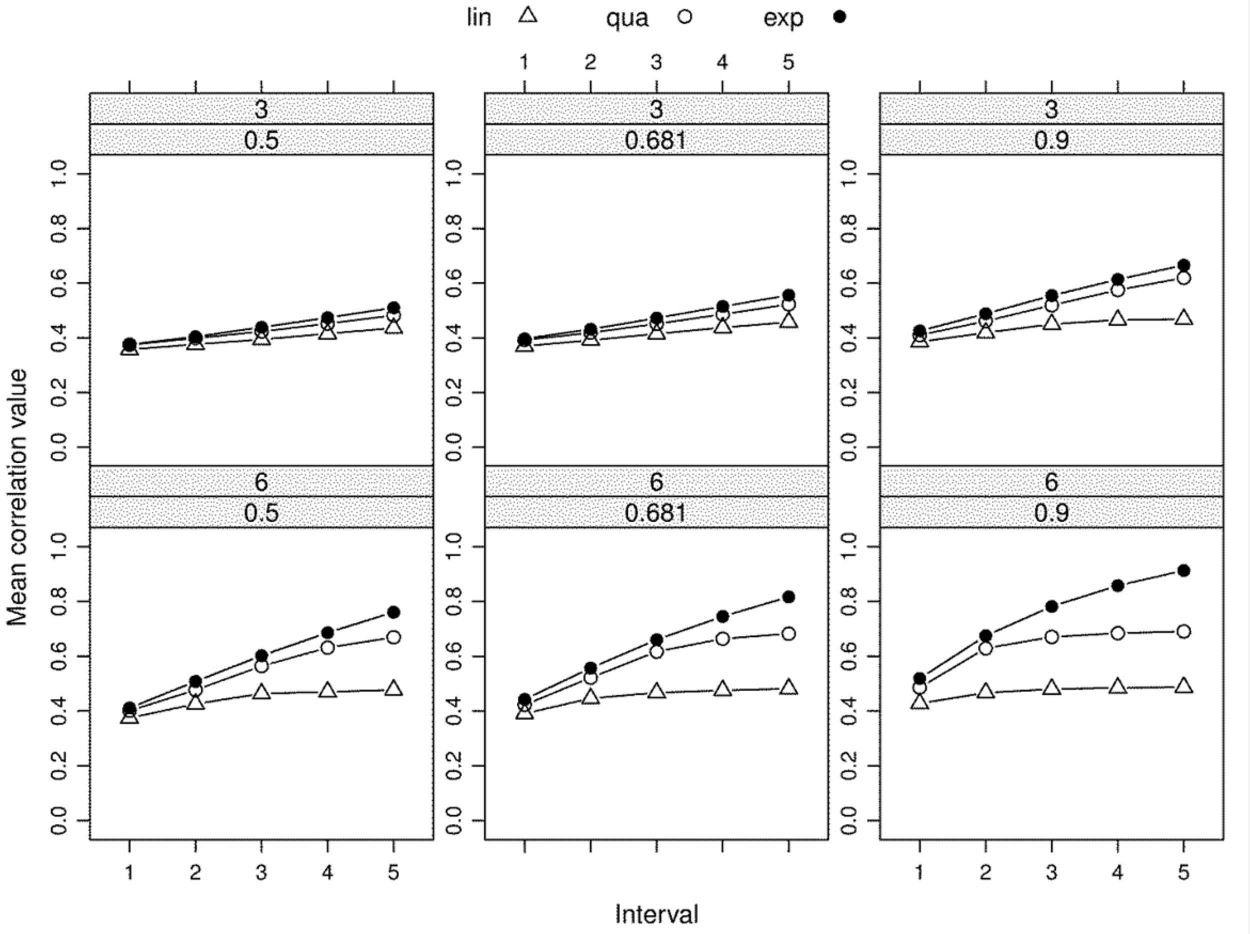
Note. Row 1: *T* = 3, row 2: *T* = 6; Column 1: GCR = .500, column 2: GCR = .681, column 3: GCR = .900.

Figure 3a: Concordance in Changes by Interval Width and Model, for γ= 0.033



Note. Row 1: T = 3, row 2: T = 6; Column 1: GCR = .500, column 2: GCR = .681, column 3: GCR = .900.

Figure 3b: Concordance in Changes by Interval Width and Model, for γ= 0.066



Note. Row 1: T = 3, row 2: T = 6; Column 1: GCR = .500, column 2: GCR = .681, column 3: GCR = .900.

Supplementary Appendix 1

Detailed description of the screening procedure

On December 2015 the first author (FA) and second author (SA) performed a systematic literature search by using three popular databases in psychology and related disciplines: Web of Science (WoS), PsycINFO (PI), and PubMed (PM). We limited our search to the previous five full years, that is, from January 1st, 2010, to December 31st, 2014. We based the search on two groups of terms, one for the statistical model and the other for the substantive field of application. All (statistical and substantive) terms were searched anywhere in the text (e.g., title, abstract, body text). We required that the records returned from the search be journal articles, book chapters, or books, written in English. The aim of the literature search was to evaluate current practice of substantive researchers in non-pathological cognitive aging, who analyzed longitudinal data with some form of growth model. Thus, we excluded hits that were statistical/methodological in nature (that were tutorials, or that focused on studying properties of such models).

Terms concerning the statistical model were: “growth curve model*”; “latent curve model*”; “multilevel model*”; “mixed effects model*”; “linear mixed model*”; “random effects model*”; “hierarchical linear model*”; “nonlinear hierarchical model*”; “generalized linear mixed model*”; “nonlinear mixed model*”. We included the wildcard “*” to include variations (such as modeling, modelling, models, etc.). Growth curve and latent curve models are by definition applied to longitudinal data, whereas those within the multilevel family can also be applied to cross-sectional data (e.g., typically hierarchically organized data, such as children within schools) or to meta-analyses (to account for both across-studies and within-study variations). Thus, for this latter class of models we added the “longitudinal” term. The terms concerning the statistical model were combined with two terms concerning the substantive application: “intelligence” and “cogniti*”. We again included the wild card “*” to assure coverage of related terms such as cognition, cognitive, cognitively, etc. We refrained from searching for specific cognitive abilities (e.g., speed, episodic or working memory, inhibition), because of the very large number of terms that such a search would have required. Moreover, we reasoned that scientific writings focused on specific abilities are very likely to include the terms “intelligence” and/or “cogniti*” in their text.

The supplemental Table 1 shows the number of records from each literature database for each combined use of statistical and substantive search terms. The last column shows the sum across the three databases. The row named Sum shows the total number of records across all search terms from each database: 593 for WoS, 571 for PI, and 89 for PM, for a total of 1253 records. First, the FA and SA independently eliminated first all duplicate records within each database and for this first step obtained full agreement. The resulting numbers of retained records were 536 for WoS, 493 for PI, and 82 for PM, for a total of 1111 records. Then, FA and SA independently eliminated duplicate and non-English records across databases, and obtained a final number of 719 entries, again with full agreement. Duplicates were established based on authors’ names, title and date of record, and name of publication.

Second, FA and SA independently read the abstracts of 182 records (a fourth) to screen them for eligibility, according to the criteria listed below. That is, despite the inclusion of the search terms, a record could be unrelated to the aims of the search (in few cases the abstract was not sufficient and portions of the text had to be read). At this stage, the FA and SA had a 0.73

agreement index. Thus, the FA and SA together analyzed, discussed, and reclassified the discordant records to reach full consensus.

Third, the FA and SA independently read and classified the abstracts of the remaining (719 – 182 =) 537 records. At this stage, the FA and SA had a 0.88 agreement index. They again reclassified the discordant records to reach full consensus. In the end, of the 719 records, the following were excluded:

- n=4, because they were commentary articles (n=2), reviews (n=1), or corrections (n=1);
- n=1, because it was a conference poster and only the abstract was available;
- n=20, because they were meta-analyses;
- n=7, because they did not include longitudinal/repeated measurement data (e.g., mixed-effects models were used on cross-sectional data with heterogeneous variances across conditions, or with siblings or neighborhoods as clusters);
- n=48, because they were of statistical or methodological nature [1];

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[1] i.e., that appeared in specialized journals (The American Statistician; Annals of Applied Statistics; Applied Psychological Measurement; Behavior research methods; Biometrical Journal; Biometrical Journal; Biometrika; British Journal of Mathematical and Statistical Psychology; Computational Statistics and Data Analysis; Frontiers in Psychology: Quantitative Psychology and Measurement; Journal of the American Statistical Association; Journal of Applied Statistics; Journal of Biometrics and Biostatistics; Journal of Computational and Graphical Statistics; Journal of Educational and Behavioral Statistics; Journal of the Royal Statistical Society, Series A, Statistics in Society; Journal of the Royal Statistical Society, Series C, Applied Statistics; Methodology; Multivariate Behavioral Research; Psychological Methods; Psychometrika; Statistical Methods in Medical Research; Statistical Modelling; Statistics in Medicine; Structural Equation Modeling; Statistical Methodology), that appeared in substantive journals but that focused on methodological/statistical issues (American Journal of Epidemiology; The American Journal of Geriatric Psychiatry; Annals of Epidemiology; Contemporary Clinical Trials; European Journal of Developmental Psychology; Journal of Cognition and Development; Neuroepidemiology; NeuroImage; Psychology and Aging; Sleep Medicine; World Journal of Biological Psychiatry), or that appeared in methodological or statistical books (e.g., Contemporary issues in exploratory data mining in the behavioral sciences; Handbook for advanced multilevel analysis; The handbook of life-span development; Handbook of structural equation modeling; Longitudinal data analysis: A practical guide for researchers in aging, health, and social sciences; Quantitative and qualitative methods in psychotherapy research).

- n=128, because they included and focused on non-normal samples (e.g., patients with Alzheimer, Parkinson, autism, depression, bipolar disorders, breast cancer, MCI, heavy drinkers);
- n=243 did not include samples of elderly individuals (age < 65 years);
- n=349 did not specify cognitive or intelligence performance as dependent variable of analysis (e.g., controlled for cognitive variables but specified non-cognitive dependent variables, or discussed relevance of findings in terms of general cognitive functioning, without explicit assessment or analysis of cognitive variables).

Many records met multiple exclusion criteria (e.g., n=149 did not include samples of elderly individuals and did not specify cognitive or intelligence performance as dependent variable of analysis; n=70 included non-normal samples and did not specify cognitive or intelligence performance as dependent variable of analysis). In the end, we retained and fully analyzed n=162 records. The screening procedure is represented in the Supplemental Figure 1.

Supplementary Appendix 2

Records in final analysis based on the literature review

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Supplementary Appendix 3

Detailed results of literature review

The literature search produced 1253 records, and after exclusion of duplicate and irrelevant records, we fully analyzed 162 records. See Supplementary Appendix 1 and Supplementary Figure 1 for full details.

Of the 162 records, the data were of panel type for 156 records, and experimental for six.

The number of repeated measurements ranged from 2 to 20, with a mean of 5.071 (median = 5, s.d. = 2.895, interquartile range = 3 to 6; information not available for nine records).

Multilevel/mixed effects type models were used in 135 records (one with a penalized linear spline; one with a thin plate regression spline; one was nonlinear in the parameters; one was a generalized mixed-effects model), whereas a latent curve type model was used in 26 records (three analyzed multiple variables in parallel; one was a 2nd level curve model; two used a structured latent curve model). Finally, the remaining record applied both models.

One hundred and two records (63%) tested only a linear change function, and of these only one had experimental data, whereas the remaining 101 were panel studies. Moreover, the number of occasions ranged from 2 to 17 (median = 4.000, mean = 4.792, s.d. = 2.927). Forty (25%) studies tested also a quadratic function, and of these all were panel studies, with between 2 and 12 occasions (median = 5.000, mean = 5.351, s.d. = 2.163). One study tested a cubic function, and this study was a panel with five occasions.

Thirteen (8%) records tested a broken-stick function (a.k.a. single-node spline; ten of which compared it to a linear or quadratic function). These were all panel studies, with between 3 and 6 occasions (median = mean = 5.000, s.d. = 1.265).

Of the remaining records, five (3%) tested an exponential function (all with experimental data, with from 5 to 20 occasions, median=8.000, mean = 9.800, s.d. = 6.017), two (1%) estimated the change function from the data (within a latent curve model; both were panel studies, with either 3 or 4 occasions), one used a multiple-node spline approach (a panel study with 7 occasions), and one did not specify the change function (a panel study with 6 occasions). Overall, of the eight records that tested a nonlinear function, five were on experimental data, with number of occasions ranging from 5 to 20 (median = 8.000, mean = 9.800, s.d. = 6.017); all used occasions of measurement as the time basis; all applied an exponential function, and one also estimated the change function within a latent curve model.

~~T~~Across all studies, the most frequent time bases were time in study (n = 76), occasions of measurement (n = 41), chronological age (n = 33), and time to event (n = 13; e.g., death, dementia, stroke, hospitalization). One record used a time-varying medical covariate as basis, and three records did not provide this information. Finally, five records used and compared two of the aforementioned bases.

Supplementary Appendix 4

Logistic regression to study the determinants of an acceptable solution

To understand which design feature most strongly influences the probability of obtaining an acceptable solution, we computed a logistic regression analysis. The dichotomous variable was AS vs. non-AS, and the predictors were model type, GCR, T, Δ, and N. We computed this analysis for the shallower exponential decline rate only ($\gamma = 0.033$), given the very high number of AS for $\gamma = 0.066$. For simplicity, we present the analyses including all main effects only (all interactions proved irrelevant). Below we display the type-III likelihood ratio tests concerning each simulation factor, with its degrees of freedom and *p*-value, and the drop in effect size measures when each simulation factor is omitted from the logistic equation. The strongest effect was by far associated to the model type, while all other factors were associated to much weaker effect sizes.

Factor (df)	LRT	$\sim R^2 CS$	$\sim R^2 N$
model (3)	5490.772	.126	.249
GCR (2)	1921.237	.042	.083
T (1)	1845.481	.040	.079
Δ (4)	1239.208	.027	.053
N (2)	225.037	.005	.009
$\sim R^2$ *CS*	.232 (.269)		
$\sim R^2$ *N*	.457 (.529)		

Note. LRT=Type-III likelihood ratio tests associated to each simulation factor and design feature (rows) in a logistic regression predicting the probability of obtaining an acceptable solution (the associated degrees of freedom are in parenthesis; all *p*-values are <.001). $\sim R^2CS$ and $\sim R^2N$ = drop in pseudo R^2 of Cox and Snell and pseudo R^2 of Nagelkerke, respectively, when that effect is removed from the regression equation. The lower panel presents the total effect size indexes of pseudo R^2 of Cox and Snell (tot. R^2 CS) and of Nagelkerke (tot. R^2 N) with only the main effects, and in parentheses the analogous estimates with the addition of all interactions.

Supplementary Appendix 5

Summary of results of analyses on rejections of the linear GM and the quadratic GM when compared to the exponential GM and of the linear GM when compared to the quadratic GM for $\gamma = 0.033$ only (based on difference in BIC greater than 10)

	Linear vs. Exponential			Quadratic vs. Exponential			Linear vs. Quadratic		
Factor (df)	LRT	R^2CS	R^2N	LRT	R^2CS	R^2N	LRT	R^2CS	R^2N
GCR (2)	1575.403	.112	.159	830.301	.084	.113	991.222	.196	.307
T (1)	2443.488	.185	.261	1324.233	.140	.187	2096.576	.251	.382
Δ (4)	2503.807	.190	.269	1236.640	.130	.173	2171.507	.208	.296
N (2)	1200.185	.083	.118	288.879	.028	.037	870.941	.139	.232
tot. R^2 CS	.511 (.539)			.403 (.547)			.514 (.538)		
tot. R^2 N	.723 (.763)			.538 (.730)			.733 (.766)		

Note. LRT=Type-III likelihood ratio tests associated to each simulation factor and design feature (rows) for the linear vs. exponential (columns 2-4), quadratic vs. exponential (columns 5-7), and linear vs. quadratic (columns 8-10) GMs in logistic regressions predicting the probability of rejecting the linear or quadratic GM when compared to the exponential GM or the linear GM when compared to the quadratic GM (the associated degrees of freedom are next to the name of each term; all *p*-values are < .001). R^2CS and R^2N = drop in pseudo R^2 of Cox and Snell and pseudo R^2 of Nagelkerke, respectively, when that effect is removed from the regression equation. The lower panel presents the total effect size indexes of pseudo R^2 of Cox and Snell (tot. R^2 CS) and of Nagelkerke (tot. R^2 N) with only the main effects, and in parentheses the analogous estimates with the addition of all interactions.

Supplementary Appendix 6

Summary of Results of Analyses on Power to Detect Change Variance for γ= 0.033

Because the true variance in change (σ^2_C) is at a boundary (i.e., cannot be negative), we used a 50:50 mixture of a 1- and 2-degree-of-freedom chi square distribution (Self & Liang, 1987; Stoel, Garre, Dolan, & van den Wittenboer, 2006) to compute all likelihood ratio tests. However, given the reservations raised by some about this methodology (e.g., Savalei & Kolenikov, 2008), we also applied a 2-degree-of-freedom test. The results were identical.

	Linear			Quadratic			Exponential		
Factor (df)	LRT	R^2CS	R^2N	LRT	R^2CS	R^2N	LRT	R^2CS	R^2N
GCR (2)	248.320	.024	.043	493.457	.058	.096	546.575	.047	.077
T (1)	702.835	.071	.125	725.443	.087	.143	741.567	.065	.106
Δ (4)	932.453	.096	.168	993.848	.122	.200	1192.894	.107	.176
N (2)	660.821	.067	.117	279.642	.032	.053	901.961	.079	.131
total ~R^2 CS	.241 (.272)			.272 (.318)			.282 (.317)		
total ~R^2 N	.422 (.477)			.448 (.524)			.464 (.522)		

Note. Type-III likelihood ratio tests associated to each simulation factor and design feature (rows) for the linear (columns 2-4), quadratic (column 5-7), and exponential (column 8-10) GMs in logistic regressions predicting the probability of rejecting the alternative models in which $\sigma^2_C = \sigma_{LC} = 0$ (the associated degrees of freedom are next to the name of each term; all *p*-values are <.001). R^2CS and R^2N = drop in pseudo R^2 of Cox and Snell and pseudo R^2 of Nagelkerke, respectively, when that effect is removed from the regression equation. The lower panel presents the total effect size indexes of pseudo R^2 of Cox and Snell (total ~R^2 CS) and of Nagelkerke (total ~R^2 N) with only the main effects, and in parentheses the analogous estimates with the addition of all interactions.

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Supplementary Table 1

Number of records from each literature database for each combined use of statistical and substantive search terms

Search terms		**Database**			
Statistical	**Substantive**	**WoS**	**PI**	**PM**	**all**
"Growth curve model*"	"cogniti*"	164	128	16	308
"Growth curve model*"	"intelligence"	22	34	4	60
"Latent curve model*"	"cogniti*"	7	5	0	12
"Latent curve model*"	"intelligence"	2	2	0	4
"multilevel model*" and "longitudinal"	"cogniti*"	74	74	1	149
"multilevel model*" and "longitudinal"	"intelligence"	12	30	1	43
"mixed effects model*" and "longitudinal"	"cogniti*"	104	84	26	214
"mixed effects model*" and "longitudinal"	"intelligence"	7	16	2	25
"linear mixed model*" and "longitudinal"	"cogniti*"	98	79	23	200
"linear mixed model*" and "longitudinal"	"intelligence"	6	17	2	25
"random effects model*" and "longitudinal"	"cogniti*"	40	19	9	68
"random effects model*" and "longitudinal"	"intelligence"	0	2	0	2
"hierarchical linear model*" and "longitudinal"	"cogniti*"	48	52	4	104
"hierarchical linear model*" and "longitudinal"	"intelligence"	3	13	0	16
"nonlinear hierarchical model*" and "longitudinal"	"cogniti*"	0	0	0	0
"nonlinear hierarchical model*" and "longitudinal"	"intelligence"	0	0	0	0
"generalized linear mixed model*" and "longitudinal"	"cogniti*"	5	13	1	19

“generalized linear mixed model*” and “longitudinal”	“intelligence”	0	3	0	3
“nonlinear mixed model*” and “longitudinal”	“cogniti*”	1	0	0	1
“nonlinear mixed model*” and “longitudinal”	“intelligence”	0	0	0	0
Sum		593	571	89	1253
Records without intra-base duplicates		536	493	82	1111
Records without inter-bases duplicates			719		
Records retained for full lecture			**162**		

Notes. WoS=Web of Science; PI=PsycINFO; PM=PubMed.

Supplementary Table 2

Parameter Estimates (and Standard Errors) of the Linear, Quadratic, and Exponential GM applied to the Recall Score in the Betula Study.

parameter	level GM	linear GM	quadratic GM	exponential GM
β_0	23.521 (0.251)	23.506 (0.214)	24.615 (0.218)	20.603 (0.439)
β_1	--	-0.254 (0.012)	-0.341 (0.013)	-4.007 (0.451)
β_2	--	--	-0.009 (<0.001)	--
γ	--	--	--	0.066 (0.004)
σ^2_L	55.518 (2.840)	33.758 (2.246)	30.779 (1.983)	30.980 (2.786)
σ^2_C	--	0.032 (0.007)	0.027 (0.006)	5.041 (1.402)
$\sigma_{L,C}$ [$\rho_{L,C}$]	--	0.638 (0.086) [0.619]	0.379 (0.072) [0.413]	-3.163 (1.599) [-0.253]
σ^2_E	18.148 (0.576)	16.444 (0.597)	14.942 (0.541)	14.541 (0.526)
-2LL	19‘453	18’911	18’692	18’686
BIC	19‘473	18’952	18’741	18’734
p	3	6	7	7

Note. GM=growth model. $\rho_{L,C}$ = correlation between level and change. *p* = number of estimated parameters. All models were estimated with age centered at 65 years. Standard errors are in parentheses. For the quadratic model and the exponential model it was not possible to estimate the variance, respectively, of the quadratic slope and of the exponential decline rate.

Supplementary Table 3

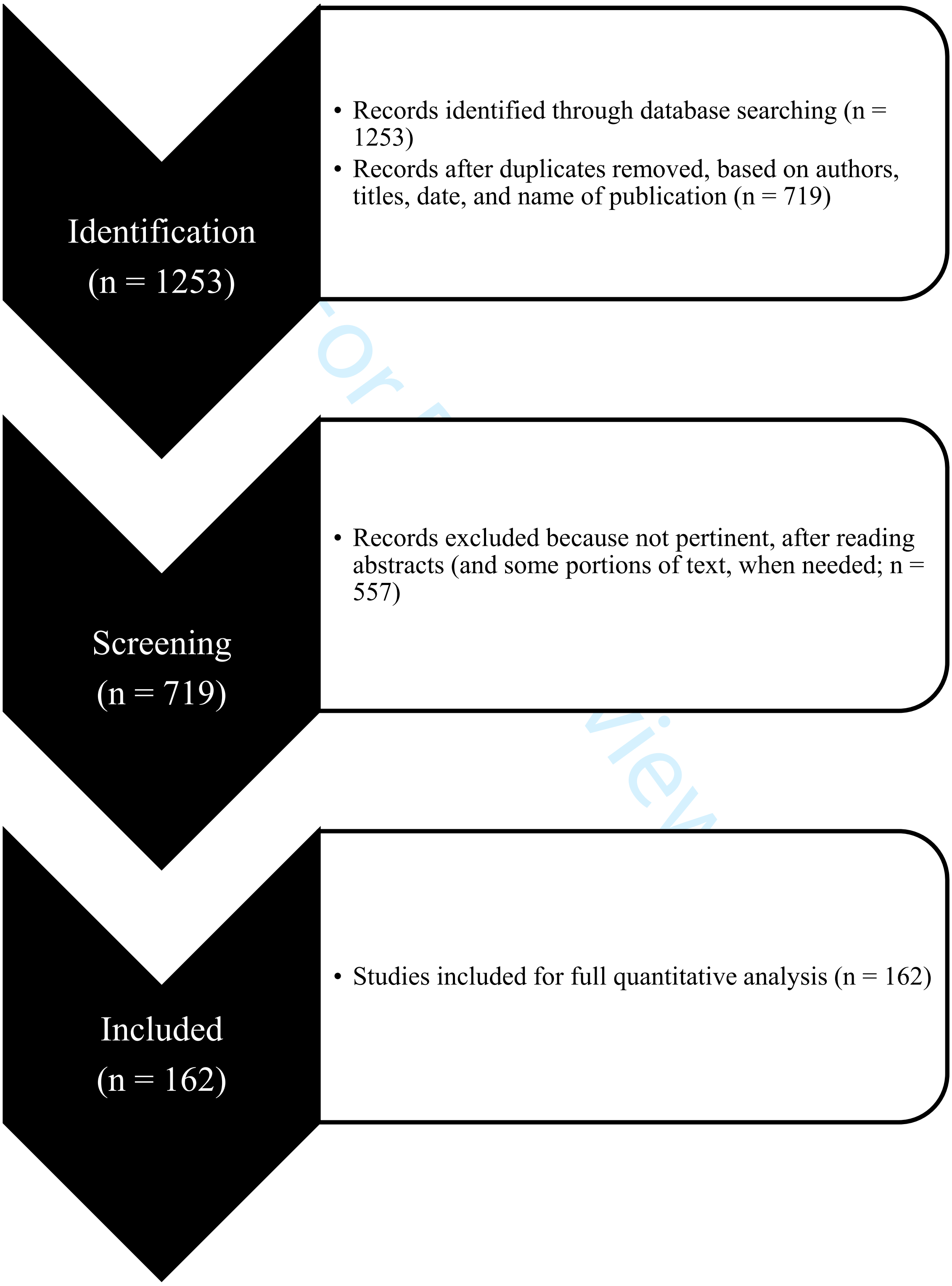
Factors in Simulation Study

Constant Simulation Factors	
Level mean (β_0)	20.603
Change mean (β_1)	-4.007
Level variance (σ^2_L)	30.980
Change variance (σ^2_C)	5.041
Level-change covariance ($\sigma_{L,C}$)	-3.163
Varying Simulation Factors	
Rate of exponential decline (γ)	0.033, 0.066
Growth Curve Reliability $\left(GCR = \frac{\sigma_L^2}{\sigma_L^2 + \sigma_E^2} \right)$	.500, .681, .900
Varying Design Factors	
Occasions (T)	3, 6
Interval (Δ)	1, 2, 3, 4, 5
Total sample size (N)	500, 1000, 2000

Note. The factors refer to the exponential decline function (Equation (4)). The full design includes 5 fully crossed varying factors (γ, GCR, T, Δ, N) for a total of 2 x 3 x 2 x 5 x 3) = 180 conditions. On each condition 4 growth models were tested (level, linear, quadratic and exponential) and each condition contained 100 replications. In the end, we obtained 180 x 4 x 100 = 72000 sets of solutions.

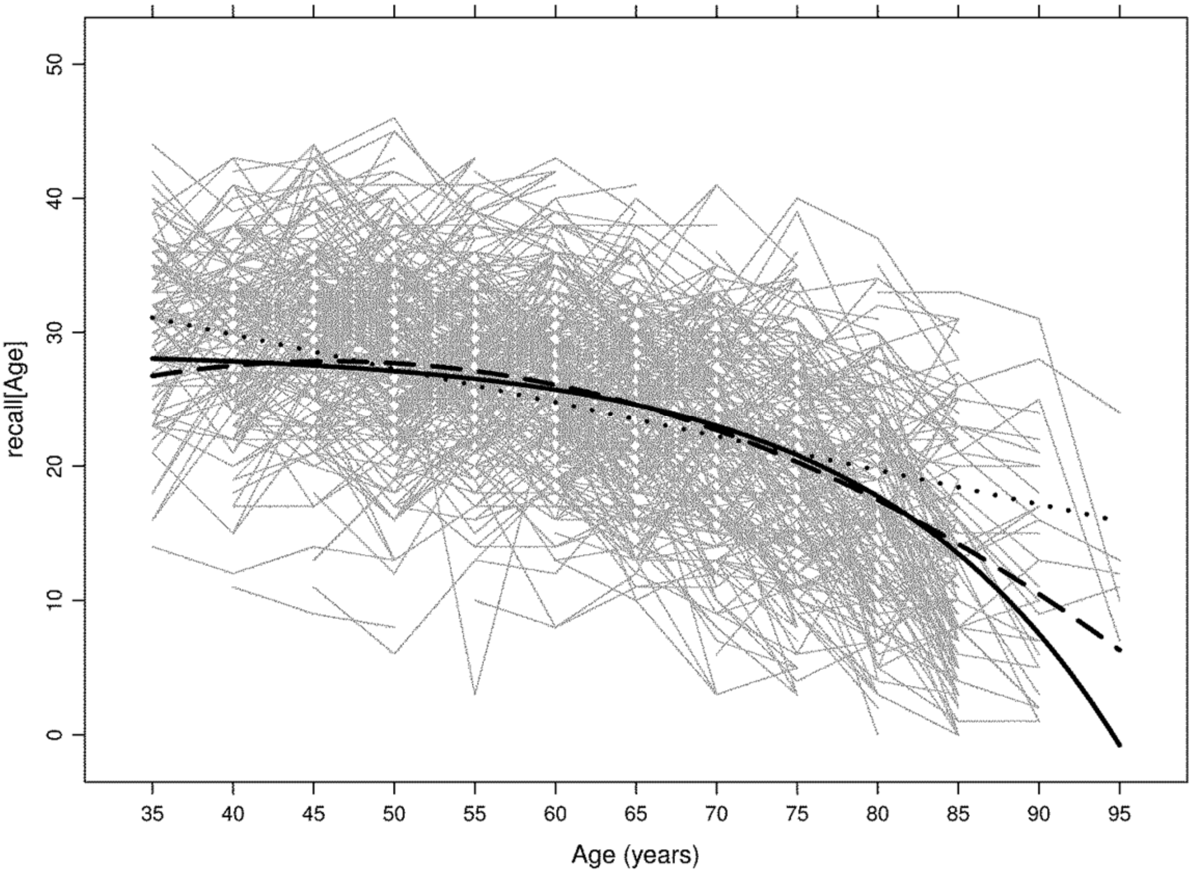
Supplementary Figure 1

Flowchart with screening procedure of articles included in the quantitative analysis



Supplementary Figure 2

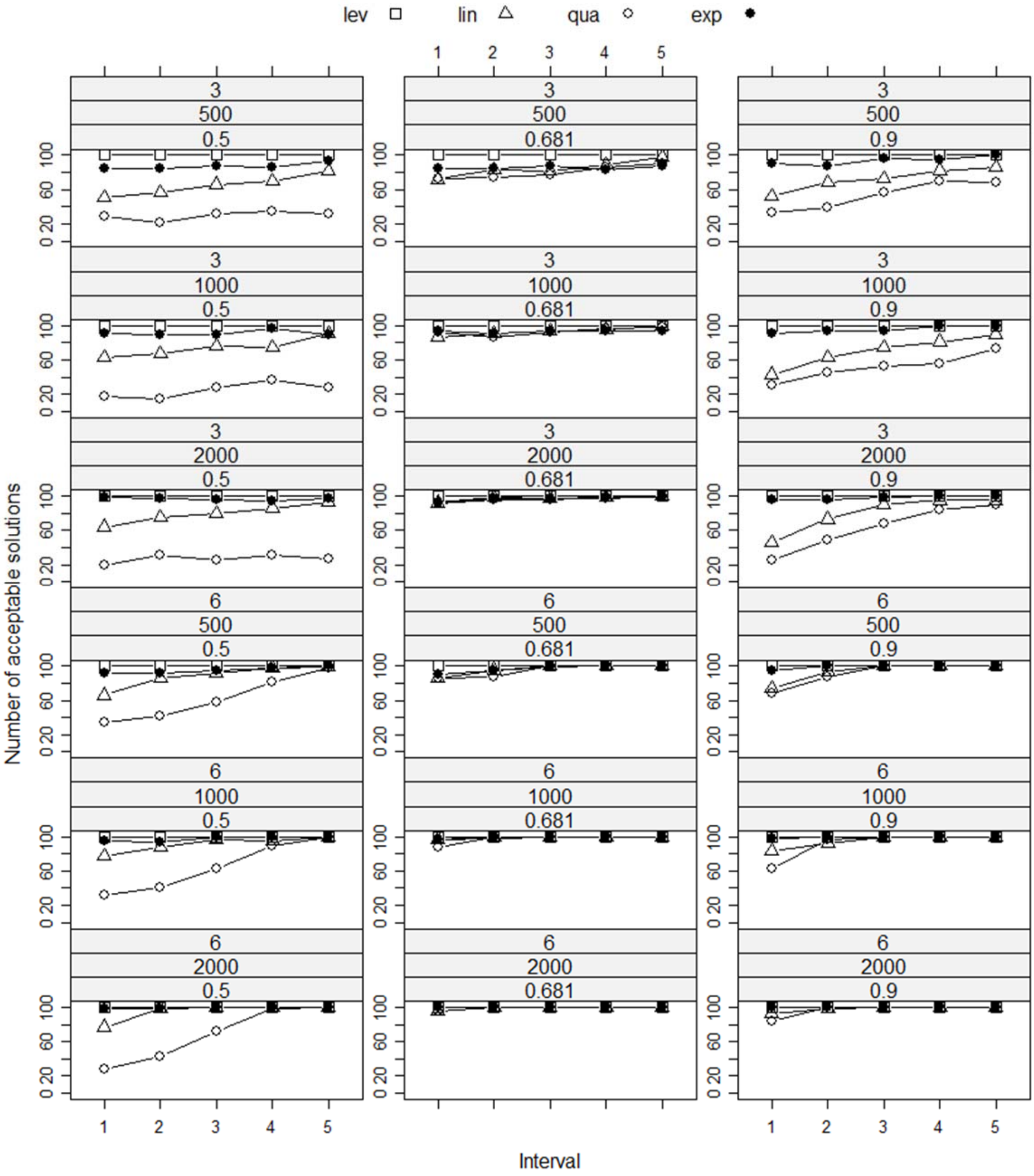
Betula recall scores by age



Note. The sample predicted trajectory is represented by the black dotted line for the linear GM, the black dashed line for the quadratic GM, and the continuous black line for the exponential decline GM. The grey lines represent the observed individual trajectories.

Supplementary Figure 3

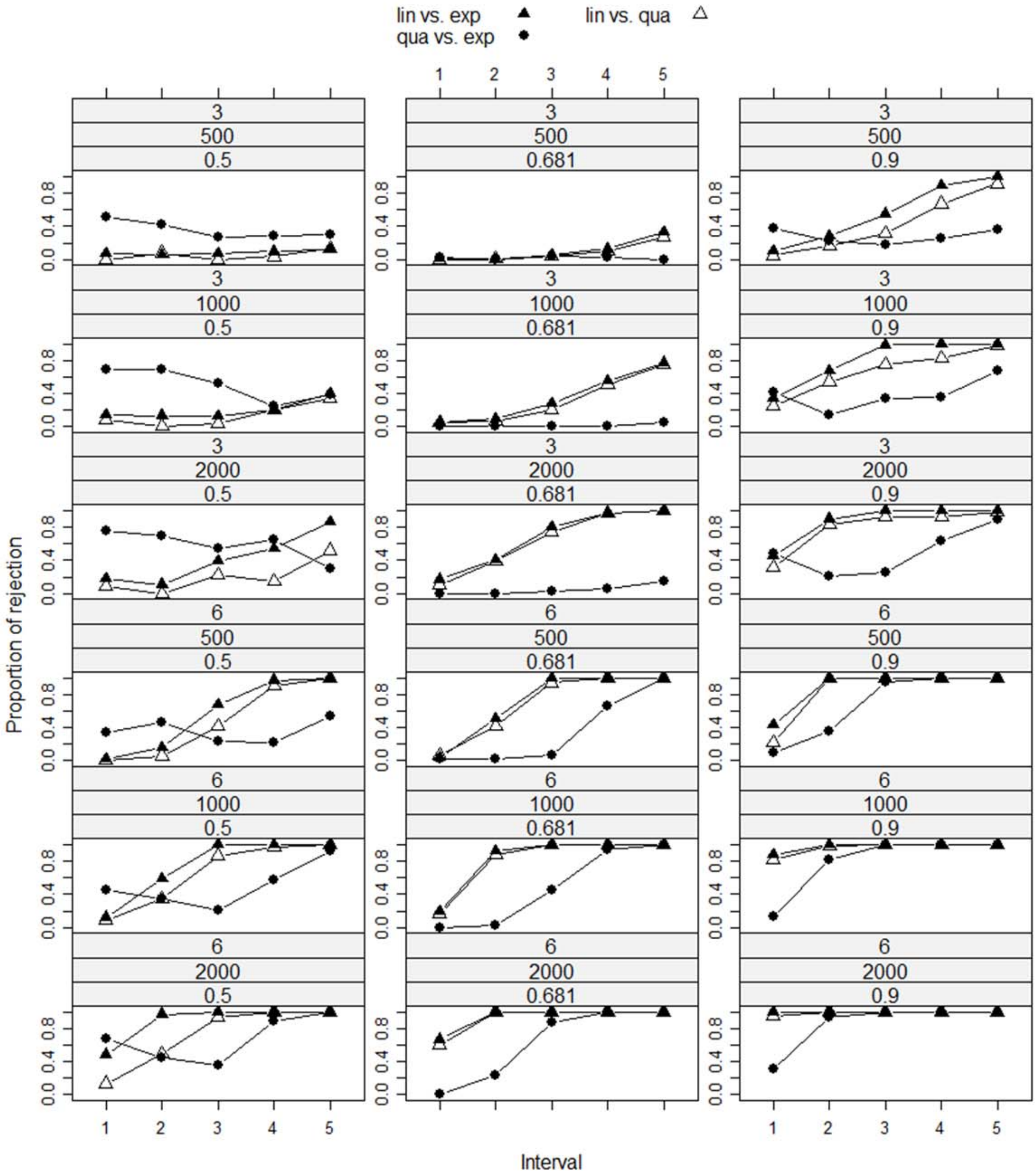
Average number of acceptable solutions by interval width for γ= 0.033, separately for each model



Note. Rows 1, 2, 3: $T = 3$, rows 4, 5, 6: $T = 6$; Rows 1, 4: $N = 500$, rows 2, 5: $N = 1000$, rows 3, 6: $N = 2000$; Column 1: GCR = .500, column 2: GCR = .681, column 3: GCR = .900.

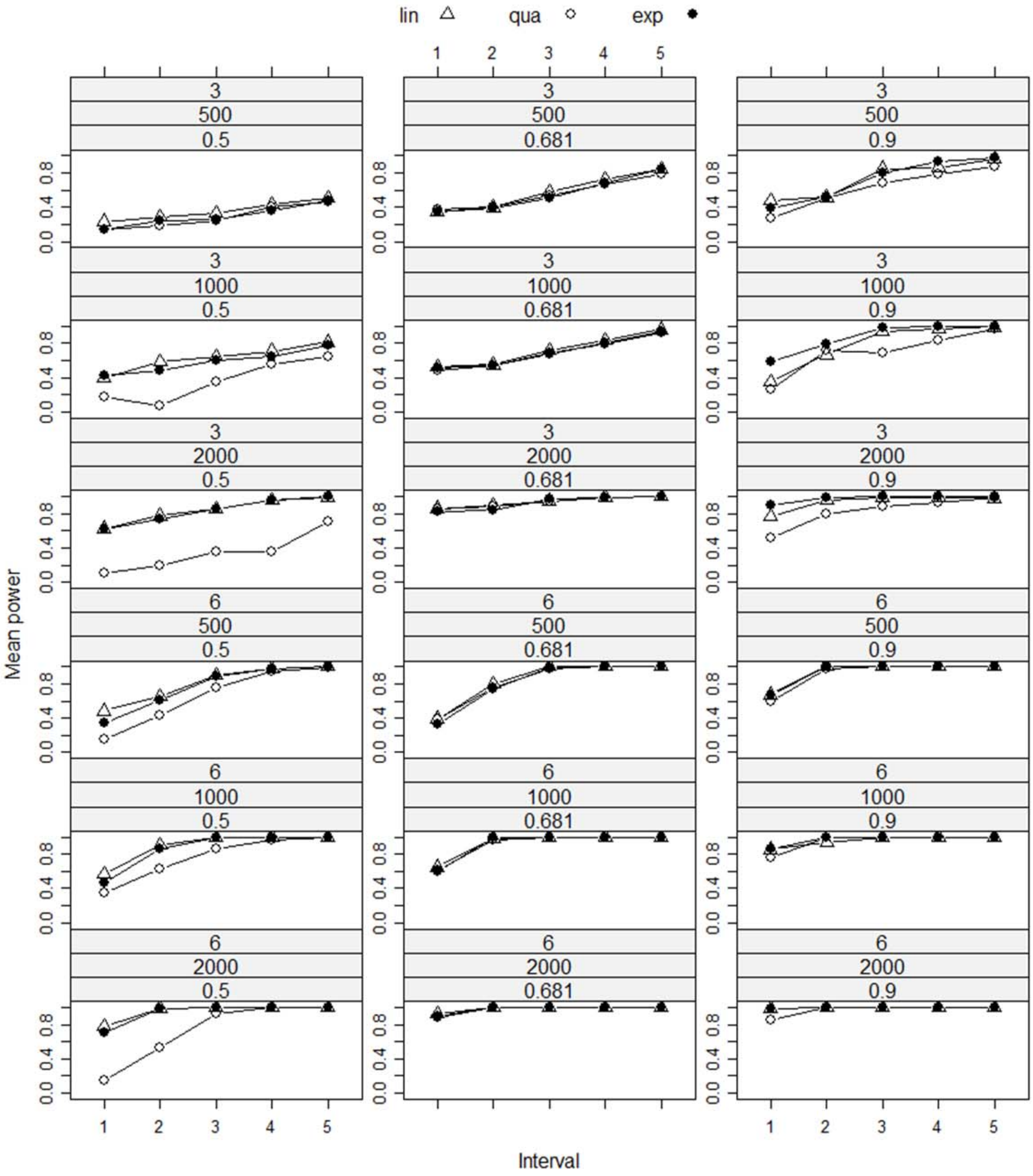
Supplementary Figure 4

Proportions of rejection of the linear GM and the quadratic GM when compared to the exponential GM and of the linear GM when compared to the quadratic GM (based on difference in BIC greater than 10) as a function of interval width for γ= 0.033 only



Note. Rows 1, 2, 3: T = 3, rows 4, 5, 6: T = 6; Rows 1, 4: N = 500, rows 2, 5: N = 1000, rows 3, 6: N = 2000; Column 1: GCR = .500, column 2: GCR = .681, column 3: GCR = .900.

Supplementary Figure 5
Power to Detect Variance in Change by Interval Width for γ= 0.033, for each Model



Note. Rows 1, 2, 3: $T = 3$, rows 4, 5, 6: $T = 6$; Rows 1, 4: $N = 500$, rows 2, 5: $N = 1000$, rows 3, 6: $N = 2000$; Column 1: GCR = .500, column 2: GCR = .681, column 3: GCR = .900.