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Examining within-person variability of each individual: How should we deal with non-varying individuals?

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Abstract
Researchers have witnessed a rapid increase in attention to within-person dynamic processes. However, individuals with observed zero within-person variability (i.e., non-varying individuals) remain understudied. This study investigates how non-varying individuals affect the estimation of within-person dynamic processes and offers practical recommendations. A motivating example of daily stressors demonstrates that including non-varying individuals can change substantive conclusions for univariate autoregressive models. Two simulation studies further explored how different proportions of non-varying individuals affect parameter estimation. Study 1 (univariate) found that non-varying individuals induce systematic upward bias in autoregressive estimates. Study 2 (bivariate) showed that, although average (fixed-effect) cross-lagged estimates may appear accurate, person-specific cross-lagged effects are systematically distorted, with some overestimated and others underestimated. Within this widely used Gaussian autoregressive modeling framework, we therefore recommend estimating dynamic parameters using a subsample that excludes non-varying individuals. We also indicate when subsample estimates can be interpreted as approximations to the full population, versus when they should be interpreted as describing the subsample population (e.g., when the proportion of non-varying individuals reaches around 10% or more in bivariate processes). The study highlights the importance of examining each individual's within-person variability and offers valuable guidance for applied researchers on handling non-varying individuals.

Keywords Within-person processes · Within-person variability · Intensive longitudinal data · Autoregressive effect · Cross-lagged effect

Introduction

Within-person processes have long been discussed in psychology and other social and behavioral sciences. With the rise of data collection (e.g., daily diary and ecological momentary assessment) and analysis methods for intensive longitudinal data, more and more research has begun to focus on within-person dynamic processes (Hamaker & Wichers, 2017). In contrast to developmental processes that typically focus on mean-level changes over longer periods, dynamic process research primarily examines within-person fluctuations over time. As a result, within-person variability, once treated as error or noise and not of interest in earlier studies, has been analyzed as meaningful fluctuations to further our understanding of within-person dynamics.

In recent years, progress has been made on many research topics related to within-person variability. Given that within-person variability is a prerequisite for studying within-person dynamics (Heck & Thomas, 2020), researchers have integrated findings from different studies to examine the proportion of within-person variance of various state constructs (Podsakoff et al., 2019; Scott et al., 2020) and explore relevant factors (i.e., constructs, measures, designs, and sample characteristics) explaining differences in within-person variance (Podsakoff et al., 2019). To better analyze

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person-specific dynamics, methodological researchers have proposed several advanced methods for modeling individuals' within-person variability (Fang & Wang, 2024; Jahng et al., 2008; Rast et al., 2022; Williams et al., 2021). Meanwhile, applied researchers have used within-person variability as a dynamic indicator of state constructs to examine their individual differences and potential predictors and outcomes across various subfields of psychology, including clinical and health (Mun et al., 2019; Veeramachaneni et al., 2019), social and personality (Mader et al., 2023; Pfund et al., 2024), developmental (Röcke et al., 2009), and educational psychology (Hausen et al., 2022).

Beyond focusing on correlates of within-person variability, several studies have examined its impact on estimating within-person dynamic processes. Research on within-person dynamic processes aimed to estimate and explain the dynamic characteristics (e.g., autoregressive effects) of one variable and the dynamic relations (e.g., cross-lagged effects) between variables. However, some studies have found that low within-person variability may lead to biased estimates of within-person effects. For example, floor effects (i.e., skewed distribution with observed low mean and low variability) may affect estimates of emotional reactivity to (un)pleasant events (Von Klipstein et al., 2022), as well as the correlation between person-specific autoregressive effects of negative affect and person mean levels of psychopathology (Haqiqatkhah et al., 2024). To address these challenges, researchers have proposed several modeling approaches. For example, the reservoir model (Deboeck & Bergeman, 2013; Whitaker et al., 2024) and dynamic two-part models (Muthén et al., 2025) provide ways to account for floor effects in dynamic processes. Additionally, Shao et al. (2025) introduced a zero-inflated process change multilevel autoregressive model to handle excess zeros in intensive longitudinal data. While these studies have examined the consequences and proposed solutions to specific patterns of low observed within-person variability, the extreme case – where some individuals exhibit no within-person variability – remains understudied.

In fact, these non-varying individuals are not uncommon in applied research.[1] Non-varying individuals are individuals whose observed scores on certain state constructs remain constant over the study period. When the number of time points is small, you can expect more non-varying individuals. In the often-used data from the National Study of Daily Experiences (NSDE) program, approximately 10% (n = 264 of 2711) of individuals did not report any stressors for 8 consecutive days (Charles et al., 2021). In a 7-day diary study of stressors, 62% (n = 93 of 150) of individuals showed never-stressor or always-stressor patterns in their individual data, suggesting a considerable proportion of non-varying individuals (Ram et al., 2017). This proportion was substantially reduced in 21-day ordinal data on stressors, with only 2% of individuals showing no intraindividual variability (Ram et al., 2017). However, increasing the number of time points does not necessarily eliminate non-varying individuals, as it also relates to how state constructs are measured. Specifically, non-varying individuals are more likely to be observed when few items, or even a single item, are used to assess state constructs. A 3-week diary study calculated average scores of three items to measure students' state academic self-concept and found that 14% (n = 41 of 291) of students had no within-person variability in their state scores over the study period (Hausen et al., 2022). Even for affective states that are generally believed to fluctuate within and between days, researchers have found a considerable proportion of individuals with the same affect scores more than 90% of 45 daily assessments (Röcke et al., 2009). Moreover, in a study that measured affect more frequently (i.e., six times a day for 14 consecutive days), some individuals still showed no variance in certain affect scores, although the exact proportion of non-varying individuals was not reported (Haslbeck et al., 2025). In studies that reported these proportions, the percentage of non-varying individuals ranged from about 2% to over 60% (Ram et al., 2017), depending on the number of time points, measures, and constructs. Taken together, these findings – though based on a subset of studies that explicitly report such proportions – suggest that non-varying individuals are indeed common in applied research.

It is important to note that an observed non-varying individual may correspond to two qualitatively different underlying situations. In one case, the constant sequence is itself a meaningful observation. The individual remains at a single level throughout the study period, and this stability reflects a real feature of their experience rather than a shortcoming of the study. For instance, in an intensive longitudinal study of suicidal ideation, the absence of any fluctuation, particularly a stable pattern of reporting no ideation, may indicate that these individuals have never experienced such thoughts and therefore constitute a qualitatively distinct group rather than cases of unobserved variation. In the other case, the constant sequence is a by-product of how the process was observed. The construct does fluctuate within the person over time, but because of design and measurement limitations, such as too few time points or a coarse single-item scale, this fluctuation is not captured, and the individual appears flat over the observation window. For example, over a sufficiently long period, individuals will likely encounter stressors of varying frequency and intensity, so some within-person variation

[1] We use the term "non-varying individuals" throughout to refer to individuals for whom the *observed* scores on certain state constructs remain constant over the study period. It does not imply that these individuals are inherently incapable of change.

in daily stressors is likely present even if it is not observed within a short study window. In this second case, the situation becomes a methodological concern if researchers overlook these individuals and apply commonly used dynamic models that assume within-person variability, treating the flat sequences as ordinary observations of a fluctuating process.

For non-varying individuals arising from such design and measurement limitations, it remains unclear how they influence estimates of within-person dynamic processes and how to address them in the analysis. An intuitive approach is to simply exclude these non-varying individuals from further analyses (e.g., Hausen et al., 2022), but this results in a loss of sample size, especially when there is a large proportion of non-varying individuals. A potentially more effective strategy within a multilevel modeling framework is to not exclude these individuals but instead fit a multilevel model, which can estimate parameters for each individual by borrowing information (or borrowing strength) from others in the sample (Gelman, 2006; Leeuw & Meijer, 2008). Specifically, by assuming particular distributions (typically normal) for within-person dynamic effects (e.g., person-specific autoregressive and cross-lagged effects), multilevel models can estimate the distributional properties of these effects, rather than directly estimating effects for each individual (McNeish, 2023). Researchers can then recover person-specific effects using empirical Bayes predictions (Liu, 2017). This lets researchers leverage data from individuals with variation to estimate dynamic effects for those without variation. Based on this idea, it is important to determine what proportion of non-varying individuals is acceptable to use the dynamic effect estimates obtained from the full sample. Further, if the proportion of non-varying individuals exceeds a certain threshold, how should we estimate and interpret the within-person dynamic effects of interest, including both average (fixed) and person-specific (random) effects (e.g., by using the results of dynamic effects from a subsample consisting of individuals with nonzero within-individual variability)?

Therefore, this study investigates the effect of non-varying individuals on the estimation of within-person dynamic processes in multilevel models and offers practical suggestions for handling these individuals. In doing so, we focus on Gaussian-based multilevel autoregressive models – a widely used framework for analyzing intensive longitudinal data in applied research. This choice lets us examine the impact of non-varying individuals in a familiar modeling context, highlighting potential biases that may arise when such models are applied without careful consideration of this data characteristic. In the following sections, we first illustrate the effects of non-varying individuals on autoregressive estimation results using an empirical dataset on daily stressors. Next, we conducted two simulation studies to explore the impacts of different proportions of non-varying individuals on parameter estimation in univariate autoregressive processes and bivariate processes (i.e., considering the lagged effect of a time-varying covariate *X* on *Y* after controlling for the autoregressive effects of *Y*). Based on the simulation results, we provide practical suggestions for addressing non-varying individuals in different conditions. Finally, we summarize our findings and their implications for future research.

Motivating example

Methods

Data

We used a 10-day diary dataset of stressors to illustrate how non-varying individuals can influence parameter estimates and potentially alter substantive conclusions. The sample comprised 164 Chinese female college students (M_{age} = 20.40 years, *SD* = 1.47), who reported whether they had experienced seven types of stressors (e.g., arguments, school-related stressors) using the Daily Inventory of Stressful Events (DISE; Almeida et al., 2002). Responses were coded 0 (“No”) or 1 (“Yes”) and summed to form a daily stressor score (*M* = 0.676, *SD* = 0.759 across all person-time observations). Participants’ compliance was high, with 94.67% (*n* = 1553) of all questionnaires (*N* = 1640; 164 participants × 10 questionnaires) completed. The study was approved by the university’s ethics committee.

Analysis

We first identified individuals whose stressor scores remained unchanged across the 10-day period (i.e., non-varying individuals). To further examine the influence of non-varying individuals on the estimation results of the dynamic process of stressors, we then estimated the first-order autoregressive effect of stressors (i.e., the predictive effect of stressors today on the following day) in the full sample and the subsample (excluding non-varying individuals). Specifically, we used Bayesian estimation in M*plus* and set two Markov chain Monte Carlo (MCMC) chains with 10,000 iterations each, 50% burn-in, and a thinning value of 10. The average (i.e., fixed effects) and person-specific autoregressive effects of stressors were examined. The autoregressive coefficients reported below are unstandardized.

Results

Identifying non-varying individuals

Of the 164 individuals in the full sample, 58 (35.37%) had stressor scores that remained constant over the 10-day study period. Among these, 42 reported no stressor during the study period (i.e., their scores remained at 0); 16 individuals consistently reported one (n = 15) or two (n = 1) stressors.

Average estimates in the full sample and the subsample

The mean number of daily stressors was 0.676 (SD = 0.759). In the full sample, the posterior median autoregressive effect of daily stressors was positive (B = 0.173, 95% credible interval = [0.060, 0.293]), and the credible interval lay entirely above zero, indicating that the data support a positive carry-over effect, whereby more stressors on one day are associated with more on the next. In the subsample excluding non-varying individuals, the posterior median was considerably smaller (B = 0.066, 95% credible interval = [– 0.019, 0.156]) and the credible interval included zero, so the data no longer clearly support a positive carry-over effect. Moreover, the full-sample estimate was approximately two to three times larger than that of the subsample. These contrasting results suggest that including or excluding non-varying individuals can lead to substantively different conclusions, thereby underscoring the importance of addressing them appropriately in applied research.

Person-specific estimates in the full sample

We further examined the person-specific autoregressive effects of stressors in the full sample. As shown in Fig. 1, all non-varying individuals (n = 58; 35.37%) had autoregressive estimates above the full-sample average. This result aligns with the expectation, as the constant scores of non-varying individuals imply "perfect" individual autocorrelation (i.e., their autoregressive effects are essentially 1). When such estimates are aggregated in a multilevel model, they pull the overall fixed effect upward, leading to a positive bias of the average autoregressive effect. We show this analytically in the Supplementary Material (uploaded to the Open Science Framework (OSF) repository (https://osf.io/fbkya); Luo, 2026).

The person-specific estimates of non-varying individuals are not identical but form a continuous distribution. This may seem counterintuitive, because a constant sequence appears to carry no information about an autoregressive coefficient. The reason is the latent-mean centering used in this model: the within-person mean is a latent quantity that is shrunk toward the grand mean, so a constant observed series (value c) is centered not at zero but at a person-specific, nonzero offset (the constant value minus the person's latent mean), and a series that remains at such an offset is most consistent with a coefficient near 1. The constant series is therefore informative about the person's autoregressive parameter, and the estimate becomes a compromise between the population mean and 1 whose strength grows with the distance of the constant value from the person's latent mean and with the number of available observations. This is why non-varying individuals differ continuously and why their estimates lie above the average, with a smaller, residual part of the spread reflecting Monte Carlo error. The Supplementary Material provides the full derivation together with empirical analyses in the full sample and in complete cases that support this account.

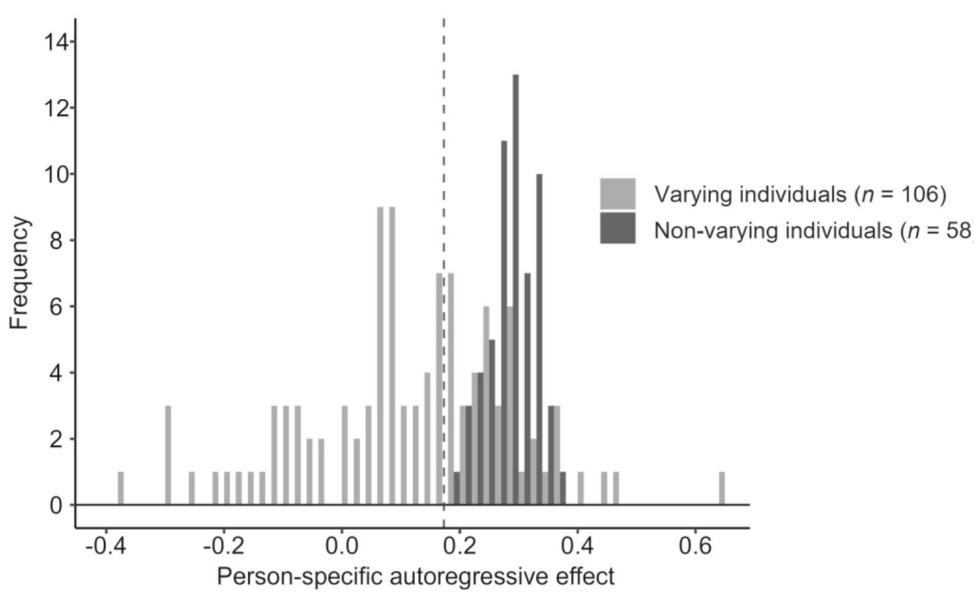


Fig. 1 Distribution of person-specific autoregressive effects of stressors. *Note*: The *vertical dashed line* indicates the average autoregressive effect of the full sample

Comparison of person-specific estimates for varying individuals across samples

To examine whether non-varying individuals affect estimates for those who do vary, we plotted each varying individual's person-specific autoregressive estimate from the full sample against the corresponding estimate from the subsample (Fig. 2). Including non-varying individuals systematically inflates these estimates. The full-sample estimates are far more dispersed and reach much more extreme values than the subsample estimates (their standard deviation is 0.18, versus 0.05 in the subsample), so that about 90% of individuals have a larger estimate in absolute value. The estimates are also shifted upward on average, with about 69% of individuals lying above the identity line. This inflation arises because including non-varying individuals raises both the estimated mean of the autoregressive random effect (from 0.07 to 0.17) and its estimated variance (from 0.02 to 0.11). The estimates of the varying individuals, which borrow information from this group-level distribution, are therefore shifted upward and, through weaker shrinkage, spread out. Individuals with less within-person variation, who depend more on the group level, tend to show somewhat larger upward discrepancies ($r = -.21$, $p = .035$). Thus, non-varying individuals do not merely add noise but systematically inflate and distort the person-specific estimates of the varying individuals.

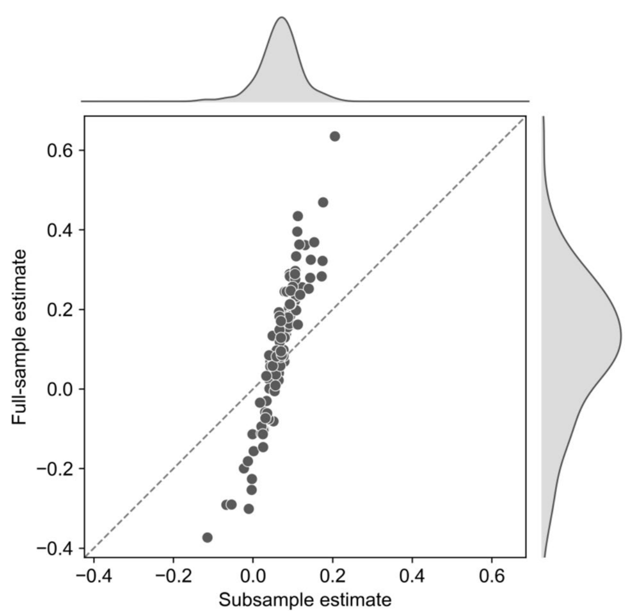


Fig. 2 Person-specific autoregressive estimates for the varying individuals (n = 106) from the full sample versus the subsample excluding non-varying individuals. The *dashed line* is the identity line, on which the two estimates would be equal. The *density curves* along the top and right margins show the distributions of the subsample and full-sample estimates, respectively

Summary and discussion

This motivating example illustrates how the inclusion of non-varying individuals can lead to diverging substantive conclusions (i.e., a clearly positive autoregressive effect in the full sample, with a credible interval excluding zero, versus a smaller and more uncertain effect in the subsample, with a credible interval including zero). This divergence stems from the upward bias induced by non-varying individuals, whose perfectly stable scores inflate fixed-effect estimates. However, the true values of the average and person-specific autoregressive effects remain unknown in these empirical data. Moreover, it is still unclear how non-varying individuals may affect more complex models, such as those involving bivariate dynamics. These considerations motivate two simulation studies that follow, in which we systematically evaluate the impact of non-varying individuals under controlled conditions and explore strategies to address them.

Simulation exploration

Conceptually, our simulation represents a population in which every individual follows a Gaussian multilevel autoregressive process, with within-person variance that differs across individuals and may be small for some, and in which no individual is truly flat. That is, given a sufficiently long observation period, every individual would display within-person variation, so that an observed non-varying individual does not arise because the underlying process itself has no variation, but because a low-variance fluctuating process is observed under conditions that fail to capture that variation, for example, too few or too widely spaced measurement occasions, or a response scale too coarse to register small changes. Within this setup, the true (population) value of a dynamic parameter is not the coefficient used to generate the continuous data, but the coefficient that the same Gaussian multilevel model recovers when fit to such long time series after they have been mapped onto the Likert response scale (i.e., the base observed dataset $D^{(0)}$ described in Step 3 below). Bias is then the deviation of the estimate obtained from a short observation window, in which some individuals appear non-varying, from this true value. Re-estimating the population value in this way means that the shift produced by the mapping is not counted as bias. Because we generate long time series and then sample short windows from them, each individual's underlying dynamics, and hence the true parameter value, remain well defined, which would not be the case if non-varying individuals were simply assigned constants.

On this basis, the simulation aimed to answer two questions: what is the impact of non-varying individuals on the estimation accuracy of both the average (i.e., fixed effects) and the person-specific (i.e., random effects) dynamic parameters (i.e., autoregressive and cross-lagged effects), and how to provide appropriate practical solutions based on the results of a subsample of varying individuals. To answer the first question, we manipulated the proportion of non-varying individuals, along with other relevant factors (i.e., effect size, sample size, and the number of time points), and examined parameter-estimation accuracy under these conditions. To answer the second question, in each condition we extracted a subsample consisting of individuals with nonzero within-person variability and compared its parameter estimates with the true values. When the bias of the subsample estimates is small, the subsample results can be used to approximate the full-sample estimates. When the bias exceeds a certain value (e.g., 10% of the true value), the subsample results should not be treated as an approximation of the full sample and need to be interpreted with respect to the population represented by the subsample. Simulation Study 1 and Study 2 explored these issues based on univariate autoregressive processes and bivariate processes, respectively.

Simulation Study 1: Univariate autoregressive processes

Methods

Data generation

The main idea underlying data generation is that individuals observed to have no variance are actually individuals with low variance in their intra-individual processes, which will show variance with a sufficient number of observations. Therefore, we first generated *a population dataset* that reflected the true dynamic process over a long period of time (T_0) for a large number of individuals (N_0) with varying degrees of within-person variability. Based on this population dataset, we then obtained *target observed datasets* over a short period of time (T) with a certain proportion of non-varying individuals $\left(N \times p_0\right)$ to examine its effect on parameter estimates.

The R Markdown code of Study 1 has been uploaded to the OSF repository (https://osf.io/fbkya; Luo, 2026).

Step 1: Generate a population dataset $\left(N_0 \times T_0\right)$ The population dataset with sufficient sample size ($N_0 = 5000$) and number of repeated observations ($T_0 = 1000$) was generated based on the univariate first-order autoregressive model:

$$y_{it} = \mu_i + Y_{it}, \tag{1}$$

$$Y_{it} = a_{0i} Y_{i,\,t-1} + \xi_{it}, \tag{2}$$

where the observed scores for person i at time t (i.e., y_{it}) are first decomposed into the between-person components (i.e., person-specific latent means; μ_i) and the within-person components (i.e., deviations from the means; Y_{it}). The within-person component for person i at time t is regressed on that for person i at time $t-1$ (i.e., $Y_{i,t-1}$). a_{0i} is the autoregressive parameter for person i, which represents the inertia or carry-over effect of Y, and is allowed to vary between individuals. ξ_{it} is the dynamic error for person i at time t, and is assumed to be normally distributed with a mean of zero (i.e., $\xi_{it} \sim N(0, \sigma^2)$). There were two possible values for the fixed effects of the autoregressive parameter ($a_0 = 0.3$ or 0.5 for small or large autoregressive effects, respectively). The random variance of the autoregressive parameter was set to 1% of the fixed effect. The within-person residual variance (σ^2) was fixed at 0.3, and the between-person variance of Y was fixed at 1. The data was generated in M*plus* 8.10.

Step 2: Adjust the population dataset To simulate observed data typical of applied research where single Likert items are used and where non-varying individuals are more likely to emerge, we adjusted the population dataset. Specifically, we rounded the generated data and changed negative numbers to 0 and values greater than 4 to 4 to simulate the observed scores obtained based on a five-point Likert scale. Subsequently, individuals exhibiting no variability across all $T_0 = 1000$ time points were excluded from the population dataset. This yielded *an adjusted population dataset* with N_0' (smaller than $N_0 = 5000$) individuals and T_0 repeated observations per individual.

Step 3: Obtain target observed datasets ($N \times T$) To obtain target observed datasets with specific proportions ($p_0 = 0\%$, 5%, 10%, 15%, 20%, 30%, 50%) of non-varying individuals, we first sampled a dataset $D^{(0)}$ with all the observations (T_0) of a certain number of individuals ($N = 100, 200, 300$) from the adjusted population dataset ($N_0' \times T_0 N_0' \times T_0$). Then, from this dataset $D^{(0)}$, we sampled target observed datasets $\{D^{(1)}{}_j\}$ with a smaller number of observations ($T = 7, 10, 14, 20$) for the same individuals (N). This process was replicated 500 times (j denotes the jth dataset, $j = 1, 2, \ldots, 500$). In the following paragraphs, we demonstrate how to obtain target observed datasets with a certain proportion of non-varying individuals using a simulation condition ($p_0 = 10\%$, $N = 100$, $T = 10$) as an example.

First, we took a sliding window of width T (= 10) to examine all the windows ($T_0 - T + 1 = 91$) for each individual in the adjusted population dataset and recorded the number of windows with no variation (m_i, i denotes the ith person).

Then, we employed a threshold-based sampling method to select individuals from the adjusted population dataset ($N_0' \times T_0$) to obtain the base observed dataset $D^{(0)}$

$(N \times T_0 N \times T_0)$, from which the target observed datasets $\{D^{(1)}{}_j\}$ $(N \times T)$ are sampled. The sampling procedure aimed to ensure that the proportion of non-varying individuals (p_j) in the jth target observed dataset $D^{(1)}{}_j$ was close to the predefined p_0.

Specifically, we used M as a threshold to extract $N \times p_0 = .10$ individuals with $m_i > M$ and $N \times \left(1 - p_0\right) = 90$ individuals with $m_i \leq M$ from the adjusted population dataset to construct a base observed dataset $D^{(0)}$ $(N \times T_0 N \times T_0)$. From this dataset, we sampled 500 target observed datasets. To avoid the proportion of non-varying individuals (p_j) in some target observed datasets deviating too far from p_0, we imposed tolerance bounds $\left|p_j - p_0\right| < 5\%$ for $p_0 = 0\%$, 5%, 10%, 15%, and 20%, and $\left|p_j - p_0\right| < 10\%$ for $p_0 = 30\%$, and 50%. The optimal threshold M^* was determined as the value that minimizes the difference between the median of the proportion of non-varying individuals across datasets (i.e., $\mathrm{Med}(p_j)$) and the predefined p_0. This procedure finally yielded 500 target observed datasets $(N \times T)$, each containing a proportion of non-varying individuals close to p_0.

Step 4: Extract subsample datasets $\left(N' \times T\right)\left(N' \times T\right)$ from full datasets $(N \times T)$ To examine the parameter estimates of data without non-varying individuals, we extracted subsample datasets $\{D^{(2)}{}_j\}$ from the full datasets $\{D^{(1)}{}_j\}$, each containing a subsample of individuals (N') whose data vary over time.

Simulation conditions

Overall, we manipulated the proportion of non-varying individuals ($p_0 = 0\%$, 5%, 10%, 15%, 20%, 30%, 50%) to examine its effect on parameter estimates. In addition, we varied the autoregressive effect ($a_0 = 0.3$ or 0.5), the sample size (N = 100, 200, 300), and the number of time points ($T = 7$, 10, 14, 20) to explore the impact of non-varying individual data on various scenarios. These four factors were fully crossed, resulting in 168 $(= 7 \times 2 \times 3 \times 4)$ simulation conditions.

Note that the autoregressive values $a_0 = 0.3$ and 0.5 are the values used to generate the population dataset. However, because of this adjustment, these autoregressive values are not the final parameter values used for bias evaluation. The empirical "true" values are re-estimated from the base observed dataset $D^{(0)}$ (see the following section for details) and are smaller than the originally set a_0. For example, under the illustrative condition ($p_0 = 10\%$, $N = 100$, $T = 10$), the generating values $a_0 = 0.3$ and $a_0 = 0.5$ correspond to re-estimated autoregressive values of 0.226 and 0.373, respectively. Importantly, we chose the two generator levels to represent a relatively smaller and a relatively larger autoregressive process. Our goal was to study whether a relatively smaller versus a larger autoregressive effect alters the influence of non-varying individuals on parameter estimation, rather than to make claims specific to the exact numeric values 0.3 and 0.5.

Estimation and evaluation

We examined the estimation accuracy of the average (i.e., fixed effects) and person-specific autoregressive effects. First, the true values of the average and person-specific autoregressive effects were obtained by fitting the base observed dataset $D^{(0)}$ to a univariate first-order autoregressive model. Across all conditions, the posterior standard errors of these base-dataset estimates were small (around 0.04 or smaller for the mean and around 0.01 or smaller for the autoregressive coefficient), so they provide a reliable benchmark for evaluating bias.

Then, the full datasets $\{D^{(1)}{}_j\}$, each containing a certain proportion of non-varying individuals, and the subsample datasets $\{D^{(2)}{}_j\}$, each excluding non-varying individuals, were fitted to the same model. The univariate autoregressive models were estimated in M*plus* 8.10 using Bayesian estimation within the dynamic structural equation modeling framework (DSEM; Asparouhov et al., 2018). Two Gibbs sampler chains were used, each with a minimum number of iterations of 3000 and a thinning value of 10. The model was considered to have converged when the potential scale reduction (PSR; Asparouhov & Muthén, 2010) of all parameters was less than 1.1. The fixed effects of the autoregressive effects were extracted directly from the output of M*plus*. To obtain the person-specific autoregressive effects, we saved the posterior draws of the autoregressive parameter using the SAVEDATA command in M*plus*, and used the median of the posterior distribution of the autoregressive parameter for each individual as a point estimate of person-specific autoregressive effects. The R package *MplusAutomation* (Hallquist & Wiley, 2018) was used to replicate the parameter estimation 500 times.

Finally, we calculated the relative bias of the fixed effect estimates of autoregressive parameters in both the full and the subsample datasets. Specifically, for each simulation condition, relative bias was defined as the average difference between the estimated and true parameter values across all replications, divided by the true parameter value. We showed how the relative bias of autoregressive parameters varied with the proportion of non-varying individuals under different simulation conditions.

While our primary interest lies in the accuracy of the average (fixed) effects, which are often the focus of applied research, we also recognize the importance of understanding the underlying person-specific dynamics that give rise to any observed bias in the fixed effects. Therefore, in addition to evaluating the fixed effects, we examine the bias in the person-specific autoregressive estimates. To do this, we introduce an individual-level metric: the number of windows (of length T) with no variation (m_i) within the long population time series. This metric captures an individual's latent propensity to exhibit no variability over shorter observation periods. By linking this propensity to the bias in their person-specific estimates, we aim to uncover how non-varying individuals distort the overall fixed effect estimates, moving beyond a purely descriptive account of the bias to a more mechanistic explanation.

Results

Parameter estimation accuracy of the full datasets

The relative bias of the fixed effect of the autoregressive parameter in the full datasets is shown in Fig. 3. In all conditions, the autoregressive effects were consistently overestimated. This overestimation became more pronounced as the proportion of non-varying individuals increased. Regarding the size of the autoregressive effect, the relative bias of the estimates of autoregressive effects was smaller for larger true values than for smaller true values. Concerning the number of time points, the number of dots (in Fig. 3) with relative bias within 0.1 increases as the number of time points increases. This indicates that more time points allow a higher proportion of non-varying individuals while keeping relative bias below 0.1. It is also noteworthy that when the number of time points is too small (e.g., $T = 7$), the bias in the estimates of autoregressive effects is unacceptable, regardless of the true values of autoregressive effects and sample size. Regarding the sample size, the results did not show its considerable impact on the relative bias of the autoregressive effect.

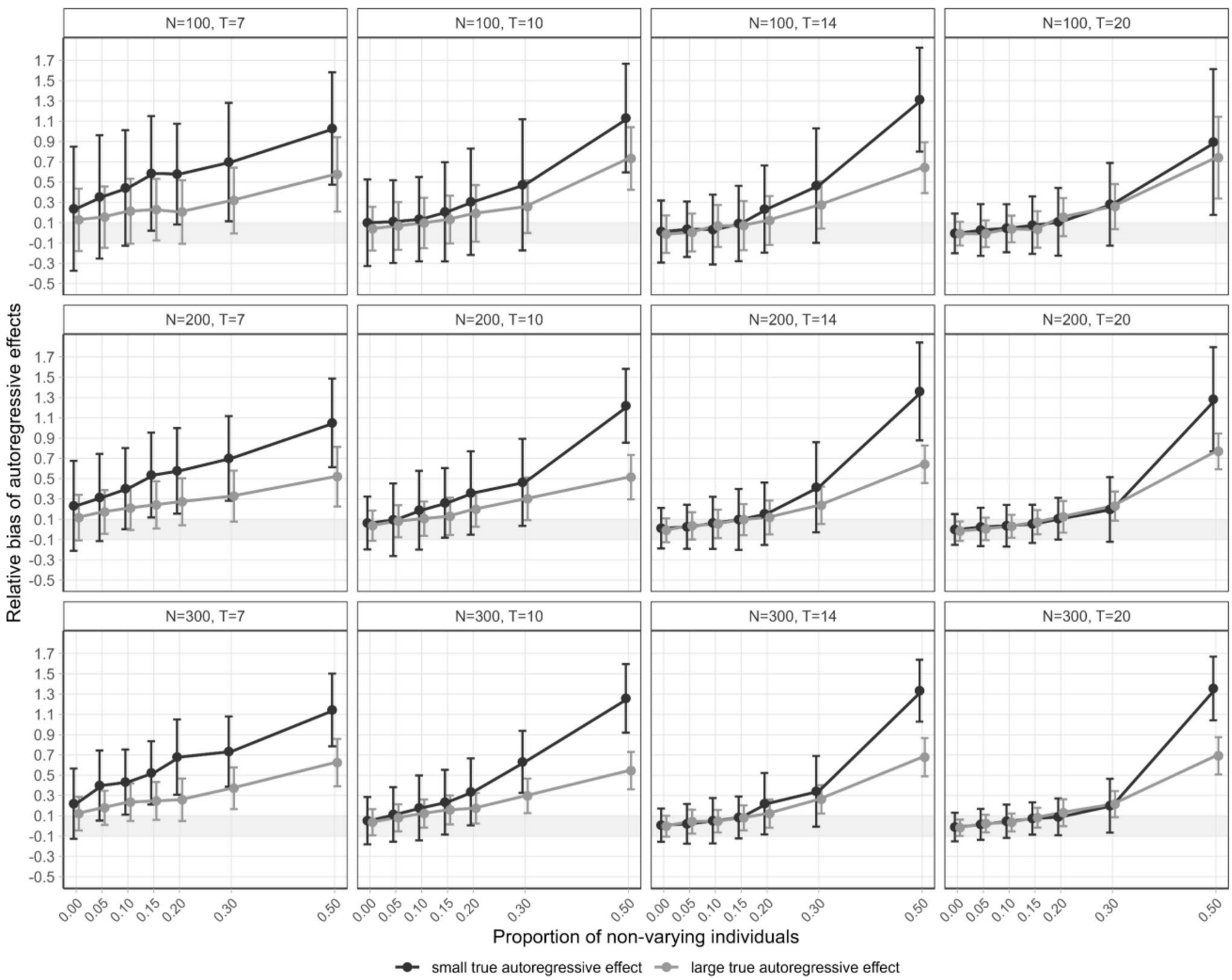


Fig. 3 Relative bias of the fixed effect of autoregressive effects in the full datasets in Simulation Study 1. *Note*: The *vertical lines* show the 95% central range (2.5th to 97.5th percentiles) of the relative bias across 500 replications. The *shaded area* indicates absolute relative bias lower than 0.1

To further examine the accuracy of parameter estimation at the individual level, we analyzed the bias of person-specific autoregressive effects for individuals with different numbers of windows with no variation. Figure 4 presents an example condition, showing the bias distribution across five groups of people with different proportions of windows with no variation (i.e., 0%, 0 ~ 5%, 5% ~ 10%, 10% ~ 30%, and 30% ~ 100%). This detailed illustration reveals how person-specific bias varies across individuals with different propensities to exhibit no variability. Figure 5 then summarizes the average person-specific bias for each of these five groups across all simulation conditions, providing a comprehensive view of how the patterns observed in the example condition generalize. This person-level analysis helps explain why and how the fixed effects become biased when non-varying individuals are present in the sample.

The results indicate that for individuals with all-varying windows (i.e., red dots) or with only a small proportion of non-varying windows (dark blue dots), the bias of person-specific autoregressive parameters was generally small (close to zero). In contrast, for those with a larger proportion of non-varying windows (i.e., light blue and grey dots), the person-specific autoregressive parameters tended to be systematically overestimated. This suggests that the upward bias in the fixed effects of autoregressive parameters may largely originate from individuals who exhibit low within-person variability in their population long time series (i.e., a large number of windows with no variation in their shorter time series).

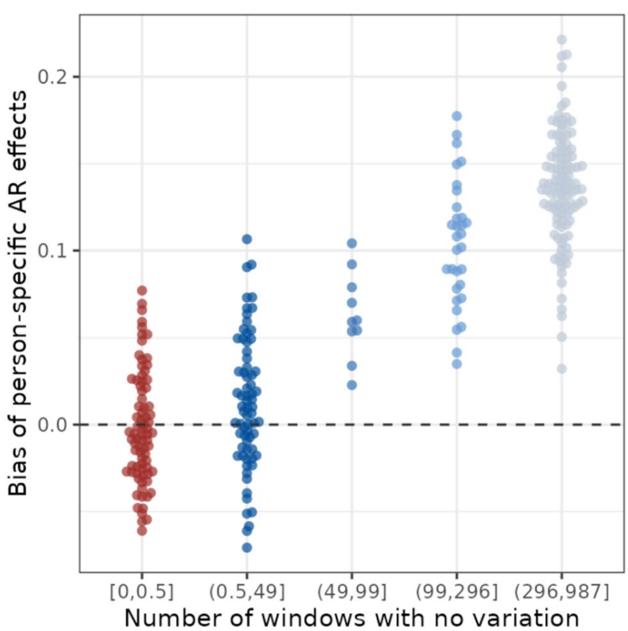


Fig. 4 Bias of person-specific autoregressive effects in an example condition in Simulation Study 1 ($p_0 = 0.3$, $a_0 = 0.3$, $N = 300$, $T = 14$)

Furthermore, we observed that autoregressive parameters were overestimated for almost all individuals when the number of time points was as small as 7. This finding is consistent with the result that the average autoregressive effect was consistently overestimated in conditions with few time points.

Parameter estimation accuracy of the subsample datasets

The relative bias of the fixed effect of the autoregressive parameter in the subsample datasets is shown in Fig. 6. When the number of time points was 7, the relative bias of the autoregressive effect exceeded 0.1 for nearly all proportions of non-varying individuals, regardless of the true values of autoregressive effects and sample size. In contrast, when the number of time points was equal to or larger than 10 and the proportion of non-varying individuals was lower than 30%, the relative bias of the autoregressive effect decreased substantially, with most values within 0.1. This suggests that with an adequate number of time points ($T \geq 10$) and a relatively low proportion of non-varying individuals, the estimates of autoregressive effects of the subsample datasets can be used to approximate the results of the full datasets.

Summary of results and practical suggestions

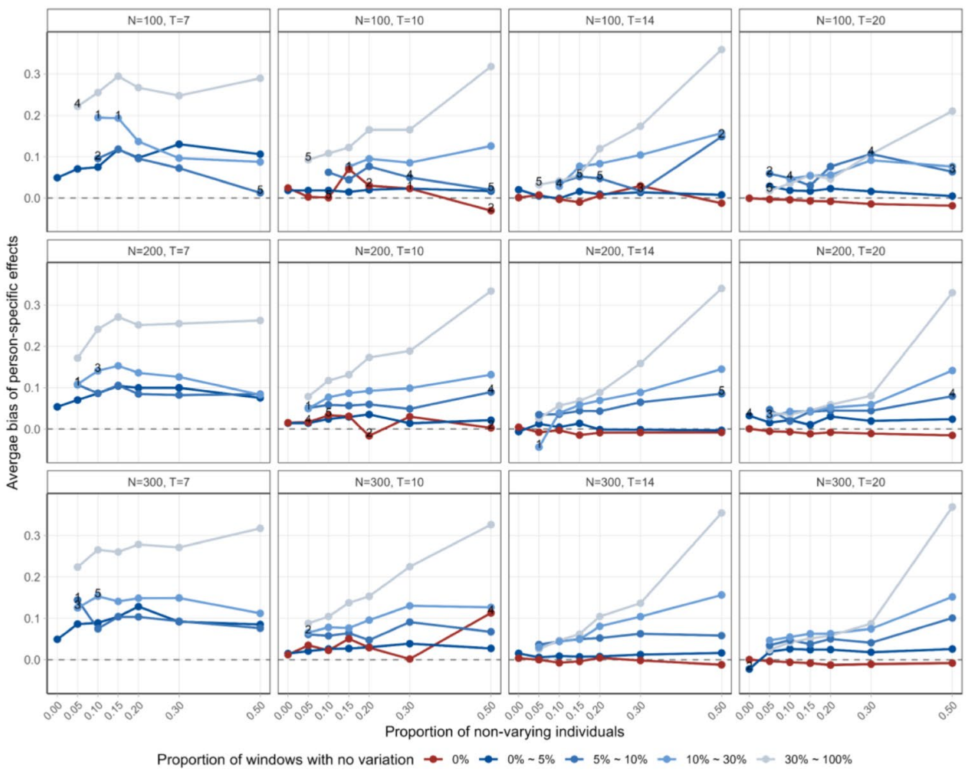
The results of parameter accuracy and corresponding practical suggestions are summarized in Fig. 7. Given the limited impact of sample size, N was not included in the figure. Likewise, although the size of the autoregressive effect (a_0) showed some influence on relative bias, it did not substantially affect the point at which relative bias exceeded 0.1, which is central to our recommendations. Therefore, Fig. 7 presents results as a function of the proportion of non-varying individuals (p_0) and the number of time points (T).

Specifically, Fig. 7a, b displays the average absolute relative bias for the full and subsample datasets, respectively, with the bold line marking the 10% boundary. Figure 7c integrates these findings to classify each condition into one of three scenarios:

(1) Both full and subsample estimates are accurate (average absolute relative bias < 10%),
(2) Only subsample estimates are accurate, or
(3) Neither full nor subsample estimates are accurate. Based on these scenarios, we offer practical recommendations for researchers, as detailed in the figure.

When the number of time points is very small (i.e., 7), or relatively large but combined with a high proportion of non-varying individuals, both the full and subsample datasets show substantial bias in estimating autoregressive effects. In

(a) Average bias of person-specific autoregressive effects for small true values.



(b) Average bias of person-specific autoregressive effects for large true values.

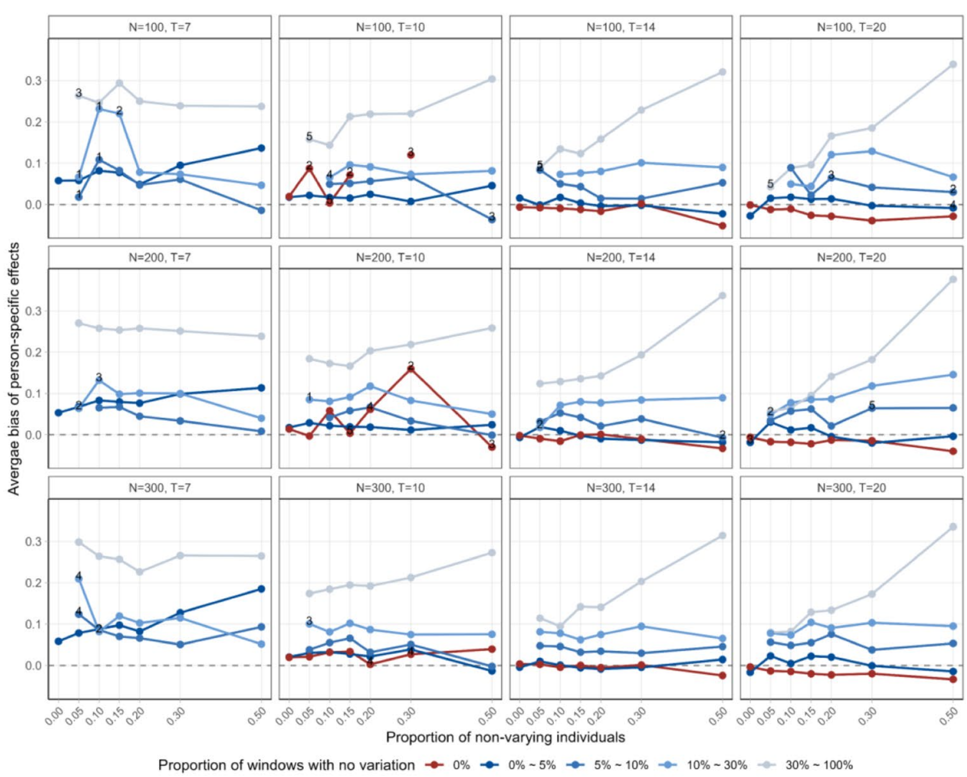


Fig. 5 Average bias of person-specific autoregressive effects per group in the full datasets in Simulation Study 1. *Note*: *Dashed horizontal line* indicates zero bias. *Numerical labels* indicate subgroup sizes when $n \leq 5$. (**a**) Average bias of person-specific autoregressive effects for small true values. (**b**) Average bias of person-specific autoregressive effects for large true values

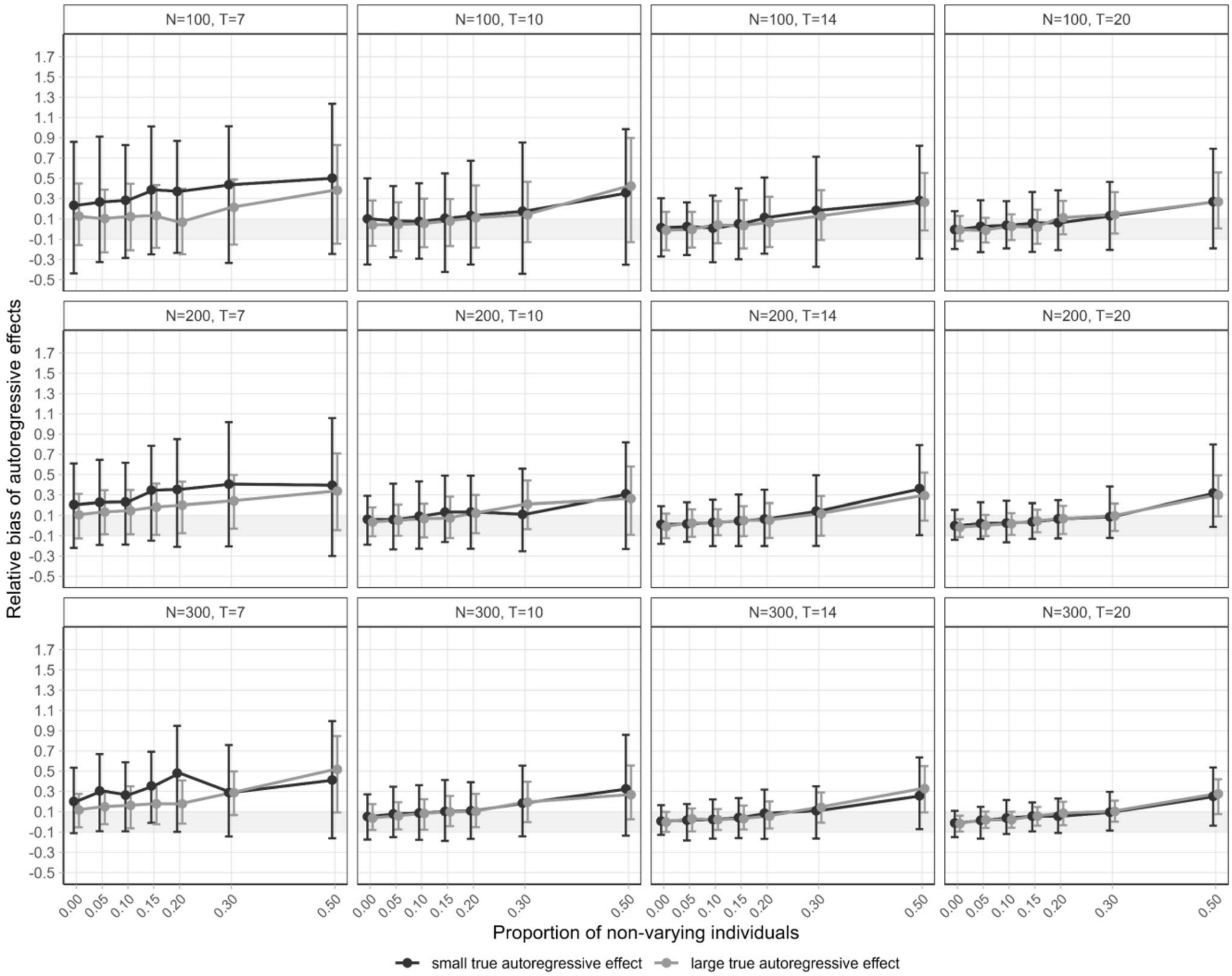


Fig. 6 Relative bias of the fixed effect of autoregressive effects in the subsample datasets in Simulation Study 1. *Note*: The *vertical lines* show the 95% central range (2.5th to 97.5th percentiles) of the relative bias across 500 replications. The *shaded area* indicates absolute relative bias lower than 0.1

these cases (indicated by the red blocks in Fig. 7c), we recommend using subsamples to estimate autoregressive effects and interpreting these estimates based on the population represented by the subsample. In contrast, when the proportion of non-varying individuals is lower, the subsample datasets show high estimation accuracy of autoregressive effects. In such cases, autoregressive estimates obtained from the subsample can be regarded as approximations of those in the full sample and interpreted in the context of the population represented by the full dataset. This recommendation holds regardless of the estimation accuracy of autoregressive effects in the full datasets, as non-varying individuals consistently introduce upward bias in autoregressive estimates. Even when the relative bias in the full datasets does not exceed 0.1, the presence of non-varying individuals still inflates the average estimate, leading to systematic bias.

Simulation Study 2: Bivariate processes

Methods

Data generation and simulation conditions

The basic idea and procedure of data generation for Simulation Study 2 were similar to those of Simulation Study 1. First, we generated bivariate data with a sufficient number of observations ($T_0 = 1000$). Specifically, after controlling for the autoregressive effect of Y, we considered the cross-lagged effect of the time-varying covariate X on Y. The fixed effect of the autoregressive parameter of Y was set to 0.5. There were two possible values for the fixed effect of the cross-lagged parameter of X on Y ($c_0 = 0.3$ or 0.5), indicating that the cross-lagged effect was lower than or similar

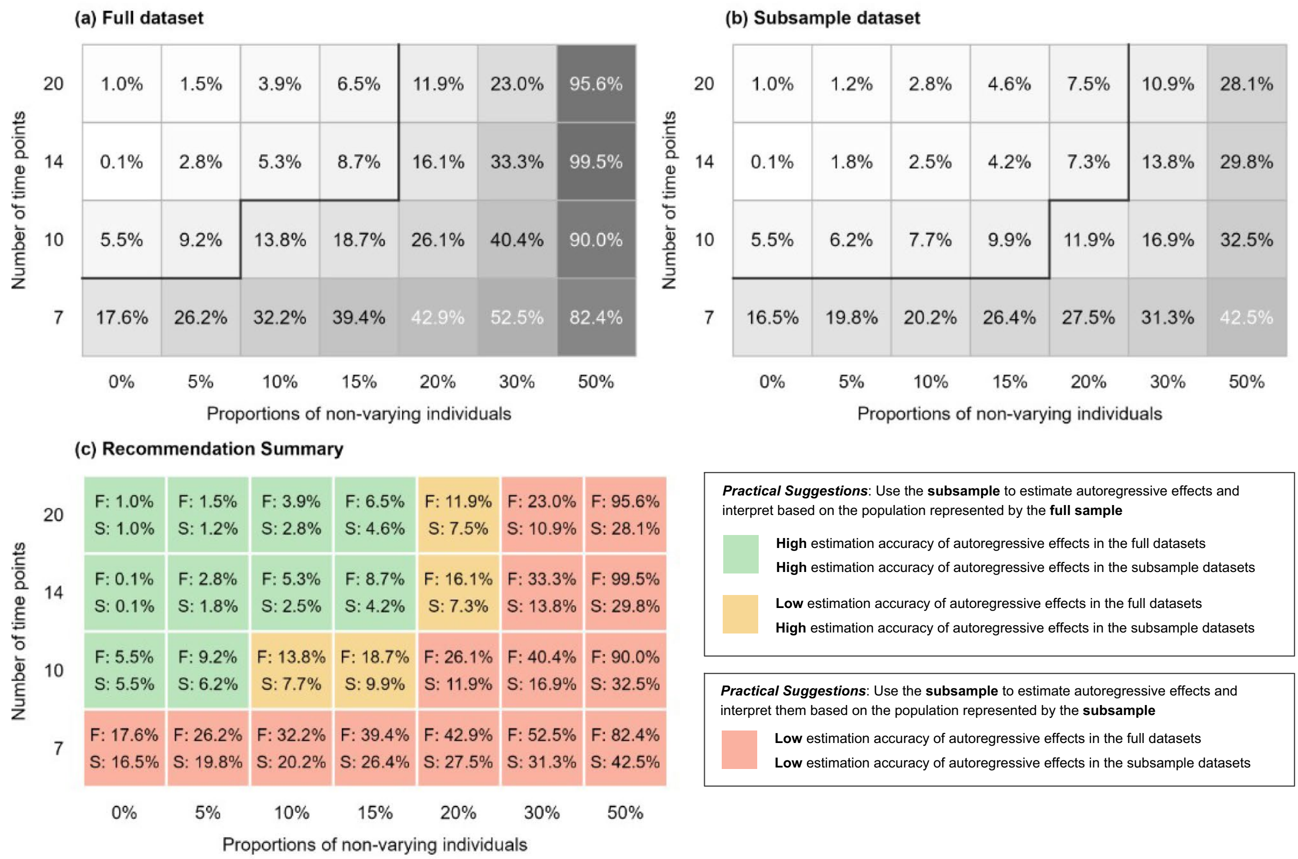


Fig. 7 Summary of parameter estimation accuracy results and practical suggestions in Simulation Study 1. *Note*: Panels **(a)** and **(b)** show the average absolute relative bias for the full and subsample datasets, respectively, for each combination of time points (T) and proportion of non-varying individuals (p_0). Values are averaged across sample size (N) and true autoregressive effect size (a_0), as these factors did not substantially affect the pattern of results. The *bold black line* indicates the boundary where the averaged bias crosses the 10% threshold. Panel **(c)** synthesizes the information from panels **(a)** and **(b)** to categorize each (T, p_0) condition into three scenarios based on whether the 10% accuracy criterion is met in the full and/or subsample datasets, and provides corresponding practical recommendations

to the autoregressive effect, respectively. The autoregressive and cross-lagged effects were allowed to vary across individuals, and the random variance was set to 1% of the fixed effects (e.g., for a fixed cross-lagged effect of 0.5, the random variance was 0.005). The within-person residual variance was fixed at 0.4, and the between-person variance was fixed at 0.5 for Y. The within-person variance was fixed at 0.5, and the between-person variance was fixed at 0.5 for X. The between-person correlation between X and Y was 0.3. Then, we adjusted Y in the generated dataset and obtained the full datasets $\{D^{(1)}{}_j\}$(j denotes the jth dataset, $j = 1, 2, \ldots, 500$) and the subsample datasets $\{D^{(2)}{}_j\}$ in the same way as in Simulation Study 1.

This simulation study varied the proportion of non-varying individuals for Y ($p_0 = 0\%, 5\%, 10\%, 15\%, 20\%, 30\%, 50\%$), cross-lagged effects of X on Y ($c_0 = 0.3$ or 0.5), sample size ($N = 100, 200, 300$), and the number of time points ($T = 7, 10, 14, 20$), resulting in 168 simulated conditions. The two c_0 levels represent relatively small and large cross-lagged effects. We aimed to test whether non-varying individuals differentially affect parameter recovery across these effect sizes, rather than to make claims tied to those exact values. The R Markdown code of Study 2 has been uploaded to the OSF repository (https://osf.io/fbkya; Luo, 2026).

Estimation and evaluation

The study examined the estimation accuracy of the average (i.e., fixed effects) and person-specific autoregressive and cross-lagged effects. The bivariate models were estimated in M*plus* 8.10 using the same settings as in Simulation Study 1. We obtained the fixed and person-specific autoregressive and cross-lagged effects and calculated their relative bias in the full and subsample datasets. As in Simulation Study 1, we examined the relative bias of the average autoregressive and cross-lagged effects in data with different proportions of non-varying individuals, and the bias of person-specific autoregressive and cross-lagged effects for individuals with different numbers of windows with no variation.

Results

Estimation bias of autoregressive effects in the full and subsample datasets

The relative bias of the fixed effect of the autoregressive parameters is shown in Fig. 8. In both the full (Fig. 8a) and subsample (Fig. 8b) datasets, the relative bias exceeded 0.1 when the proportion of non-varying individuals was around 30% or higher. By contrast, the true value of the cross-lagged effect, the number of time points, and the sample size appeared to have only a limited and inconsistent influence on this bias. We also examined the average bias of the person-specific autoregressive parameters across all groups and simulation conditions in the full datasets. The results revealed a similar pattern to that shown in Fig. 5, where individuals with more non-varying windows exhibited larger upward bias in their autoregressive estimates.

Estimation bias of cross-lagged effects in the full and subsample datasets

In the full datasets, the absolute value of the relative bias of the fixed effects of the cross-lagged parameters remained below 0.1 across all simulation conditions. At first glance, this suggests that even when up to 50% of individuals are non-varying, the accuracy of fixed-effect estimates for cross-lagged parameters is largely unaffected. However, further analyses of person-specific cross-lagged parameters tells a different story.

Figure 9 presents the bias distribution of person-specific cross-lagged effects in an example condition, and Figure 10 shows the average bias across all simulation conditions. They revealed a systematic pattern: cross-lagged parameters were *overestimated* for individuals with a large number of non-varying windows and, more importantly, *underestimated* for individuals with all-varying windows (i.e., red dots in Figs. 9 and 10). This pattern persisted across different true values of the cross-lagged effect, number of time points, and sample sizes. One might expect that individuals with all-varying windows would yield unbiased person-specific estimates, but we found that their average bias actually increased as the proportion of non-varying individuals increased.

These findings suggest that the seemingly high accuracy of the average (fixed-effect) cross-lagged estimates should be interpreted with caution, as it likely reflects the overestimation of some individual parameters and the underestimation of others. In fact, person-specific cross-lagged effects are systematically distorted, even when group-level fixed effects appear unbiased.

In the subsample datasets, estimation accuracy of the cross-lagged parameters decreased as the proportion of non-varying individuals increased. Across all conditions, relative bias exceeded 0.1 once the proportion of non-varying individuals reached around 10% or more. This indicates that when the proportion of non-varying individuals is about 10% or higher, subsample estimates should be interpreted with respect to the population they represent (i.e., individuals with varying responses), rather than as approximations to the full population.

Summary of results and practical suggestions

For the autoregressive effects, relative bias in both the full and subsample datasets exceeded 0.1 when the proportion of non-varying individuals was around 30% or higher. For the cross-lagged effects in the full datasets, fixed-effect estimates appeared accurate, but person-specific estimates were systematically biased under all conditions. For the cross-lagged effects in the subsample datasets, relative bias exceeded 0.1 when the proportion of non-varying individuals was around 10% or higher.

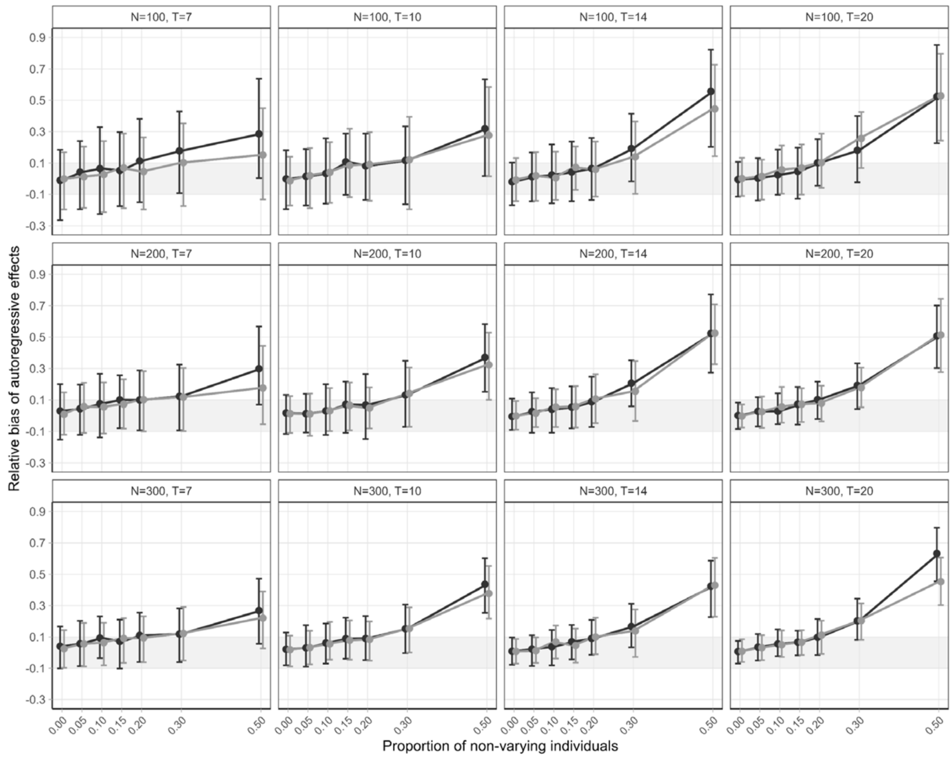
Bringing these findings together, we offer two practical suggestions for studies involving non-varying individuals. When the proportion of non-varying individuals is below 10%, researchers can use the subsample (excluding non-varying individuals) to estimate autoregressive and cross-lagged effects and interpret these estimates in the context of the full-sample population. By contrast, when the proportion is around 10% or higher, we recommend estimating effects using the subsample and interpreting the results strictly with respect to the population represented by that subsample.

Discussion

Psychology has witnessed a rapid growth of interest in within-person dynamic processes (Hamaker & Wichers, 2017). Studies modeling within-person variability of state constructs consistently show substantial individual differences in this variability. Meanwhile, several studies have shown the negative impact of low within-person variability on the estimation of dynamic effects. Despite the increasing interest in within-person variability, a particular group of individuals with zero within-person variability has been largely understudied. This gap poses a practical challenge for applied researchers collecting intensive longitudinal data to examine within-person dynamic processes, who lack clear guidance on how to handle these non-varying individuals (Charles et al., 2021; Hausen et al., 2022; Röcke et al., 2009).

In this study, we conducted a preliminary investigation of the influence of non-varying individuals and provided practical suggestions for addressing them using Bayesian

(a) Relative bias of the fixed effect of autoregressive effects in the full datasets.



(b) Relative bias of the fixed effect of autoregressive effects in the subsample datasets.

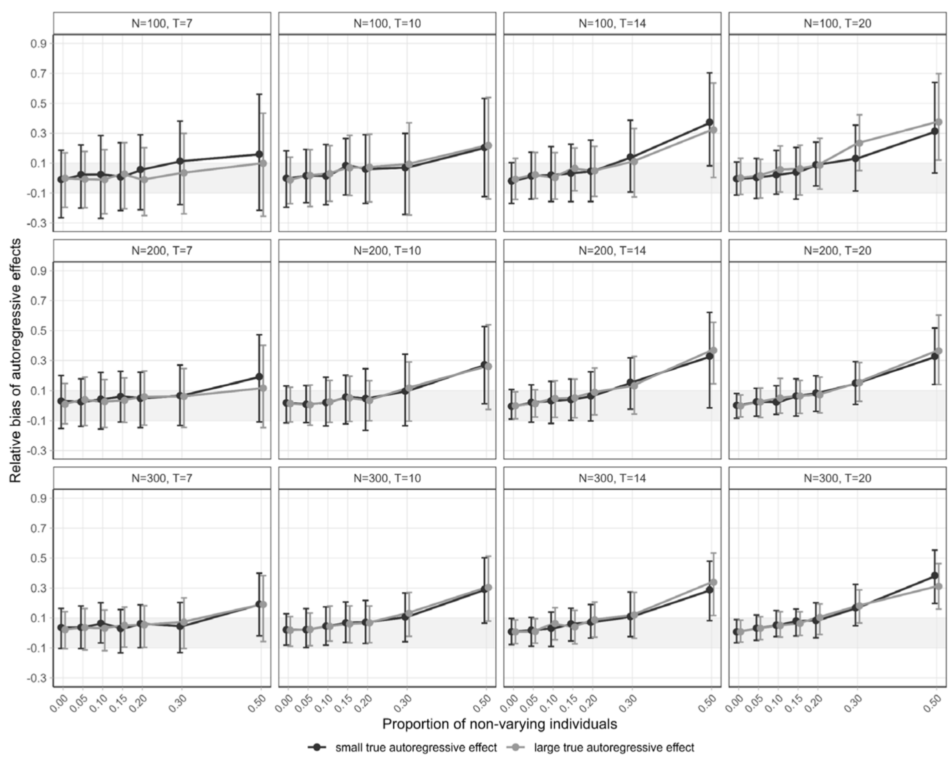


Fig. 8 Relative bias of the fixed effect of autoregressive effects in the full and subsample datasets in Simulation Study 2. *Note*: The *vertical lines* show the 95% central range (2.5th to 97.5th percentiles) of the relative bias across 500 replications. The *shaded area* indicates absolute relative bias lower than 0.1. **(a)** Relative bias of the fixed effect of autoregressive effects in the full datasets. **(b)** Relative bias of the fixed effect of autoregressive effects in the subsample datasets

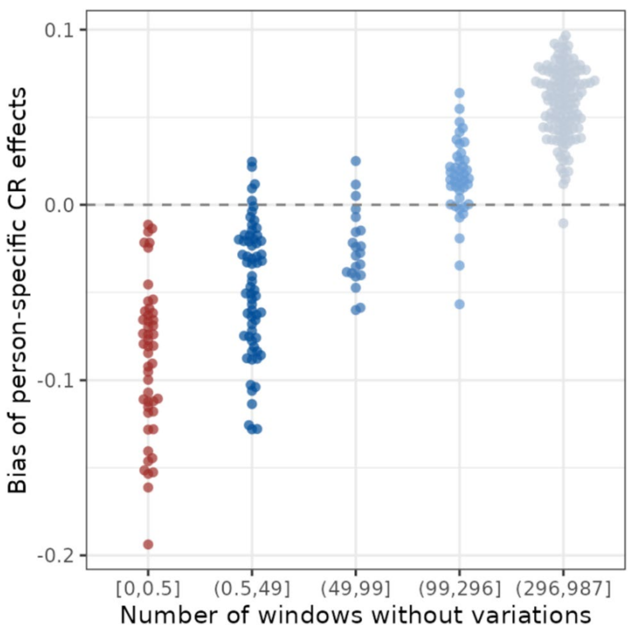


Fig. 9 Bias of person-specific cross-lagged effects in an example condition in Simulation Study 2 ($p_0 = 0.3$, $a_0 = 0.3$, $N = 300$, $T = 14$)

multilevel models. For both univariate and bivariate processes, the impact of non-varying individuals on estimates of dynamic effects (i.e., autoregressive and cross-lagged effects) became increasingly unignorable as their proportion grew. A simple and straightforward solution is to estimate dynamic effects using a selected subsample consisting of only individuals with nonzero within-person variability. In some cases (e.g., small proportions of non-varying individuals), subsample estimates can approximate full-sample results. However, in most cases, especially when the proportion of non-varying individuals reached around 10% or higher in bivariate processes, researchers should exclude non-varying individuals and interpret results strictly with respect to the subsample population.

Implications and recommendations

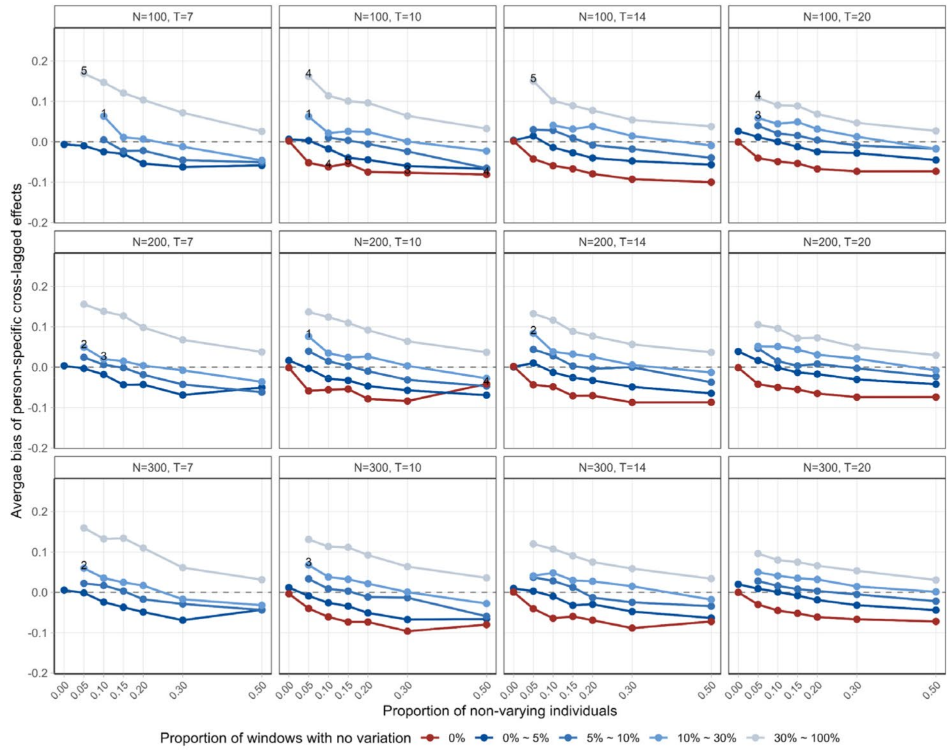
Our findings provide valuable insights for future research. First, it is crucial to identify and report the proportion of non-varying individuals after collecting intensive longitudinal data. Previous studies suggest that datasets with fewer time points or fewer measurement items (particularly single items) are at a higher risk of containing non-varying individuals (Charles et al., 2021; Röcke et al., 2009). Even with a larger number of time points or multiple measurement items (e.g., three items) for constructs such as affective states, non-varying individuals can still be present (Haqiqatkhah et al., 2024; Haslbeck et al., 2025; Hausen et al., 2022). Given the prevalence of limited time points and few items for state constructs in intensive longitudinal studies (Vogelsmeier et al., 2024), it is essential to check within-person variability for each individual before further analyses. This practice enhances research transparency and facilitates critical evaluation of whether subsequent analyses and interpretations are appropriate.

Second, researchers should not treat non-varying individuals as a trivial nuisance; instead, handling decisions should be guided by the characteristics of the data (especially the proportion of non-varying individuals, the number of time points, and the size of the dynamic effects). Overall, we find that non-varying individuals systematically distort dynamic estimates: (a) in univariate processes, they tend to produce systematic overestimation of autoregressive effects; and (b) in bivariate processes, although the average cross-lagged effects appear accurate, person-specific cross-lagged effects are systematically biased (i.e., some individuals' effects are overestimated and others' underestimated). Therefore, we recommend estimating dynamic parameters using a subsample that excludes non-varying individuals, as non-varying cases consistently introduce bias. Building on this principle, we further offer two suggestions on interpreting the subsample estimates: when the proportion of non-varying individuals is relatively low (see the "Summary of results and practical suggestions" sections in Study 1 and Study 2 for details), subsample estimates can approximate full-sample results and can be interpreted as applying to the original target population (i.e., the population represented by the full sample). By contrast, when the proportion is larger (notably when it reaches roughly 10% or more in the bivariate cases), researchers should interpret subsample estimates strictly with respect to the population represented by the subsample (i.e., inferences should be restricted to individuals with nonzero within-person variability). These recommendations provide a practical, preliminary guide for handling non-varying individuals in intensive longitudinal studies.

It is important to note that the 10% threshold we propose is based on a conventional accuracy criterion (relative bias < 10%) for fixed-effect estimates, and should be interpreted as a practical guideline rather than a strict cutoff. Even when the proportion of non-varying individuals falls below 10%, some bias may still be present; the threshold serves as a heuristic to alert researchers that when the proportion exceeds this level, the potential for distortion becomes substantial enough to warrant deliberate handling of these individuals in the analysis. In addition, we encourage researchers to explicitly compare individuals with and without within-person variation (Hausen et al., 2022; Ram et al., 2017), which can help identify distinct groups with qualitative differences in the dynamic processes of interest.

Third, our findings have implications for the design and conduct of intensive longitudinal studies, particularly when deciding how many time points to collect and what measurement instruments to use. The presence of non-varying

(a) Average bias of person-specific cross-lagged effects for small true cross-lagged effects.



(b) Average bias of person-specific cross-lagged effects for large true cross-lagged effects.

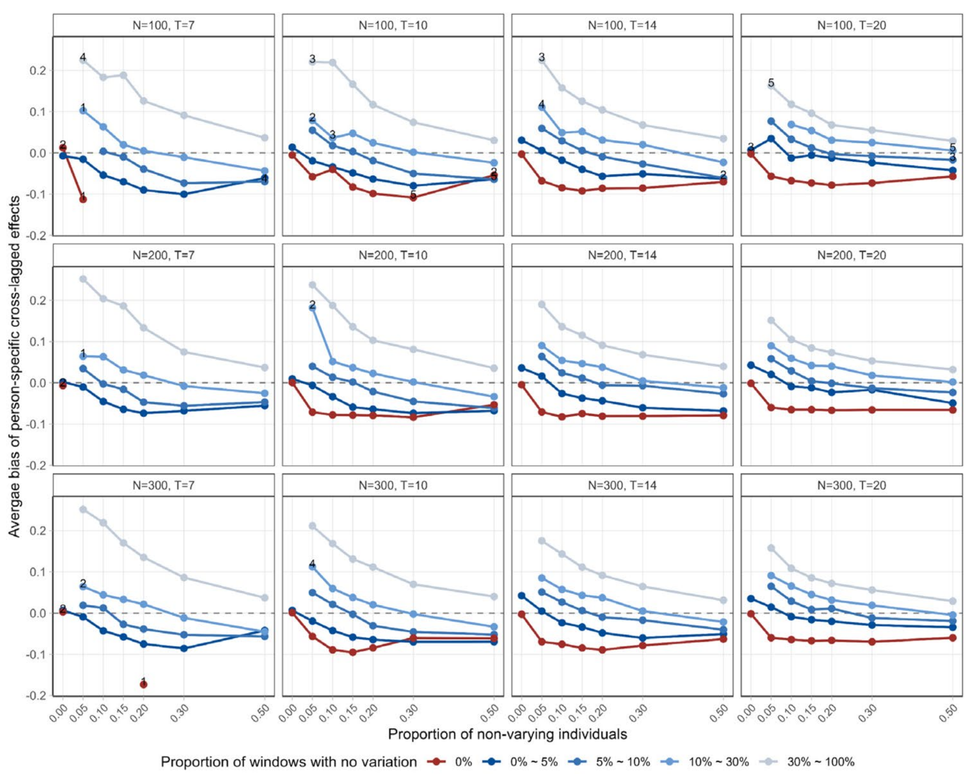


Fig. 10 Average bias of person-specific cross-lagged effects per group in the full datasets in Simulation Study 2. *Note*: *Dashed horizontal line* indicates zero bias. *Numerical labels* indicate subgroup sizes when $n \leq 5$. (**a**) Average bias of person-specific cross-lagged effects for small true cross-lagged effects. (**b**) Average bias of person-specific cross-lagged effects for large true cross-lagged effects

individuals may indicate that the number of time points is insufficient to capture within-person dynamics. We suggest that during the data collection process, researchers may continuously monitor the proportion of non-varying individuals based on the accumulated data (e.g., recalculating this proportion each time a new wave of data is added). If most participants show within-person variability, it may suggest that sufficient information has been collected for the constructs of interest. Still, we caution that such decisions should be informed not only by within-person variability but also by other factors, such as the fluctuation characteristics of the constructs and the statistical power required for planned analyses. Beyond the number of time points, researchers should also consider whether the measurement scale itself is sufficiently sensitive to capture within-person fluctuations. Recent work comparing Likert-type and visual analog scales (VAS) in ecological momentary assessment suggests that VAS may be more sensitive to subtle within-person changes, particularly for constructs that tend to cluster at scale endpoints (Haslbeck et al., 2025). Therefore, when studying constructs that are theoretically expected to fluctuate but are measured with coarse response scales (e.g., 5-point Likert items), researchers may consider whether a more fine-grained measurement approach, such as VAS, could better capture the intended within-person dynamics.

Fourth, we encourage researchers to carefully consider observations of non-varying individuals, considering what they reflect before deciding how to handle them in the analysis. As noted in the Introduction, a constant observed sequence can reflect either a truly stable individual or a fluctuating individual whose variation was not captured over the observation window, and these two situations call for different analytic strategies. The present study is directly relevant to the second situation. When non-variability is plausibly a by-product of limited observation, the biases reported in the current study apply, and researchers can use our proportion-based results to assess the extent to which these individuals affect their estimates and to decide whether to exclude them. When non-variability instead reflects a stable subgroup, treating that subgroup as part of a single fluctuating population is not appropriate, and approaches that allow for population heterogeneity, such as dynamic models with latent classes or an explicit comparison of stable and varying individuals, are more suitable. In some cases, such individuals may not belong to the intended target population and may need to be modeled separately or excluded. Importantly, these two situations usually cannot be distinguished from the observed data alone, because a flat observed sequence is consistent with both. The distinction instead depends on theoretical considerations about the construct, such as whether it is expected to fluctuate over a sufficiently long period and whether the population is plausibly heterogeneous in this respect. For constructs such as momentary affect or daily stressors, some within-person variation is generally expected in most people over time, so flat sequences are more readily attributed to limited observation. For a construct such as suicidal ideation, a stable absence may characterize a meaningful subset of individuals, so flat sequences may instead indicate a distinct subgroup. We therefore encourage researchers to consider theory about the construct, together with the design features of their study, when distinguishing between these situations and selecting an analytic strategy.

In conclusion, this study highlights the importance of attending to non-varying individuals in intensive longitudinal data, both as a statistical concern and as a substantive observation. By examining their prevalence and impact, and by reflecting on what their presence means for the construct under study, researchers can make more informed decisions about data collection, analysis, and interpretation, and thereby improve the robustness and validity of their findings.

Limitations and future directions

The study is a preliminary exploration of the influences of non-varying individuals in dynamic processes and strategies for addressing them. We examined time-series data and individual-level variability, focusing on a group of individuals with zero within-person variability. However, we considered only basic and relatively simple settings, while the actual situations may be more complex. Therefore, several limitations of this study should be noted.

First, we focused on one variable to examine the impacts of individuals with zero within-person variability. However, in studies examining relations among multiple variables, researchers may also need to consider the within-person variability of each variable. For example, in research exploring bidirectional relations between variables, it is important to account for how within-person variability in each variable could influence the results. Future research could further investigate how to address this more complex situation by incorporating the variability of multiple variables simultaneously.

Second, we did not account for the influence of missingness. In the motivating example, individuals were identified as non-varying if their available observations (excluding missing data) remained constant throughout the study period, and the proportion of missingness in this example data was relatively low (less than 6%). Moreover, our simulation studies did not consider the impact of missingness on parameter estimation. Nonetheless, our findings provide relevant insights. Non-varying responses may become more likely when missingness increases, especially if missingness is related to variability. In addition, simple approaches such as mean or median imputation may artificially increase the number of non-varying responses, thereby further biasing fixed parameter estimates, particularly when individual-level missingness is high. Given the prevalence of missingness in intensive longitudinal studies, future research could investigate the joint impact of missingness and non-varying, and consider alternative approaches for handling missing data.

Third, although non-varying individuals in our simulations may be constant at different scores, we did not systematically manipulate or examine whether the specific constant score at which an individual remains stable differentially affects parameter bias. Previous research suggests that individuals stabilizing at different levels may reflect qualitative differences (Ram et al., 2017), which could have distinct implications for dynamic process estimates. Future methodological research could adopt a more fine-grained experimental design that systematically varies the constant values (e.g., floor, ceiling, mid-scale) to explore whether and how the specific score level moderates the impact of non-varying individuals on parameter estimation.

Fourth, this study focused on data measured on Likert-type scales with a small number of response categories, as these are common in intensive longitudinal research and are prone to producing non-varying individuals. However, the generalizability of our findings to other measurement contexts (e.g., visual analogue scales (VAS) or binary items) remains unclear. Recent research has shown that Likert and VAS scales can yield different results in intensive longitudinal studies, with VAS potentially offering greater sensitivity to within-person fluctuations (Haslbeck et al., 2025). Future studies should investigate the impact of non-varying individuals and the effectiveness of handling strategies in datasets collected with other measurement tools.

Fifth, our data generation maps a continuously generated Gaussian process onto a five-point Likert scale, and this mapping may itself contribute to the bias we report. As noted earlier, the population value is re-estimated from long time series to which the mapping has already been applied, so that the shift it produces is not counted as bias. Even so, the influence of the response format and that of non-varying individuals are not easy to separate, since the mapping is also part of how non-varying individuals come to be observed. The bias we report is therefore best understood as reflecting the observation process as a whole, and separating the two more explicitly is a valuable direction for future work.

Sixth, our simulation conditions covered a relatively short range of time points ($T = 7$ to 20), whereas intensive longitudinal designs in practice can span a wider range and involve more measurement occasions, with averages around 50 (Wrzus & Neubauer, 2023; Siepe et al., 2025). We concentrated on shorter designs because non-varying individuals are most prevalent there, and designs as short as 7 or 14 occasions make up a substantial share of intensive longitudinal studies analyzed with dynamic structural equation models (Fang & Wang, 2024; Luo et al., 2024). Although our results suggest that the bias attenuates as the number of time points increases, we did not examine longer designs comprehensively, and a non-negligible proportion of non-varying individuals can still arise in longer studies when constructs are measured with single or coarse items. Future work could more systematically examine how the bias behaves across a wider range of realistic designs.

Finally, it is important to situate our findings within the broader landscape of modeling choices for intensive longitudinal data. Throughout this study, we employed Gaussian-based multilevel autoregressive models – a popular and accessible framework for applied researchers. However, data from intensive longitudinal studies may exhibit features such as limited variability, floor or ceiling effects, and skewness, which may be better accommodated by models with non-Gaussian distributions (e.g., zero-inflated models or beta regression). Our decision to focus on Gaussian models was motivated by two considerations. First, given their prevalence in applied research, we aimed to demonstrate the potential biases that can arise when these commonly used models are applied without careful attention to a specific data characteristic (i.e., the presence of non-varying individuals). Second, existing non-Gaussian alternatives, while valuable for addressing related issues (e.g., excess zeros at the observation level), were not designed to handle the unique challenge of individuals who exhibit no within-person variability across the entire measurement period. The mechanisms underlying such complete stability may be qualitatively different, and it remains unclear which distributional assumptions are most appropriate for modeling these individuals. Therefore, our study should be seen as a preliminary step that highlights the importance of attending to non-varying individuals, rather than as a prescription for using Gaussian models in all circumstances. We encourage future methodological work to explore the performance of non-Gaussian models in the presence of non-varying individuals, and to develop tailored approaches that can accommodate the complexity of within-person dynamics, including individuals who show no variability over the observation window.

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Authors' contributions Conceptualization: Xiaohui Luo, Yueqin Hu, Hongyun Liu; Methodology: Xiaohui Luo; Formal analysis and investigation: Xiaohui Luo; Visualization: Xiaohui Luo; Writing - original draft preparation: Xiaohui Luo; Writing - review and editing: Yueqin Hu, Hongyun Liu; Funding acquisition: Yueqin Hu, Hongyun Liu.

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Data availability Data has been uploaded to the OSF repository (https://osf.io/fbkya; Luo, 2026). This study was not preregistered.

Code availability Code has been uploaded to the OSF repository (https://osf.io/fbkya; Luo, 2026).

Declarations

Conflicts of interest The authors have no conflicts of interest.

Ethics approval The study was approved by the university's ethics committee.

Consent to participate Informed consent was obtained from all participants involved in the study.

Consent for publication Consent for publication was obtained from all participants.

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