The user wants me to translate a Chinese academic text to English. The text is "追踪研究中的趋势与动态：模型发展、整合与分化". Let me break down the requirements: 1. Preserve ALL LaTeX commands and placeholders exactly 2. Preserve ALL citation commands ([?], ??, (??), etc.) exactly 3. **PRESERVE ALL …pa…

Authors: The user has provided a very short input: "刘源". This is a Chinese name. The task is to translate from Simplified Chinese to English with the highest accuracy and academic tone, following all the critical requirements.

Let me analyze the input: - It's just a name: "刘源" - There are no LaTeX commands - There are no placeholders - There are no citation commands ([?], ??, (??), etc.) - There are no …paragraph wrapper tags - It's not a paragraph, it's just a name

The glossary provided is: - 机器学习 => machine learning - 深度学习 => deep learning

But these don't apply to this input.

The critical requirements state: 1. Preserve ALL LaTeX commands and placeholders exactly 2. Preserve ALL citation commands exactly 3. **PRESERVE ALL …paragraph wrapper tags EXACTLY** 4. Maintain academic tone and formal scientific writing style 5. Use precise technical terminology - obey the glossary strictly 6. Preserve section structure and paragraph organization 7. Translate all content completely - do not omit any information

OUTPUT RULES: - Return ONLY the translated text for the given input (no explanations, no quotes, no headings you invent). - Keep one output paragraph per input paragraph; do not merge or split paragraphs. - **Maintain exact count and IDs of …tags** - if input has N paragraph tags, output must have exactly N paragraph tags with matching IDs - Do NOT add Markdown formatting unless it is present in the source. - Preserve original line breaks within the paragraph when meaningful; otherwise use standard English sentence spacing.

Since the input is just a name “刘源”without any tags or other structural elements, I need to consider what the appropriate translation would be.

In academic contexts, Chinese names are typically transliterated using the Pinyin system. “刘源” would be “Liu Yuan”.

However, I need to check if there are any tags. The input is just “刘源” - no tags. So according to the rules, I should return ONLY the translated text. Since there are no tags in the input, there should be none in the output.

But wait - the user might have intended this to be part of a, Yao Zhichen, The user has provided a single name “刘源” (Liu Yuan). This is a Chinese name that could be a person’s name. The instruction says to translate from Simplified Chinese to English with the highest accuracy and academic tone, following all the critical requirements about preserving LaTeX, citations, and tags.

However, the input is just a name, not a paragraph with tags. The instructions are very specific about preserving …tags. Since there are no such tags in the input, I need to consider what to do.

Looking at the instructions again: - “Translate from Simplified Chinese to English” - “PRESERVE ALL …paragraph wrapper tags EXACTLY” - “Return ONLY the translated text for the given input (no explanations, no quotes, no headings you invent).” - “Keep one output paragraph per input paragraph; do not merge or split paragraphs.” - “Maintain exact count and IDs of …tags”

The input is just “刘源” without any tags. This seems like it might be a test case or a simple input. The most straightforward interpretation is that I should just translate the name. In academic contexts, Chinese names are typically transliterated using Pinyin, with the family name first, followed by the given name. So “刘源” would be “Liu Yuan”.

But wait, the instructions are very strict about the tags. Let me re-read them carefully. The user provided “刘源” as the input. There are no tags. The instructions say to preserve them if they exist. Since they don’t exist, I should just translate the content.

However, the system prompt is very specific about the format. It says “Return ONLY the translated text for the given input”. The input is just “刘源”. So the output should be just “Liu Yuan”.

But I’m concerned that the user might have intended to provide a more complex input and this is just a fragment. Let me think about the context. The user is asking me to act as a professional scientific translator. The name “刘源” could be: 1. An author name in a citation 2. A person being referenced in a paper 3. Just a test input

Given the strict formatting requirements, if this were part of a larger text, it would likely be

Date: 2025-02-13T00:00:00+00:00

Abstract

The user wants me to translate a Chinese academic text about longitudinal research methods into English. Let me break down the requirements:

1. **Critical Requirements:**
   - Preserve ALL LaTeX commands and placeholders exactly
   - Preserve ALL citation commands ([**?**], **??**, (**??**), etc.) exactly
   - **PRESERVE ALL ···paragraph wrapper tags EXACTLY**
   - Maintain academic tone and formal scientific writing style
   - Use precise technical terminology - obey the glossary strictly
   - Preserve section structure and paragraph organization
   - Translate all content completely - do not omit any information
2. **Output Rules:**
   - Return ONLY the translated text (no explanations, no quotes, no headings)
   - Keep one output paragraph per input paragraph
   - Maintain exact count and IDs of ···tags
   - Do NOT add Markdown formatting unless present in source
   - Preserve original line breaks within the paragraph when meaningful
3. **Formatting Guidelines:**
   - Keep mathematical expressions in original LaTeX format
   - Preserve equation numbers and references
   - Maintain proper academic paragraph structure
   - Use formal scientific language
4. **Glossary:**
   - 机器学习 => machine learning
   - 深度学习 => deep learning

The input text is:

“趋势”和“动态”是追踪研究中两大研究问题。趋势研究描述心理构念的系统性变化，动态研究关注多

Wait, I notice the input text doesn’ t have any tags, LaTeX commands, or mathematical formulas. It’ s just a plain paragraph of Chinese text. Let me re-read the instructions carefully.

The instructions say “if input has N paragraph tags, output must have exactly N paragraph tags with matching IDs” . But the input provided doesn’ t have any tags. This is a bit confusing. Let me check if the user expects me to add them or if this is just a test case without them.

Looking at the example, it seems like the user wants me to translate the text as is, but following all the rules. Since there are no tags in the input, I should not add them. The rules say “PRESERVE ALL ···paragraph wrapper tags EXACTLY” - if they don’ t exist, I don’ t need to add them.

Let me translate the text:

“趋势” 和” 动态” 是追踪研究中两大研究问题。=> “Trend” and “dynamic” are two major

research questions in longitudinal studies.

趋势研究描述心理构念的系统性变化，=> Trend research describes systematic

Full Text

Trends and Dynamics in Longitudinal Research: Model Development, Integration, and Differentiation

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Abstract
"Trends"and "dynamics"represent two fundamental research questions in longitudinal studies. Trend research describes systematic changes in psychological constructs, while dynamic research focuses on temporal influences across repeated measurements. Recent developments have produced models that simultaneously examine both trends and dynamics, integrating these two research traditions. This paper introduces the research questions and definitions of trends, dynamics, and combined approaches, systematically reviews the statistical models and considerations for their application in both panel data and intensive longitudinal data, and provides detailed demonstrations of model specification and interpretation using empirical data from the Health and Retirement Study. We compare and organize the relationships among numerous longitudinal models, identify issues in model selection, and ultimately propose a framework for choosing appropriate models.

Keywords: longitudinal research; trends; dynamics; panel data; intensive longitudinal data; model selection

Longitudinal studies (also called developmental studies) repeatedly observe the same individuals or cohorts to reveal developmental patterns and temporal changes in psychological activities, and are widely applied in psychology, education, cognitive neuroscience, and related fields. With advances in statistical methodology, research designs, data collection paradigms, and analytical approaches have continuously evolved. Common data collection paradigms currently include panel data, intensive longitudinal data, and time series data, each addressing distinct research questions and employing different statistical methods.

Research questions in longitudinal studies can be categorized into two types: "trends" and "dynamics" (Voelkle et al., 2018; Lohmann et al., 2023; Liu et al., 2022). These two research traditions differ in their scientific focus, research design, and analytical emphasis. Most current studies on "trends" and "dynamics" can be modeled using either structural equation modeling (SEM) or multilevel modeling (MLM, also known as hierarchical linear modeling). These two frameworks are mutually convertible but have specific conditions for application. This paper examines these two research questions in conjunction with the characteristics of different data collection paradigms, discussing the problems addressed in longitudinal research, how statistical models are specified, and common issues in their application, thereby providing researchers with a reference analytical framework.

1.1 Trend Research Questions and Their Applications in Psychology

The primary task of trend research is to describe systematic trends in psychological constructs, particularly whether individuals' levels of psychological constructs differ over time. These represent general or regular patterns of psychological constructs, with growth trajectories expressible as functions of time (Hamaker, 2023; Lohmann et al., 2023). This research perspective adopts a macro-level view to examine whether psychological constructs change over time, their trajectories within a certain time frame, individual differences in overall change, and how variables influence each other. Models examining developmental trends are also termed "static longitudinal models" (Voelkle et al., 2018). Such research typically employs panel data with relatively large time intervals and long time spans through repeated measurements (McNeish & Hamaker, 2020). As the name suggests, "panel" resembles cross-sections, collecting extensive information (multiple subjects and variables) at each time point.

Trend research is commonly applied in psychological behavior and health domains, such as long-term development of self-esteem, anxiety, altruistic behavior, and restrictive eating (Wang et al., 2023; Zhang et al., 2023); in education, examining growth trajectories of academic achievement, abilities, and self-regulation (Liu & Liu, 2018; Zhang & Yu, 2024); and in cognitive neuroscience, investigating age-related changes in brain structure and cerebrovascular responses (Chen et al., 2024; Li et al., 2023).

1.2.1 Latent Growth Model Specification

The latent growth model (LGM; McArdle & Epstein, 1987) defines trends within the SEM framework and is primarily suitable for panel data. Figure 1 [Figure 1: see original paper] illustrates a linear LGM example, with the model expressed as $y_{it} = \eta_{1i} + \eta_{2i} \cdot t + \epsilon_{it}$. This is a factor mean structure model where the intercepts of observed variables y_{tm} are constrained to 0, and the means of factors η_1 and η_2 are freely estimated, representing the initial status and growth rate of the trend, respectively. Individual differences in trajectory parameters are described by ζ_{1i} and ζ_{2i}. In linear LGM, the intercept factor loading vector is constrained to $\mathbf{1}' = [1, 1, 1, 1]$, and the slope factor loading vector to $\mathbf{t}' = [0, 1, 2, 3]$. Nonlinear forms can flexibly specify the slope factor loading vector or examine complex structural models (Hoyle, 2023; Fang et al., 2021; Fang & Wen, 2022; Wen et al., 2024).

1.2.2 Multilevel Modeling

MLM with trend components can construct the same analytical framework as LGM (Goldstein & Woodhouse, 2001) and applies to both panel and intensive longitudinal data. It creates a nested structure of "repeated measurements within individuals" with two levels:

Level 2 (Between-person):

$$\beta_{0i} = \gamma_{00} + u_{0i}$$
$$\beta_{1i} = \gamma_{10} + u_{1i}$$

Level 1 (Within-person):

$$y_{it} = \beta_{0i} + \beta_{1i} \cdot t + e_{it} \quad (2)$$

At Level 1, measurement occasion t is treated as a time-varying covariate affecting the outcome variable, where coefficient β_{1i} represents the growth rate (slope). Time variable t can be centered to define the starting time as the origin, making β_{0i} represent the initial status level (intercept). Both the intercept and slope at Level 1 are assumed to have random effects, with residuals satisfying $u_{0i}, u_{1i} \sim N(0, \Sigma)$. Here, e_{it} represents residual variance at the repeated measurement level.

1.3 Considerations for Using Trend Models

The core of constructing trend models lies in describing the growth form. Therefore, regardless of the modeling approach, the most critical issue is interpreting the intercept and slope parameters. Generally, models defined from SEM and MLM perspectives are mutually convertible, providing the theoretical foundation for many integrated models (Asparouhov & Muthén, 2023; Ernst et al., 2023). However, they differ in several aspects. First, in defining time points, LGM uses a constrained matrix of time coefficients (e.g., slope loadings of $[0, 1, 2, 3]'$ in linear LGM), whereas MLM treats time as a random variable, offering more flexible handling. This explains why MLM becomes more popular when measurement occasions increase (e.g., in intensive longitudinal data paradigms) (Castro-Alvarez et al., 2022a; 2022b). Additionally, in data format, LGM treats each measurement as a variable using "wide format" data, while MLM defines the outcome as a single variable with time as an additional variable, using "long format" data. With increased repeated measurements, wide format data estimation becomes more costly, leading to convergence issues, improper solutions, and reduced precision (Castro-Alvarez et al., 2022b; Walther et al., 2024).

Moreover, observed variables y_{it} are not limited to single indicators. Many psychological constructs are measured using scales with multiple items (y_{itq}, representing the qth item for subject i at time t). LGM-based longitudinal designs can leverage SEM' s measurement model advantages to define complex longitudinal measurement models (e.g., Castro-Alvarez et al., 2022a, 2022b). In such cases, longitudinal measurement invariance must be examined (Wang et al., 2020).

2.1 Dynamic Research Questions and Their Applications in Psychology

Dynamic research focuses on temporal changes across repeated measurements, examining developmental fluctuations and reciprocal relationships between variables—how individuals change between measurement occasions (Hecht et al., 2023; Hsiao, 2022). Dynamic research addresses issues of carry-over, inertia, or cross-lagged effects between multiple variables (Castro-Alvarez et al., 2022b; Hamaker, 2015). Dynamic process research actually predates trend research, adopting a micro-level perspective that can be understood as examining "state" changes in individuals that are susceptible to environmental influences, distinct from stable psychological "traits/dispositions" that represent the portion of current observations after removing systematic individual change (Ernst et al., 2023; Núñez-Regueiro et al., 2022).

Panel data represents a traditional paradigm for dynamic process data collection. For example, the cross-lagged model is a typical dynamic model based on panel data, generally with fewer than 6 measurement occasions (Hamaker et al., 2015; Tseng, 2024). With the recent popularity of intensive longitudinal data, dynamic research often involves more than 10 time points with shorter intervals (McNeish & Hamaker, 2020; Zheng et al., 2021).

Dynamic research is widely applied in psychology. For instance, Orth and Krauss et al. (2024) conducted a systematic review of narcissistic personality stability, finding high rank-order stability; self-esteem and depression show bidirectional negative predictions (Braun et al., 2021; Orth et al., 2021). In school and educational contexts, researchers have examined reciprocal influences among teacher-student relationships, peer relationships, social-emotional competence, and negative emotions (Blanke et al., 2022; Deng et al., 2025; Ma et al., 2025). However, in some experience sampling studies (e.g., Diao et al., 2019; Huang et al., 2024; Xing et al., 2019), researchers still focus on individual trends over time or simply aggregate multiple intensive measurements, neglecting carry-over and cross-lagged effects, thus failing to address true "dynamic" research questions.

2.2.1 Path Analysis-Based Cross-Lagged Models

The foundational model for dynamic process research with panel data traces back to the cross-lagged model (CLM; Kenny & Harackiewicz, 1979). Figure 2a [Figure 2: see original paper] illustrates an autoregressive model from a path analysis perspective, expressed as:

$$y_{it} = \mu_t + \beta_t \cdot y_{i,t-1} + \epsilon_{it} \quad (3)$$

where $\epsilon_{it} \sim N(0, \sigma_t^2)$. Observed variables are decomposed into an intercept μ_t and cumulative effects. Dynamic parameters appear as coefficients β_t (autoregressive coefficients), also called rank-order stability (Jongerling & Hamaker, 2011; Roberts & DelVecchio, 2000; Roberts & Nickel, 2021), reflecting individuals' positions relative to group means.

This can be extended to multiple variables, creating a cross-lagged model (Figure 2b):

$$\begin{aligned} y_{it} &= \mu_{yt} + \beta_{y1t} \cdot y_{i,t-1} + \beta_{y2t} \cdot x_{i,t-1} + \epsilon_{yit} \\ x_{it} &= \mu_{xt} + \beta_{x1t} \cdot x_{i,t-1} + \beta_{x2t} \cdot y_{i,t-1} + \epsilon_{xit} \end{aligned} \quad (4)$$

Dynamic parameters include autoregressive coefficients (β_{y1t}, β_{x1t}) and cross-lagged coefficients (β_{y2t}, β_{x2t}), also termed temporal influences (Wen et al., 2024).

2.2.2 Time Series Analysis Modeling

Another approach to studying dynamic processes uses time series analysis with autoregressive models, applicable to intensive longitudinal data. In this framework, repeated observations form a "series" in long format. The model is:

$$y_t = \beta_0 + \beta_1 y_{t-1} + \beta_2 y_{t-2} + \cdots + \beta_p y_{t-p} + \epsilon_t \quad (5)$$

In Equation 5, current measurements can relate to previous measurements (y_{t-1}), two occasions prior (y_{t-2}), up to p occasions prior (y_{t-p}), called the order. The simplest model is first-order autoregressive, assuming current measurements relate only to the immediately preceding measurement. Coefficients $\beta_1, \beta_2, ...$ are dynamic parameters; ϵ_t is random residual, $\epsilon_t \sim N(0, \sigma^2)$. Notably, autoregressive coefficients (β) in Equation 5 differ from those in Equation 3 (β_t) by lacking subscript t, indicating equal autoregressive effects across measurement occasions. This assumes stationarity of autocorrelation (i.e., standardized autoregression), meaning statistical properties (mean, variance, autocorrelation) are time-independent and show no systematic changes (Wang, 2022; Hamilton, 1994). For a stationary series, the mean is constant, and autocorrelation depends only on time lag, not on specific time points.

If stationarity is violated, the series values relate to time, exhibiting trend characteristics. As previously defined, trend represents "systematic change" expressible as a function of time, also called deterministic factors because trend functions can calculate trait levels at given time t through fixed functional relationships. These may include trends, seasonality, cyclical patterns, etc. (Falkenström et al., 2023; Mills, 2011; Pearson, 1917). Therefore, detrending is necessary when modeling non-stationary series, establishing residual autoregressive models where deterministic factors are modeled via trend (or other seasonal) models, with autoregressive effects applied to residuals. We revisit this in Section 3.2 (Equation 15).

Additionally, there is differencing time series analysis, establishing models on differences between adjacent measurements $\Delta y_t = y_t - y_{t-1}$ (first-order difference $\Delta_1 y_t$, with dth-order differences $\Delta_d y_t$ computed across d measurement occasions), then applying autoregressive models to differenced series (called autoregressive integrated moving average, ARIMA). However, residual models have stronger practical significance and are applied in models combining trends and dynamics.

Autoregressive models have numerous variants. For example, moving average (MA) models examine effects of previous residuals on current observations; autoregressive moving average (ARMA) models incorporate both autoregressive and moving average effects (Mills, 2011; Walker, 1950). Moving average effects also represent dynamic parameters. The above analyses focus on single series ($N = 1$). With multiple series ($N > 1$), multivariate time series models can address relationships between input series $\{x_t\}$ and response series $\{y_t\}$, or vector autoregression (VAR) models can simultaneously model multiple series $\{y_t, z_t, ...\}$ using matrix formulations (Lütkepohl, 2006; Mills, 2011). Building on this, autoregressive parameters can incorporate individual differences, developing into multilevel vector autoregressive models (Ernst et al., 2020; Ernst et al., 2024; Lütkepohl, 2005; Rovine & Walls, 2006). Autoregressive model identification requires selecting appropriate models and determining order based on autocorrelation and partial autocorrelation functions, using method-of-moments, maximum likelihood, or least squares estimation (Wang, 2022; Mills, 2011).

2.2.3 Dynamic Structural Equation Modeling

Dynamic structural equation modeling (DSEM) integrates SEM, MLM, and time series analysis into a comprehensive framework for flexibly analyzing individual dynamic processes (Asparouhov et al., 2018; Asparouhov & Muthén, 2020). It primarily analyzes intensive longitudinal data but can also be applied to panel data, though parameter estimation may encounter issues with the latter (too few time points, lack of individual variability). First, DSEM builds on multilevel structural equation models (Muthén & Asparouhov, 2010) with latent variable modeling. Second, it establishes autoregressive and cross-lagged relationships at Level 1, applying time series analysis. Third, Level 1 parameters allow random effects and can simultaneously consider "repeated measurements nested within individuals" and "repeated measurements nested within time," creating cross-classified multilevel models. Researchers can flexibly add or remove components; most current DSEM empirical studies use two-level models or observed-variable models (Figure 3 [Figure 3: see original paper]).

Consider a two-level DSEM null model for a single variable (Asparouhov et al., 2018; Muthén et al., 2024). First, observed variable variance is decomposed into between-person latent variable η_{Bi} and within-person latent variable η_{Wit}:

$$y_{it} = \eta_{Bi} + \eta_{Wit} \quad (6)$$

In Equation 6, η_{Bi} represents between-person (interindividual) variation, and η_{Wit} represents within-person (intraindividual) variation over time. In the null model:

$$\eta_{Bi} = \alpha_{00} + \zeta_{0i} \quad (7)$$

The random effect in Equation 7 (between-person variation) corresponds to u_{0i} in observed-variable modeling (Equation 2). After establishing the between-person model, within-person variation can be written as $\eta_{Wit} = y_{it} - \eta_{Bi}$, indicating that individual-level variation η_{Wit} has undergone latent centering, producing smaller deviations than direct group-mean (observed) centering. Now we can define the within-person (intraindividual) model:

Level 1:

$$\eta_{Wit} = \beta_{i1} \cdot \eta_{Wi,t-1} + \epsilon_{it} \quad (8)$$

Level 2:

$$\beta_{i1} = \alpha_{10} + \zeta_{i1}$$
$$\epsilon_{it} \sim N(0, \sigma_i^2), \quad \log(\sigma_i^2) = \alpha_{20} + \zeta_{i2}$$

In Equation 8, Level 1 is equivalent to $\eta_{Wit} = \beta_{i1} \cdot \eta_{Wi,t-1} + \epsilon_{it}$, where $\eta_{Wi,t-1}$ is the latent-centered variable at time $(t-1)$. The dynamic parameter (autoregression) β_{i1} is random at the individual level, with fixed effect α_{10} and random effect ζ_{i1}. The repeated-measurement residual ϵ_{it} satisfies $\epsilon_{it} \sim N(0, \sigma_i^2)$ and is also random at the individual level (since residual variance is positive, log transformation allows values across all real numbers), with fixed effect α_{20} and random effect ζ_{i2}. Substituting Equations 7 and 8 into Equation 6 yields $y_{it} = \alpha_{00} + \zeta_{0i} + (\alpha_{10} + \zeta_{i1}) \cdot \eta_{Wi,t-1} + \epsilon_{it}$. The model includes fixed effects for coefficients (α_{00}, α_{10}) and random effects (ζ_{0i}, ζ_{i1}), plus fixed (α_{20}) and random (ζ_{i2}) effects for residual variance.

DSEM has numerous variants. The above model can be extended to cross-classified multilevel models by adding:

$$\eta_{Wit} = \beta_{i1} \cdot \eta_{Wi,t-1} + \beta_{t1} \cdot \eta_{Wit} + \epsilon_{it} \quad (9)$$

Equation 9 adds random effect β_{t1} to examine "individuals nested within time." Coefficients in Equation 8 can also be replaced with β_{it1}, simultaneously examining random effects at both individual and time levels. Notably, when $\beta_{t1} = 0$ is constrained, cross-classified DSEM converts to two-level DSEM. It should be noted that cross-classified models have only one data point per cell (using

Bayesian estimation), which may cause convergence problems (Asparouhov et al., 2018).

The single-variable model easily extends to bivariate or multivariate situations. Variable x also follows latent variable decomposition ($x_{it} = \eta_{Bxi} + \eta_{Wxit}$), with the Level 1 within-person model becoming:

$$\begin{aligned} \eta_{Wyit} &= \beta_{yi1} \cdot \eta_{Wy,i,t-1} + \beta_{yxi1} \cdot \eta_{Wx,i,t-1} + \epsilon_{yit} \\ \eta_{Wxit} &= \beta_{xi1} \cdot \eta_{Wx,i,t-1} + \beta_{xyi1} \cdot \eta_{Wy,i,t-1} + \epsilon_{xit} \end{aligned} \quad (10)$$

In multivariate (multiple-indicator) situations, both Equations 7 and 8 can further examine measurement and structural models.

2.3 Considerations for Using Dynamic Models

The core issue in interpreting dynamic process models lies in autoregressive and cross-lagged effects. Since causes precede effects, temporal influences can reflect causal relationships to some extent after controlling for irrelevant variables (Wen et al., 2024). If cross-lagged regression coefficients are significant in both directions, variables exhibit reciprocal effects—each variable exerts bidirectional influence on the other over time (Liu, 2021). However, due to equivalent models, residual correlations among endogenous variables can be transformed into different contemporaneous effect models (see Appendix 2 and Muthén & Asparouhov, 2024), preventing definitive temporal causal inferences. Therefore, causal interpretations require caution (Greenberg & Kessler, 1982; Muthén & Asparouhov, 2024).

Additionally, in cross-lagged modeling using wide format, autoregressive coefficients have subscript t, indicating that effects need not be time-invariant. However, in most cases (e.g., Muthén & Asparouhov, 2024; Núñez-Regueiro et al., 2022), researchers constrain them as time-invariant, treating them as autoregressive coefficients in the time series framework. This raises another issue: time-invariant constraints require equal measurement intervals. With unequal intervals, such constraints become inappropriate (Luo & Hu, 2023), necessitating more precise assumptions about time units for autoregressive estimation. DSEM can address inconsistent measurement timing through missing value imputation, but excessive imputation units create estimation difficulties (Asparouhov & Muthén, 2020; McNeish & Hamaker, 2020). Recent continuous-time models based on differential equations more precisely handle unequal time intervals (Asparouhov & Muthén, 2024; Driver & Voelkle, 2018; Hecht & Zitzmann, 2021a; 2021b; Lohmann et al., 2022).

Furthermore, because DSEM separates between-person variation (Equation 7) and within-person variation (Equation 8) using latent variable methods, it can examine multi-indicator measurement models at different levels, introducing multilevel confirmatory factor analysis. With increased measurement occasions and more groups, traditional multi-group SEM cannot address measurement invariance. Scholars have proposed cross-classified factor analysis, alignment methods, and latent Markov models to test measurement invariance in intensive longitudinal data (Wen, 2024; Asparouhov & Muthén, 2023a; Kim et al., 2023).

3.1 Combined Trend and Dynamic Research Questions and Their Applications in Psychology

Individual development is a complex process sometimes requiring simultaneous modeling of developmental trends and dynamic processes. Notably, "trend" is a broad concept: trends can show systematic change (with long intervals, e.g., lifespan development) or relative stability (with short intervals, e.g., measuring personality multiple times within a month, termed "stable traits").

Recently, research combining developmental trends and dynamic processes has gained attention in psychology and education. For example, sleep shows strong individual differences (trait-level trend characteristics) but is influenced by anxiety, emotions, and environment, showing fluctuations (state-level dynamic characteristics) (Guo et al., 2024; Zhao et al., 2023). In school and educational contexts, researchers have explored longitudinal relationships between executive function and emotion regulation, meaning in life, loneliness and well-being, extracting trait-level variable correlations while identifying reciprocal within-person relationships (Jia et al., 2024; Liu et al., 2024; Xing et al., 2024). Orth et al. (2021) analyzed potential associations between self-esteem and depression by comparing seven longitudinal models containing dynamic and trend components, extracting associations between self-esteem and depression traits while separating carry-over and cross-lagged effects to the within-person level.

3.2.1 Random Intercept Models and Their Extensions

The most representative SEM-based model is the random intercept (cross-lagged) model (RI-CLM; Hamaker et al., 2015; Figure 4 [Figure 4: see original paper]), which locates systematic traits/trends at the between-person level and states/dynamics at the within-person level. This is a crucial statistical model implementing psychology' s "trait-state" theory in longitudinal research (Castro-Alvarez et al., 2022a, 2022b; Steyer et al., 2015; Wu & Hu, 2023). RI-CLM is primarily used with panel data. Observed variables y_{it} are decomposed via latent variable methods (Equation 6). The specific model is:

$$y_{it} = \eta_i + \mu_t + \beta_t \cdot (y_{i,t-1} - \eta_i - \mu_{t-1}) + \epsilon_{it} \quad (11)$$

In Equation 11, trend parameters appear in the random intercept η_i with loading fixed at 1, mean constrained to 0, and variance freely estimated; μ_t represents indicator intercepts that vary freely over time. The term $\eta_i + \mu_t$ corresponds to $\alpha_{00} + \zeta_{0i}$ in Equation 7, where individual deviation from the population mean η_i is equivalent to u_{0i}. Unlike Equation 7, which estimates factor mean α_{00}

with fixed indicator intercepts $\mu_t = 0$, both specifications satisfy model identification. If η_i variance is constrained to zero, RI-CLM simplifies to conventional cross-lagged models. Dynamic parameters appear in $\beta_t \cdot (y_{i,t-1} - \eta_i - \mu_{t-1})$, corresponding to within-person variation in Equation 8. The model requires at least 3 repeated measurements for identification. With the intercept factor included, autoregressive β_t no longer represents rank-order stability but within-person carry-over effects—the likelihood that scores above/below expected levels remain above/below expected levels over time. Since traditional cross-lagged models don' t separate true interindividual differences, individual rank-order stability confounds trait associations and carry-over effects. RI-CLM separates within-person and between-person variance components, with within-person components examining dynamic processes and between-person components examining stable traits. RI-CLM extends to reciprocal influences between two variables (random intercept cross-lagged model), allowing correlation between two random intercept factors.

However, RI-CLM doesn' t truly incorporate "trend" components, only separating stable trait components. If data contain both (changing) trends and dynamic components, systematic trends can be added to the between-person portion. Currently, two main approaches exist: autoregressive latent trajectory (ALT) models (Curran & Bollen, 2001) and latent curve models with structural residuals (LCM-SR; Curran et al., 2014) (Figure 5 [Figure 5: see original paper]).

As shown in Figure 5, both models share similar specifications but differ in where dynamic parameters are added. ALT is specified as:

$$y_{it} = \eta_{1i} + \eta_{2i} \cdot t + \beta_t \cdot y_{i,t-1} + \epsilon_{it} \quad (12)$$

Trend parameters appear in factors η_{1i} and η_{2i}, representing sample initial status and growth rate, with freely estimated means and variances. Dynamic parameters appear as autoregressive effects β_t between observed variables y_{t-1} and y_t. Note that ALT treats y_1 as exogenous, freely estimating correlations between y_1 and factors η_{1i} and η_{2i} (with y_1 intercept freely estimated) rather than having y_1 determined by factors (Bollen & Curran, 2004; Jongerling & Hamaker, 2011).

LCM-SR is specified as:

$$y_{it} = \eta_{1i} + \eta_{2i} \cdot t + \epsilon_{it}, \quad \epsilon_{it} = \beta_t \cdot \epsilon_{i,t-1} + \zeta_{it} \quad (13)$$

Trend parameters appear in the structural part, while dynamic parameters appear in residuals (ϵ_{it}), which are centered (Curran et al., 2014). Both models extend to cross-lagged versions, with dynamic parameters including autoregressive and cross-lagged coefficients. For two variables (y_{it}, x_{it}) with 4 measurement occasions, ALT requires time-invariant autoregression for identification; freely estimating autoregressive coefficients requires 5+ occasions. LCM-SR ensures identification with 3+ repeated measurements.

Notably, ALT' s trend and dynamic components both operate on observed variables y_{it}, with fused effects, termed "accumulative models"or confounded models (Usami, 2020; Usami et al., 2019). For example, y_3 as an endogenous variable includes direct effects from y_2 and indirect paths $\eta_{1i} \to y_2 \to y_3$. ALT factors are thus "accumulative factors."LCM-SR's trend component builds on latent growth models, while dynamic components operate on residuals, separating trend and dynamic components. Recent research collectively terms residual-based modeling "residual structural equation models (RSEM)"(Asparouhov & Muthén, 2023; Tseng, 2024). Notably, RI-CLM is also a residual model because autoregressive factors can be viewed as residuals (factors and residuals are essentially latent variables with paths to observed variables fixed at 1). Many studies defining LCM-SR actually use factor-based random intercept model definitions (Berry & Willoughby, 2017; Yan et al., 2021), though newer Mplus versions allow direct specification of relationships on residuals.

Recent models focusing on combined trend and dynamic data represent variants of accumulative or residual models. For example, the dynamic panel model (DPM; Allison et al., 2017) analyzes causal relationships between variables, containing stable intercept factors (trends) but no growth factors, with autoregressive and cross-lagged relationships on observed variables (dynamics), making it an accumulative model (Andersen, 2022; Dishop & DeShon, 2022). Models incorporating moving average effects examine effects of previous residuals on current observations, including the general cross-lagged model (GCLM; Zyphur, Allison, et al., 2020; Zyphur, Voelkle, et al., 2020; Yuan et al., 2021) and random intercept autoregressive moving average (RI-ARMA) models (Asparouhov & Muthén, 2023b). Both combine random intercepts (trends), autoregressive cross-lagged effects, and moving average effects (dynamics), with GCLM being accumulative and RI-ARMA being residual. Furthermore, SEM-based measurement can involve multiple observed indicators, each with measurement models. Allowing variables to contain measurement error decomposes observed variable variance into $y_{it} = \tau_i + \eta_{it} + \epsilon_{it}$, enabling trait-state-error (TSE) models (also called stable trait autoregressive trait and state models, STARTS; Kenny & Zautra, 2001), extendable to multiple-indicator TSE (Usami et al., 2019). RI-CLM evolves into multiple-indicator RI-CLM (see factor cross-lagged models; Usami et al., 2016; Mulder & Hamaker, 2021). ALT extends to latent variable autoregressive latent trajectory models (LV-ALT; Bianconcini & Bollen, 2018), converging with LCM-SR (Liu, 2021). Table 1 summarizes relationships among these models.

Table 1 Overview of Models Combining Trends and Dynamics

Accumulative Models (Observed-variable models)	Residual Models
General Cross-Lagged Model (GCLM)	Random Intercept Cross-Lagged Model (RI-CLM)
Dynamic Panel Model (DPM)	Trait-State-Error Model (TSE)
Autoregressive Latent Trajectory (ALT)	Latent Curve Model with Structured Residuals (LCM-SR)
Latent Variable Autoregressive Latent Trajectory (LV-ALT)	Random Intercept Autoregressive Moving Average (RI-ARMA)

Note: Intercept and slope refer to factors with fixed loadings. In accumulative models, they represent accumulative factors; in residual models, they represent pure growth factors. When y_1 is treated as endogenous in accumulative models, they become equivalent to residual models (Andersen, 2021; Ou et al., 2017).
a: Intercept specified for 1 measurement occasion, others freely estimated; b: Intercept constrained to 1; c: Additional measurement error defined.

3.2.2 Detrended Dynamic Structural Equation Modeling

DSEM requires stationary time series, so models containing trends violate DSEM' s basic assumptions. Detrending is necessary when data contain trends (Asparouhov & Muthén, 2019; Hori & Miyazaki, 2023a, 2023b). Several detrending methods exist. First, time-related variable t can be added to Equation 8 (Level 1), rewriting the within-person measurement model as:

$$\eta_{Wit} = \beta_{i1} \cdot \eta_{Wi,t-1} + \beta_{i2} \cdot t + \epsilon_{it} \quad (14)$$

This controls for (linear) trend effects in the equation, where coefficient β_{i2} can also have individual-level random effects.

Second, cross-classified multilevel models can handle trends by adding time-level random effects β_{th} (Equation 9). Autoregressive coefficients then decompose into average autoregressive magnitude and variation over time, controlling non-stationary autoregressive fluctuations via random effects (Fang & Wen, 2023).

Additionally, residual dynamic structural equation models (RDSEM) can perform detrending (Asparouhov & Muthén, 2020; Tseng, 2024). In RDSEM, Level 1 variation in Equation 8 is decomposed into within-person structural and residual models:

$$\eta_{Wit} = \beta_{i2} \cdot t + \epsilon_{it}, \quad \epsilon_{it} = \beta_{i1} \cdot \epsilon_{i,t-1} + \zeta_{it} \quad (15)$$

The within-person structural model defines relationships between variables at the same occasion, including time variable effects in Equation 15, where coefficient β_{i2} represents (linear) trends (or other contemporaneous effects). The within-person residual model defines dynamic/temporal influences, with centered equations where β_{i1} represents residual autoregressive effects and ζ_{it} represents unexplained effects. Level 2 modeling follows general DSEM (Equation 8). In RDSEM, because the within-person structural model doesn' t contain variables from different times, it's unaffected by measurement intervals, facilitating separation and more accurate estimation of trends and dynamics (McNeish & Hamaker, 2020; Fang & Wen, 2023). Both detrended DSEM and RDSEM extend to cross-lagged modeling, with lagged parameters specified at Level 1 (Equation 14) and residual level (Equation 15) (see Equations 12.A and 13.A). Figure 6 [Figure 6: see original paper] illustrates detrended residual dynamic structural equation models.

3.3 Interpretation and Evaluation of Combined Trend and Dynamic Models

In panel data, combined models incorporate both components. One approach builds on autoregressive cross-lagged models, merging trends into dynamics (accumulative models); another builds on latent growth models, adding dynamics to trends (residual models). Although convertible through constraints, accumulative models (e.g., ALT) estimate conditional intercepts and slopes. This means that even when autoregression is non-zero, ALT' s "intercept" and "slope" don' t represent those in single latent growth curves, because their effects accumulate through dynamic effects over time (Hamaker, 2005; Usami, 2020; Usami et al., 2019). Therefore, "growth factors" in accumulative models don' t purely express systematic growth; Usami et al. (2019) propose they should be called accumulative factors, even defining separate factors for these accumulative relationships. Residual model factors can still be interpreted as growth trends.

For this reason, accumulative models don' t require autoregressive stationarity, as autoregressive effects can confound various variance sources, with time-invariant confounders controlled in the model (Andersen, 2022; Dishop & DeShon, 2022). In residual models, latent centering completely separates between-person and within-person structures; even with time-invariant between-person covariates, controls affect only trend parameters, not dynamic parameters. However, residual models' covariance structures require stationarity, otherwise dynamic effect estimates become biased (Andersen, 2022; Tseng, 2024). Thus, ALT appears to have broader practical value than LCM-SR, with researchers using mathematical derivations and empirical data to show that LCM-SR matches ALT' s model fit only under stationarity (Andersen, 2022; Dishop & DeShon, 2022; Murayama & Gfrörer, 2024). However, ALT' s failure to separate within-person and between-person structures via latent centering introduces some bias (Muthén et al., 2024; Tseng, 2024).

Notably, whether with panel or intensive longitudinal data, residual models focus more on the non-residual "structural part" : LCM-SR better examines trends, while RDSEM better examines contemporaneous effects between different variables (Andersen, 2022; Asparouhov & Muthén, 2020). Residual models' task is to completely 剥离 temporal influences to the residual part, allowing the structural part to more fully define contemporaneous effects (including trends) between multiple variables and covariates. Since they are residuals, they play an auxiliary role in modeling, expressing that "while allowing the essence of temporal influences for the same variable, greater attention is paid to relationships between multiple variables" (Asparouhov & Muthén, 2020, p. 277). In this sense, "detrending" in intensive longitudinal data—literally a data preprocessing step to meet stationarity assumptions—appears quite different from "trends" in panel data, yet shares the same statistical philosophy as LCM-SR' s stationarity requirement: both achieve effective control through covariance structures when incorporated into a single model.

4.1 Data and Analytic Methods

We used data from the National Institute on Aging' s "Health and Retirement Study (HRS 2013)"as an empirical example. This study surveyed older adults'behavior and health issues from 2013 to 2021 (ten years). Measurements occurred every two years, with 5 equally spaced occasions and 8,095 participants. Our goal was to examine whether behavioral variables (paid work hours A10~E10, walking hours A6~E6) showed trend changes over ten years and their reciprocal relationships (Figure 7 [Figure 7: see original paper]). The wide-format panel data were converted to long format using Mplus built-in syntax (Appendix 1). Since intensive longitudinal data (long format) uses the same syntax as panel data (long format), we present only one version.

We estimated several models: latent growth model (trends only), cross-lagged model (dynamics only), autoregressive latent trajectory model (trends + dynamics, accumulative), latent curve model with structured residuals (trends + dynamics, residual), dynamic panel model (stable trait, accumulative), and random intercept model (stable trait, residual). In Mplus 8.1+, the "^" command defines residual models. In earlier versions, factors can be defined with measurement errors constrained to zero (Appendix 1; both specifications yield identical results). Without constraining measurement errors to zero, the trait-state-error (TSE) model is obtained. In accumulative models, the first observation is treated as exogenous, with correlations with factors freely estimated. All model syntax appears in Appendix 1; long-format results are in Appendix 3.

4.2 Results

Trend Analysis. Descriptive statistics (Figure 7) show a linear decreasing trend in paid work hours, while walking hours show no clear trend. Latent growth model fitting confirmed a significant decreasing trend in work hours (slope factor mean Est. = -1.246, S.E. = 0.067) but no trend in walking hours (non-significant slope factor mean).

Dynamic Analysis. Cross-lagged models revealed carry-over in both work hours and walking: previous work/walking hours positively predicted subsequent work/walking hours (Est. = 0.766, S.E. = 0.025; Est. = 0.336, S.E. = 0.008). Positive reciprocal effects also emerged: longer previous work/walking predicted longer subsequent walking/work (Est. = 0.025, S.E. = 0.008; Est. = 0.051, S.E. = 0.005).

However, since trends were detected, they needed to be excluded. Combined trend and dynamic models showed better fit for models containing growth trends (ALT, LCM-SR) than those containing only stable traits (DPM, RI-CLM). Accumulative and residual models showed similar fit (Table 2).

Table 2 Overall Model Fit Indices

Model	RMSEA
Latent Growth Model (LGM)	0.035
Cross-Lagged Panel Model (CLPM)	0.042
Autoregressive Latent Trajectory (ALT)	0.031
Latent Curve Model with Structured Residuals (LCM-SR)	0.030
Dynamic Panel Model (DPM)	0.038
Random Intercept Cross-Lagged Model (RI-CLM)	0.036

Using ALT as an example (Table 3), paid work hours showed a significant decreasing trend with individual differences in initial values and slope changes. After controlling for individual differences, work hours showed strong carry-over, while walking hours showed minimal carry-over. Reciprocal predictive relationships emerged: longer work hours in one period led to longer walking hours in the next, and vice versa.

Table 3 Parameter Estimates for Main Longitudinal Models

Parameter	ALT (Accumulative)	LCM-SR (Residual)	DPM (Accumulative)	RI-CLM (Residual)
Work → Work	<.001	<.001	<.001	<.001
Walk → Walk	<.001	<.001	<.001	<.001
Walk → Work	<.001	<.001	<.001	<.001
Work → Walk	<.001	<.001	<.001	<.001

Note: DPM and RI-CLM estimate observed variable intercepts, constraining latent means to 0.

Results differed between accumulative (ALT, DPM) and residual (LCM-SR, RI-CLM) models. Accumulative models showed significant dynamic parameters but 2 non-significant trend variance parameters; residual models showed non-significant cross-lagged parameters but all significant trend variances, confirming that residual models better estimate trends. This may also relate to data violating stationarity (due to existing trends), potentially biasing residual models' dynamic parameter estimates. However, accumulative models risk improper slope variance estimates, providing evidence of parameter estimation bias. Additionally, combined models' autoregressive coefficients were nearly half those of cross-lagged models, indicating that the latter' s "autoregression" didn' t exclude between-person factors, confounding "trait associations" and "carry-over," insufficient to represent pure temporal influences.

5.1 Model Relationships and Comparisons

As shown in Table 1, under accumulative or residual perspectives, models are mutually convertible through parameter addition/deletion, exhibiting nested relationships. Accumulative and residual models are also convertible: accumulative models (ALT or DPM) can transform into residual models (LCM-SR or RI-CLPM) by constraining exogenous variables to specific path coefficients, making accumulative models nest residual models (Andersen, 2022). Usami and colleagues (2019, 2020) established different integration frameworks, but their frameworks are conceptual and cannot simultaneously contain accumulative and growth factors for direct comparison (Bainter & Howard, 2016; Tseng, 2024).

Despite unified integration frameworks, substantial differences remain. First, the research questions differ. Dynamic models focus on within-person changes, emphasizing temporal continuity between adjacent occasions (e.g., $y_{t-1} \rightarrow y_t$). Individual differences in these effects can exist (e.g., multilevel VAR) but are control factors rather than core issues. Conversely, trend models, though using repeated measurements to estimate each individual' s independent trajectory across all time points, focus more on between-person "average" developmental patterns or individual differences. This aligns with some literature' s definition of "between-person" as components not described by temporal changes (Asendorpf, 2021; Hamaker, 2023). This difference is sometimes called "mechanism," determined by innate factors or specific environmental experiences during development and is irreversible (Orth et al., 2021). Thus, in subsequent integration frameworks (e.g., Asparouhov & Muthén, 2023; Ernst et al., 2023), trends are defined at the between-person level and dynamics at the within-person level. In this sense, "systematic change" in trends reveals psychological laws and individual differences, while dynamics address within-person evolution.

Second, basic statistical methods and assumptions differ. Dynamic models require stationary time series, as only stationarity allows estimating average effects of previous occasions on current occasions. Mathematically, stationarity appears as autoregressive estimates with absolute values < 1 (Bühler & Orth, 2022). Autoregressive coefficients > 1 violate stationarity, suggesting acceleration ("trends") and requiring trend or combined models. In combined models, residual models require stationarity, while accumulative models do not.

Third, interpretation differs. In dynamic models, rank-order stability magnitude reflects individual position changes relative to the population, representing stability characteristics of psychological variables. If a psychological characteristic' s relative position doesn' t shift, it' s "trait-like" ; otherwise, it' s a "state." Time span matters: longer intervals reduce rank-order stability even for stable traits (e.g., an autoregressive coefficient of 0.8 yields third-order stability of $0.8^3 = 0.5$, substantially reduced). Trend models (e.g., random intercept models) define traits via fixed-loading factors constrained as time-invariant, without decay. Since Hamaker et al. (2015) proposed RI-CLM, they have argued for separating within-person and between-person effects, though others counter that traits/dispositions can have varying degrees of rank-order stability (e.g., intelligence, Big Five, self-esteem, life satisfaction) (Lucas & Donnellan, 2007; Trzesniewski et al., 2003), and traits may not be completely immutable across different time spans (Asendorpf, 2021; Hamaker, 2023; Orth et al., 2021).

5.2 Issues in Model Selection

Model selection and separating trends from dynamics remain challenging. Empirical results show that except for cross-lagged models, the other five models had similar fit, with not all indices favoring ALT. This complicates model selection in practice. Recent simulation and empirical studies have explored which models perform stably, but numerous preconditions and different data assumptions substantially affect model selection (Falkenström et al., 2023; Orth et al., 2021). Rogosa and Willett (1985) generated data with five measurement occasions from a latent growth model, then fit an autoregressive model that described the data well. They criticized autoregressive models as misleading because they fit data from latent growth models better than the true model. Bollen and Curran (2004) re-fit these data with univariate ALT, finding no significant autoregressive coefficients at any order; with autoregressive coefficients constrained to zero, ALT fit equivalently to LGM. This showed ALT doesn' t support dynamic parameters but favors trend parameters. Jongerling and Hamaker (2011) also found ALT tends to indiscriminately estimate any "developmental form" as a trend, but researchers overlooked time span effects on "developmental forms."

Based on Falkenström (2023), even data generated from pure autoregressive structures in short panel designs can show "deterministic" trends. We generated an autoregressive effect scatterplot (Figure 8 [Figure 8: see original paper]) confirming this conclusion. Extracting specific time segments (e.g., t_1-t_5 or t_{16}-t_{20}) yields different "trends." Thus, trends in panel data may stem from either objective "deterministic" trends or dynamic processes (whether stationarity is achieved). Precisely distinguishing dynamics from trends remains an urgent problem. Future research should explore accurate separation, particularly how different time spans affect trajectories, theoretically distinguishing "developmental laws" from "continuity" and empirically further interpreting both.

5.3 Recommendations for Model Selection

From an empirical perspective, researchers can adopt a data-driven approach, fitting multiple models and selecting the best-fitting one for interpretation, even when modeling conditions diverge from research hypotheses. However, this makes model selection difficult, requiring researchers to return to theory, particularly psychology' s popular "state-trait" theory, which may provide theoretical guidance for model usage.

From a mathematical perspective, we summarize a framework for using longitudinal models (Figure 9 [Figure 9: see original paper]), highlighting critical steps. First, considering research design and target psychological characteristics, choose panel or intensive longitudinal data and determine measurement intervals. Use panel data for $ $10 occasions or long intervals; use intensive longitudinal data otherwise (McNeish & Hamaker, 2020). Second, examine variable numbers, column-to-row ratios, or measurement characteristics. Use long format for many variables or small column-to-row ratios (Walther et al., 2024); use wide format for few variables, when measurement invariance or temporal consistency is violated, or when extracting specific factor scores. Intensive longitudinal data should directly use long format to minimize numerical issues (non-convergence, improper solutions). Third, since dynamic models require stationarity, panel data can first use LGM or MLM with time covariates to test for trends; intensive longitudinal data (time series) can use unit root tests (e.g., KPSS, ADF; Kwiatkowski et al., 1992) to check stationarity. We recommend preliminary descriptive analysis to identify developmental forms, particularly whether group means in intensive data show monotonic growth or periodic changes (3 times daily for 5 days can detect cyclical patterns; Muthén et al., 2024). If (growth) trends exist, panel data should use integrated trend+dynamic models; intensive data should use detrended or differenced models. If periodicity exists (intensive data), moving average, ARIMA, exponential smoothing, or cosinor models can exclude seasonal effects (Wang, 2022) or incorporate cycles into RDSEM (Muthén et al., 2024). Without trends, dynamic models can be used directly. Specifically, to separate trends from dynamics with focus on trends, prioritize residual models (e.g., RI-CLM, LCM-SR, RDSEM, cosinor RDSEM); for focus on dynamics, use accumulative models (e.g., ALT, DPM).

Figure 9 Framework for Longitudinal Modeling with Trend and Dynamic Research Questions

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Appendix 1. Mplus Syntax for Combined Trend and Dynamic Models

A1.1 Wide-format data for SEM

```
TITLE: THIS IS AN EG OF WIDE DATA
DATA: FILE IS cams(-9).dat;
VARIABLE: NAMES ARE ***;
  USEV ARE A10 B10 C10 D10 E10 A6 B6 C6 D6 E6;
  MISSING ARE ALL (-9);
```

```
! Accumulative model / Autoregressive Latent Trajectory model
MODEL:
  I1 S1 | B10@1 C10@2 D10@3 E10@4; ! Define trends
  I2 S2 | B6@1 C6@2 D6@3 E6@4;
  I1-S2 A10 A6 WITH I1-S2 A10 A6; ! Define factor correlations
  I1 S1 WITH A6@0; ! Constrain exogenous variable correlations to 0
  I2 S2 WITH A10@0;
  B10-E10 PON A10-D10 (1); ! Define dynamics with stationarity
  B6-E6 PON A6-D6 (2);
  B6-E6 PON A10-D10 (3);
  B10-E10 PON A6-D6 (4);
  B10 WITH B6; ! Define residual correlations
  C10 WITH C6;
  D10 WITH D6;
  E10 WITH E6;
OUTPUT: SAMPSTAT;

! Residual model / Latent Curve Model with Structured Residuals
MODEL:
  I1 S1 | A10@0 B10@1 C10@2 D10@3 E10@4; ! Define trends
  I2 S2 | A6@0 B6@1 C6@2 D6@3 E6@4;
  B10^-E10^ PON A10^-D10^(1); ! Define dynamics with stationarity
  B6^-E6^ PON A6^-D6^(2);
  B6^-E6^ PON A10^-D10^(3);
  B10^-E10^ PON A6^-D6^(4);
  I1-S2 WITH I1-S2; ! Define factor correlations
  A10 WITH A6; ! Define residual correlations
  B10 WITH B6;
  C10 WITH C6;
  D10 WITH D6;
  E10 WITH E6;

! Accumulative model / Dynamic Panel Model
MODEL:
  I1 BY B10@1 C10@1 D10@1 E10@1; ! Define stable trends
  I2 BY B6@1 C6@1 D6@1 E6@1;
  I1 WITH A10; ! Define exogenous variable-factor correlations
  I2 WITH A6;
  I1 WITH I2; ! Factor correlations
  I1 WITH A6@0; ! Constrain cross-variable exogenous correlations to 0
  I2 WITH A10@0;
  B10-E10 PON A10-D10 (1); ! Define dynamics with stationarity
  B6-E6 PON A6-D6 (2);
  B6-E6 PON A10-D10 (3);
  B10-E10 PON A6-D6 (4);
```

```
  B10 WITH B6; ! Define residual correlations
  C10 WITH C6;
  D10 WITH D6;
  E10 WITH E6;

! Residual model / Random Intercept Model
MODEL:
  I1 BY A10@1 B10@1 C10@1 D10@1 E10@1; ! Define stable trends
  I2 BY A6@1 B6@1 C6@1 D6@1 E6@1;
  I1 WITH I2; ! Factor correlations
  B10^-E10^ PON A10^-D10^ (1); ! Define dynamics with stationarity
  B6^-E6^ PON A6^-D6^ (2);
  B6^-E6^ PON A10^-D10^ (3);
  B10^-E10^ PON A6^-D6^ (4);
  A10 WITH A6; ! Define residual correlations
  B10 WITH B6;
  C10 WITH C6;
  D10 WITH D6;
  E10 WITH E6;

! Using latent variable approach (without residual command)
MODEL:
  FA10 BY A10; FB10 BY B10; FC10 BY C10; FD10 BY D10; FE10 BY E10;
  FA6 BY A6; FB6 BY B6; FC6 BY C6; FD6 BY D6; FE6 BY E6;
  A10-E10@0; A6-E6@0; ! Define "latent variable" residuals
  I1 BY A10@1 B10@1 C10@1 D10@1 E10@1; ! Define stable trends
  I2 BY A6@1 B6@1 C6@1 D6@1 E6@1;
  I1 WITH I2; ! Factor correlations
  FB10-FE10 PON FA10-FD10 (1); ! Define dynamics with stationarity
  FB6-FE6 PON FA6-FD6 (2);
  FB6-FE6 PON FA10-FD10 (3);
  FB10-FE10 PON FA6-FD6 (4);
  FA10 WITH FA6; ! Define residual correlations
  FB10 WITH FB6;
  FC10 WITH FC6;
  FD10 WITH FD6;
  FE10 WITH FE6;
  I1 I2 WITH FA10@0 FA6@0; ! Constrain factor-exogenous latent factor correlations to 0
  ! This path (exogenous variable correlation) is estimated by default in Mplus
```

A1.2 Long-format data for DSEM

```
TITLE: THIS IS AN EG OF LONG DATA
DATA: FILE IS sl_{cams}.dat;
DATA WIDETOLONG: ! Mplus built-in wide-to-long conversion
  WIDE = A10 B10 C10 D10 E10 | A6 B6 C6 D6 E6;
  LONG = T10 | T6;
```

```
  IDVARIABLE = PERSON;
  REPETITION = TIME;
VARIABLE: NAMES ARE ***;
  USEV ARE T10 T6 PERSON TIME; ! Use converted long variables
  MISSING ARE ALL (-9);
  CLUSTER = PERSON;
  WITHIN = TIME;
  LAGGED = T10(1) T6(1);
ANALYSIS: TYPE = TWOLEVEL;
  ESTIMATOR = BAYES; ! Time series requires Bayesian estimation
  PROCESSORS = 2;
  BITERATIONS = (2000);

! Accumulative model
MODEL:
  %WITHIN%
    T10 T6 ON TIME; ! Define trends
    T10 ON T10&1 T6&1; ! Define dynamics
    T6 ON T6&1 T10&1;
    T10 WITH T6;
  %BETWEEN%
    T10 T6; ! Between part estimates means by default
    T10 WITH T6; ! Can also use [T10 T6] to represent means

! Residual model
MODEL:
  %WITHIN%
    T10 T6 ON TIME; ! Define trends
    T10^ ON T10^1 T6^1; ! Define dynamics
    T6^ ON T6^1 T10^1;
    T10 WITH T6;
  %BETWEEN%
    T10 T6;
    T10 WITH T6;

! Accumulative model with random slopes (trend random effects shown)
MODEL:
  %WITHIN%
    TREN1 | T10 ON TIME; ! Define trend random effects
    TREN2 | T6 ON TIME;
    T10 ON T10&1 T6&1; ! Define dynamics
    T6 ON T6&1 T10&1;
    T10 T6;
    T10 WITH T6;
  %BETWEEN%
    [T10 T6]; ! Estimate trend fixed effects
```

```
    T10 T6;
    T10 WITH T6;
    [TREN1 TREN2]; ! Estimate trend random effect variances
    TREN1 TREN2;
    TREN1 WITH TREN2; ! Estimate trend random effect covariances

! Residual model with random slopes (trend random effects shown)
MODEL:
  %WITHIN%
    TREN1 | T10 ON TIME; ! Define trend random effects
    TREN2 | T6 ON TIME;
    T10^ ON T10^1 T6^1; ! Define dynamics
    T6^ ON T6^1 T10^1;
    T10 WITH T6;
  %BETWEEN%
    [T10 T6]; ! Estimate trend fixed effects
    T10 T6;
    T10 WITH T6;
    [TREN1 TREN2]; ! Estimate trend random effect variances
    TREN1 TREN2;
    TREN1 WITH TREN2; ! Estimate trend random effect covariances

! Full random slopes model (demonstrates random dynamic parameters and random residuals)
! This model takes long to estimate and doesn't converge in residual models
! Shown for syntax demonstration; interested readers can adjust as needed
MODEL:
  %WITHIN%
    TREN1 | T10 ON TIME; ! Define trend random effects
    TREN2 | T6 ON TIME;
    AUTO1 | T10 ON T10&1; ! Define dynamic random effects
    CLAG1 | T10 ON T6&1;
    AUTO2 | T6 ON T6&1;
    CLAG2 | T6 ON T10&1;
    LOGV1 | T10; ! Define residual random effects
    LOGV2 | T6;
  %BETWEEN%
    [T10 T6]; ! Estimate fixed effects
    T10 T6;
    [TREN1-LOGV2]; ! Estimate random effect variances and covariances
    TREN1-LOGV2;
    T10 WITH T6;
    TREN1 WITH TREN2;
    AUTO1-CLAG2 WITH AUTO1-CLAG2;
    LOGV1 WITH LOGV2;
```

Appendix 2. Contemporaneous Effect Model Diagrams

Note. Three equivalent model diagrams (3 time points shown). All models have identical overall fit and parameter counts. Figure a shows standard cross-lagged model; Figure b changes residual correlation to unidirectional $x \rightarrow y$ effect, representing contemporaneous effects; Figure c moves cross-lagged paths to the same time point, showing $x \rightarrow y$ and $y \rightarrow x$ contemporaneous effects. More contemporaneous effect specifications and parameter estimation issues are discussed in Muthén and Asparouhov (2024).

Appendix 3. Parameter Estimation Results for DSEM (Long Format)

Parameter	DSEM (Random Intercept Only)	RDSEM (Intercept Only)	DSEM (Random Slopes)	RDSEM (Random Slopes)
	Est.	Post. SD	95% CI	Est.
Work → Work				
Walk → Work	-0.08			
Walk → Walk				
Work → Walk				
Within random effects				
Between random effects				
Trend covariance				

Note: Only random slope models with trend effects are shown. Random slope models for dynamic and residual effects don’ t converge (estimation time > 30 minutes) and are omitted. Random effect definitions appear in Appendix 1. This subsample includes N = 2,689. Results show significant dynamic parameters in accumulative models but non-significant trend parameters; residual models show decreasing work hour trends, with only walking hour autoregression showing instability.

Note: Figure translations are in progress. See original paper for figures.

Source: ChinaXiv —Machine translation. Verify with original.