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Capturing Change in a Rapidly Evolving World: A Composite Longitudinal Analysis Framework for Theorizing, Modeling, and Analyzing Change Using PLS-SEM

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Abstract: Partial least squares structural equation modeling (PLS-SEM) serves as a longitudinal research tool for elucidating individual developments from various perspectives. However, much of the literature in this domain compares cross-sectional designs rather than examining the changes of interest. This oversight stems from the lack of clear guidelines for applying PLS-SEM in this context. We present a methodological framework for the effective use of PLS-SEM to model growth and development processes and an example of its application. Our guidelines will help scholars develop meaningful hypotheses, build models addressing construct changes over time, apply PLS path-modeling techniques to evaluate the models, and ultimately gain a deeper understanding of the nature of change.

Keywords: modeling change; PLS-SEM; longitudinal modeling; framework; guidelines

1. Introduction

Over the past two decades, the popularity of partial least squares structural equation modeling (PLS-SEM) in the social and behavioral sciences has steadily increased [1]. As a fully developed and general system [2], and a powerful, multifaceted methodology for analysis [3], it imposes fewer restrictions on data distribution than traditional linear regression-based models, especially in considering higher-order constructs [4–6]. Its adoption has also been facilitated and supported by the wide availability of both open-source libraries (e.g., LavaaN, MatrixPLS, SeminR in R) and commercial products (e.g., WarpPLS and SmartPLS). Because of its advantages, academic and industry researchers are leveraging it to investigate complex research questions [7]. Beyond business research, PLS-SEM is also used in such fields as healthcare, drug discovery, and analysis [8].

However, except in a few cases [9], the use of PLS-SEM has been limited to one-time, cross-sectional studies that employ survey instruments to ask subjects about constructs of interest [10]. Although researchers consistently call for more longitudinal studies, its extension in this arena has been hampered by the lack of clarity about what constitutes longitudinal research, in contrast to, for example, multigroup research [3,11]. Information Systems researchers see longitudinal research as a means to clarify complex socio-technical systems and their outcomes, including cybersecurity [12], and human-computer interactions [13]. Combining the PLS-SEM toolset used in academia and industry with modern data collection technologies can provide new insights and solve problems of vital social relevance.

To seize on missed opportunities, ref. [10] provides a decision tree that can help researchers follow one of two general pathways (one includes two subtypes). However, these pathways have two major shortcomings. First, they conceptualize change as the difference between two groups (models across time) and build on the multigroup analysis notion and difference-score calculations to define the change. Second, their so-called two-wave design, using only two timepoints (t1–t0) to establish a baseline and test a change, has considerable limitations e.g., [14–16]. The issue is rooted in the constraints of the two-wave design, not in any fundamental deficiency of the difference score that may result in a meaningful reduction of variance [17]. A two-way design can only provide a linear estimate of the change, which may turn out to be a local effect as opposed to a curve [18]. Consequently, they lack the precision needed to capture the rate of intraindividual change over time [14].

These deficiencies can be addressed through multiwave (three or more) measurements of the same units across time. Researchers can then capture the rate of change and estimate the growth (change) function. This article puts forward a theory and framework that enables researchers to conduct multiwave longitudinal analyses using PLS-SEM. Consider an example from [19], they propose a nonlinear relationship between human capital effectiveness related to the units' (such as team, division, or organization) effectiveness over time and find the proposed relationship stronger in some units than others. They demonstrate that measuring changes in human capital over time, instead of at one time, better predicts changes in unit sales. In other words, a cross-sectional measure of human capital is not an adequate explanation of that unit's effectiveness even though changes in human capital were strongly related to changes in unit effectiveness.

Drawing on the principles of latent-growth modeling (LGM), originally developed for covariance-based structural equation modeling (CB-SEM) [20] as well as Measurement Invariance of Composite Models (MICOM) [21], this article introduces and applies a composite-based change-modeling technique for PLS-SEM analysis. It takes advantage of interpretations in the areas of unobserved heterogeneity [22] and the prediction-oriented models of the applied social sciences [23]. It provides guidelines for using PLS-SEM to model and investigate the effects of growth and development on behavioral research constructs.

First, we explain the proposed composite longitudinal analysis (CLA) methodology and compare it to existing ones. Next, we define its theoretical underpinnings; our research design and data; invariance testing; and parameterization, and we evaluate the resulting measurements and the structural model. We then demonstrate a practical deployment on a primary dataset, forming hypotheses, parameterizing the model, confirming configural invariance, and evaluating performance. We conclude by elaborating on contributions and directions for future research.

2. Composite Longitudinal Analysis (CLA)

Longitudinal studies offer unique insights that other study designs cannot provide. Two key areas of interest in tracking changes in behavior include cause-and-effect relationships and patterns. Researchers can capture trajectories—the rates of change—as well as interunit differences. The captured measures can be considered either the cause or the effect of the phenomenon under study [14,19]. This design and analysis can inform hypotheses about growth, incorporate time-varying covariates, and derive a common developmental trajectory from the data, thus ruling out the cohort effect or within-group common identity [18].

The literature on longitudinal design for SEM-based methods includes three approaches to modeling change. Ref. [24] investigates how constructs change over time. They adopt a mean comparison approach, creating two models using data pertaining to each time period. They then use a paired-sample t-test to evaluate the statistical significance of any differences indicating change. Ref. [10] builds on this approach, introducing two PLS-SEM specific methods. One focuses on changes in path coefficients using multigroup analysis with two subtypes, differentiating on whether the data can be paired. The other investigates changes in construct scores. Both general types rely on the comparison of mean analysis borrowed from [24].

In contrast to the existing comparison-based methods of [10,24], our approach is focused on investigating how the rate of change in exogenous constructs of interest impacts the endogenous ones. Unlike previous change modeling techniques, our approach does not require researchers to gather data for the whole model at all time periods and allows research to focus on a construct of interest, the rate of change of which is theorized to impact outcome constructs. The proposed approach does not require multiple comparisons as the ones discussed earlier yet incorporates the change as the rate of change over time, regardless of the number of measurements in time.

2.1. Step 1: Theoretical Foundations

The underlying theoretical model is the key to understanding longitudinal analysis [25]. There are two types of theoretical approaches to modeling change: (1) the theory may predict a change in a construct of interest; or (2) the theory may conceptualize the effects of the rate of change as either an exogenous or endogenous construct. Most of the longitudinal studies focused on explaining and predicting changes are cross-sectional studies based on post-hoc analyses of a construct of interest [10] and do not theorize and investigate how the rate of change in a construct may affect other constructs. For example, researchers have argued that the perceived ease of use affects intention to use less in the later stages of an adoption process. However, ref. [26] found that the effect of perceived usefulness increases in the case of technology adoption and use. Still, their research does not theoretically account for changes in constructs over time and their effects on each other, so they do not define the nature of any change or its effects. We argue that longitudinal research can assign causality based on theories that suggest that the rate of change in an exogenous construct could cause changes in an endogenous construct. For instance, previous research has failed to show how the rate of change of each construct, usefulness, and ease of use, affects IT adoption and use. It also does not explain how changes in these constructs affect behavioral intentions. This article offers a methodology that comprehensively captures the nature of change.

This research uses a dynamical system analogy to conceptualize change as a latent-growth construct. A dynamical system represents the mathematical abstraction of an evolving state [27]. It consists of a state space (*S*), an ordered time continuum (*T*), and an evolution operator (Θ). Formally, $\Theta: S \times T \rightarrow S$ gives the consequent to a realized state $s \in S$: the evolution operator predicts/implements the next (consequent) state from a current state $\boldsymbol{s}$. The forward trajectory (e.g., a growth curve) of a state $\boldsymbol{s}$ is the sequential collection of consequent time-ordered states. A dynamical system is considered a model when it describes a specific temporal evolution process and where the state space (*S*) is the collection of all coordinates s that exhaustively capture the evolution of the state of the variable of interest [28].

One form of a dynamical model often used in business research is the stock and flow model. Economists use it in analyzing job markets and employment (e.g., [29]) and macroeconomic interest and pricing theory (e.g., [30,31]); operations researchers apply it to inventory modeling and capacity planning [32]; and IS researchers use it to analyze organizational knowledge [33]. Consider the stock and flow modeling of the double entry accounting system (e.g., [34,35]). Here, a firm's balance sheet abstracts the concept of stock (the state of the economic health of the firm), which represents the state S of the underlying dynamical system at a given time (e.g., the end of year 1). The underlying evolution operator Θ is the net flow of appreciations (e.g., acquiring new assets) and depreciations (e.g., incurring new debts) that influence the realization of the consequent states, i.e., the balance sheets at the end of year 2, year 3, and so on—on the ordered time continuum (*T*). Similarly, consider the case where an IS researcher is interested in the growth curve of computer self-efficacy (CSE) among a group taking computer training. The researcher could theorize the growth of CSE as a dynamical system, and abstract it in a stock and flow model, where the state S (CSE, the stock) changes under the influence of the evolution operator Θ (repeated training intervention/s, the flow) over specified periods of time *T*.

We adopt the stock-and-flow modeling approach and conceptualize the growth construct as a sequential 2-step process whose boundaries are modeled in the design phase and operationalized through 3 waves of data collection. The state S of the underlying dynamical system is conceptualized as Intercept (*C*)—the stock parameter—while the flow parameter is conceptualized as the slope (*M*), which embodies the evolution operator (Θ) that changes the state S over time *T*.

The deliberate choice of slope (*M*) and intercept (*C*) as the flow and stock parameters is justified for four reasons. First, between every pair of adjacent realizations of state S, we can invoke an elegant and well-known linear combination—the slope-intercept form of a straight line $Y = MX + C$ to approximate the growth trajectory. Second, the linear combination of the slope and intercept mimics the conceptualization of a composite growth construct. Third, the model can capture changes in growth between several pairs of adjacent realizations of the state S, leading to an integrated trajectory, albeit piecewise but without any loss of generalization (explained later) because no further constraining domain assumptions are made. Fourth, for every pair of adjacent realizations of the state, the slope-intercept form of the straight line $Y = MX + C$ facilitates the measurement of the stock parameter c directly, while the point-slope form of the straight line, i.e., $(y - c) = m(x - t)$ provides an easy way to derive the flow parameter m, which we further explain in subsection step-4 under "change model parameterization." The stock and flow model of growth is presented on the *X*-*Y* plane in Figure 1, where the *X*-axis represents the ordered time T of the underlying dynamical system, and the *Y*-axis represents the measure of the state *S*.

In this three-wave design, the first wave of data collection measures the initial state, while the third wave measures the final state. The second wave defines the intermediate state. These three states are used to estimate the overall growth trajectory. By design, the data collection points are sufficiently far apart on the timeline, and the growth interventions coincide with the data collection points. Figure 1 diagrammatically presents these realized states as the initial state (*I*), intermediate state (ϵ), and final state (*F*). The intermediate state is shared between the two sequential steps of growth.

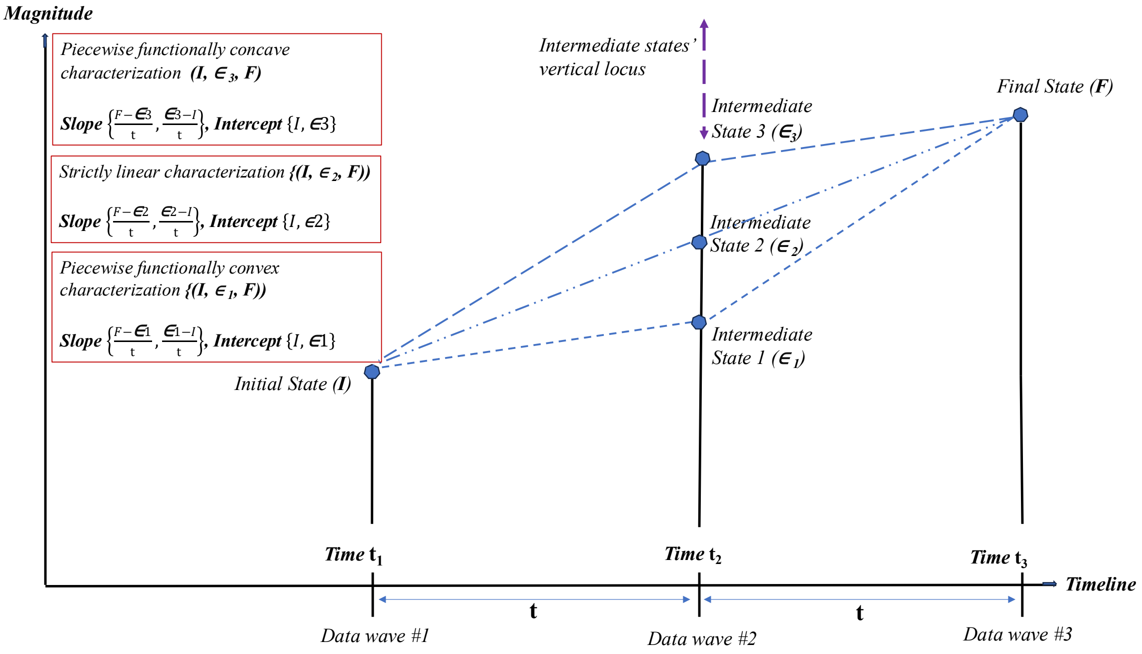

Figure 1. Nature of change.

In the proposed methodology, each step includes the two-stage standard heuristic of a growth-modeling process [18]. In stage 1, a regression curve (linear here) is fitted to the two repeated measures (the two adjacent states) of each respondent. In stage 2, the parameters of each individual regression curve are analyzed. As a result, each step in our growth-modeling process results in a slope-intercept couple similar to the flow-and-stock components of the higher order growth construct, which represents the underlying dynamical system. Taken together, the two steps constitute the overall growth process and internalize the true nature of growth. By modeling the two-stage growth heuristic in each step, the proposed growth model captures both (a) factor means, or the group-level information, and (b) the variances, representing individual differences [18].

The deliberate two-step growth model can accommodate contextually different natures of growth. This capability is obvious when two or more states of the contexts differ or when only the initial or final state is distinct. It becomes more interesting when both the initial and final states of the different contexts are the same, but the growth processes differ substantively. Noting that the loci of all possible realizations of the intermediate state lie on a vertical straight line, the following observations are in order (Figure 1). First, when the intermediate state lies on the straight line drawn between the initial and final states, (ϵ_2), we have a strictly linear growth process, for example, the accrued rental income of a residential property. Second, when the intermediate state lies above the straight line, (ϵ_3), we have a concave growth process. For example, consider the case of IT security investment to secure the network perimeter of an organization, where the diminishing marginal return of investment increasingly plateaus the rate of growth of the impregnability of the network. Third, when the intermediate state lies below the straight line, (ϵ_1), we have a convex growth process; for example, a pandemic spreads increasingly faster as more and more people become ill.

Finally, the latent growth construct which embodies the 2-step growth model, and a set of cross-sectional constructs are analyzed together to determine their combined effects on the outcomes. Note that the 2-step conceptualization of the growth process is a parsimonious but generalized approach that captures the convexity/concavity of the growth in a piecewise manner [36,37]. Of course, with more data collection waves, many intermediate states could be modeled to smooth the piecewise trajectory. Any refinement in the above piecewise approximation requires domain-specific information of the nature of growth (e.g., logarithmic, exponential, etc.), in which case closer estimation of parameters is possible, but only at the expense of the generalizability of the model.

2.2. Step 2: Research Design

Ref. [10]'s review of PLS-SEM longitudinal research identifies two general designs. The first variation (Type A) creates a PLS-SEM model for each time period and runs a multigroup analysis to determine their different outcomes in terms of structural (e.g., path coefficients) and measurement (e.g., convergent and discriminant validities) outcomes. Type A has two subvariants: panel data are gathered from the same participants at different times, and cross-sectional data from different participants at different times. Both are used to investigate only two static states, leaving the researcher to infer whether any change affected or was affected by another construct. Type B uses a paired samples t-test to determine any significant statistical difference between construct indicators at the two timepoints and, and if so, creates one PLS-SEM model based on the difference score constructs. Since the model uses difference score constructs, the model tests whether linear changes in one construct are related to changes in other constructs.

To accurately assess change, research must consider the nature of change that occurs in a construct when baseline effects are controlled. Two measurement points can only estimate a straight line, while actual change may follow a curve [14]. Because one difference score construct (t_2–t_1) is just a snapshot of the rate between the two times, at least two sets of difference scores (three observations over time) are needed [38,39]. This paper demonstrates a longitudinal change model that captures data collected in three waves on the timeline.

Following [40], we conceptualize our growth construct as data-driven to support empirical testing of our hypotheses. Instead of modeling latent-growth constructs reflectively, as customary in CB-SEM, we propose to create a composite construct assuming that the indicators together form the construct by means of linear combinations so that we can capture the fact that the variations in the indicators precede the variations in the construct and maintain the idea that the measurement model is data-driven [41]. A PLS model provides this unique advantage, avoiding the limitations of the reflective latent construct.

Our stock-and-flow model of the underlying dynamical system relies on the slope (M) and the intercept (C). Each component depends on one or more of the growth states (initial, intermediate, final), so they are correlated, and through the linear combination of the slope (M) and the intercept (C), $Y = MX + C,$ they represent the higher order growth construct. This approach is consistent with the underlying PLS-SEM algorithm that also uses regression-based optimization. Note that the slope and intercept must occur together to represent the underlying growth process—they are correlated, but they are not interchangeable as in a reflective construct. Formally, for an n-step process, the design formally yields:

$$Y = MX + C,$$

$$|M| = \{m_k\}, k = \{1, 2, \ldots.., n\}, -\infty \leq m_k \leq \infty$$

$$|C| = \{c_k\}, k = \{1, 2, \ldots.., n\}, 0 \leq c_k < \infty$$

The actual parameterization of the above model for the three waves of data collection is explained later.

2.3. Step 3: Invariance Testing

Collecting construct information at different time points might produce different interpretations and scales. Equating them all could be confounding, especially when the measures are not invariant. Conclusions could be misleading or even false [42–45]. For example, research has shown that respondents' estimations of relational knowledge change over time, which, based on the context, may lead to interpretational confounding of insights regarding such knowledge [46]. To test for composite-construct invariance and prevent such confounding, ref. [21] developed MICOM, which addresses three factors: (1) configural invariance, (2) compositional invariance, and (3) composite mean and variance equality. In the context of growth modeling, stages 2 and 3 are irrelevant. Stage 3 (equivalence of mean) is not relevant to longitudinal analysis, which hypothesizes a change in composite mean and variance over time. Stage 2 ensures that composites are formed equally across groups, a prerequisite condition for multigroup analysis that applies to longitudinal analysis (see [10]) only in the context of change modeling built on group comparison.

The configural invariance test is used to determine conceptual equivalence or congeneric equivalence [47]. Configural invariance is a condition that must be met before intercept and slope constructs can be created. Its absence indicates that the measured construct is not conceptually the same at different times, and estimating a growth curve is meaningless. In PLS-SEM, congeneric equivalence is ensured by using the same items to define a construct across all measurements and ensuring that the data are treated identically using the same algorithmic settings across measurements [21].

2.4. Step 4: Change Model Parameterization

In step 2, we established the general form of the n-step growth process theorized as a dynamical system in step 1. For our specific case of 2-step growth, the slope (M) and the intercept (C) of the stock-and-flow model are represented as,

$$|\boldsymbol{M}| = \begin{cases} m_1, -\infty \leq m_1 \leq \infty \\ m_2, -\infty \leq m_2 \leq \infty \end{cases}, \quad |\boldsymbol{C}| = \begin{cases} c_1, 0 \leq c_1 < \infty \\ c_2, 0 \leq c_2 < \infty \end{cases},$$

where subscripts 1 and 2 represent the first and second steps of the growth process. The slopes, assumed as linear here, together with the intercepts represent a piecewise, straight/convex/concave growth. The initial state (*I*), intermediate state (ϵ), and final state (*F*) are located as the salient points of measured growth on the *X*-*Y* plane (Figure 1). The pairs $\{m_1, m_2\}$ and $\{c_1, c_2\}$ constitute the higher order construct that integrates the longitudinal process in the overall cross-sectional model. Both slope and intercept—$\{m_1, m_2\}$ and $\{c_1, c_2\}$—satisfy the PLS-SEM requirement for at least two observations; the timeline being scaled and the waves of data collection equidistant on the timeline (Figure 1).

Figure 1 demonstrates the scenario on the *X*-*Y* (state-time) plane that captures the slope-intercept conceptualization of growth. Measurements involve the following:

(a) The intercepts are directly measured on the *Y* (magnitude) axis, which provides the measures for the states $\{s_1, s_2, \ldots.\}$ as $\{c_1, c_2, \ldots.\}$. They are collected directly from the survey instrument during the three waves of data collection.
(b) The slopes are derived measures. Our piecewise, linear conceptualization of growth conceives each pair of adjacent states on a straight line. Now, we conveniently represent the growth process for each step in the point-slope form. Knowing that each pair of adjacent states lies on a straight line, we can write $(y - c_1) = m_1(x - t_1)$, and $(y - c_2) = m_1(x - t_2)$, which solves $m_1 = (c_2 - c_1)/(t_2 - t_1)$. Proceeding similarly, $m_2 = (c_3 - c_2)/(t_3 - t_2)$.
(c) By design, $(t_3 - t_2) = (t_2 - t_1) = t$, and is scaled (for a general analysis, please see Appendix A) as *1* without any loss of information.

Model refinement in terms of identification and integration of higher order derivatives of the change function (convexity/concavity) must accompany additional waves of data collection but may introduce response fatigue and other costs [48]. For example, four waves are suggested for a model to estimate quadratic change [49]. In our stock-and-flow dynamical system, and by the conceptualization of latent growth with piecewise linear approximation with (n) number of data waves, the (n) salient states $\{s_1, s_2, s_3, \ldots., s_n.\}$ are measured as $\{c_1, c_2, c_3, \ldots., c_n.\}$. These (n) states, in turn, identify $(n-1)$ slopes. Thus, scaling and normalizing the timeline for unitary, equidistant data waves, the general formulation of the measurement model yields:

$$Y = MX + C,$$

where,

$$|M| = \{(c_2 - c_1)/(t_2 - t_1), (c_3 - c_2)/(t_3 - t_2), \ldots., (c_n - c_{n-1})/(t_n - t_{n-1}).\}, \text{ and}$$
$$|C| = \{c_1, c_2, c_3, \ldots., c_{n-1}.\}$$

while $\{(t_2 - t_1) = (t_3 - t_2) =, \ldots., = (t_n - t_{n-1}) = t.\}$: normalized and scaled at t_1.

2.5. Step 5: Measurement and Structural Model Evaluation

The last part of the analysis is the evaluation of the measurements and the structural model. For theoretical explanation, we defer to the large body of literature that reports the building and testing of measurement and structure using PLS-SEM [50]. Here, we explore the practical aspects and provide guidelines for interpreting results.

3. Composite Longitudinal Analysis: Applying the 5-Step Method

This section provides detailed guidelines for successfully conducting longitudinal research based on theorizing and modeling the rate of change using PLS-SEM. For each of the five steps, we demonstrate how to design, analyze, and interpret the study within this methodological framework.

3.1. Step 1: Theoretical Justification for the Slope

In line with previous work on extensions of PLS-SEM techniques [51,52] and following recommendations to maximize the model's significance [53], we choose the established technology acceptance model (TAM [54]). TAM derives from the theories of reasoned action [55] and planned behavior [56], which is used to investigate behavioral intent (BI) in relation to technology use. According to TAM, two primary exogenous constructs, perceived usefulness (PU) and perceived ease of use (PEoU), influence the intention to use technology. The base model has been validated many times in regard to initial adoption [57]. It supports these hypotheses:

H1. *Perceived usefulness positively affects the behavioral intention to adopt*.

H2. *Perceived ease of use positively affects the behavioral intention to adopt*.

However, some researchers argue for a change in the model's nomological composition because perceptions change with continued use; the importance of PEoU decreases, while the importance of PU increases [26]. Thus, instead of the original TAM constructs, we address how the initial state and rate of change in users' computer self-efficacy (CSE) affect PU and PEoU over time. Previous cross-sectional research has focused on how predispositions about outcomes or abilities, known collectively as computer self-efficacy, affect users' psychological attitudes and intention to adopt. Note that they also change with experience [58,59]. Figure 2 shows the initial state and rate of change in CSE.

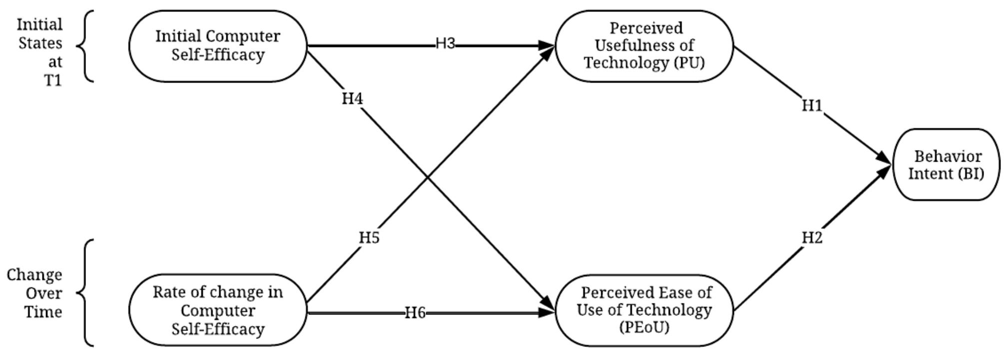

Figure 2. Research model: Initial states (intercept) and rate of change (slope) construct.

3.1.1. Initial State Construct

CSE is defined as users' belief in their own ability to use technology to execute general work tasks [60,61]. Previous studies have demonstrated the salience of CSE in determining users' perception of technology's usefulness and ease of use (e.g., [59,62,63]). We are interested in exploring the effects of its initial state and rate of change. Numerous studies have shown a positive correlation between CSE and users' perceptions of the technology's usefulness, ease of use, and their intention to use it [64]. However, when comparing experts and novices [65,66] or task differences [67], variations in these factors showed no significant impact. While some evidence seems to support the impact of initial states on technology-acceptance variables, its decline presents a theoretical challenge we discuss in the next section. For initial states, we hypothesize:

H3. *Initial state computer self-efficacy (intercept) positively affects perceived usefulness*.

H4. *Initial state computer self-efficacy (intercept) positively affects perceived ease of use*.

3.1.2. Rate-of-Change Construct

Research shows that CSE changes [68] and the rate of such changes affects intention to use and performance. In specific cases where the self-efficacy rate changes too steeply, the effect on long-term performance may be negative [69].

Here, we show that the rate of change in CSE explains the TAM's nomological network from first to continued use. While users' CSE levels predict their individual PU and PEoU levels, the rate at which their CSE changes predict the change in PEoU. As CSE increases with practice, initial inhibitions about interacting with technology gradually diminish, replaced by a higher emphasis on the advantages of technology in achieving work-related goals [68]. Thus, we hypothesize:

H5. *The rate of change in initial computer self-efficacy (slope) positively affects perceived usefulness*.

H6. *The rate of change in initial computer self-efficacy (slope) positively affects perceived ease of use*.

3.2. Step 2: Research Design

A multiwave longitudinal data set was collected using a classroom setting, while the data was collected using a web-based instrument right after the training. We outline the procedure and sample next.

Procedure: The participants were students in a classroom setting. The students were asked to provide training on Excel. Our CSE measures were collected at three timepoints, t_1, t_2, and t_3 (see Figure 3). Only at t_3, we collected data on the endogenous variables of PU, PEoU, and the behavioral intent to use technology.

Figure 3. CSE measurement across time.

Sample: The students were given incentives to participate. This allowed for substantial control on data gathering. In the next step, students with advanced Excel knowledge were eliminated. Our study followed established protocols from similar technology training research [68,70]. To map participants across training sessions, we gave each a dummy code. This was done to maintain internal validity, and the theoretical requirement to study CSE change. Thus, there was a purposeful selection criterion with minimal dropout rates, controlling for attrition bias. Overall, 701 were recruited; 433 were part of the data collection; 60% were women, and 40% men.

3.3. Step 3: Measurement Invariance across Timepoints

Step 3 concerns measurement invariance. As mentioned earlier, the main purpose of this step is to prevent interpretational confounding. Consistent with the MICOM process, which compares constructs across time, we focus on measurement invariance across time. MICOM process has three steps, each outlined in our context below.

Step 1—Configural invariance: In this step, we ensured that the construct (CSE) used the same items to define and measure it across all three time periods. The repeated-measures design used the same instrument to assess changes in an individual's self-efficacy across three time points (t_1, t_2, and t_3). The items were: (1) SE1—I cannot use Excel yet as well as I would like; (2) SE2—I am able to perform tasks well using Excel; (3) SE3—I think my ability to use Excel can be improved substantially. Based on the same pattern of fixed and free items and the repeated-measures design, configural invariance was established for self-efficacy.

Step 2—Compositional /Measurement Invariance: While the same instrument was used across time, it is also important to establish that the same loadings were achieved across time. Thus, we tested whether the composite CSE construct is formed identically across timepoints. Results confirm compositional invariance, ensuring that the weights and indicator relationships are stable. This has been reported in Figure 4.

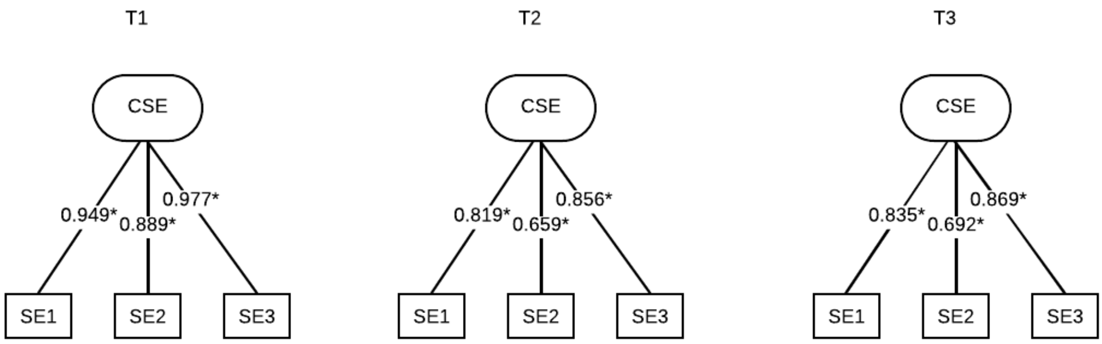

Figure 4. Measurement invariance. * Statistically significant at $p < 0.05$

Step 3—Mean and Variance Equality: This step tests whether composite means and variances are equal across groups/time. In growth modeling, we explicitly hypothesize and expect change in means and variances over time. Thus, testing for equality would contradict the fundamental purpose of growth analysis. This step is appropriate for multigroup comparison (e.g., comparing means across different populations), not for within-group longitudinal analysis. Thus, this step is not relevant.

3.4. Step 4: Change-Model Parameterization

The first part of this process is to ensure that CSE does change over the three timepoints. We leverage a unique advantage of PLS-SEM based analysis to calculate the raw (rescaled) latent value score (LVS) for CSE at each timepoint. Table 1 reports the means, standard deviation (SD), minimum (Min), and maximum (Max) as reported by SmartPLS v.4. It is important to note that these are raw means. We also calculated the mean difference as outlined earlier, and based on a paired t-test, they differed statistically. The following data represents LVS from 0–100 as reported by SmartPLS. This is an inherent property that improves numerical stability and interpretability.

Table 1. Sample frame attrition.

Category	n	Percentage of Initial
Initial Recruitment	701	100%
Eligibility Exclusions	245	34.9%
True Attrition (Dropout)	5	0.7%
Data Quality Exclusions	18	2.6%
Final Analytical Sample	433	61.8%

Next, using the point-slope form described in our Figure 1 and methodology, each individual's intercept (C_i) represents their estimated CSE value at a reference point on the timeline. Given our piecewise linear model with two segments:

C1_i = individual's T1 measurement (rescaled)

C2_i = individual's T2 measurement (rescaled)

The composite Intercept construct is then formed as a weighted linear combination of C1 and C2 using the formative measurement model in PLS-SEM. Finally, slopes are calculated for each individual:

M1_i = (C2_i − C1_i) / time interval between T1 and T2

M2_i = (C3_i − C2_i) / time interval between T2 and T3

The composite Slope construct is formed as a weighted linear combination of M1 and M2. The means and SD for the intercept and slope are reported in Table 2. This allows us to build the equation $Y = MX + C$ for the CSE construct.

Table 2. Descriptive statistics for CSE.

	T1_CSE	T2_CSE	T3_CSE
Means	15.19	37.83	45.10
SD	23.05	16.18	17.02
Min	0	0	0
Max	90.795	100	100
Mean Difference (T2–T1), (T3–T2)	-	22.65 *	7.27 *

* Statistically Significant at $p < 0.05$.

3.5. Step 5: Measurement Model and Structural Model Evaluation

For longitudinal analysis, slope and intercept are measured as higher order constructs, and we use the two-step method to specify, estimate, and validate them. They are regarded as composites, or a linear combination of their indicator's value. Table 3 provides the descriptive statistics for intercept and slope. Evaluation of this measurement model proceeds as follows: interpret the relationships between higher and lower order components as loadings and assess convergent validity, internal consistency, and discriminant validity metrics for the reflectively measured constructs (PU, PEoU, BI). Collinearity is also assessed for the formatively measured composite constructs (slope and intercept). The structural model uses standard evaluation criteria without the lower order components.

3.5.1. Measurement Model Evaluation

We first focus on formative measurement evaluation criteria to assess the quality of slope and intercept. We then measure the rest of the model constructs (BI, PU, PeoU) reflectively. According to [71], accurate measure of formative constructs rests on measures of convergent validity, indicator collinearity, and the relevance of outer weights.

We discussed the general theoretical and mathematical underpinnings of slope and intercept in step 2 and showed how they are created using the CSE example. The theory provides sufficient support for items' convergent validity and relevance to slope and intercept as formative composite constructs. Further, the variance inflation factors (VIFs) (see Table 4) for all items pertaining to slope and intercept are under the suggested threshold of 5 and the ideal threshold of 3 [72], indicating no collinearity. Bootstrapping results using 10,000 subsamples also reveal that slope and intercept indicators are all statistically significant at the 0.05 level. These results, together with the mathematical logic behind the formulation of the slope and intercept indicators, provide ample support for the relevance and statistical significance of the outer weights.

Table 3. Descriptive statistics for intercept and slope.

	Intercept	Slope
Mean	49.85	78.87
SD	12.61	31.48
Min	4.22	−33.90
Max	87.85	155.83

The remaining constructs (PU, PEoU, BI) are defined and measured reflectively and, hence, require different quality-assessment criteria [71] based on indicator reliability, internal consistency, convergent validity, and discriminant validity.

Table 4. VIF and outer weight measures.

Construct/Item	VIF	Original Sample	Sample Mean	Standard Deviation	*p* Values
Intercept 1	1.069	0.259	0.263	0.125	0.020
Intercept 2	1.069	0.902	0.892	0.067	0.000
Slope 1	1.226	−0.464	−0.466	0.073	0.000
Slope 2	1.226	1.107	1.104	0.023	0.000
BI 1	3.441	0.521	0.521	0.007	0.000
BI 2	3.441	0.521	0.521	0.008	0.000
PEOU 1	2.645	0.341	0.341	0.015	0.000
PEOU 2	1.647	0.181	0.181	0.019	0.000
PEOU 3	2.904	0.292	0.292	0.013	0.000
PEOU 4	2.719	0.334	0.334	0.014	0.000
PU 1	3.626	0.269	0.269	0.008	0.000
PU 2	3.630	0.274	0.274	0.007	0.000
PU 3	3.608	0.269	0.269	0.007	0.000
PU 4	2.316	0.298	0.299	0.015	0.000

Indicator reliability scores (Table 5) for all constructs range from 0.73 to 0.96, exceeding the suggested threshold of 0.70 [73]. The lack of major cross-loadings further suggests adequate indicator reliability and discriminant validity. The composite reliability scores are all above the recommended cutoff point of 0.70 [4], indicating sufficient internal consistency. Additionally, average variance extracted (AVE) values are all higher than 0.7, exceeding the recommended value of 0.5, which suggests good levels of convergent validity. Discriminant validity is further assessed through the heterotrait-monotrait (HTMT) ratio (Table 6). According to [7], HTMT values less than 0.9 indicate sufficient discriminant validity for constructs involved in the measurement model. The highest HTMT value for our model, 0.81 between BI and PU, attests good discriminant validity.

Table 5. Item loadings and cross loadings.

Item/Construct	BI	PEOU	PU
BI 1	**0.96**	0.52	0.71
BI 2	**0.96**	0.51	0.72
PEOU 1	0.51	**0.90**	0.43
PEOU 2	0.30	**0.73**	0.17
PEOU 3	0.45	**0.90**	0.35
PEOU 4	0.53	**0.90**	0.45
PU 1	0.64	0.39	**0.91**
PU 2	0.66	0.36	**0.92**
PU 3	0.65	0.37	**0.91**
PU 4	0.72	0.42	**0.87**

Table 6. Internal consistency, convergent validity, and discriminant validity (HTMT).

Construct	Cronbach's Alpha	Composite Reliability	AVE	BI	PEoU
BI	0.91	0.91	0.92		
PEOU	0.88	0.92	0.74	0.58	
PU	0.92	0.92	0.81	0.81	0.45

3.5.2. Structural Model Evaluation

Evaluating the structural model starts with checking for possible collinearity between directly related constructs. Table 7 presents the collinearity statistics for the inner (structural) model, demonstrating no high collinearity.

Table 7. Inner model collinearity statistics.

	BI	Intercept	Slope
PEoU	1.23	1.02	1.01
PU	1.23	1.35	1.15

PLS-SEM path coefficients and variance explained are similar to regression coefficients and R-squared, representing the strength of the relationship between constructs [4]. The statistical significance of the path coefficients is assessed using a bootstrapping sampling procedure with 10,000 runs. Figure 5 shows that all of the proposed relationships are statistically significant and in accordance with the hypothesized direction of influence, providing adequate support for all of our hypotheses.

Finally, PLS-SEM is considered a strong predictive method, so it is more appropriate for evaluating a model's predictive power than its fit [42,74,75]. We consider the model's predictive power using a $PLS_{predict}$ procedure built on the cross-validation logic of the predictive analysis. $Q^2_{predict}$ statistics indicate that the model's prediction error is lower than the error generated by the most naïve benchmark model. As reported in Figure 5, all $Q^2_{predict}$ values are positive, indicating good predictive power [76,77]. Predictive power is a good measure of a model's accuracy and fit.

The results demonstrate that the slope construct and the initial states capture the rate of change as measured by the intercept construct and positively affect PU and PEoU as theorized. The slope constructs maintain a stronger association with perceived usefulness, indicating that the rate of change in CSE has a stronger impact on users' perception of the technology's usefulness than of its ease of use, while the intercept construct follows a reverse pattern. Thus, users' initial sense of self-efficacy has a stronger impact on their perception of a system's ease of use than of its usefulness. In other words, users who start with greater CSE find a system easier to use but not necessarily more useful. However, as they become more confident in their ability to use the system, their perception of its usefulness changes more than their evaluation of ease of use.

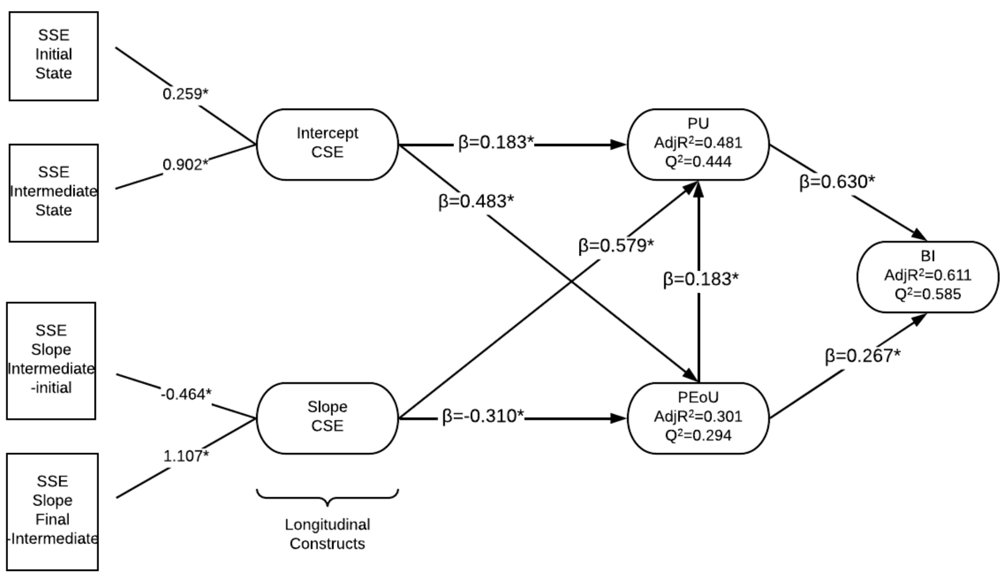

Figure 5. Structural model, * $p < 0.05$.

These results indicate that training programs that increase self-efficacy increase users' positive perceptions of PU and PEoU. They support our claim that researchers should focus on how to implement construct changes beyond a particular state captured at a single time. Finally, our results explain prior findings that do not theorize the relationship between PU and PEoU [78]. Our findings indicate that similar changes in the antecedents of PU and PEoU have not been explored as underlying factors in their observed relationship.

4. Discussion

This research argues that measuring change rather than merely comparing two or more states can capture the full growth process. The proposed model incorporates the concept of stock-and-flow modeling in the composite growth parameters of the intercept *C* (the stock) and the slope *M* (the flow).

To capture incremental change, we consider the growth process in two steps and capture their boundary states in three waves of data collection that enumerate the valence of the stock parameter, the intercept *C*. The equidistant data collection points enable determination of the overall rate of change, the flow parameter slope *M*. This approach enables our model to capture whether a change is linear, concave, or convex parsimoniously and functionally [79–82]. In other words, it exhibits the general capability to capture all domain-specific growth processes.

The proposed change-modeling framework demonstrates and refines the impact of growth on PU and PEoU in the empirical example. It helps us compare the differential influences of the stock-and-flow variables—intercept and slope—on the respondents' perceived PU and PeoU. In the example of training data, the flow variable (the slope *M*) has a higher impact on PU in comparison to the stock variable (the intercept *C*) and the reverse for PEoU. Results suggest that higher rates of change in CSE through intense training interventions may make users perceive the system as more useful, possibly because they can discover more applications for their features. In contrast, unless they have a high degree of CSE initially, users may not realize the benefits of new features and systems.

5. Limitations and Future Research

In this section, we focus on three limitations/future research areas: (A) Autoregressive Effects and Time-Varying Covariances, (B) Measurement of Endogenous Variables Only at t3 and (C) Non-Equidistant Time Intervals.

Our growth trajectory model captures intraindividual change through intercept and slope constructs that summarize each individual's complete growth pattern across $t1 \rightarrow t2 \rightarrow t3$, but does not explicitly model autoregressive effects or time-varying covariances between CSE and outcome variables. Traditional autoregressive cross-lagged panel models would examine how CSE at each specific timepoint influences outcomes at subsequent timepoints, potentially revealing time-specific dynamics that our trajectory-based approach does not capture [20]. However, our research question focuses on how overall growth patterns (not time-specific states) influence post-training outcomes, which aligns with our stock-and-flow conceptualization where cumulative change trajectories are theoretically meaningful [18]. Future research could employ comparative designs examining growth trajectory models versus autoregressive cross-lagged models to determine which approach best captures the CSE → technology acceptance relationship or utilize parallel process growth models to examine the co-evolution of CSE and acceptance attitudes across training stages.

A limitation of our design is that perceived usefulness (PU), perceived ease of use (PEoU), and behavioral intention (BI) were measured only at t3, which limits causal inference compared to a full panel design where all constructs would be measured at all time points. This design choice reflects our theoretical focus on how cumulative CSE growth trajectories predict post-training technology acceptance outcomes, and the practical consideration that acceptance attitudes are most meaningful and stable after participants have gained sufficient experience through complete training [68,70]. However, this precludes testing reciprocal causation—whether early-stage PU/PEoU influence subsequent CSE growth—and prevents examination of time-varying effects where CSE → outcome relationships might change across training stages. While temporal precedence is established (growth occurs before outcome measurement) and our methodological demonstration goals are served, comprehensive theory testing would benefit from full panel designs that enable cross-lagged panel analysis and examination of dynamic interplay between evolving CSE and acceptance attitudes throughout the training process.

Our study employed equidistant time intervals between measurement waves due to the controlled experimental training schedule where all participants followed identical timing. However, researchers applying this methodology in naturalistic settings may encounter non-equidistant intervals between timepoints. As detailed in our Appendix A, the stock-and-flow calculation method readily accommodates varying time intervals by adjusting slope calculations to reflect actual elapsed time: $M_1 = (C2 - C1)/\Delta time_1$ and $M_2 = (C3 - C2)/\Delta time_2$. This adjustment maintains interpretability as "rate of change per unit time" and ensures that growth parameters accurately reflect the temporal dynamics of the phenomenon under study, with closer timepoints capturing more granular change and greater spacing capturing more substantial cumulative change [36,37].

6. Conclusions

The importance of longitudinal research and associated analytical methods has been well-established in literature [83]. However, discussion of PLS-SEM use in longitudinal research has mostly been restricted to comparing two or more cross-sectional studies [10], rather than examining the dynamic changes of interest. We posit that the limited use of PLS-SEM methodologies in longitudinal research is not due to their limited capabilities but the absence of clear theoretical background and precise guidelines. This work demonstrates a five-step Composite Longitudinal Analysis (CLA) method to conceptualize, design, and analyze longitudinal research using PLS-SEM, focusing on the importance of theorizing change, including its rate; measuring constructs across at least three time points; and testing invariance across those periods [1].

Traditional latent growth modeling using covariance-based structural equation modeling (CB-SEM) treats intercept and slope as reflective latent variables, assuming that unobserved "true" growth factors cause the observed measurements at each timepoint [20]. This approach requires strong distributional assumptions, typically multivariate normality, and optimizes for reproducing the observed covariance matrix with the goal of recovering population parameters for theory testing [1]. In contrast, our composite-based approach using PLS-SEM conceptualizes intercept and slope as formative constructs where the observed states and changes form the growth parameters through linear combination [50]. This aligns with the stock-and-flow conceptualization where measurements at different timepoints drive the calculation of growth parameters, maintaining that "variations in the indicators precede the variations in the construct" and that "the measurement model is data-driven" [41].

Our PLS-SEM composite approach offers distinct advantages for prediction-oriented research in applied contexts. The variance-based PLS algorithm optimizes for maximizing explained variance in dependent variables rather than parameter recovery, making it particularly appropriate when prediction and practical application are prioritized over theory testing [23,74]. This approach requires minimal distributional assumptions, handles complex models efficiently, and is effective with moderate sample sizes [71]. The formative composite specification recognizes that slope and intercept "must occur together to represent the underlying growth process—they are correlated, but they are not interchangeable as in a reflective construct," and through their linear combination ($Y = \boldsymbol{M}X + \boldsymbol{C}$), they represent the higher-order growth construct in a manner "consistent with the underlying PLS-SEM algorithm that also uses regression-based optimization" [50].

We demonstrate how researchers can derive the intercept and slope using a composite construct structure to capture change comprehensively, building on recent methodological advances including MICOM [21] and interpretations in the areas of unobserved heterogeneity [22] and prediction-oriented models of the applied social sciences [23]. When these growth parameters are conceptualized as formative composites, they can be used in a standard PLS-SEM model to examine how rates of change influence outcomes. Our work applies the proposed method to show the theoretical implications of modeling changes, testing invariance across timepoints, and evaluating structural and measurement models, demonstrating that longitudinal studies should focus on change, not static comparisons. A summary of the comparison can be found in Appendix B.

Future research can use the proposed methodological framework to develop hypotheses about the effects of change and test them using PLS-SEM. With technological advances in collecting cleaner panel data over extended periods and increasing PLS-SEM skills in the researcher community, our approach is poised to support much-needed studies of longitudinal changes in industrial and managerial systems. This composite-based approach represents an intentional methodological innovation that extends PLS-SEM capabilities to longitudinal growth modeling, offering a rigorous alternative to traditional LGM when research goals emphasize prediction and practical application in applied social science contexts.

Author Contributions

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Institutional Review Board Statement

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Informed Consent Statement

Informed consent was obtained from all subjects involved in the study.

Data Availability Statement

The research data are available upon request from the first author.

Conflicts of Interest

The authors declare no conflict of interest.

Use of AI and AI-Assisted Technologies

During the preparation of this work, the author(s) used Grammarly to assist with editorial issues. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the published article.

Appendix A. An Analysis of the Location of the Data Waves on the Timeline

Figure 1 in our paper shows the longitudinal data collection arrangement for this work. In general, domain experts decide when data is collected in a longitudinal study given their specific research agenda and the types of intervention studies. For example, in clinical studies, factors like disease trajectory, expected time of maximum effect, optimal density of observation, data logistics, etc., influence the data collection timings and intervals; and doctors may study patients' wellness/improvement factors beginning with the first intervention, and till the end of the study period following the final intervention [39]. The initial and final data collections are heavily specified by the domain experts [39]; thus, we focus on the selection of the intermediate data collection (Wave #2).

In what follows, we now access the theoretical underpinnings of our model to specify, within the above limits, when it is opportune to run the intermediate data wave. To facilitate understanding of the theoretical analysis, we utilize the familiar Figure 1 of this work (albeit in a slightly different format) as the graphical illustration here (Figure A1).

A piecewise linear approximation attempts to follow the actual growth curve but achieves a certain degree of fidelity because of the linearity assumption. It is easy to see that the higher the number of discrete data points on the growth curve, the better is the piecewise approximation. Thus, an appropriate approach to select the optimal intermediate data wave would be such that it minimizes the shaded area that is under the growth curve but is above the convex combinations of the data collection points on the growth curve (Figure A1). It is thus appropriate to flexibly optimize the intermediate data wave (Wave #2) within the bounds that the domain experts specify so that the resultant shaded area is minimized.

The above general approach for all growth curves is plausible and appropriate, because, by Jensen's inequality, when x_1 and x_2 are two points on the growth curve $y(x)$, and $0 \leq q \leq 1$;

- For convex growth curves, all the secants (slope lines in our model) are above the growth curve, i.e., $y(q.x_1 + (1-q).x_2) \leq q.y(x_1) + (1-q).y(x_2)$; and similarly,
- For concave growth curves $\{-y(x)\}$, all the secants (slope lines in our model) are below the growth curve.

We now continue to utilize a similar graphical framework like Figure 1; now with the clear depiction of the underlying growth curve that is being measured (Figure A1).

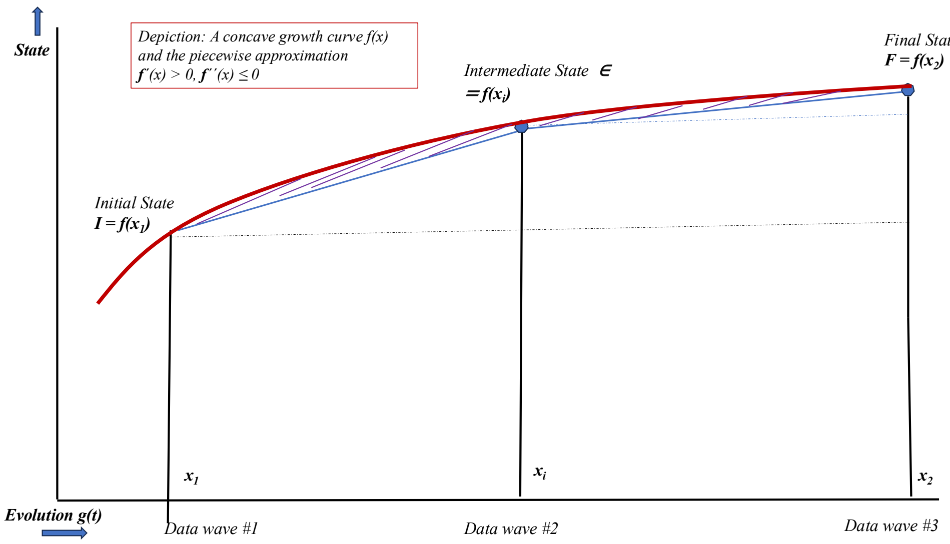

Figure A1. Efficient intermediate data wave location.

The minimization problem for a bounded optimal location of data wave #2 can be written as:

$$Minimize_{x_i}\left\{\int_{x_1}^{x_2} f(x)-(T_1+T_2+T_3+T_4)\right\}$$

or $Minimize_{x_i}\{[F(x_2)-F(x_1)]-(T_1+T_2+T_3+T_4)\}$, where the terms,

$$T_1 = (x_2-x_1).f(x_1)$$

$$T_2 = (x_2-x_i).\{f(x_i)-f(x_1)\}$$

$$T_3 = \frac{1}{2}.(x_i-x_1).\{f(x_i)-f(x_1)\}$$

$$T_4 = \frac{1}{2}.(x_2-x_i).\{f(x_2)-f(x_i)\}$$

Note that for any selection of the intermediate data wave, x_i, this minimization problem changes its argument, but the terms $[F(x_2)-F(x_1)]$ and T_1 do not alter because they do not contain x_i. In other words, the above minimization problem can be construed as:

$$Maximize_{x_i}\{(T_2+T_3+T_4)\}$$

or,

$$Maximize_{x_i}\ [\tfrac{1}{2}.f(x_i)\{x_2-x_1\}+\{x_2.f(x_2)-x_1.f(x_1)\}\ -\ x_i\{f(x_2)-f(x_1)\}-f(x_1)\{x_2-x_1\}]$$

By the first order condition, $\frac{d}{dx_i}\ (T_2+T_3+T_4)\ =0$, i.e., $\frac{1}{2}.f'(x_i^*)\{x_2-x_1\}-\frac{1}{2}.\{f(x_2)-f(x_1)\}=0$, or

$$x_i^* = f'^{-1}\{\tfrac{f(x_2)-f(x_1)}{x_2-x_1}\} \tag{A1}$$

The above closed form solution definitively locates the efficient intermediate data wave on the timeline.

Example A1. *Assume that the underlying growth curve can be estimated as a natural logarithmic growth curve, i.e.,* $Y(x)=ln(x)$, *so that* $Y'(x)=1/x$.

Delineating the growth curve from $x_1=5$ (first data wave) to $x_2=30$ (third data wave), we can calculate the optimal location of the intermediate data wave (also graphically presented in Figure A2),

$$\frac{1}{x_i^*}=\frac{ln(30)-ln(5)}{30-5}=\frac{3.4-1.6}{25}=\frac{1.8}{25}$$

Thus, $x_i^*\ =13.88$ (see the diagram below)

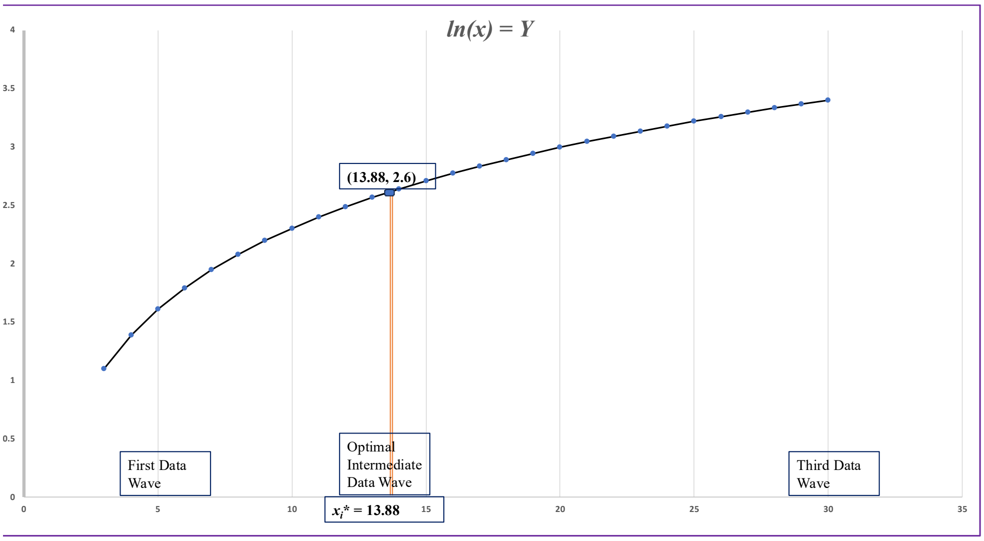

Figure A2. Example efficient intermediate data wave location. The asterisk * denotes the optimal value of the variable Xi.

Thus, the generalized solution steps are below:

Step 1. Run the unconstrained Maximization problem $Maximize_{x_i}\{(T_2 + T_3 + T_4)\}$, get x_i^*, like we demonstrate above. If $d \le x_i^* \le D$, stop, select x_i^*. If not, proceed as below:

Step 2. Calculate $\{(T_2^* + T_3^* + T_4^*)\}, \{(T_2^d + T_3^d + T_4^d)\}$, and $\{(T_2^D + T_3^D + T_4^D)\}$.

Step 3. Pick the maximum of $\{(T_2^* + T_3^* + T_4^*)\}, \{(T_2^d + T_3^d + T_4^d)\}$, and $\{(T_2^D + T_3^D + T_4^D)\}$, and select the intermediate data wave at $x_i^*, \nabla\, x_i^*\ (d \le x_i^* \le D)$; d: or D; as the case may be, where, T_k^*, T_k^d, T_k^D are the values of the terms $T_2, T_3,$ and T_4 evaluated at $x_i = x_i^*$, $x_i = d$ and $x_i = D$ respectively.

A per unit measure of the locational sensitivity (smaller values are better than larger values) of the intermediate data wave can then be assessed as $\frac{\left\{1-(T_2^k+T_3^k+T_4^k)/(T_2^*+T_3^*+T_4^*)\right\}}{|x_k - x_i^*|}$, when the selection for the intermediate data wave is $x_i = x_k$, while the optimal is $x_i = x_i^*$.

When the functional form of the underlying growth can be estimated, like we have exemplified above, one could also use Excel to replicate the above solution steps by using the GOAL function and then comparing with the value of the objective function at *d* and *D*, where *d* and *D* are the lower and upper bounds of the intermediate data wave provided by domain experts, and both lie between the first and the final data waves.

Appendix B. Traditional CB-LGM vs PLS-SEM Composite Growth Model

Table A1. Traditional CB-SEM vs PLS-SEM longitudinal modeling comparison.

Dimension	Traditional LGM (CB-SEM)	PLS-SEM Composite Approach
Construct Type	Reflective latent variables	Formative composite constructs
Causal Direction	Latent growth factors → Observed timepoints	Observed states/changes → Growth parameters
Theoretical Basis	Common factor model	Stock-and-flow dynamical systems
Indicator Relationship	Interchangeable manifestations	Unique, non-interchangeable contributions
Estimation Method	Maximum likelihood (covariance-based)	Partial least squares (variance-based)
Optimization Goal	Reproduce covariance matrix	Maximize predictive accuracy
Distributional Assumptions	Multivariate normality is typically required	Minimal; non-parametric
Sample Size Requirements	Large samples needed for stable estimates	Effective with smaller samples
Model Specification	Fixed loadings (theory-driven)	Data-driven weights (empirically optimized)
Primary Purpose	Theory testing, parameter recovery	Prediction, practical application
Handling of Complexity	Struggles with complex, non-normal data	Robust to violations of normality
Interpretation	"True" latent growth trajectory	Composite growth pattern from observed data
Measurement Error	Explicitly modeled and separated	Absorbed into the composite
Generalizability	Population parameter estimates	Sample-specific prediction optimization

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