Communications of the Association for Information Systems

Volume 50 Article 22

6-8-2022

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Youyou Tao
Loyola Marymount University, youyou.tao@lmu.edu

Abhay Mishra
Iowa State University, abhay@iastate.edu

Katherine E. Masyn
Georgia State University, kmasyn@gsu.edu

Mark Keil
Georgia State University, mkeil@gsu.edu

Recommended Citation

Tao, Y., Mishra, A., Masyn, K. E., & Keil, M. (2022). Addressing Change Trajectories and Reciprocal Relationships: A Longitudinal Method for Information Systems Research. Communications of the Association for Information Systems, 50, pp-pp. https://doi.org/10.17705/1CAIS.05018

Communications of the Association for Information Systems

Research Article | DOI: 10.17705/1CAIS.05018 | ISSN: 1529-3181

Addressing Change Trajectories and Reciprocal Relationships: A Longitudinal Method for Information Systems Research

Youyou Tao
Information Systems and Business Analytics
Loyola Marymount University
youyou.tao@lmu.edu

Abhay Nath Mishra
Information Systems and Business Analytics
Iowa State University
abhay@iastate.edu

Katherine Masyn
Population Health Sciences
Georgia State University
kmasyn@gsu.edu

Mark Keil
Computer Information Systems
Georgia State University
mkeil@gsu.edu

Abstract:

This paper makes a focused methodological contribution to the information systems (IS) literature by introducing a bivariate dynamic latent difference score model (BDLDSM) to simultaneously model change trajectories, dynamic relationships, and potential feedback loops between predictor and outcome variables for longitudinal data analysis. It will be most relevant for research that aims to use longitudinal data to explore longitudinal theories related to change. Commonly used longitudinal methods in IS research – linear unobserved effects panel data models, structural equation modeling (SEM), and random coefficient models – largely miss the opportunity to explore rate of change, dynamic relationships, and potential feedback loops between predictor and outcome variables while incorporating change trajectories, which are critical for longitudinal theory development. Latent growth models help address change trajectories, but still prevent researchers from using longitudinal data more thoroughly. For instance, these models cannot be used for examining dynamic relationships or feedback loops. BDLDSM allows IS researchers to analyze change trajectories, understand rate of change in variables, examine dynamic relationships between variables over time, and test for feedback loops between predictor and outcome variables. The use of this methodology has the potential to advance theoretical development by enabling researchers to exploit longitudinal data to test change-related hypotheses and predictions rigorously. We describe the key aspects of various longitudinal techniques, provide an illustration of BDLDSM on a healthcare panel dataset, discuss how BDLDSM addresses the limitations of other methods, and provide a step-by-step guide, including Mplus code, to develop and conduct BDLDSM analyses.

Keywords: Bivariate Dynamic Latent Difference Score Model, Latent Growth Model, Longitudinal Research, Measurement Invariance, Structural Equation Modeling, Health IT.

This manuscript underwent peer review. It was received 9/13/2019 and was with the authors for 20 months for three revisions. Tom Eikebrokk served as Associate Editor.

1 Introduction

In recent years, scholars in multiple disciplines have strongly recommended longitudinal theorizing and data analysis (Bolander et al., 2017; Kher & Serva, 2014; Ployhart & Vandenberg, 2010; Zheng et al., 2014). Buoyed by the increasing availability of public and private longitudinal datasets, researchers in information systems (IS) have been using longitudinal data analysis techniques to examine phenomena that evolve over time. Commonly employed techniques include linear unobserved effects panel data models (e.g., fixed/random effects models), structural equation modeling (SEM), and random-coefficient models (Zheng et al., 2014). Although these methods have enabled researchers to move beyond cross-sectional, single-point analyses, they suffer from two major drawbacks. First, these methods fail to incorporate change trajectories (time-dependent changes in variables between repeated measurements across time) in predictor and/or outcome variables, despite the fact that IS phenomena often involve constantly changing variables in dynamic relationships. For example, when users start using an IT application for task accomplishment, the number of IT features used could possibly change over time. This change trajectory in the number of IT features used needs to be taken into consideration when examining the impact of IT feature use on task performance (Benlian, 2015). Traditional panel data analyses cannot support trajectory change assessment adequately. For example, in fixed-effects models, variation over time is absorbed by the time fixed effects and is treated as incidental fluctuation (Wooldridge, 2010; Zheng et al., 2014). This model cannot be applied to assess trajectory changes of predictor and outcome variables, or to incorporate such trajectory changes in model assessment. Research examining change trajectories in variables, however, is important in theory building, both to understand change patterns and to explore the dynamic longitudinal relationships among variables. This is because a number of IS theories, such as Information Technology (IT) adoption theories, technology diffusion theories, and information processing theories, are rooted in the change patterns of variables and their longitudinal relationships over time (Zheng et al., 2014).

Latent growth modeling (LGM), which was recently introduced in the IS literature (Bala & Venkatesh, 2013; Benlian, 2015; Serva et al., 2011; Söllner et al., 2016; Zheng et al., 2014), addresses the first drawback. It enables the examination of change trajectories in variables and has been used to model how the change process evolves (Zheng et al., 2014). LGM, however, does not address the second drawback of traditional models, namely their inability to examine feedback loops between predictor and outcome variables over time. A feedback loop captures the causality between two variables with reciprocal causal links (Fang et al., 2018). We define a positive feedback loop as one that has the tendency to reinforce the initial action, and a negative feedback loop as one that has the tendency to oppose the initial action (de Gooyert, 2019). Feedback loop consideration is relevant in many IS phenomena. For example, while the IT business value literature has established that IT investments can improve firm performance, recent research suggests that such improvements also lead to subsequent IT investments, which suggests a positive feedback loop between IT investment and firm performance (Baker et al., 2017). Yet, neither traditional panel data models nor LGM can examine whether a positive feedback loop exists between IT investment and firm performance in a single model while incorporating change trajectories in variables. As a result, our understanding of the relationship between IT investment and firm performance has been limited to a unidirectional view, while there might be more subtle and complex two-way causal interactions between these two variables over time.

This study introduces a more comprehensive and advanced method, a bivariate dynamic latent difference score model (BDLDSM), also known as a latent change score model, to study how relationships between the predictor variable and the outcome variable evolve over time. BDLDSM addresses both of the limitations discussed above. Digital phenomena where longitudinal data can be brought to bear to examine dynamic and reciprocal relationships between variables abound. BDLDSM enables IS researchers to examine these phenomena and facilitates longitudinal theory extension and development. Specifically, BDLDSM enables IS researchers to (1) understand the rate of change in a variable over time, (2) examine constructs from a reciprocal, longitudinal development perspective, (3) gain a nuanced understanding of the dynamic longitudinal relationship between the predictor and outcome variables while addressing reverse causality, and (4) examine feedback loops between variables. We discuss each of these advantages next.

First, BDLDSM enables IS researchers to gain a comprehensive understanding of the overall rate of change in variables as the outcome of interest by allowing them to identify the sources of the change. The method enables researchers to ascertain if the overall rate of change in outcome variable comes from constant change over time; is proportional to the level of outcome variable at the previous time point; or is influenced by the level of predictor at the previous time point.

Second, BDLDSM enables IS researchers to examine traditionally static constructs from a reciprocal, longitudinal development perspective, which may lead to considerable theory extension. For example, trust is commonly treated as a static concept in the IS research due to methodology limitations (Serva et al., 2011; Söllner et al., 2016; Zheng et al., 2014), but perceptions of trust may evolve over time. Further, it may have a reciprocal relationship with other constructs. Serva et al. (2011) introduced a scenario for longitudinal designs in which researchers usually study the initial trust of users when they first contract with e-vendors. However, the perception of trust may evolve over time, as the users' relationship develops with e-vendors. Thus, it is important to study the change trajectory of the perception of trust over time. BDLDSM can be applied to study the change trajectory of trust, and how trust dynamically impacts other constructs, such as transaction intentions, while accounting for change trajectories. In addition, BDLDSM can be used to examine the reciprocal nature of trust. For example, Serva et al. (2005) investigated the reciprocal trust between interacting teams. BDLDSM can be applied to further examine how the trust from one party changes over time when this party observes the action of another party and reconsiders one's subsequent trust-related attitudes and behaviors (Serva et al., 2005).

Third, BDLDSM enables IS researchers to gain a nuanced understanding of the dynamic longitudinal relationship between the predictor and outcome variables, which cannot be resolved by other longitudinal research models, including LGM. For example, using LGM, Zheng, Pavlou and Gu (2014) investigated the longitudinal relationship between the weekly word of mouth (WOM) volume and the weekly sales rank. Using BDLDSM, IS researchers can answer the following type of research question: Does weekly WOM volume positively or negatively affect the subsequent change of weekly sales rank while accounting for the reverse causality from weekly sales rank to WOM volume and further accounting for the weekly sales from the previous week and the constant change of weekly sales over the course of the study?

Fourth, BDLDSM enables IS researchers to examine feedback loops between variables. This method can contribute to the ongoing discussion in the IS literature about the nature of causal relationships between IT investments, use, and performance by emphasizing the feedback loops between these variables. For example, IT use among individuals, groups, organizations, and countries and the relationship of such use with various economic, social, cognitive, and other outcomes is an established area of inquiry in the IS literature. BDLDSM allows researchers to test the potential feedback loops between IT use and these outcomes. By facilitating the analysis of such data, BDLDSM can help IS researchers disentangle the true nature of the relationship between IT use and outcomes. Results obtained from these analyses can spur longitudinal theory creation and subsequent testing.

In this research, we illustrate the application of BDLDSM by investigating the longitudinal relationship between health information technology (HIT) applications and hospital performance. Extant research largely relies on a static framework, despite using panel data methods, to study the relationship between HIT implementation and hospital performance. Such a static framework may not be able to reveal the dynamic relationship between HIT and hospital performance. Further, very few prior studies that applied a dynamic framework have examined the influence of trajectory changes and potential feedback loops between HIT and hospital performance (e.g., Menon & Kohli, 2013). Considering trajectory changes for both HIT implementation and hospital performance is vital when examining dynamic lead-lag association. A dynamic lead-lag association examines how the *levels* of the predictor variable temporally precede and lead changes in the outcome variable (Grimm et al., 2012). Overlooking these trajectory changes can impact the significance levels and the directions of the effects of HIT implementation on hospital performance. Further, HIT implementation and hospital performance may develop feedback loops over time. For example, an increased HIT implementation level may lead to hospital performance improvement and that improved hospital performance may further lead to a higher level of HIT implementation. Thus, we plan to extend the current literature that studies HIT impact on healthcare performance to provide further empirical tests while accounting for reverse causality and change trajectory. In this study, to illustrate the application of BDLDSM, we focus on one hospital performance measure, experiential quality, which evaluates patients' perceptions of the quality of care they receive at a hospital based on their interactions with healthcare providers (Angst et al., 2012; Chandrasekaran et al., 2012; Pye et al., 2014; Senot et al., 2016; Sharma et al., 2016).

Our study contributes to the IS literature in two major ways. First, to the best of our knowledge, this is the first paper in the IS field that introduces BDLDSM, which is an emerging methodological approach that is ideally suited to understand the overall rate of change in variables and to study dynamic, longitudinal relationships between variables, while incorporating their change trajectories. Despite BDLDSM's significant potential for confirming longitudinal theoretical models, it has not, to our knowledge, been applied in the IS literature. We demonstrate that BDLDSM can be used to examine research questions for which other existing, widely used methods are inadequate such as theorizing longitudinal change and examining feedback loops between predictor and outcome variables. Our paper aids longitudinal theory development by enabling IS researchers to theorize and test *forms of changes* (e.g., linear or nonlinear), *levels of changes* (e.g., within units change, between units change, or both), and dynamic longitudinal relationships in both descriptive and explanatory longitudinal research. Second, to the best of our knowledge, the interplay between HIT implementation levels and hospital performance over time has not been previously studied by incorporating the growth rate of HIT implementation levels and hospital performance variables within a dynamic framework to incorporate the dynamic effects. Our paper is the first to evaluate this interplay over time by incorporating the change trajectories of HIT implementation levels and hospital performance variables. Our paper not only extends the current HIT value literature by examining HIT impact on experiential quality from a dynamic and nonlinear perspective, but also provides insights regarding the nonlinear change trajectories of HIT implementation levels and the potential feedback loop between HIT implementation levels and hospital performance. We provide well-documented Mplus code with a covariance matrix (see Appendices E and F) that IS researchers can easily adapt for their own uses, and a bibliography section of BDLDSM that points to foundational references on BDLDSM.

2 Literature Review

We conducted a systematic review of published longitudinal research in the top IS journals from 2004-2018 (15 years). Our review reveals that longitudinal research methods used in IS research have largely ignored change trajectories in variables over time. We then review these methods and then discuss LGM, which is a research method that incorporates change trajectories in variables over time but fails to examine the dynamic lead-lag association or feedback loops between variables.

2.1 Review of Longitudinal Research in Information Systems

We begin our analysis by reviewing longitudinal research published in the "Senior Scholars' Basket of Journals" because these journals are accepted in the IS community as top journals, and Management Science (MS) because it is a highly-rated general-purpose journal, where IS colleagues regularly publish their work.[1] We identified 190 articles involving longitudinal research that applied quantitative methods between 2004 and 2018. The most common analysis techniques were linear unobserved effects panel data models (66 papers), SEM (36 papers), random coefficient models (11 papers), and other regression models (e.g., ordinary least squares (OLS), Negative Binomial (NB), Difference-in-Difference (DID)) (15 papers) (see Appendix A for more details on the search process, search result summary, and the articles that were identified for each data analysis method). Below, we discuss the advantages and disadvantages of the two most frequently applied analysis techniques.

The most commonly applied longitudinal analysis technique in the IS field is the linear unobserved effects panel data model. Two commonly used linear unobserved effects models are the fixed effects model and the random effects model. In the fixed effects model, the unobserved effects are allowed to arbitrarily correlate with the predictors. In the random effects model, the unobserved effects are not allowed to arbitrarily correlate with the predictors. Random effects models are also used when the time-invariant estimators are important (e.g., Langer et al., 2014).

Both fixed and random effects models make strict exogeneity assumptions wherein predictors in each period are expected to be uncorrelated with the idiosyncratic error in each period. The assumption no longer holds if a lagged dependent variable is one of the predictors. In recent years, researchers have published a number of papers that apply dynamic panel models to address this issue (Aral et al., 2012; Bhargava & Mishra, 2014; Menon & Kohli, 2013; Tambe & Hitt, 2012). A special type of dynamic panel models that can be applied in a system of equations is called a panel vector autoregressive model

[1] Specifically, the journals we reviewed include *European Journal of Information Systems* (EJIS), *Information Systems Journal* (ISJ), *Information Systems Research* (ISR), *Journal of the Association for Information Systems* (JAIS), *Journal of Information Technology* (JIT), *Journal of Management Information Systems* (JMIS), *MIS Quarterly* (MISQ), *Journal of Strategic Information Systems* (JSIS), and *Management Science* (MS). Only those papers that were accepted by the IS department at MS were included in this analysis, however, BDLDSM has not been used in papers published in other departments by IS scholars.

(PVAR). In recent years, a small number of IS studies have used a PVAR model to examine the relationship between a system of interdependent variables (Adomavicius et al., 2012; Chen et al., 2015; Dewan & Ramaprasad, 2014; Thies et al., 2016).

In summary, fixed and random effects models can test if a relationship exists between predictor and outcome variables over time; dynamic panel models can account for dynamic outcome variables and predictors that are not strictly exogenous; PVAR can be used for a system of interdependent variables to address autocorrelations and joint endogeneity. None of these approaches, however, can be applied to model change trajectories or capture dynamic relations between two variables over time.

SEM, which is a multivariate technique that analyzes causal relationships among latent variables (Bollen, 2011), is the second most common longitudinal analysis technique in the IS literature. Researchers have typically collected predictor and the outcome variables at different time points to study adoption, system use, and post-adoption impacts (Sun, 2013; Sykes et al., 2009; Venkatesh et al., 2011; Venkatesh et al., 2011). Although separation of predictor and outcome variables, such that predictors precede outcomes, establishes temporal precedence, it does not lend itself to tracking changes in variables over time. To examine the change trajectory of the predictor and outcome variables, IS researchers apply LGM (Bala & Venkatesh, 2013; Benlian, 2015; Serva et al., 2011), discussed in the next section.

Finally, prior research in IS has also used random coefficient models, other regression models (e.g., OLS, NB, DID models), survival models, and ANOVA (and ANOVA like) techniques to analyze longitudinal datasets. Please see Appendix A for the list of papers that applied these methods.

2.2 Review of LGM Research in Information Systems

To date, the use of LGM in the IS field has been limited (Li et al., 2015; Serva et al., 2011; Zheng et al., 2014). A major advantage of LGM over traditional SEM is that it offers precise information on longitudinal change trajectories in variables over time (Benlian, 2015; Zheng et al., 2014), which is important from a theoretical perspective. It is important to note that traditional SEM models are based on cross-sectional analysis and do not account for longitudinal relationships (Zheng et al., 2014). Zheng, Pavlou, and Gu (2014) have discussed the importance of introducing LGM in the IS field from both theoretical and practical perspectives and provided analysis guidelines to help IS researchers better describe, measure, analyze, and theorize longitudinal change. A few researchers in the IS field have applied LGM in their research. For instance, Bala and Venkatesh (2013) employed LGM to develop a job characteristic change model during an enterprise system implementation. Benlian (2015) adopted LGM and tested three functional forms of change in IT usage. LGM models provide researchers with a dynamic view of interactions between predictor and outcome variables over time.

Despite its benefits, LGM has two significant limitations. First, LGM cannot uncover the feedback loop between the predictor and the outcome variable over time. However, it is important that IS researchers be equipped with an analytical technique that has this capability. For instance, in the IT business value research, the possibility of a positive feedback loop between IT investment and a firm's productivity over time is widely discussed (Baker et al., 2017), but without the use of a dynamic and reciprocal analysis framework, researchers have not been able to examine this feedback loop. Reciprocal favors between buyers and sellers in the online marketplace (Ou et al., 2014) or reciprocity norms within a dyadic relationship in knowledge exchange (Beck et al., 2014) are other areas where dynamic reciprocal feedback may be relevant but has not been tested. Clearly, the ability to examine feedback loops and reciprocal behaviors can help IS researchers to explore and understand dynamics more fully across a variety of different contexts.

Second, LGM only captures static or time-invariant associations between variables (Grimm et al., 2016). This static association cannot be used to examine effects related to subsequent changes. This limitation may lead to an inadequate development of dynamic change theories. For instance, Zheng et al. (2014) use LGM to examine the relationship between WOM communication and book sales over time. They find a negative correlation between the slope of WOM communication and the slope of Amazon sales rank, indicating that products with a slower growth of WOM communication tend to exhibit a faster decrease in sales compared to other products. This association is a static, between-person association. The framework does not unveil dynamic lead-lag associations between the predictor variable and the outcome variable; LGM cannot be used to examine if *levels* in WOM communication precede subsequent *changes* in the sales rank, and thus cannot be used to conclude that a slower growth of WOM communication is predicted to yield a faster decrease in book sales.

To uncover the feedback loops between variables over time and to examine the dynamic association between the predictor and outcome variables over time, we need to extend our current understanding of LGM. Thus, we introduce an advanced dynamic LGM, BDLDSM, which is a proper subset of LGM, which is itself a proper subset of SEM.

3 BDLDSM Model

3.1 The Value of and Need for BDLDSM in the IS Field

Contemporary research on longitudinal data analysis is shifting its focus toward tracking change trajectories over time; as such, it calls for methods that combine features of existing techniques to analyze longitudinal data more rigorously, answer new research questions, test change-related hypotheses, and promote time-related theory development (McArdle, 2009). BDLDSM combines the features of LGM, cross-lagged, and autoregressive models (Eschleman & LaHuis, 2014; McArdle, 2009). LGM provides information about how growth in variables is related over time and answers research questions that focus on change from starting point to finishing point (O'Rourke, 2016). BDLDSM not only answers research questions that LGM answers, but also more involved and nuanced ones. Using BDLDSM, researchers can model the change process (change in one variable from time *t-1* to time *t*) by incorporating both growth change components that represent the average change during the study time period and a proportional change component that represents the variable level at time *t-1* (Rudd & Yates, 2020). Cross-lagged models can be applied to assess directional and reciprocal influences on intra-unit changes between predictor and outcome variables over time (Rudd & Yates, 2020). However, unlike BDLDSM, cross-lagged models use covariances but not mean structures, and thus cannot be applied to model growth over time. Autoregressive model can be applied to assess the effect of the previous value but cannot be applied to model within-unit changes. BDLDSM allows researchers to model complex change trajectories (incorporating both *within-unit change* that measures the trajectory change of each individual unit and *between-unit change* that assesses how individual units vary in their trajectories) (Rudd & Yates, 2020). It provides information about dynamic relations between variables and enables modeling patterns of change by incorporating both growth change components and a proportional change component (McArdle, 2009).

BDLDSM has been applied in several disciplines, including education, sociology, and psychology to study the dynamic interplay between the predictor and outcome variables. For example, Grimm et al. (2016) used BDLDSM to examine the dynamic lead-lag relationship between children's mathematics ability and their visual motor integration. Grimm (2007) employed BDLDSM to examine how the change of depression over time can be predicted by previous academic achievement scores, and vice versa. In the psychology literature, Sbarra and Allen (2009) used BDLDSM to study developmental issues related to sleep and mood disturbances, while Kim and Deater-Deckard (2011) studied developmental issues related to dynamic changes in anger and to externalizing and internalizing problems.

Having been established as a robust method in other fields in recent years, BDLDSM offers IS scholars an opportunity to model the change between two time points for several measurement waves, analyze longitudinal association between two variables, and advance longitudinal theorizing. BDLDSM can be used to unpack research questions that cannot be answered by traditional longitudinal models. For example, while traditional longitudinal models may conclude that a predictor variable has a positive influence on an outcome variable, the result may merely suggest an average upward trajectory. In fact, the outcome variable may drop during the early stages and then increase rapidly to overcome the earlier disadvantage. Further, the change in the predictor variable level itself may be driven by the change in the outcome variable. Disentangling the driving force between the predictor variable and the outcome variable and investigating their dynamic relationships in a more nuanced way is of interest to both IS researchers and practitioners who want to gain a better understanding of the longitudinal effects in real-world phenomena. For example, in section 4, we demonstrate the use of BDLDSM in probing the relationship between HIT implementation level and an important measure of hospital performance, experiential quality, by asking the following research questions: 1) What is the nature of the change process in experiential quality variable (change in experiential quality from time *t-1* to time *t*)? 2) What is the dynamic relationship between HIT implementation level and experiential quality variables across time? Specifically, what is the best model for explaining the relationship between them? 3) Is there a feedback loop between HIT implementation level and experiential quality variables? Using BDLDSM, IS researchers can answer similar questions in their own studies in a variety of contexts.

3.2 A Brief Introduction to BDLDSM

Since BDLDSM needs to fit the latent difference score (LDS) framework, it requires a few assumptions regarding observed data and latent variables in the LDS model: 1) change in the model applies only to the latent variables (true scores) where true scores and errors are separated at each time point, 2) the change function does not vary for individuals over time, however, the constant change (growth) factors may vary for individuals, 3) the time interval between each set of latent variables is equal to the time interval between every other set of latent variables in the model, 4) difference equations which approximate differential equations are applied to represent change, and 5) means, variances, and covariances of observed variables over time are given a restrictive structure in order to fit SEM frameworks (Hamagami & McArdle, 2007; O'Rourke, 2016). Also, similar to other longitudinal models, in BDLDSM, measurement invariance needs to hold over time to make sure the same constructs were measured over time (Kim et al., 2020; McArdle, 2009).

For BDLDSM, the specification of the LDS must account for measurement error and time-specific, construct-irrelevant variance in the observed scores at each time point (McArdle, 2009). Below, we specify each observed repeated measure as a function of a true score and an unobserved random error:

$$Y_{ti} = y_{ti} + e_{yti} \quad (1)$$

$$X_{ti} = x_{ti} + e_{xti} \quad (2)$$

where Y_{ti} and X_{ti} are the observed scores, y_{ti} and x_{ti} are true scores, and e_{yti} and e_{xti} are the corresponding measurement errors at time *t* for the individual unit *i*. We then specify latent difference scores of y_{ti} (Δy_{ti}) and x_{ti} (Δx_{ti}) as the differences between the true scores at time *t* and *t-1* in the individual unit *i*. The resulting equations are:

$$\Delta y_{ti} = y_{ti} - y_{[t-1]i} \quad (3)$$

$$\Delta x_{ti} = x_{ti} - x_{[t-1]i} \quad (4)$$

or

$$y_{ti} = y_{[t-1]i} + \Delta y_{ti} \quad (5)$$

$$x_{ti} = x_{[t-1]i} + \Delta x_{ti} \quad (6)$$

where Δy_{ti} and Δx_{ti} are true change scores for the individual unit *i* from time *t-1* to time *t*, y_{ti} and x_{ti} are true scores for the individual unit *i* at time *t*, and $y_{[t-1]i}$ and $x_{[t-1]i}$ are the true scores for the individual unit *i* at time *t-1*.

The trajectory of each set of change scores over time is parameterized using a random slope factor, with loadings adjustable to reflect linear or nonlinear trajectories. The latent change score at each time period is then a function of the random slope factor as well as prior levels of both y and x. The following two equations represent models that have linear change trajectories:

$$\Delta y_{ti} = g_i + \beta_y y_{[t-1]i} + \gamma_y x_{[t-1]i} \quad (7)$$

$$\Delta x_{ti} = j_i + \beta_x x_{[t-1]i} + \gamma_x y_{[t-1]i} \quad (8)$$

where g_i and j_i are constant growth factors, which measure the stable, constant change (rate of growth) over the course of the study; β_y and β_x, called *proportional change parameters*, are within-variable proportional changes where the predicted changes are proportional to the level of the variable at time *t-1*; and γ_y and γ_x are *coupling parameters* that specify cross-variable effects which determine how changes in one variable from time *t-1* to time *t* are predicted by the level of the other variable at time *t-1*. We can infer that changes in y and x for the individual unit *i* from time *t-1* to *t* come from three sources: the constant growth factors (*g* and *j*), within-variable proportional effects (β_x and β_y), and cross-variable coupling effects (γ_y and γ_x). In other words, the changes in y and x from time *t-1* to time *t* are functions of three components: constant change over the course of the study, proportional effect, and coupling effect. To account for the nonlinear trajectory of change scores, we first need to specify growth models based on latent change scores, which require the first derivative of the functional form of change with respect to time. For example, if the growth factor follows a cubic form with respect to time *t*, we can assume the following cubic growth model:

$$y_{ti} = b_{1i} + b_{2i} \times t + b_{3i} \times t^2 + b_{4i} \times t^3 + e_{yti} \text{ (9)}$$

The first derivative of (9) can be written as:

$$\Delta y_{ti}/\Delta \mathrm{t} = b_{2i} + 2b_{3i}t + 3b_{4i}t^2 \text{ (10)}$$

We then incorporate the derivative function into the bivariate latent change score framework:

$$\Delta y_{ti} = b_{2i} + 2b_{3i}t + 3b_{4i}t^2 + \beta_y y_{[t-1]i} + \gamma_y x_{[t-1]i} \text{ (11)}$$

where b_{2i}, b_{3i}, and b_{4i} are latent growth factors for the latent changes scores, b_{2i} *is* the constant growth factor (same as g_i), b_{3i} is the linear growth factor, and b_{4i} is the quadratic growth factor. β_y represents within-variable proportional change parameter and γ_y represents the cross-variable coupling parameter. Corresponding derivative and change score model equations can be written for growth models with other functional forms. Further, although not explored in this paper, BDLDSM can be extended to explore group differences in relationships and to study how changes proceed in different subgroups with multilevel modeling. A step-by-step guide to help researchers develop and conduct BDLDSM analyses is provided in appendix B.

4 An Application of BDLDSM

We now illustrate the application of BDLDSM to examine the dynamic, longitudinal relationship between HIT implementation and experiential quality. A synthesis of research suggests that the current literature has yet to sufficiently explore if a positive or negative feedback loop exists between HIT implementation levels and experiential quality. For example, if there is a positive feedback loop between HIT implementation levels and experiential quality, it may be that an increased HIT implementation level drives experiential quality improvement and that hospitals with improved experiential quality are more likely to adopt additional HIT. Accordingly, we chose to use BDLDSM because it enables us to tease out complex and potentially reciprocal associations between HIT implementation and experiential quality.

4.1 Sample and Data Collection

We use data from three sources for this study. First, to obtain experiential quality data, we use the Hospital Consumer Assessment of Healthcare Providers and Systems (HCAHPS) survey data collected annually for 2008–2013. This dataset records patients' perceptions of the quality of care they received during their inpatient hospital stays. Second, to obtain HIT implementation data, we use IT supplement files from American Hospital Association (AHA) collected annually for 2008–2012. The AHA IT supplement database is a hospital-level database containing HIT implementation-level information on three hospital IT functions: electronic clinical documentation (ECD), computerized provider order entry (CPOE), and decision support (DS). Third, to obtain hospital characteristics data, we use AHA's annual survey dataset for 2008–2013. The AHA survey dataset provides hospital demographics, organization structure, and operational and financial information. After mapping these three datasets, our resulting dataset is an unbalanced panel data set including 791 hospital-level observations from seven states[2] in the U.S. with five waves of HIT implementation data and six waves of experiential quality data.

Experiential quality measures healthcare providers' ability to engage in meaningful communications with the patients (Angst et al., 2012; Pye et al., 2014; Senot et al., 2016). We used communication score to measure experiential quality. This score is obtained by averaging respondent answers to four topics in the HCAHPS survey. In keeping with prior research (Senot et al. 2016), we applied a logit transformation on the computed average score to meet the assumption of normality.[3] The following equation gives the communication score, with *i* as the individual hospitals measured in year *t* and *Q* as the average score for four communication items:

$$Communication\ Score_{it} = Ln\left[\frac{Q_{it}}{1 - Q_{it}}\right] \text{ (12)}$$

[2] These seven U.S. states are California, Florida, Maryland, North Carolina, New York, New Jersey, and Washington.

[3] The functional form of the change process as well as the parameter estimates related to the dual change processes would not necessarily hold on the untransformed scale of communication score.

More details about the measurement of communication score can be found in Appendix C, part I.

To assess the levels of HIT function implementation at each wave, we used a total of 16 items to create three HIT constructs: ECD enables care providers to access and record patient information; CPOE allows physicians to give instructions and order medicines and procedures; and DS supports decision making by giving care providers access to information that helps them accurately diagnose patient conditions, consult the latest evidence, and provide patient-specific care. We decided to form factor scores for three HIT constructs instead of modeling these constructs directly as latent variables for two reasons. First, the psychometric properties of these items and constructs have been established in the literature, and the reliability and validity of the 16 HIT measurement items used in this paper have already be verified (Adler-Milstein et al., 2015; Ayabakan et al., 2017; Everson et al., 2014), Second, forming factor scores for three HIT constructs can give us better control in model identification in a complex BDLDSM model. More details about these measurements can be found in Appendix C, part II.

To account for other factors that may influence communication score and HIT implementation level, we included five control variables: hospital bed size, profit status, teaching status, dummy variables for state effect, and market competition. We obtained hospital bed size, profit status, teaching status variables from AHA survey datasets. We measured market competition using the Herfindahl-Hirschman index (HHI). For a focal hospital, we operationalized market competition at the hospital referral region (HRR) level and aggregated hospitals into HRRs.

It is important to mention that our datasets included missing responses from some hospital in some years. Specifically, not all hospitals provide details on HIT implementation variables (the AHA IT survey) and communication scores (the HCAHPS survey) every year. Since there is no evidence found based on the official data documentations[4] that the propensity of missingness on AHA IT and HCAHPS survey depend on the HIT implementation levels and communication score respectively, we rule out the missing not at random (MNAR) assumption. We further examine whether the missing data is under missing at random (MAR) assumption or missing completely at random (MCAR) assumption. Our analysis result based on our dataset shows for-profit hospitals are more likely than non-for-profit hospitals to have missing HIT implementation data and hospitals with fewer beds are more likely to have missing communication scores than hospitals with more beds. Since MAR allows missingness to depend on other observed variables (e.g., hospital's profit status and hospital size in our case), missing data in the dataset are assumed to occur at random under MAR assumption. Thus, full information maximum likelihood (FIML), a commonly applied method that handles the incompleteness in longitudinal studies, is applied to estimate the BDLDSM models using all available information in the presence of missing data (Grimm, 2007; Grimm et al., 2017; Klopack & Wickrama, 2020; McArdle & Hamagami, 2001).

4.2 Data Analysis and Results

We propose a three-step process to develop and conduct the BDLDSM analysis. This three-step process is described in further detail in Appendix B. *The first step* is to test measurement invariance to establish whether the same constructs were measured over time. We began our test by confirming configural invariance, metric invariance, and scalar invariance of the three-factor structure for HIT (see Appendix D). Configural invariance is to test whether the same items measure the constructs across time; metric invariance is to test whether the factor loadings of the items that measure the constructs are equivalent across time; scalar invariance tests whether the items' intercepts are equivalent across time. Upon confirmation, we subsequently computed the resultant factor scores for each hospital at each time point and used them as the HIT implementation variables in all the longitudinal models.

4.2.1 Modeling Growth Trajectories for the Predictor and Outcome Variable

The *second* step in our analysis involved modeling growth trajectories for the predictor and outcome variable to determine the proper functional form of change for each. Researchers need to appropriately choose the best-fit change trajectory functions before implementing BDLDSM to ensure accurate representation of the dynamic associations between the predictor variable and the outcome variable.

We assume that HIT implementation levels increase in a nonlinear manner over time for two theoretical reasons. First, from a resource-based perspective, hospitals need to change their current clinical processes to fit adopted technologies with existing resources and processes. This transition process takes

[4] Source: The AHA IT survey and the HCAHPS survey documentation and data.

time (Atasoy et al., 2018). Second, from the business value of IT perspective, there is a learning curve associated with the use of technologies in hospitals during the first few years after the adoption. Based on these two reasons, hospitals may adopt technologies at a relatively slow rate in the first few years but at a faster rate during subsequent years. In other words, technology implementation levels in hospitals may grow with a positive accelerating rate over time to cope with the learning curve associated with the use of technologies.

We next discuss the growth rate of communication score. As we described in section 4.1, the communication score is captured by the HCAHPS survey. Results of the HCAHPS survey began to be reported on the Hospital Compare website in 2008. Public reporting of patient hospital experience, including communication with healthcare providers, allows patients to compare and choose better-performing hospitals. Thus, at the early stage of public reporting, hospitals would apply different ways and methods to monitor and improve communication quality (Elliott et al., 2015). Yet, according to the law of diminishing returns, there may be a diminishing value of successive interventions to further improve communication quality. Thus, we assume that the growth rate of communication score may diminish over time. Accordingly, we assume that communication score may increase in a nonlinear manner over time as well.

We examined how the average trajectories of HIT and communication score variables change over time. Figure 1 illustrates the average growth trajectories of ECD, CPOE, DS, and communication score, respectively. Although the average change trajectory plots can be useful graphical summaries, they may not reflect the shape of the individual hospital trajectories. To explore the functional form of intra-hospital change over time, we conducted an extensive descriptive analysis to understand the nature and idiosyncrasies of each hospital's temporal pattern of growth (Singer & Willett, 2003). We began with a simple graphic visualization by examining randomly selected arrays of individual hospitals' empirical growth plots. We then used a nonparametric approach for smoothing each hospital's temporal idiosyncrasies without imposing a specific functional form. We present examples of selected Lowess Smoothing plots of ECD, CPOE, DS, and communication score in Appendix E. From Figure 1 and Appendix E, we notice that the trajectories of ECD, CPOE, DS, and communication score variables suggest the possibility of non-linearity. Hence, we fit the variables into three types of growth models—a linear growth model, a quadratic growth model, and a cubic growth model—to identify the best functional form of change (see Appendix B, step 2 for more details on modeling growth trajectories for the predictor and outcome variables). There was no need to test a no-growth model because all variable trajectories were clearly increasing over time.

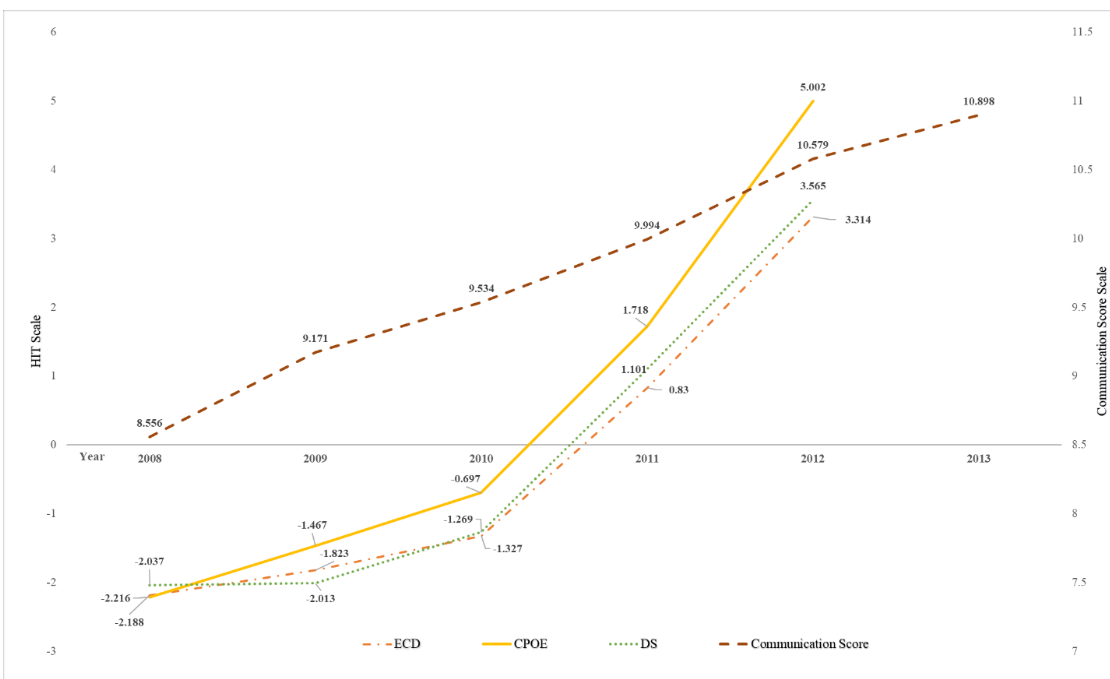

Figure 1. Growth Trajectory of ECD, CPOE, DS, and Communication Score

To systematically test which model provided the best fit, we applied chi-square difference tests to evaluate comparative fit in a pairwise fashion. Since chi-square is sensitive to sample size, four additional fit indices were also examined to assess model fit: the root mean square error of approximation (RMSEA), the comparative fit index (CFI), Tucker-Lewis index (TLI), and the standardized root mean square residual (SRMR). The most commonly used criteria for fit statistics include RMSEA < 0.08, CFI > 0.95, TLI > 0.95, and SRMR < 0.08 (Hu & Bentler, 1999; Zheng et al., 2014). Table 1 shows fit statistics for the linear growth model, quadratic growth model, and cubic growth model for each HIT and communication score variables. From Table 1, we find that the best fitting HIT models, quadratic growth models, show adequate model fit and are selected by the strict chi-square difference test, whereas the worse fitting linear growth models do not. We also note that even though linear and quadratic models for communication scores provide reasonable model fit, the cubic model provides the best fitting index and is selected by the strict chi-square difference test. Thus, we conclude that quadratic growth models provide the best fit for the three HIT variables (ECD, CPOE, and DS), whereas the cubic growth model provides the best fit statistics for communication score.

Table 1. Model Comparison of Change Form

Variable	Model	$\chi2$ (DF)	Model Comparison	$\Delta\chi^2$	ΔDF	RMSEA [90% C.I.]	CFI	TLI	SRMR	Best Model
ECD	M1: Linear Growth	92.16 (10)	–	–	–	0.100 [0.082, 0.119]	0.871	0.871	0.089	M2: Quadratic Growth
	M2: Quadratic Growth	8.54 (6)	M1 vs. M2	83.61***	4	0.023 [0.000, 0.054]	0.997	0.995	0.020	
	M3: Cubic Growth	3.64 (1)	M1 vs. M3	88.51***	9	0.057 [0.000, 0.124]	0.997	0.970	0.011	
			M2 vs. M3	4.9	5					
CPOE	M1: Linear Growth	111.95 (10)	–	–	–	0.111 [0.093, 0.130]	0.811	0.811	0.095	M2: Quadratic Growth
	M2: Quadratic Growth	11.08 (6)	M1 vs. M2	100.87***	4	0.032 [0.000, 0.061]	0.992	0.987	0.025	
	M3: Cubic Growth	2.01 (1)	M1 vs. M3	109.94***	9	0.035 [0.000, 0.107]	0.998	0.985	0.009	
			M2 vs. M3	9.07	5					
DS	M1: Linear Growth	74.91 (10)	–	–	–	0.089 [0.071, 0.108]	0.878	0.878	0.073	M2: Quadratic Growth
	M2: Quadratic Growth	4.16 (6)	M1 vs. M2	70.75***	4	0.000 [0.000, 0.036]	1.000	1.000	0.017	
	M3: Cubic Growth	2.16 (1)	M1 vs. M3	72.74***	9	0.038 [0.000, 0.109]	0.998	0.982	0.010	
			M2 vs. M3	1.99	5					
Communi-cation Score	M1: Linear Growth	126.86 (16)	–	–	–	0.093 [0.078, 0.109]	0.969	0.970	0.047	M3: Cubic Growth
	M2: Quadratic Growth	69.60 (12)	M1 vs. M2	57.26***	4	0.078 [0.060, 0.096]	0.990	0.987	0.045	
	M3: Cubic Growth	34.97 (7)	M1 vs. M3	91.89***	9	0.071 [0.048, 0.095]	0.995	0.990	0.033	
			M2 vs. M3	34.63***	5					

Note: *** p<0.001, ** p<0.01, * p<0.05, + p<0.1

4.2.2 Finding the Best BDLDSM Model and Interpreting the Results

The third step is to find the best BDLDSM model to test the impact of HIT implementation level on communication score. We evaluated three models to test dynamic relationships between HIT implementation and communication score – Model 1: no coupling effects; Model 2: a coupling effect from HIT implementation to the change of communication score (ΔCommunication); Model 3: full coupling effects. We use Model 1 to test if there exists a dynamic association between HIT implementation and communication score, Model 2 to examine if HIT implementation is a leading indicator (predictor of subsequent changes) of communication score, and Model 3 to estimate if there is a feedback loop between HIT implementation and communication. We mapped time-invariant covariates (hospital bed size, profit status, teaching status, market competition, and state effect) as predictors of the intercept and growth factors for CPOE, ECD, DS, and communication score. Because the three HIT variables (CPOE, ECD, and DS) have the best fit statistics in the quadratic models and communication score measure has the best fit statistics in the cubic growth model, we fit the former using BDLDSM with the first derivative quadratic growth function and the latter using the first derivative cubic growth function (equations are presented in equation (9) to (11)).

Table 2 shows the chi-square model comparison among the three models for each pair of the predictor variable and the outcome variable and the standard SEM fit indices (RMSEA, CFI, TLI, and SRMR) for each model. According to the chi-square difference test and the fit indices, the model with the coupling effects from CPOE to the ΔCommunication has good overall fit and best represent the dynamic association between communication and CPOE.[5] The full coupling models have good overall fit and best represented the dynamic associations between communication and ECD and between communication and DS.[6]

Table 2. Model Comparison of BDLDSM (Nonlinear Change Function)

Pairs of DV and IV	Model	χ2 (DF)	Model Comparison	$\Delta\chi^2$	ΔDF	RMSEA [90% C.I.]	CFI	TLI	SRMR	Best Model
CPOE and Communi-cation	M1: No coupling	141.648 (77)	–	–	–	0.033 [0.024, 0.041]	0.991	0.980	0.016	M2: IV to ΔDV
	M2: IV to ΔDV	115.523 (76)	M1 vs. M2	26.125^{***}	1	0.026 [0.016, 0.035]	0.994	0.988	0.016	
	M3: Full coupling	114.047 (75)	M1 vs. M3	27.601^{***}	2	0.026 [0.015, 0.035]	0.994	0.988	0.016	
			M2 vs. M3	1.476	1					
ECD and Communi-cation	M1: No coupling	132.445 (77)	–	–	–	0.030 [0.021, 0.039]	0.992	0.984	0.016	M3: Full Coupling
	M2: IV to ΔDV	112.999 (76)	M1 vs. M2	19.446^{***}	1	0.025 [0.014, 0.034]	0.995	0.989	0.016	
	M3: Full coupling	106.505 (75)	M1 vs. M3	25.94^{***}	2	0.023 [0.012, 0.033]	0.996	0.990	0.015	
			M2 vs. M3	6.494^{***}	1					
DS and Communi-cation	M1: No coupling	133.79 (77)	–	–	–	0.031 [0.022, 0.039]	0.992	0.983	0.017	M3: Full Coupling
	M2: IV to ΔDV	104.476 (76)	M1 vs. M2	29.314^{***}	1	0.022 [0.010, 0.031]	0.996	0.991	0.017	
	M3: Full coupling	98.962 (75)	M1 vs. M3	34.828^{***}	2	0.020 [0.006, 0.030]	0.997	0.992	0.016	
			M2 vs. M3	5.514^{*}	1					

Note: (1) M1: BDLDSM with no coupling effects; M2: BDLDSM with a coupling effect from HIT implementation to the change of communication score (ΔCommunication); M3: BDLDSM with full coupling effects. (2) All control variables including hospital bed size, profit status, teaching status, state effect, and market competition are included. (3) *** p<0.001, ** p<0.01, * p<0.05, + p<0.1

The BDLDSM with a coupling effect from CPOE to the change of communication score (ΔCommunication) can be written as:

$$\Delta Communication_{it} = b_{2i} + 2b_{3i}t + 3b_{4i}t^2 + \beta_c Communication_{i[t-1]} + \gamma_c CPOE_{i[t-1]} \quad (13)$$

$$\Delta CPOE_{it} = a_{2i} + 2a_{3i}t + \beta_{IT} CPOE_{i[t-1]} \quad (14)$$

where b_{2i} and a_{2i} represent the constant growth factor, b_{3i} and a_{3i} represent the linear growth factor, b_{4i} represents the quadratic growth factor. Since all control variables including hospital bed size, profit status, teaching status, state effect, and market competition were modeled as time-invariant, we regressed the growth factors on these five control variables. β_c and β_{IT} are the self-feedback coefficients, which capture

[5] According to the chi-square difference test presented in Table 2, the fit of Model 2 is significantly better than Model 1, and the fit of Model 3 is not significantly better than Model 2 for the following pair: communication and CPOE.
[6] According to the chi-square difference test presented in Table 2, Model 2 has a better fit than Model 1 at a significance level, and Model 3 has a better fit than Model 2 at a significance level, which indicate Model 3 as the best fit for the following two pairs of variables communication and ECD, and communication and DS.

proportional change—that is the effect of the same variable at the previous state of the change, γ_c is the coupling coefficient, representing a coupling effect from CPOE implementation level to ΔCommunication.

Next, we present the BDLDSM with full coupling, which accounts for coupling effects in both directions, i.e., from ECD or DS implementation level to the change of communication and vice versa. The latent change equations to examine the relationship between ECD and communication score can be written as:

$$\Delta Communication_{it} = b_{2i} + 2b_{3i}t + 3b_{4i}t^2 + \beta_c Communication_{i[t-1]} + \gamma_c ECD_{i[t-1]} \quad (15)$$

$$\Delta ECD_{it} = a_{2i} + 2a_{3i}t + \beta_{IT} ECD_{i[t-1]} + \gamma_{IT} Communication_{i[t-1]} \quad (16)$$

The latent change equations to examine the relationship between DS and communication score can be written as:

$$\Delta Communication_{it} = b_{2i} + 2b_{3i}t + 3b_{4i}t^2 + \beta_c Communication_{i[t-1]} + \gamma_c DS_{i[t-1]} \quad (17)$$

$$\Delta DS_{it} = a_{2i} + 2a_{3i}t + \beta_{IT} DS_{i[t-1]} + \gamma_{IT} Communication_{i[t-1]} \quad (18)$$

where γ_c is the coupling coefficient, representing the coupling effect from ECD or DS implementation level to the change of communication score ($\Delta Communication$), and γ_{IT} is the coupling coefficient, representing the coupling effect from communication score to the change of ECD or DS implementation level (ΔECD or ΔDS). Other parameters have the same interpretations as in previous equations (equations 13 and 14).

A path diagram of this bivariate dynamic latent difference score model with full coupling is illustrated in Figure 2, and the definition of the parameters are presented in Table 3. Time-invariant covariates including hospital bed size, profit status, teaching status, state effect, and market competition are included as predictors of the growth factors, although we do not show this in Figure 2. The unlabeled paths are fixed at 1 and residual variances on all the endogenous latent variables are fixed at 0. The other BDLDSM models can be adapted from this full-coupling path diagram. For example, the path diagram for BDLDSM with a coupling effect from CPOE to the change of communication score (ΔCommunication) does not have the paths from communication score to the change of HIT implementation levels (ΔHIT), thus does not have the coupling effect of γ_{IT}.

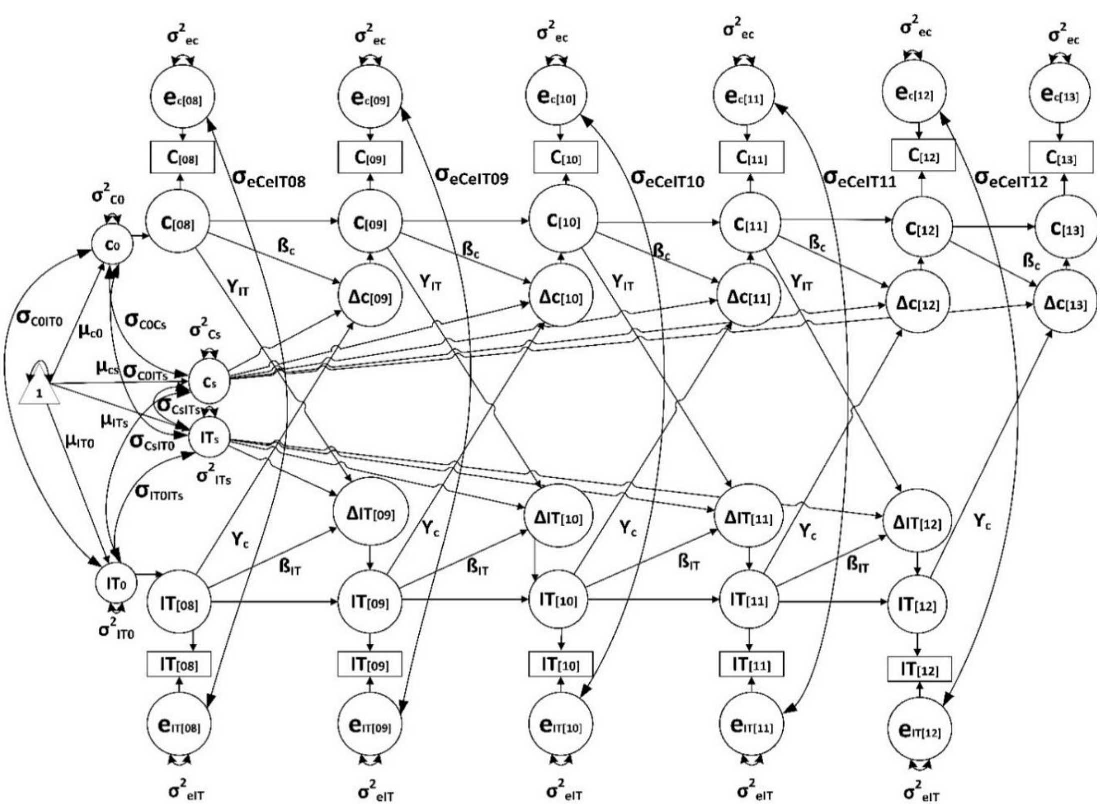

Figure 2. Path Diagram of a Bivariate Dynamic Latent Difference Score with Full Coupling

Table 3. Definition of Parameters of the BDLDSM Model in Figure 2

Parameter	Definition
$c_{[t]}$ in circles	Latent true scores for communication score at year *t* (from year 2008 to 2013)
$IT_{[t]}$ in circles	Latent true scores for HIT implementation levels at year *t* (from year 2008 to 2012)
$C_{[t]}$ in rectangles	Observed scores for communication score at year *t* (from year 2008 to 2013)
$IT_{[t]}$ in rectangles	Observed scores for HIT implementation levels at year *t* (from year 2008 to 2012)
$e_{c[t]}$	Measurement error for communication score at year *t* (from year 2008 to 2013)
$e_{IT[t]}$	Measurement error for HIT implementation levels at year *t* (from year 2008 to 2012)
$\Delta c_{[t]}$	Latent change scores in communication score for each repeated assessment
$\Delta IT_{[t]}$	Latent change scores in HIT implementation levels for each repeated assessment
γ_c	Coupling coefficient that represents the coupling effect from HIT implementation levels to the change of communication score (Δc)
γ_{IT}	Coupling coefficient that represents the coupling effect from communication score to the change of HIT implementation levels (ΔIT)
β_c	Self-feedback coefficient that captures proportional change of communication score at the previous occasion
β_{IT}	Self-feedback coefficient that captures proportional change of HIT implementation levels at the previous occasion
c_0 , c_s	The intercept and the slope of latent communication score and change scores respectively. The slope component of communication score (c_s) includes the constant growth factor (b_{2i}), the linear growth factor (b_{3i}), and the quadratic growth factor (b_{4i}).
IT_0 , IT_s	Intercept and the slope component of latent HIT implementation levels and changes scores respectively. The slope component of HIT implementation levels (IT_s) includes the constant growth factor (b_{2i}) and the linear growth factor (b_{3i}).
μ_{c0} , μ_{cs}	Intercept mean and slope mean for communication score respectively
μ_{IT0} , μ_{ITs}	Intercept mean and slope mean for HIT implementation respectively
σ^2_{ec} , σ^2_{eIT}	Residual variance for communication score and HIT implementation levels respectively
σ^2_{c0} , σ^2_{IT0}	Variance of initial conditions for communication score and HIT implementation levels respectively
σ^2_{cs} , σ^2_{ITs}	Variance of slopes for communication score and HIT implementation levels respectively
σ_{c0IT0}	Covariance of initial conditions of variables communication score and HIT implementation levels
σ_{c0Cs}	Covariance of initial conditions and slope of communication score
σ_{IT0ITs}	Covariance of initial conditions and slope of HIT implementation levels
σ_{csITs}	Covariance of slope of variables communication score and HIT implementation levels
σ_{c0ITs}	Covariance of initial conditions of communication score and slope of HIT implementation levels
σ_{csIT0}	Covariance of initial conditions of HIT implementation levels and slope of communication score
$\sigma_{eCeIT08}$, $\sigma_{eCeIT09}$, $\sigma_{eCeIT10}$, $\sigma_{eCeIT11}$, $\sigma_{eCeIT12}$	Covariance of residuals from variables communication score and HIT implementation levels for year 2008, 2009, 2010, 2011, 2012 respectively

Lastly, we present the parameter estimates in Table 4 and interpret the results for the best fitting BDLDSM models. Model 1 shows the reported parameters for the relationship that is best represented by the model with the coupling effects from CPOE to the ΔCommunication. Models 2 and 3 in Table 4 show the parameters for the two relationships that were best represented by full coupling effect model (i.e., ECD and Communication and DS and Communication).

Table 4. Model Estimation of BDLDSM with Full Coupling Effect

	Model 1 CPOE and Communication	Model 2 ECD and Communication	Model 3 DS and Communication
Dynamic Coefficients			
Proportion β_c	-0.965*** (0.112)	-1.248*** (0.147)	-1.303*** (0.152)
Coupling γ_c	-0.519 (0.394)	-0.251** (0.091)	-0.362* (0.154)
Proportion β_{IT}	0.427 (0.407)	0.841+ (0.496)	0.733 (0.485)
Coupling γ_{IT}		2.025* (0.933)	1.721 (1.083)
Latent Means			
b_{2i}	9.343*** (1.188)	12.139*** (1.387)	12.583*** (1.489)
b_{3i}	0.693+ (0.357)	0.467*** (0.085)	0.573*** (0.122)
b_{4i}	0.091 (0.069)	0.037** (0.014)	0.052* (0.023)
a_{2i}	2.038** (0.716)	-15.837+ (8.086)	-13.26 (9.291)
a_{3i}	0.234 (0.283)	-0.474 (0.418)	-0.375 (0.496)
Note: (1) *** p<0.001, ** p<0.01, * p<0.05, + p<0.1 (2) All control variables including hospital bed size, profit status, teaching status, state effect, and market competition are included (3) Standard errors in parentheses			

The change of communication score from one year to the next (ΔCommunication) has three sources: 1) a constant change of growth in the level of communication score each year which includes the constant growth factor (b_{2i}), the linear growth factor (b_{3i}), and the quadratic growth factor (b_{4i}); 2) prior state of communication score (β_c); and 3) prior state of HIT implementation levels (γ_c). The constant growth factor (b_{2i}) is positively significant in models 1, 2 and 3, and the linear growth factor (b_{3i}) and the quadratic growth factor (b_{4i}) are positively significant in models 2 and 3, indicating that the change of communication score is positive across the course of this study. The proportional change effect (β_c) is negatively significant in models 1, 2, and 3, indicating that a higher level of communication score is associated with a slower subsequent increase in communication score. The coupling effects of γ_c is not statistically significant in Model 1, suggesting that CPOE is not a significant leading indicator of subsequent changes in communication score. The coupling effects of γ_c are negatively significant in models 2 and 3, indicating that increased implementation level of ECD or DS is a negative leading indicator of the subsequent change in communication score. In other words, hospitals that have a high ECD or DS implementation level in the current year tend to show less positive changes in communication score.

In conclusion, the change in communication score from one year to the next (ΔCommunication) is positively predicted by constant change of growth in the level of communication score each year, negatively predicted by communication score from the previous year, and negatively predicted by ECD and DS implementation levels. In other words, hospitals would expect a constant increase in communication scores across the years. One plausible explanation of this steady increase over time is communication score may be enhanced based upon repeated feedback from patients (Senot et al. 2016; Sharma et al. 2016). If the current year's communication score is high, hospitals may experience a slower subsequent change (increase) in communication score. Hospitals with a higher implementation level of ECD or DS in the current year may also experience a slower subsequent change (increase) in communication score.

We next analyze the dynamic lead-lag associations between HIT implementation levels and communication scores to assess if there are feedback loops between these variables. We noticed that the coupling effect of γ_{IT} is insignificant in Model 3, indicating that the communication score is not a leading indicator for the subsequent changes in DS implementation. We also noticed that the coupling effect of γ_{IT} is significant in Model 2, implying that an increased communication score leads to a higher subsequent change in ECD implementation level. As we discussed in the previous paragraph, the coupling effects of γ_c are negatively significant in Model 2 as well. This results in a dynamic process where the implementation level of ECD has a tendency to impact changes in communication score in a negative manner and communication score has a tendency to impact changes in the implementation level of ECD in a positive matter. That is to say, there is a feedback loop between ECD and communication score where hospitals with higher implementation levels of ECD in the current year may experience a slower subsequent increase in communication score and hospitals with higher communication score in the current year tend to show more positive changes in ECD implementation level.

Our examination of the dynamic relationship between HIT implementation level and experiential quality variables across time reveals no effect for prior CPOE implementation levels on changes in communication score. According to prior research, it is possible that CPOE facilitates the communication process by supporting task execution and clinical workflow, and at the same time, it also introduces errors in the communication process by misrepresenting communication as information transfer rather than interactive sense-making (Coiera et al., 2016; Queenan et al., 2011).

We also find that an increased DS implementation level in the current year is predicted to decrease the subsequent change of communication score. The reason may be that hospitals have to go through an adaptation process in an adjustment period before the benefits from advanced clinical HIT, such as DS, can be fully realized. During this adjustment period, healthcare providers may need to spend an increased amount of time and energy to learn the new and sophisticated technologies and to adjust to the new clinical routines in the presence of the patients (Sharma et al., 2016). Thus, there may be a reduction in communication score in hospitals as a result of this adaptation process.

We identified one feedback loop between ECD implementation and communication score. Increased ECD implementation is a leading indicator for a slower subsequent increase in communication score, and increased communication score is a leading indicator for more positive changes in the subsequent ECD implementation level. This result may reveal the two-sided effects of ECD. For example, the use of ECD may yield less communication with patients, which might be more efficient but results in less satisfaction from patients' side due to lack of personalized interaction with care providers. Prior research indicates that adopting higher levels of HIT can shift healthcare providers' attention to standardized aspects of healthcare delivery and away from communication-related activities because during care delivery, completing all clinical tasks may take precedence over listening to the patients (Chandrasekaran et al. 2012). On the other hand, increased communication score may indicate that, while patients are more satisfied because they interact more with a care provider, a hospital may conceive that as their weakness in efficiency and consequently implement ECD at a higher level.

Very few prior studies have analyzed how HIT implementation levels impact experiential quality, and none has done so after accounting for reverse causality and incorporating trajectory change. This may explain why some prior studies reported findings that appear to contradict the results we obtained. For example, Sharma, Chandrasekaran, Boyer, and McDermott (2016) found two different types of HIT jointly enhanced experiential quality, and Queenan, Angst, and Devaraj (2011) found that CPOE use was positively related to experiential quality. To the best of our knowledge, our study is the first to investigate how experiential quality impact on HIT implementation levels, and the first to unveil the dynamic process between HIT implementation levels and experiential quality.

5 Discussion

5.1 Key Contributions

This study makes two major contributions to the IS literature. First, we show how BDLDSM can be used to model the change process (change in one variable from time *t-1* to time *t*) and to examine the dynamic relationships between variables, thus enhancing the ability of IS researchers to develop and test longitudinal theories of various phenomena. Our work provides the first demonstration in the IS literature of quantitatively studying feedback loops between the predictor and outcome variables over time. We also offer detailed guidelines for researchers to examine change as an outcome and to test the dynamic relationship between the predictor variable and the outcome variable, while simultaneously considering the functional forms of change. Further, our study presents the first description in the IS field of how to incorporate functional forms of change in both the predictor and outcome variables in a BDLDSM, which facilitates theory development relating to change. BDLDSM is equipped to assess the *form of change* (e.g., linear or nonlinear), the *level of change* (e.g., within units change, between units change, or both), and dynamic longitudinal relationships (Ployhart & Vandenberg, 2010). IS researchers can apply the form of change to develop *descriptive longitudinal research,* which illustrates how a phenomenon changes over time. IS researchers can also use the level of change and dynamic associations in *explanatory longitudinal research,* which explains how the level of change in a predictor variable affects the subsequent change in the outcome variable over time (Ployhart & Vandenberg, 2010). Both descriptive and explanatory longitudinal research can be extended to explore and examine longitudinal dynamic relationships in the IS field.

From the HIT value perspective, we extend the current literature that studies HIT impact on experiential quality to include a dynamic and nonlinear perspective. We find that HIT implementation levels increase in a quadratic way over time, and communication score grows with cubic trajectories over time. This suggests the need for researchers to examine the relationship between HIT impact on communication score using a model that incorporates nonlinear functional forms of change for both the HIT and communication score variables.

Further, we tested dynamic lead-lag relationships between three HIT functions and experiential quality using BDLDSM and obtained a more comprehensive understanding of the rate of change in communication score. Our results suggest that hospitals would expect a constant increase in communication scores across the course of this study; however, this constant change is limited by the communication score and implementation levels of ECD or DS at the preceding time point. We also identified a negative feedback loop between ECD implementation level and communication score, indicating that hospitals with higher implementation levels of ECD in the current year may experience a slower subsequent increase in communication score and hospitals with higher communication score in the current year tend to show more positive changes in ECD implementation level. However, we did not find a dynamic lead-lag relationship between CPOE and communication score. A plausible explanation is that a learning curve may exist between the CPOE implementation and communication score improvement, and the impact of CPOE may take a longer duration to manifest. The insights from this study has significant implications for decision makers in hospitals as well. In particular, managers need to be aware of the dynamic relationship between HIT implementation levels and communication score to better allocate HIT resources. In order to help facilitate the use of this method, we have provided the MPlus code in Appendix F, covariance matrix, mean, and sample size in Appendix G, and the bibliography section for BDLDSM in Appendix H.

5.2 The Choice of Statistical Techniques in Longitudinal Research

Based on the review of frequently applied longitudinal analysis techniques in the IS field between 2004 and 2018 in the literature review section and based on the advantages of BDLDSM in facilitating longitudinal theory extension and development, we have developed guidelines for IS researchers to determine which statistical techniques to use when conducting longitudinal research, especially when examining the nature of change in variables across time points. Table 5 compares the data requirements and the characteristics of the longitudinal models mentioned in this paper. To determine which statistical techniques to use, we offer the following four guidelines. *First*, researchers should identify the role of time in the theory-building process and ensure that their design and analysis align with the theory (George & Jones, 2000; Mitchell & James, 2001). If researchers want to address the time lag between the predictor variable *X* and the outcome variable *Y* for causal inference, they can use SEM, a linear unobserved effects model, or a random-coefficients model. If they want to incorporate the trajectory change of *X* or *Y* in the longitudinal model, they can use random-coefficients model, LGM, or BDLDSM. If researchers want to examine the dynamic associations or feedback loop between *X* and *Y*, they can consider applying BDLDSM. If researchers want to decompose the dynamic effect of variables, they need to use BDLDSM. For instance, changes in the outcome variable may be influenced by the prior level of the outcome variable, the prior level of the predictor variable, and the overall trajectory change of the outcome variable over time. If researchers want to study other aspects of time, such as frequency, cycles, intensity, and duration, they can use other specific analysis techniques to examine the role of time. For example, if researchers want to study when events occur by using time duration as an outcome, they can use survival analysis techniques.

Second, researchers should consider how many waves of repeated measures they have collected. While linear unobserved effects models and random-coefficients models need at least two time points of repeated measures, LGM and BDLDSM need at least three time points of data (Zheng et al., 2014). At least three waves of data are needed to identify and conceptualize the trajectory of change (Bala & Venkatesh, 2013; Chan, 1998) and to distinguish nonlinearities in LGM and BDLDSM (Raudenbush, 2001).

Third, researchers should consider the hypotheses underlying the model of change and choose an analysis technique accordingly (Ferrer & McArdle, 2003). For example, if identifying growth in each variable is important for the hypothesis testing and can be detected in the data, LGM is preferred. If the overall rate of change at each measurement and the dynamic relations between variables over time are the outcomes of interest, BDLDSM is preferred. If identifying growth or change in variables is not important to the hypotheses or the theory, researchers do not need to use growth analysis techniques.

Fourth, researchers should consider whether they need to test multilevel hypotheses. If so, they need to use either a random-coefficients model or multi-level SEM/LGM/BDLDSM. Linear unobserved effects models are not well suited for such investigations.

Table 5: Summary of Longitudinal Methods and Data Length Requirements

	SEM		LGM	BDLDSM	Linear Unobserved Effects Model	Random Coefficient Model
Time periods	1	>=2	>=3	>=3	>=2	>=2
Within-unit Change	No	No	Yes	Yes	Yes	Yes
Between-unit Change	No	Yes	Yes	Yes	Yes	Yes
Change of Trajectory	No	No	Yes	Yes	No	Yes
Dynamic Lead-Lag Relationship	No	No	No	Yes	No	No
Dynamic Effect Identification	No	No	No	Yes	No	No
Feedback Loop (X<->Y)	No	No	No	Yes	No	No

5.3 Limitations and Conclusions

BDLDSM has its limitations. First, the causal lag examined in BDLDSM may be limited by the data sample in terms of measurement resolution and sample size (Sbarra & Allen, 2009). For example, we used one-year spacing between measurements, but it is likely that the causal lag between HIT and communication score may be shorter or longer. If the true causal lag has a lower measurement resolution, however, it will lead to an inflation of the parameter estimation (Sbarra & Allen, 2009). If the true causal lag has a longer measurement resolution, BDLDSM may be able to address it by modifying the corresponding specifications but only if the lag corresponds to exactly two or more time units (e.g., a two-year lag). Additionally, in our analysis, we noticed that some parameters (e.g., coupling effects parameter) are not significant at the 0.05 level even though the selected model suggested significant parameters. One of the reasons might be that our sample size is not large enough to show all statistically significant coupling parameters. Researchers need to have an adequate sample size to identify change trajectory and reliably estimate growth models such as BDLDSM (Curran et al., 2010). Determining an adequate sample size depends on a few factors, including the complexity of the model, the size of measurement errors, effect size, attrition, and the number and spacing of measurement occasions (Grimm et al., 2012). Consequently, researchers should take the causal lag and sample size into consideration when using BDLDSM. Future research may collect data using a higher or lower resolution of the measurement and an adequate sample size. This could help researchers test the causal lag with different time spacing between measurements and compare the fits of various models with data to identify the best model.

Second, BDLDSM's complexity may lead to difficulties in interpreting results. Researchers need to not only explain the form of change for both predictor and outcome variables but also interpret the various BDLDSM parameters. Also, given the model's complexity, it is difficult to use graphs to illustrate BDLDSM. Consequently, we suggest that researchers use this model only if they want to probe the dynamic interplay between variables over time. Further, BDLDSM cannot reveal the underlying mechanism of the result. For example, in the illustration, we find that higher level of communication score leads to a slower subsequent change (increase) in communication score. However, we are not sure what leads to this effect. Further research is needed to unveil the underlying mechanisms behind the BDLDSM results. Moreover, applying the BDLDSM model without theoretical support in model development may result in overfitting problems. We suggest researchers follow the principle of parsimony and apply BDLDSM with both theoretical and empirical support.

Third, BDLDSM can only analyze two repeatedly measured variables in the model. Further, BDLDSM excludes additional confounding or interacting constructs from the model. Thus, we need to explain the model with caution and limit the conclusion to the variables studied as well as the studied timespan (Grimm et al., 2017). For example, the demonstrated example in this paper examined the longitudinal relationship between HIT implementation and experiential quality during the observation period.

Although we employed BDLDSM in the context of HIT implementation and experiential quality, the method can be easily applied to other areas of interest to IS researchers. We have provided a few example application domains in the introduction section. We believe that the generalized method we introduce in this paper is agnostic to application context and can be used by researchers to simultaneously account for change trajectories, model the change process, and test for dynamic lead-lag associations and feedback loops between predictor and outcome variables. To our knowledge, this is the first time that BDLDSM has been introduced to the IS literature. It is our hope that IS researchers will use this method to examine new phenomena using newly collected data and revisit older phenomena by reanalyzing already collected data to advance longitudinal data analysis and theorizing.

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Appendix A: Review of Longitudinal Papers in the IS Field

We started the search process with two keywords, “longitudinal” and “panel”, used on the ISI Web of Science database. We identified 178 quantitative papers that employed longitudinal data sets. We also identified 12 papers that employed longitudinal datasets but are not in the search result because they do not have “longitudinal” or “panel” in their title, abstract, or keywords. Thus, the resulting number of papers in our analysis is 190.

The majority of these papers were published in ISR (61 papers), MISQ (52 papers), JMIS (25 papers), and MS (23 papers). We found that 20 papers were published between 2004 and 2008, 68 between 2009 and 2013, and 102 between 2014 and 2018, suggesting increased interest in quantitative longitudinal research in recent years. We coded the papers based on the time span of collected data and analysis techniques. The time span of collected data ranged from 75 minutes to 87 years. An analysis of the methods used in these papers yielded interesting patterns.

An analysis of the methods used in these papers yielded interesting patterns. We present the detailed paper information for each data analysis method in the following table:

Data Analysis Method	IS Papers from 2004 – 2018
Linear Unobserved Effects Model (Fixed Effects and Random Effects Models)	Li & Wu (2018), Kumar et al. (2018), Pan et al. (2018), Burtch et al. (2018), Foerderer et al. (2018), Adjerid et al. (2018), Yan et al. (2018), Gong et al. (2018), Müller et al. (2018), Lu et al. (2018), Bavafa et al. (2018), Atasoy et al. (2018), Huang et al. (2018) , Hong & Pavlou (2017), Pang (2017), Kwon et al. (2017), Baker et al. (2017), Li & Agarwal (2017), Huang et al. (2017), Lin et al. (2017), Cavusoglu et al. (2016), Kim et al. (2016a), Kwon et al. (2016), Atasoy et al. (2016), Yin et al. (2016), Luo et al. (2016), Pang et al. (2016), Parker et al. (2016), Huang & Zhang (2016), Chan et al. (2016), Kim et al. (2016b), Driouchi et al. (2015), Yaraghi et al. (2015), Yan et al. (2015), Liu & Aron (2015), Mani et al. (2015), Lin & Heng (2015), Qiu et al. (2015), Khansa et al. (2015), Dong & Wu (2015), Salge et al. (2015), Tambe & Hitt (2014), Langer et al. (2014), Parker & Weber (2014), Belo et al. (2014), Bhargava & Mishra (2014), Mehra et al. (2014), Menon & Kohli (2013), Dedrick et al. (2013), Lim et al. (2013), Tafti et al. (2013), Kleis et al. (2012), Butler & Wang (2012), Aral et al. (2012), Tambe & Hitt (2012), Gu et al. (2012), Chang & Gurbaxani (2012), Zhang & Wang (2012), Soper et al. (2012), Altinkemer et al. (2011), Ghose & Han (2011), Chellappa et al. (2010), Chellappa & Saraf (2010), Pathak et al. (2010), Ghose (2009), Hahn (2009)
SEM/PLS	Bala & Bhagwatwar (2018), Wu et al. (2017), Zhang & Venkatesh (2017), Sykes & Venkatesh (2017), Venkatesh et al. (2017), Steinbart et al. (2016), Sun & Fang (2016), Bhattacherjee & Lin (2015), Barnett et al. (2015), Hu et al. (2015), Sykes (2015), Boss et al. (2015), Bhattacherjee & Park (2014), Tsai & Bagozzi (2014), Ou et al. (2014), Venkatesh & Sykes (2013), Sun (2013), Venkatesh & Windeler (2012), Goh & Wasko (2012), Venkatesh et al. (2011a), Venkatesh et al. (2011b), Hsieh et al. (2011), Tallon (2010), Chengalur-Smith et al. (2010), Kim et al. (2009), Sykes et al. (2009), Kim (2009), Venkatesh et al. (2008), Lam & Lee (2006), Venkatesh & Agarwal (2006), Pavlou & Fygenson (2006), Kim et al. (2005), Kim & Malhotra (2005), Pavlou & Gefen (2004), Jarvenpaa et al. (2004), Bhattacherjee & Premkumar (2004)
Random-Coefficient Models	Angst et al. (2017b), Xiaojun et al. (2017), Venkatesh et al. (2016), Ma et al. (2014), Ma et al. (2013), Setia et al. (2012), Sasidharan et al. (2012), Ko & Dennis (2011), Lu & Ramamurthy (2010), Goes et al. (2010), Rai et al. (2009)
Other Regression Models (e.g., OLS, NB, DID models)	Daniel et al. (2018), Gómez et al. (2017), Ayabakan et al. (2017), Saunders & Brynjolfsson (2016), Qiu et al. (2015), Rai et al. (2015), Veiga et al. (2014), Liu et al. (2014), Im et al. (2013), Wang et al. (2013), Han et al. (2011), Kleis et al. (2012), Ghose & Yao (2011), Gao et al. (2010), Park et al. (2007)
Survival Analysis	Kanat et al. (2018), Dewan et al. (2017), Huang & Zhang (2016), Yaraghi et al. (2015), Joseph et al. (2015), Scherer et al. (2015), Zhang et al. (2013), Li et al. (2010), Jeyaraj et al. (2009), Miller & Tucker (2009), Susarla & Barua (2011), Bhattacharjee et al. (2007),
Latent Growth	Benlian (2015), Zheng et al. (2014), Bala & Venkatesh (2013)

Model	
Dynamic Panel Data Model	Pang et al. (2016), Bhargava & Mishra (2014), Bapna et al. (2013), Menon & Kohli (2013), Aral et al. (2012), Butler & Wang (2012), Tambe & Hitt (2012)
Panel Vector Autoregressive Model	Thies et al. (2018), Thies et al. (2016), Chen et al. (2015), Dewan & Ramaprasad (2014), Adomavicius et al. (2012)
ANOVA/MANOVA /T-test	Du et al. (2014), Gupta & Bostrom (2013), Cotteleer & Bendoly (2006), Venkatesh & Ramesh (2006), Willcoxson & Chatham (2004)
Social Network Analysis	Zhang et al. (2018), Wu et al. (2017), Xiaojun et al. (2017), Sykes & Venkatesh (2017), Sykes et al. (2009), Vidgen et al. (2007)
Other Methods Not Listed Above	Kim et al. (2018), Wright (2018), Chen et al. (2018), Angst et al. (2017a), Trantopoulos von Krogh et al. (2017), Lu et al. (2017), Goode et al. (2017), Venkatesh et al. (2016), Gómez et al. (2016), Susarla et al. (2016), Ramasubbu & Kemerer (2016), Han et al. (2016), Srivastava et al. (2016), Ma et al. (2015), Yeow & Goh (2015), Singh et al. (2014), Peng et al. (2014), Pang et al. (2014b), Chang & Gurbaxani (2013), Burtch et al. (2013), Bang et al. (2013), Han & Mithas (2013), Soper et al. (2012), Langer et al. (2012), Deng & Chi (2012), Gao & Hitt (2012), Xue et al. (2012), Joseph et al. (2012), Aron et al. (2011), Ransbotham & Kane (2011), Singh et al. (2011), Sawyer et al. (2010), Gnyawali et al. (2010), Morris & Venkatesh (2010), Vitari & Ravarini (2009), Du et al. (2008), He et al. (2007), Roberts et al. (2006), Johnson et al. (2004)

Appendix B: Step-by-Step Guide for BDLDSM Analysis

We propose a three-step process to develop and conduct the BDLDSM analysis.

Step 1: Establish Measurement Invariance over Time

This step is a prerequisite to latent growth or change model analysis because we must ensure that the same construct is measured using the same metric with the same precision at each wave (Bala & Venkatesh, 2013; Benlian, 2015; Grimm et al., 2017; McArdle, 2009). Measurement invariance allows the interpretation of growth trajectories in direct, meaningful ways and ensures that observed changes reflect changes in individual units, but not changes in the measurement (Chan, 1998; Grimm et al., 2017). There are four levels of measurement invariance: configural invariance (whether the same items measure the constructs across time); metric invariance (whether the factor loadings of the items that measure the constructs are equivalent across time); scalar invariance (whether the items' intercepts are equivalent across time); and strict invariance (whether the residual variances are equal across data waves) (Chen, 2007). In practice, a strict invariance test is not recommended because this criterion is too strict and is difficult to establish. Thus, we recommend testing configural invariance, metric invariance, and scalar invariance to establish measurement invariance.

Step 2: Modeling Growth Trajectories for the Predictor and Outcome Variables

We examine the predictor and outcome variables to determine the nature of their growth trajectories. Common models used for this include the no-change model, linear change model, and nonlinear change model. We then compare these models using the chi-square difference test to identify the growth model with the best fit.

In the following paragraphs, we first introduce the no-growth model and then present linear growth and nonlinear growth models. We adapted the equations here from Grimm et al. (2017).

The no-growth models have only one latent variable (the intercept), which represents the overall level of variables over time. All the no-growth and growth models are two-level models: level-1 is the individual level, while level-2 is the sample level—that is, the level for the entire sample. This two-level model not only allows individual scores to change over time, but also allows change among individual units.

We model the level-1 (individual) equation for the no-growth model as follows:

$$y_{ti} = b_{1i} + u_{ti} \ (1),$$

where y_{ti} is the repeatedly measured variable at time *t* for individual unit *i*, b_{1i} is the random intercept or predicted score for individual unit *i* when t = 0, and u_{ti} is the time-dependent residual.

We model the level-2 (sample) equation by specifying the random intercept, b_{1i}, with a sample mean for the intercept, β_1, and an individual deviation from the sample mean, or *fixed effect*, d_{1i}:

$$b_{1i} = \beta_1 + d_{1i} \ (2).$$

Combining level-1 and level-2 equations, we get the following complete no-growth model equation:

$$y_{ti} = (\beta_1 + d_{1i}) + u_{ti} \ (3).$$

Unlike the no-growth models, which have only one latent variable (the intercept), the linear growth model has two latent variables: the intercept, b_{1i}, and the linear rate of change, or *random slope*, b_{2i}.

We model the level-1 linear growth model as

$$y_{ti} = b_{1i} + b_{2i} \times t + u_{ti} \ (4),$$

where y_{ti} is the repeatedly measured variable at time *t* for individual unit *i*, b_{1i} is the random intercept or predicted score for individual unit *i* when t = 0, b_{2i} is the linear rate of change (linear slope) for individual unit *i* when t = 0, and u_{ti} is the time-dependent residual.

Besides specifying the random intercept, we also need to specify the linear slope for the level-2 linear growth equation, where β_2 is the sample-level mean for the linear slope and d_{2i} is the individual deviations from the sample-level mean:

$$b_{2i} = \beta_2 + d_{2i} \ (5).$$

Combining level-1 and level-2 equations, we get the following complete linear growth model equation:

$$y_{ti} = (\beta_1 + d_{1i}) + (\beta_2 + d_{2i}) \times t + u_{ti} \, (6).$$

However, if the variables are measured over a relatively long period, we will likely detect some degree of nonlinearity in their trajectories, meaning that the variables will likely change at different rates. To measure the nonlinear functional forms of change, we can apply different nonlinear growth models. There are two major types of nonlinear growth models. The first comprises growth models with nonlinearity in time; in these models, changes depend only on the known time assessment. The second type comprises growth models with nonlinearity in parameters, in which changes depend on unknown entities (Grimm et al. 2016). Examples of growth models with nonlinearity in time are quadratic and cubic models, which account for nonlinearity by adding a quadratic term of time (in the quadradic model) and both a quadratic term and a cubic term of time (in the cubic model); and spline models, which allow for separate growth models for distinct spans of time. Examples of growth models with nonlinearity in parameters are the Jenss-Bayley growth model, which combines linear and exponential trajectories, and the latent basis growth model, which allows free factor loadings of time. Here, we introduce only the growth models with nonlinearity in time, such as quadratic and cubic growth models.

We specify the level-1 quadratic growth model with three latent variables: the intercept, b_{1i}; the linear rate of change, b_{2i}; and the quadratic rate of change, b_{3i}:

$$y_{ti} = b_{1i} + b_{2i} \times t + b_{3i} \times t^2 + u_{ti} \, (7).$$

The level-2 equation for quadratic slope, b_{3i}, is written as

$$b_{3i} = \beta_3 + d_{3i} \, (8),$$

where β_3 is the sample-level mean for the quadratic slope and d_{3i} is the individual deviations from the sample-level mean of the quadratic slope.

Combining level-1 and level-2 equations, we get the following complete quadratic growth model equation:

$$y_{ti} = (\beta_1 + d_{1i}) + (\beta_2 + d_{2i}) \times t + (\beta_3 + d_{3i}) \times t^2 + u_{ti} \, (9).$$

Similarly, we can specify the level-1 cubic growth model as

$$y_{ti} = b_{1i} + b_{2i} \times t + b_{3i} \times t^2 + b_{4i} \times t^3 + u_{ti} \, (10),$$

where b_{4i} is the cubic change for the individual unit *i* when t = 0.

The level-2 equation for the cubic slope is

$$b_{4i} = \beta_4 + d_{4i} \, (11),$$

where β_4 is the sample-level mean for the cubic slope and d_{4i} is the individual deviations from the sample-level mean of the cubic slope. Combing level-1 and level-2 equations, the cubic growth model can be specified as

$$y_{ti} = (\beta_1 + d_{1i}) + (\beta_2 + d_{2i}) \times t + (\beta_3 + d_{3i}) \times t^2 + (\beta_4 + d_{4i}) \times t^3 + u_{ti} \, (12),$$

where β_4 is sample-level mean for the cubic slope and d_{4i} is the individual deviations from the sample-level mean of the cubic slope.

To incorporate the above growth models into a structural equation modeling framework, we fitted growth models with latent variables for the intercept and slope to represent the change:

$$\boldsymbol{y_i} = \boldsymbol{\Lambda \eta_i} + \boldsymbol{u_i} \, (13),$$

where $\boldsymbol{y}_i$ is a T × 1 vector of the repeatedly measured observed scores for individual unit *i;* T represents the number of repeated assessments based on the selected time metric; $\boldsymbol{\Lambda}$ is a T × R matrix of factor loadings defining the latent growth factors; R is the number of growth factors (R = 1 for the no-growth model, R = 2 for the linear growth model, R = 3 for the quadratic growth model, and R = 4 for the cubic growth model); and η_i is an R × 1 vector of the factor scores for the individual unit *i*. For example, the linear growth model has two factor scores: η_1 is the intercept factor score, and η_2 is the linear factor score. In addition to intercept and linear factor scores, the quadratic growth model has η_3 as the quadratic factor score, and the cubic growth model has both the quadratic factor score, η_3, and the cubic factor score, η_4. $\boldsymbol{u}_i$ is an R × 1 vector of residual for the individual unit *i*. Figures B1-B3 display the path diagrams for the linear, quadratic, and cubic growth models. In Figures B1-B3, y_1 to y_5 represent the measurement of *y* in five different time periods, and the numbers in the arrows are the default fixed time score loadings. The number in the path represents time values that remain constant for the intercept (η_1), change linearly for the linear factor score (η_2), change quadratically for the quadratic factor score (η_3), and change in a cubic way for the cubic factor score (η_4).

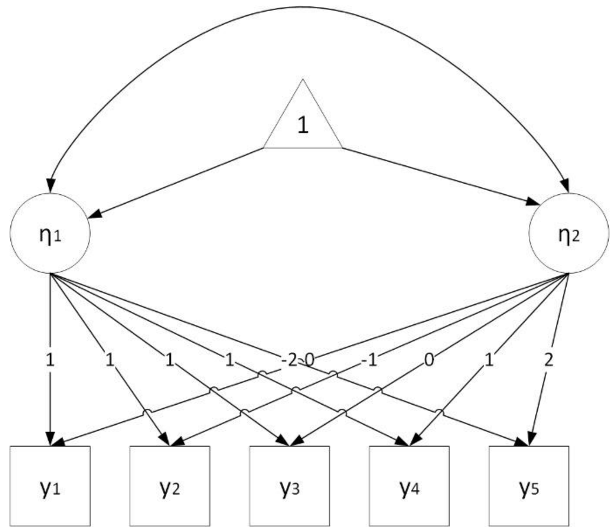

Figure B1. Linear Growth Model

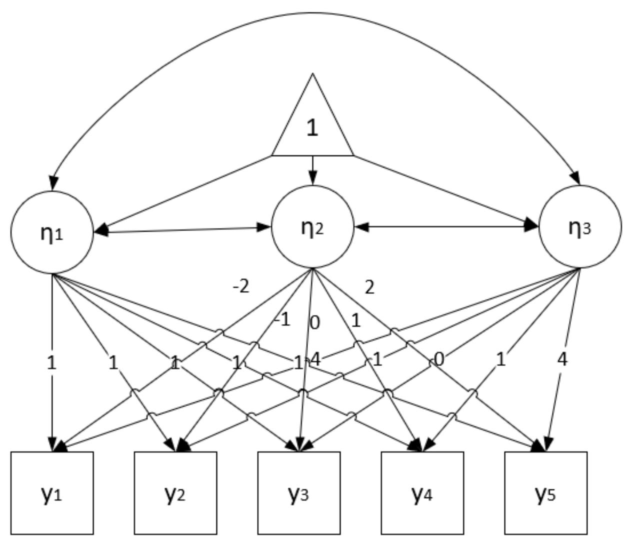

Figure B2. Quadratic Growth Model

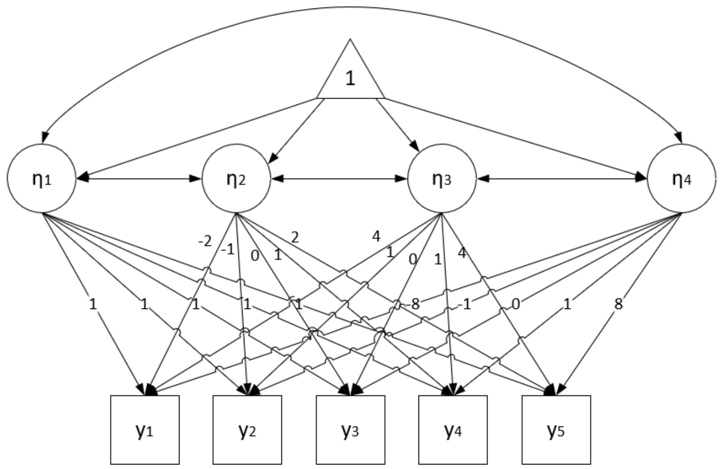

Figure B3. Cubic Growth Model

Step 3: Finding the Best BDLDSM Model and Interpreting the Results

Once the growth trajectory models are established in step 2, we incorporate the functional forms of change for the predictor variable and the outcome variable into the BDLDSM model.

To better understand the dynamic relationship between predictor (X) and outcome (Y) variables, we can examine four BDLDSM models:

(1) BDLDSM with no coupling effects

(2) BDLDSM with a coupling effect from X to the change of Y (ΔY)

(3) BDLDSM with a coupling effect from Y to the change of X (ΔX)

(4) BDLDSM with full coupling effects, including coupling effects from X to ΔY and Y to ΔX

From the current literature, there are two proposed model selection approaches to identify the best representation of the dynamic associations between predictor (X) and outcome (Y) variables. The first approach has been widely applied, which is to compare various BDLDSM models by beginning with no coupling model and examine the improvement in the model fit (change of chi-square and change of parameters) for the two coupling models from X to ΔY and from Y to ΔX, and then compare the improvement in fit of these two coupling models with the full coupling model (Grimm et al., 2016; Grimm et al., 2017; Rudd & Yates, 2020; Sbarra & Allen, 2009). A limited number of studies followed the other approach, which is to present the parameter estimation of the full coupling model directly and then evaluate the dynamic associations between the predictor and outcome variables based on the significance level of the coupling parameters (Arias et al., 2020; Eschleman & LaHuis, 2014).

Even though there is no standalone approach for model comparison, in this paper, we followed the first approach for model selection because it provides statistical support to whether adding coupling parameter(s) yields a significant improvement in the overall fit. From a theory development perspective, however, we suggest testing and comparing only the no-coupling effect model, the coupling effect from X to ΔY model, and the full coupling effect model (models 1, 2, and 4). We then compare these three models using the chi-square difference test and four additional mode fit indices (RMSEA, CFI, TLI, SRMR) to select the model with the best model specification. We next estimate the parameters in the best-fitting model and interpret the result.

Appendix C: Measures

Part I. Survey Items for Experiential Quality (Source: HCAHPS Survey)

The core of the HCAHPS survey comprises 21 items measuring a patient's perception of his/her experience during a hospital stay. These items encompass 11 key topics that relate to communication with doctors, communication with nurses, responsiveness of hospital staff, pain management, communication about medicines, discharge information, cleanliness of the hospital environment, quietness of the hospital environment, transition of care, hospital rating, and willingness to recommend hospital. A random sample of recently discharged patients (between 48 hours and 6 weeks after discharge) from a hospital are asked to complete this survey. This patient-level data is later aggregated at the hospital-level by Centers for Medicare & Medicaid Services (CMS) and published on Hospital Compare website. Following CMS guidelines, only experiential quality items based on a sample of more than 100 respondents were included in our study.

For this study, we select four topics related to communication. The topics related to communication are composites that are constructed from two or three survey items. We present the topics and items in the following list with items formatted in italics:

Communication

(1) How often did nurses communicate well with patients?

During this hospital stay:

How often did nurses treat you with courtesy and respect?

How often did nurses listen carefully to you?

How often did nurses explain things in a way you could understand?

(2) How often did doctors communicate well with patients?

During this hospital stay:

How often did doctors treat you with courtesy and respect?

How often did doctors listen carefully to you?

How often did doctors explain things in a way you could understand?

(3) How often did staff explain about medicines before giving them to patients?

Before giving you any new medicine:

How often did hospital staff tell you what the medicine was for?

How often did hospital staff describe possible side effects in a way you could understand?

(4) Were patients given information about what to do during their recovery at home? (Yes /No)

During this hospital stay:

Did hospital staff talk with you about whether you would have the help you needed when you left the hospital?

Did you get information in writing about what symptoms or health problems to look out for after you left the hospital?

The response categories for questions in topics (1) - (3) are "Never/Sometimes", "Usually" or "Always", and the response categories for questions in topic (4) are "Yes" or "No". For question (1) to (3), we used the sum of the percentage of respondents who answered "Always" and "Usually", and for question (4), the percentage of patients who answered "Yes" to measure communication score. We then calculated the average of these four items for further analysis.

Part II. IT Items Scale (Source: AHA IT Supplement Files)

HIT implementation is measured by a six-point scheme as follows:

1 = Fully implemented across all units

2 = Fully implemented in at least one unit

3 = Beginning to implement in at least one unit

4 = Have resources to implement in the next year

5 = Do not have resources but considering implementing

6 = Not in place and not considering implementing

Although the original items were measured on a six-point ordinal scale, we coded each item on a four-point scale so that a single lowest category would reflect all forms of non-implementation. The resulting ordered IT implementation scheme is as follows: 0 (no implementation), 1 (beginning to implement in at least one unit), 2 (fully implemented in at least one unit), and 3 (fully implemented across all units), with full implementation indicating that IT has completely replaced paper record functionally. Descriptive statistics and correlations between HIT variables can be found in Table C1.

Table C1: Descriptive Statistics and Pairwise Correlations among HIT Variables

	HIT Category	Item Name	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1		Nursing Notes	2.10	1.13															
2		Problem lists	1.63	1.27	0.752														
3	ECD	Medication lists	2.26	1.10	0.818	0.776													
4		Discharge summaries	2.11	1.19	0.735	0.697	0.759												
5		Advanced directives	1.85	1.33	0.721	0.684	0.744	0.669											
6		Laboratory tests	1.42	1.28	0.555	0.526	0.573	0.514	0.505										
7		Radiology tests	1.41	1.28	0.556	0.527	0.574	0.515	0.506	0.912									
8	CPOE	Medications	1.35	1.27	0.563	0.534	0.581	0.522	0.512	0.924	0.926								
9		Consultation requests	1.24	1.27	0.569	0.54	0.588	0.528	0.518	0.935	0.937	0.949							
10		Nursing orders	1.42	1.29	0.558	0.53	0.577	0.518	0.508	0.917	0.918	0.93	0.941						
11		Clinical guidelines	1.31	1.28	0.592	0.562	0.612	0.549	0.539	0.688	0.689	0.698	0.707	0.693					
12		Clinical reminders	1.42	1.31	0.63	0.598	0.651	0.585	0.574	0.58	0.581	0.588	0.595	0.584	0.892				
13		Drug allergy alerts	2.20	1.17	0.672	0.638	0.694	0.623	0.611	0.618	0.619	0.627	0.635	0.622	0.794	0.845			
14	DS	Drug_drug interaction alerts	2.19	1.16	0.675	0.641	0.698	0.626	0.615	0.621	0.623	0.63	0.638	0.625	0.798	0.849	0.905		
15		Drug_Lab interaction alerts	1.82	1.30	0.642	0.609	0.663	0.596	0.584	0.591	0.592	0.599	0.606	0.595	0.759	0.807	0.861	0.865	
16		Drug dosing support	1.75	1.30	0.637	0.604	0.658	0.591	0.58	0.586	0.587	0.595	0.602	0.59	0.753	0.801	0.854	0.858	0.816

Appendix D: Tests of Measurement Invariance for IT Factors

To establish measurement invariance, we estimated and compared three models: configural model, metric model, and scalar model (Chen, 2007; Cheung & Rensvold, 2002). In these models, we progressively added constraints and compared their fits to assess configural invariance, metric invariance, and scalar invariance for the three HIT constructs ECD, CPOE and DS. Details are below:

Model 1 (Configural Model): In this model, we free both factor loadings and the intercepts (the levels of the items) to assess configural invariance.

Model 2 (Metric Model): In this model, we constrained factor loadings to be equal at each time point for the same items to test metric invariance.

Model 3 (Scalar Model): In this model, we constrained both factor loadings and item intercepts to be equal at each time point for the same items to test scalar invariance.

Table D1 reports fit statistics for Model 1 to Model 3 for each HIT factor. Model 1 has acceptable fit statistics across all HIT factors, indicating that configural invariance is established for all three HIT factors. We then compare Model 2 (metric model) with Model 1 (configural model) to assess metric invariance and compare Model 3 (scalar model) with Model 2 (metric model) to assess scalar invariance. We adopted changes in CFI (≥ -0.01) for nested models to evaluate metric invariance and scalar invariance because this criterion is independent of model complexity and sample size and commonly applied by scholars (Chen 2007; Cheung & Rensvold 2002). As shown in table D1, the value of change in CFI for nested models are all much smaller than -0.01, suggesting that the null hypothesis of invariance should not be rejected. Thus, both metric and scalar invariance are established, in addition to configural invariance. Since we did not find a significant reduction in fit statistics from Model 1 to Model 3 for each factor, we choose the most parsimonious model (Model 3) for ECD, CPOE, and DS for further analysis.

Table D1: Establishing Measurement Invariance

	χ^2	DF	RMSEA	CFI	Model Comparison	ΔCFI	TLI	SRMR
Factor 1 (ECD)								
Model 1: Configural Model	372	215	0.03	0.989			0.985	0.048
Model 2: Metric Model	504	231	0.038	0.981	M2 vs. M1	-0.008	0.975	0.06
Model 3: Scalar Model	654	287	0.039	0.974	M3 vs. M2	-0.007	0.973	0.061
Factor 2 (CPOE)								
Model 1: Configural Model	350	215	0.028	0.999			0.999	0.025
Model 2: Metric Model	575	231	0.043	0.998	M2 vs. M1	-0.001	0.997	0.026
Model 3: Scalar Model	778	287	0.046	0.997	M3 vs. M2	-0.001	0.997	0.029
Factor 3 (DS)								
Model 1: Configural Model	1140	335	0.054	0.98			0.974	0.066
Model 2: Metric Model	1171	355	0.053	0.979	M2 vs. M1	-0.001	0.975	0.068
Model 3: Scalar Model	1305	423	0.05	0.978	M3 vs. M2	-0.001	0.977	0.068

The resulting factor loadings across different time periods are presented below in Table D2.

Table D2: Item Loadings across Time Periods

HIT Factors	Item Name	2008	2009	2010	2011	2012
	Nursing Notes	0.906	0.921	0.926	0.935	0.953
	Problem lists	0.766	0.796	0.807	0.825	0.868
ECD	Medication lists	0.81	0.836	0.845	0.861	0.897
	Discharge summaries	0.727	0.76	0.772	0.793	0.841
	Advanced directives	0.688	0.724	0.736	0.759	0.812
	Laboratory tests	0.985	0.978	0.977	0.978	0.987
	Radiology tests	0.988	0.984	0.983	0.984	0.98
CPOE	Medications	0.986	0.981	0.98	0.98	0.995
	Consultation requests	0.957	0.94	0.937	0.939	0.982
	Nursing orders	0.966	0.953	0.95	0.952	0.969
DS	Clinical guidelines	0.858	0.868	0.87	0.902	0.883

	Clinical reminders	0.872	0.881	0.883	0.912	0.895
	Drug allergy alerts	0.964	0.967	0.968	0.977	0.972
	Drug_drug interaction alerts	0.977	0.979	0.98	0.985	0.982
	Drug_Lab interaction alerts	0.866	0.875	0.877	0.908	0.89
	Drug dosing support	0.852	0.862	0.865	0.898	0.878

Appendix E: Selected Lowess Smoothing Plots of ECD, CPOE, DS, and Communication Score

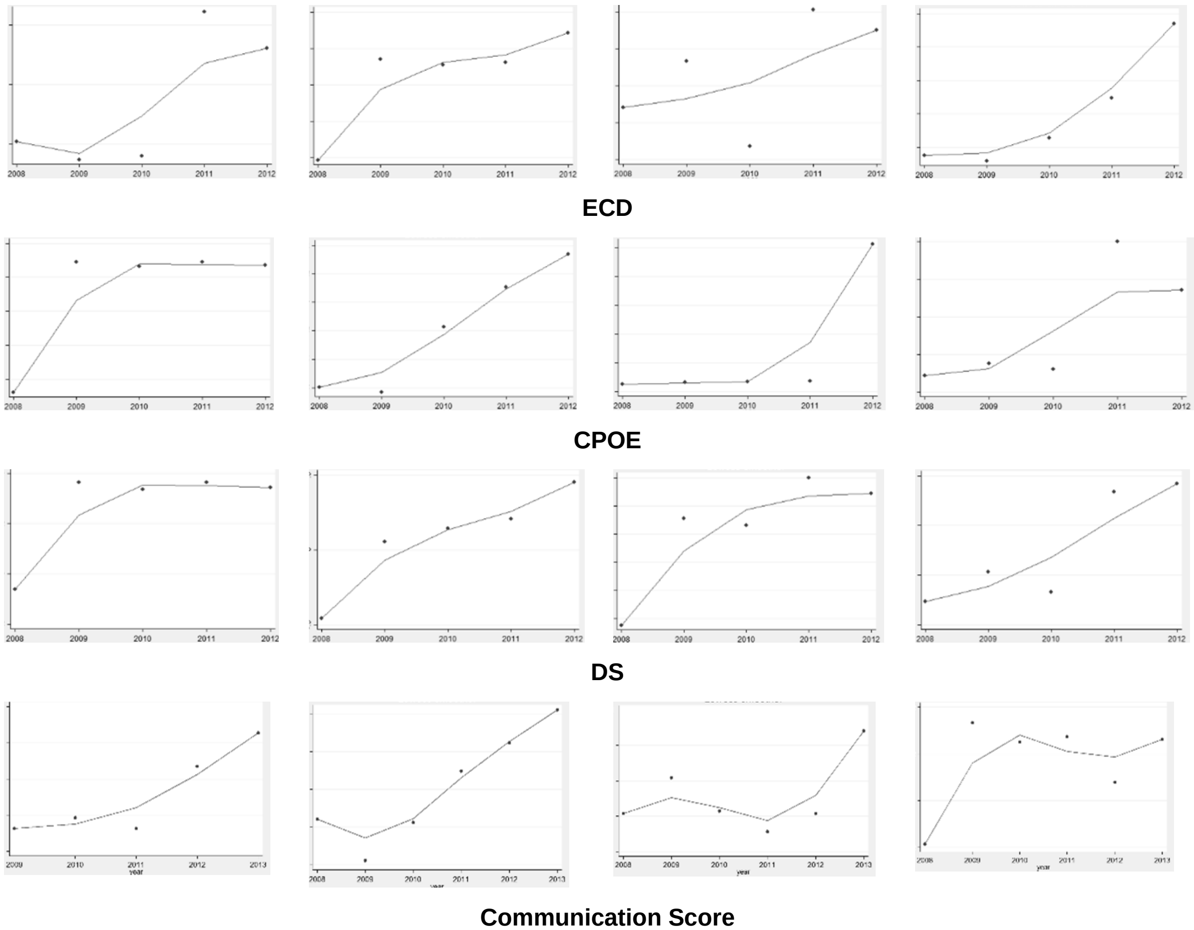

Figure E1. Selected Lowess Smoothing Plots of ECD, CPOE, DS, and Communication Score[7]

[7] We randomly selected 100 hospitals from our sample and plotted Lowess Smoothing for these hospitals. We only reported Lowess Smoothing plots for four hospitals in Appendix E for space considerations.

Appendix F. Mplus 7 Code to Conduct BDLDSM Analysis

We have provided the sample Mplus7 code for estimating the BDLDSM model with full coupling effect between communication and ECD. The code is similar for other HIT variables.

```
!Import Data
   Data:
!! If input is raw data, use the following statement:
  file is dv_iv_control_state.txt;
!! If input is observed covariance matrix and means, add the following two statements:
!! TYPE = MEANS COVARIANCE;
!! NOBSERVATIONS = 791;
  Variable:
! Describe Variables
! comm08, comm09, comm10, comm11, comm12, comm13 are outcome variable (communication score) measured in 2008, 2009, 2010, 2011, 2012, 2013
! ecd08, ecd09, ecd10, ecd11, ecd12 are predicor variable (electronic clinical documentation) measured in 2008, 2009, 2010, 2011, 2012
! market, logbed, noprofit, and teaching are control variables: market competition, hospital bed size (logged), profit status, teaching status
! hospst1 – hospst6 capture state effects

 names are
 id comm08 comm09 comm10 comm11 comm12 comm13
 ecd08 ecd09 ecd10 ecd11 ecd12
 market      logbed      noprofit  teaching
 hospst1 hospst2 hospst3
 hospst4 hospst5 hospst6;

 usevar =
 comm08 comm09 comm10 comm11 comm12 comm13
 ecd08 ecd09 ecd10 ecd11 ecd12
 market      logbed      noprofit
 teaching  hospst1 hospst2
 hospst3     hospst4 hospst5 hospst6;
 missing id-     group (-99);

 DEFINE:
!! Rescale using the DEFINE command. Both communication score and electronic clinical documentation implementation levels are scaled up and multiplied by 10 for further analysis. Multiplication by 10 does not affect the model fit but help to increase the value of variances for easier estimation.
```

```
!! If data is covariance matrix and means, please skip the DEFINE step.
  comm08 = comm08 * 10;
  comm09 = comm09 * 10;
  comm10 = comm10 * 10;
  comm11 = comm11 * 10;
  comm12 = comm12 * 10;
  comm13 = comm13 * 10;

  ecd08 = ecd08 * 10;
  ecd09 = ecd09 * 10;
  ecd10 = ecd10 * 10;
  ecd11 = ecd11 * 10;
  ecd12 = ecd12 * 10;

!!Describe Analysis methods
  ANALYSIS:
          TYPE= MEANSTRUCTURE;
          COVERAGE=0;
          processors = 40;

  MODEL:
! Use BY command to indicate which latent variables are measured by which items
! * followed by a number means providing a start value to aid model estimation
! The starting values used in BDLDSM model are estimated using automatic starting values provided by MPLUS from latent change score models. We first estimated one latent change score model for communication score (incorporated cubic change form) and one latent change score model for ECD implementation (incorporated quadratic change form) to obtain the starting values automatically generated in these two models. We then applied the starting values from these two models in this BDLDSM model.
! Specify latent true scores ly1 – ly6
! Factor loadings for ly1- ly6 are fixed at 1
     ly1 BY comm08@1;
     ly2 BY comm09@1;
     ly3 BY comm10@1;
     ly4 BY comm11@1;
     ly5 BY comm12@1;
     ly6 BY comm13@1;

! dy represents latent change scores ∆y (the change of communication score)
! Factor loadings for dy2- dy6 are fixed at 1
     dy2 BY ly2@1;
```

```
    dy3 BY ly3@1;
    dy4 BY ly4@1;
    dy5 BY ly5@1;
    dy6 BY ly6@1;

! b_2yi represents constant change factor
! Factor loadings for b_2yi are fixed at 1
    b_2yi BY dy2@1;
    b_2yi BY dy3@1;
    b_2yi BY dy4@1;
    b_2yi BY dy5@1;
    b_2yi BY dy6@1;

! b_3yi represents linear growth factor for communication score
! Factor loadings for b_3yi changes linearly and multiply by 2  (according to 2b_3i)
! Factor loadings: -2*2, -1*2, 0, 1*2, 2*2

    b_3yi BY dy2@-4;
    b_3yi BY dy3@-2;
    b_3yi BY dy4@0;
    b_3yi BY dy5@2;
    b_3yi BY dy6@4;

! b_4yi represents quadratic growth factor for communication score
! Factor loadings for b_3yi changes quadratically and multiply by 3 (according to 3b_4i )
! Factor loadings: 4*3, 1*3, 0, 1*3, 4*3

    b_4yi BY dy2@12;
    b_4yi BY dy3@3;
    b_4yi BY dy4@0;
    b_4yi BY dy5@3;
    b_4yi BY dy6@12;

! Autoregressions
    ly2 ON ly1@1;
    ly3 ON ly2@1;
    ly4 ON ly3@1;
    ly5 ON ly4@1;
```

```
    ly6 ON ly5@1;

! Proportional Effects
! pi_y represents the proportional change parameter for communication score
    dy2 ON ly1*-1.22029 (pi_y);
    dy3 ON ly2*-1.22029 (pi_y);
    dy4 ON ly3*-1.22029 (pi_y);
    dy5 ON ly4*-1.22029 (pi_y);
    dy6 ON ly5*-1.22029 (pi_y);

! Covariance
    ly1 WITH b_2yi*7.50249;
    ly1 WITH b_3yi*-0.50301;
    ly1 WITH b_4yi*0.10612;
    b_2yi WITH b_3yi*-0.10361;
    b_2yi WITH b_4yi*-0.02776;
    b_3yi WITH b_4yi*-0.01400;

! Specify the intercepts
    [ comm08@0 ];
    [ comm09@0 ];
    [ comm10@0 ];
    [ comm11@0 ];
    [ comm12@0 ];
    [ comm13@0 ];

    [ ly1*8.77831 ];
    [ ly2@0 ];
    [ ly3@0 ];
    [ ly4@0 ];
    [ ly5@0 ];
    [ ly6@0 ];
    [ dy2@0 ];
    [ dy3@0 ];
    [ dy4@0 ];
    [ dy5@0 ];
    [ dy6@0 ];

    [ b_2yi*11.60411 ];
```

```
    [ b_3yi*0.22889 ];
    [ b_4yi*0.01956 ];

! Label for the residual variance for communication scores is sigma2_u
    comm08*0.34152 (sigma2_u);
    comm09*0.34152 (sigma2_u);
    comm10*0.34152 (sigma2_u);
    comm11*0.34152 (sigma2_u);
    comm12*0.34152 (sigma2_u);
    comm13*0.34152 (sigma2_u);

! Specify Residual Variances
    ly1*9.01256;
    ly2@0;
    ly3@0;
    ly4@0;
    ly5@0;
    ly6@0;
    dy2@0;
    dy3@0;
    dy4@0;
    dy5@0;
    dy6@0;
    b_2yi*9.47906;
    b_3yi*0.09324;
    b_4yi*0.00795;

! Specify latent true scores lx1 – lx5
! Factor loadings for lx1- lx5 are fixed at 1
    lx1 BY ecd08@1;
    lx2 BY ecd09@1;
    lx3 BY ecd10@1;
    lx4 BY ecd11@1;
    lx5 BY ecd12@1;

! dx represents latent change scores ∆x (the change of ECD)
! Factor loadings for dx2- dx5 are fixed at 1
    dx2 BY lx2@1;
    dx3 BY lx3@1;
```

```
    dx4 BY lx4@1;
    dx5 BY lx5@1;

! b_2xi represents constant change factor for ECD
! Factor loadings for b_2xi are fixed at 1
    b_2xi BY dx2@1;
    b_2xi BY dx3@1;
    b_2xi BY dx4@1;
    b_2xi BY dx5@1;

! b_3xi represents linear growth factor for ECD
! Factor loadings for b_3yi changes linearly and multiply by 2  (according to 2a_2i)
! Factor loadings: -1*2, 0, 1*2, 2*2
    b_3xi BY dx2@-2;
    b_3xi BY dx3@0;
    b_3xi BY dx4@2;
    b_3xi BY dx5@4;

! Autoregressions
    lx2 ON lx1@1;
    lx3 ON lx2@1;
    lx4 ON lx3@1;
    lx5 ON lx4@1;

! Proportional Effects
! pi_x represents the proportional change parameter for ECD
    dx2 ON lx1*0.72088 (pi_x);
    dx3 ON lx2*0.72088 (pi_x);
    dx4 ON lx3*0.72088 (pi_x);
    dx5 ON lx4*0.72088 (pi_x);

! Covariance
    lx1 WITH b_2xi*-23.40836;
    lx1 WITH b_3xi*0.66594;
    b_2xi WITH b_3xi*2.26084;
! Specify the intercepts
    [ ecd08@0 ];
    [ ecd09@0 ];
```

```
[ ecd10@0 ];
[ ecd11@0 ];
[ ecd12@0 ];
[ lx1*-2.67705 ];
[ lx2@0 ];
[ lx3@0 ];
[ lx4@0 ];
[ lx5@0 ];
[ dx2@0 ];
[ dx3@0 ];
[ dx4@0 ];
[ dx5@0 ];
[ b_2xi*3.13733 ];
[ b_3xi*0.35770 ];

! Label for the residual variance for ECD is sigma2_s
ecd08*17.07641 (sigma2_s);
ecd09*17.07641 (sigma2_s);
ecd10*17.07641 (sigma2_s);
ecd11*17.07641 (sigma2_s);
ecd12*17.07641 (sigma2_s);

! Specify Residual Variances
lx1*29.81328;
lx2@0;
lx3@0;
lx4@0;
lx5@0;
dx2@0;
dx3@0;
dx4@0;
dx5@0;
b_2xi*24.77468;
b_3xi*2.83590;

! Including time-invariant control variables in the model and regressing the growth factors on the time-invariant control variables
ly1 b_2yi b_3yi b_4yi on market    logbed
noprofit    teaching hospst1 hospst2
```

```
hospst3      hospst4 hospst5 hospst6;

  lx1 b_2xi b_3xi  on market   logbed
  noprofit     teaching hospst1 hospst2
hospst3      hospst4 hospst5 hospst6;

! Bivariate Information
     ly1 WITH lx1*-4.27001;
     ly1 WITH b_2xi*-1.73666;
     ly1 WITH b_3xi*0.26032;

     b_2yi WITH b_3xi;

     lx1 WITH b_2yi*-2.97771;
     lx1 WITH b_3yi*0.30969;
     lx1 WITH b_4yi*-0.13135;

     b_2xi WITH b_2yi*-1.90278;
     b_2xi WITH b_3yi;
     b_2xi WITH b_4yi;

     b_3xi WITH b_3yi*-0.07306;
     b_3xi WITH b_4yi;

! Covariance between communication score and ECD at each time point and constrained to be equal across time by the common label, sigma_su
  comm08 WITH ecd08 (sigma_su);  comm09 WITH ecd09 (sigma_su);
  comm10 WITH ecd10 (sigma_su);  comm11 WITH ecd11 (sigma_su);
  comm12 WITH ecd12 (sigma_su);

! Communication Score -> ΔECD
! Coupling parameters from Communication Score to ΔECD is specified and labeled as delta_x
  dx2 ON ly1 (delta_x);     dx3 ON ly2 (delta_x);
  dx4 ON ly3 (delta_x);     dx5 ON ly4 (delta_x);

! ECD -> ΔCommunication Score
! Coupling parameters from ECD to ΔCommunication Score is specified and labeled as delta_y
  dy2 ON lx1 (delta_y);     dy3 ON lx2 (delta_y);
  dy4 ON lx3 (delta_y);     dy5 ON lx4 (delta_y);     dy6 ON lx5 (delta_y);
```

plot:

type = plot3;

series = comm08 comm09 comm10 comm11 comm12 comm13 (*);

Output:

patterns tech1 residual fsdet stdyx tech4

modindices sampstat svalues;

Appendix G. Sample Size, Mean, and Covariance Matrix

The covariance matrix is also downloadable from this address:
https://drive.google.com/file/d/174HTqIld6JGJ9CYmsMhTi7CYIyACe9dN/view?usp=sharing

	Sample Size	Mean	COMM08	COMM09	COMM10	COMM11
COMM08	770	8.556	8.156			
COMM09	767	9.171	6.003	6.029		
COMM10	765	9.534	5.569	5.139	5.804	
COMM11	763	9.994	5.269	4.831	5.12	5.592
COMM12	755	10.579	5.063	4.573	4.863	5.003
COMM13	740	10.898	4.729	4.271	4.434	4.565
ECD08	399	-2.188	-0.894	0.445	1.177	0.89
ECD09	519	-1.823	-1.012	-0.15	1.072	1.251
ECD10	526	-1.327	-2.004	-0.221	0.454	0.631
ECD11	481	0.830	-3.245	-1.232	-0.285	0.118
ECD12	522	3.314	-1.852	-0.423	0.881	0.952
CPOE08	399	-2.216	-0.519	-0.061	-0.009	-0.522
CPOE09	519	-1.467	-1.995	-1.418	-0.758	-0.666
CPOE10	526	-0.697	-3.011	-1.493	-0.926	-0.817
CPOE11	481	1.718	-2.869	-1.227	-0.793	-0.712
CPOE12	522	5.002	-2.55	-0.798	0.058	0.505
DS08	399	-2.037	-1.729	-0.148	0.427	0.549
DS09	519	-2.013	-1.471	-0.674	0.644	0.963
DS10	526	-1.269	-3.099	-0.733	0.044	0.359
DS11	481	1.101	-3.249	-1.583	-0.878	-0.161
DS12	522	3.565	-2.508	-0.893	0.262	0.451
MARKET	791	0.172	0.13	0.101	0.099	0.103
LOGBED	791	5.254	-0.872	-0.719	-0.717	-0.748
NOPROFIT	791	0.666	0.274	0.149	0.137	0.125
TEACHING	791	0.105	-0.062	-0.058	-0.076	-0.068
State=CA	791	0.076	-0.03	-0.038	-0.04	-0.038
State=FL	791	0.056	0.024	-0.006	-0.008	-0.009
State=MD	791	0.118	0.368	0.318	0.314	0.311
State=NC	791	0.18	-0.214	-0.062	-0.056	-0.061
State=NJ	791	0.075	0.132	0.099	0.112	0.111
State=NY	791	0.302	-0.257	-0.262	-0.213	-0.199

	COMM12	COMM13	ECD08	ECD09	ECD10	ECD11
COMM12	5.597					
COMM13	4.843	5.261				
ECD08	0.772	0.527	32.856			
ECD09	0.852	0.492	23.3	39.894		
ECD10	0.514	0.384	20.255	27.987	39.574	
ECD11	0.275	0.469	18.663	25.604	27.303	44.43

ECD12	1.056	1.254	14.619	16.464	18.834	26.262
CPOE08	0.136	0.027	19.482	13.951	12.84	9.649
CPOE09	-0.713	-0.903	16.2	27.388	22.736	20.481
CPOE10	-0.691	-0.613	14.647	23.149	28.401	20.884
CPOE11	-0.209	-0.396	15.416	22.062	20.529	34.558
CPOE12	0.887	1.527	11.777	15.796	17.369	25.008
DS08	0.247	0.16	27.28	18.811	16.038	13.701
DS09	0.584	0.466	23.18	32.952	23.647	22.586
DS10	0.076	-0.014	18.689	26.063	33.135	24.386
DS11	-0.195	0.048	17.899	22.614	24.226	39.817
DS12	0.705	0.985	13.586	14.46	16.275	23.759
MARKET	0.106	0.087	-0.023	-0.017	-0.056	-0.035
LOGBED	-0.717	-0.68	0.999	1.444	1.452	1.424
NOPROFIT	0.159	0.16	-0.237	-0.191	-0.108	-0.071
TEACHING	-0.069	-0.07	0.201	0.306	0.275	0.257
State=CA	-0.037	-0.037	0.095	-0.037	-0.017	-0.112
State=FL	-0.005	-0.027	0.056	0.057	0.071	0.024
State=MD	0.298	0.292	0.166	0.05	0.055	-0.055
State=NC	-0.087	-0.068	0.377	0.358	0.416	0.589
State=NJ	0.115	0.088	0.005	0.172	-0.009	0.022
State=NY	-0.135	-0.138	-0.454	-0.346	-0.354	-0.278

	ECD12	CPOE08	CPOE09	CPOE10	CPOE11	CPOE12
ECD12	43.857					
CPOE08	7.305	47.034				
CPOE09	12.727	24.555	50.086			
CPOE10	14.307	21.195	33.552	49.994		
CPOE11	23.667	17.358	25.869	27.95	52.077	
CPOE12	37.642	11.195	16.091	18.227	28.313	48.359
DS08	14.754	22.411	14.685	14.131	11.926	13.186
DS09	16.227	18.089	29.666	23.51	20.917	16.54
DS10	17.977	15.514	24.246	30.81	21.157	17.849
DS11	25.305	14.107	21.399	21.221	37.426	27.405
DS12	37.036	11.851	14.207	13.475	22.687	34.706
MARKET	0.017	-0.08	0.031	-0.118	-0.01	0.044
LOGBED	1.002	1.562	1.708	1.543	1.713	0.858
NOPROFIT	-0.157	0.041	-0.105	0.036	0.084	-0.063
TEACHING	0.269	0.533	0.588	0.546	0.459	0.354
State=CA	0.039	0.271	0.106	0.125	0.082	0.107
State=FL	-0.016	0.062	0.099	0.074	0.08	-0.013
State=MD	0.1	0.075	-0.055	-0.063	-0.106	-0.111
State=NC	0.479	-0.054	0.141	0.125	0.372	0.321
State=NJ	0.126	-0.074	0.047	-0.057	-0.025	0.081
State=NY	-0.364	-0.414	-0.461	-0.337	-0.54	-0.425

	DS08	DS09	DS10	DS11	DS12	MARKET
DS08	38.681					
DS09	23.018	44.016				
DS10	19.418	26.994	45.616			
DS11	15.055	23.225	26.004	49.181		
DS12	16.167	16.514	19.109	25.76	45.821	
MARKET	-0.074	0.005	-0.064	-0.015	-0.009	0.026
LOGBED	1.171	1.362	1.575	1.42	0.933	-0.037
NOPROFIT	-0.32	-0.178	-0.171	-0.026	-0.175	0.003
TEACHING	0.269	0.339	0.365	0.293	0.19	-0.006
State=CA	0.142	0.083	0.04	0.022	0.051	0
State=FL	0.056	0.084	0.047	0.1	0.016	0
State=MD	0.235	0.135	0.082	0.01	0.047	0.01
State=NC	0.351	0.233	0.516	0.514	0.389	0.001
State=NJ	-0.025	0.115	-0.05	-0.055	0.104	0.003
State=NY	-0.529	-0.418	-0.558	-0.517	-0.321	-0.009

	LOGBED	NOPROFIT	TEACHING	State=CA	State=FL	State=MD
LOGBED	0.798					
NOPROFIT	0.045	0.222				
TEACHING	0.114	0.001	0.094			
State=CA	0.029	0.018	0.005	0.07		
State=FL	0.006	0.017	0.002	-0.004	0.053	
State=MD	-0.031	-0.002	-0.006	-0.009	-0.007	0.104
State=NC	0.026	-0.04	-0.009	-0.014	-0.01	-0.021
State=NJ	-0.047	-0.008	-0.005	-0.006	-0.004	-0.009
State=NY	-0.036	-0.022	-0.013	-0.023	-0.017	-0.036

	State=NC	State=NJ	State=NY
State=NC	0.147		
State=NJ	-0.013	0.069	
State=NY	-0.054	-0.023	0.211

Appendix H. Bibliography Section for BDLDSM

Readers interested in further details related to BDLDSM method, applications of BDLDSM, programming for BDLDSM modeling, and measurement invariance are encouraged to consult the following references:

	Articles
BDLDSM Method	Grimm et al. (2016), Ferrer & McArdle (2003), Grimm et al. (2017), McArdle & Hamagami (2001), McArdle (2009), Ferrer & McArdle (2010), Grimm et al. (2013), Grimm et al. (2012), Curran et al. (2014), Curran et al. (2010), Bollen & Curran (2005), Usami et al. (2016)
Applications of BDLDSM	Sbarra & Allen (2009), Grimm (2007)
Programming for BDLDSM	Klopack & Wickrama (2020), Ghisletta & McArdle (2012),
Measurement Invariance	Cheung & Rensvold (2002), Chen (2007)

About the Authors

Youyou Tao is an assistant professor in the Department of Information Systems and Business Analytics at Loyola Marymount University. She received her M.S. degree in Information Systems from the University of Washington, Seattle, and her Ph.D. in computer information systems from Georgia State University. Her research focus is on healthcare analytics and informatics. In particular, she applies the lenses of IT complementarity, business value, causal reasoning, and predictive analytics to examine the myriad intriguing issues in the healthcare industry. She has published in premier information systems and health informatics journals such as Information Systems Research and Journal of Medical Internet Research.

Abhay Nath Mishra is an associate professor and Kingland Faculty Fellow in Business Analytics at the Debbie and Jerry Ivy College of Business at Iowa State University. He received his Ph.D. from University of Texas at Austin. Abhay's research has focused on the application of digital innovations and analytics on organizations and individuals. He has also studied the use of digital innovations among physicians, nurses, pharmacists, public health benefits recipients, and students. Abhay's research has been published in premier information systems, operations management, and healthcare journals.

Katherine Masyn is a Professor of Biostatistics and Chair of the Department of Population Health Sciences in the School of Public Health at Georgia State University. Previously she worked as an associate professor at the Harvard Graduate School of Education. She earned her BS in Mathematics from the College of William and Mary, MA in Biostatistics from UC Berkeley, and PhD in Advanced Quantitative Methods in Social Research at UCLA. Katherine's research focuses on the development and application of latent variable statistical models related to: survival and event history analysis; multivariate and multi-faceted longitudinal processes and, more broadly, the characterization and parameterization of both observed and unobserved population heterogeneity in cross-sectional and longitudinal settings.

Mark Keil is a Regents' Professor of the University System of Georgia and the John B. Zellars Professor of Computer Information Systems at Georgia State University. He holds B.S.E., S.M., and D.B.A. degrees from Princeton University, M.I.T. Sloan School of Management, and Harvard Business School, respectively. Keil's research focuses on IT project management and includes work on preventing IT project escalation, identifying and managing IT project risks, improving IT project status reporting, and IT implementation and use. He has published more than 100 refereed journal articles in such outlets as the MIS Quarterly, Information Systems Research, Journal of Management Information Systems, Decision Sciences, Strategic Management Journal, IEEE Transactions on Engineering Management, Sloan Management Review, and California Management Review.