

2008

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Recommended Citation

Qureshi, Israr; Wang, Yinglei; Compeau, Deborah; and Meister, Darren, "Capturing the dynamics of adoption through Latent Curve Modeling" (2008). *DIGIT 2008 Proceedings*. 2.

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Capturing the dynamics of adoption through Latent Curve Modeling

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Capturing the dynamics of adoption through Latent Curve Modeling

Abstract

Geared towards capturing change, longitudinal research is able to provide insight into a variety of phenomena of interest to IS researchers, especially IT adoption and use. However, its potential is constrained by the data analysis methods typically used. In this paper, we introduce an advanced technique – Latent Curve Modeling – and demonstrate how this technique supports longitudinal data analysis using system use data collected at an international management consulting firm. Latent Curve Modeling helps capture temporal patterns better than existing methods, and provides methods to identify the causes of change in patterns. With rich information in the discussion of the technique and the results of the empirical tests, we recommend it as a valuable option for IS researchers who are interested in research involving temporal changes.

Introduction

Despite the increasing use of longitudinal studies over the last several decades in social and behavioural sciences (Bollen and Curran, 2006), longitudinal research in the Information Systems literature appears to be relatively rare. There are some isolated examples that use two or three cross-sections (Burke and Chidambaram, 1999; Compeau et al., 1999; Cotteleer and Bendoly, 2006; Du et al., 2008; Hunton and Beeler, 1997; Newman and Sabherwal, 1996; Olfman and Mandviwalla, 1994; Pavlou and Gefen, 2005; Simon et al., 1996; Venkatesh and Brown, 2001; Watson et al., 1998) but rarely do these efforts go beyond three time points.

The main reason for IS researchers to conduct longitudinal research is that it allows a researcher to draw causal inferences, given that one of the conditions for causality is that cause must be prior to effect (Born, 1949). It is usually done by measuring independent variables and dependent variables at different times and examining how prior events/traits affect future events/behaviours with lag models. For instance, Compeau et al. (1999) measured computer self-efficacy and outcome expectations in a survey and their outcomes in another one a year later, and concluded based on a lag model that they indeed caused the outcomes.

Another use of longitudinal research is to detect performance patterns of variables, e.g., the differences in the influences of antecedents on information systems adoption and use at different points in time. Karahanna et al (1999) used a novel field design to collect a single cross-sectional data from two groups in an organization who were at different level of adoption (potential adopters and users) and thus were able to compare attitude and intention toward continued usage at pre and post adoption. Venkatesh and Davis (2000) collected data at three time points and described the coefficients of TAM at each of these time point to establish the consistency of TAM model in predicting attitude and intention towards usage.

Nevertheless, there seems to be little IS research that looks into temporal changes, for example, how individuals evolve over time in their intention to use, and how their individual trajectories differ from each other. One reason may be that IS researchers do not have proper tools to undertake this kind of inquiry. On the one hand, most of the designs currently employed in the IS literature are geared towards finding changes in the strength of relationships at two 'time points', e.g., comparing coefficients of subjective norm-behavioural intention between potential adopters and users (Karahanna et al., 1999). Limited time points make it difficult to detect patterns over time because, for example, with two time points only a linear trend can be fit to the data, making it impossible to capturing non-linear trajectories in the change patterns. On the other hand, even if there are enough time points, there are limited techniques available to IS researchers to understand and interpret patterns statistically and most of the efforts are limited to plotting the graphs. Conventional methods such as panel data models (random effects and fixed effects models) focus more on capturing relationships that occur across temporal periods (e.g., the influence of IT spending at time 1 on firm profitability at time 2 rather than on truly capturing the dynamics of change in firm profitability over time) whereas autoregressive models are generally used for predicting current status of a phenomenon based on past information about the same phenomenon (e.g., current profitability according to all past information about profitability or current usage based on all past usage). Neither of these techniques actually models the dynamics of change in phenomenon. In addition, none of these techniques is capable of modeling inter-relationships between two or more growth processes, as they do not incorporate measurement model (i.e. multi-indicator constructs), does not provide overall model fit indices, and have limited capabilities for incorporating time invariant coefficients for explaining individual differences in growth processes.

In contrast to the lack of research, effort in this area is of great importance, especially to research and practice regarding the adoption and continuous use of information systems. Prior research has suggested that initial adoption does not guarantee return on investments in information systems; instead, organizations can only benefit when the systems are actually used on an ongoing basis (Bhattacharjee, 2001). However, continuous use of information systems cannot be taken for granted; it may decline without proper interventions (Garud and Kumaraswamy, 2005). It is thus crucial to track how individual usage evolves, find out what causes patterns to change, and how individuals differ in their usage patterns, so that organizations can design and apply proper interventions to facilitate system use, which cannot be done without proper methods.

Therefore, we believe there is an opportunity to contribute to the literature by introducing an advanced statistical technique, namely Latent Curve Modeling (also referred to as Latent Growth Modeling) – which has not been used in management or IS research though is now increasingly used in sociology and developmental research. This technique can capture patterns and discover causes of variability in patterns at the same time, making it a suitable tool for researchers who are interested in identifying the antecedents of certain outcomes at a given time point, as well as the determinants of changes in patterns over time. As this technique is implemented in the structural equation modeling (SEM) framework, all the advantages of SEM, such as possibility of using multiple indicator constructs, testing model fit, comparing different nested models, and comparing models for multiple group, are available. In the following sections, we explain how this technique works and demonstrate its implications for analyzing temporal trajectories in the context of IS research in general and adoption research in particular with an empirical example.

Latent curve modeling (LCM)

LCM helps the researcher identify the pattern of changes over time by utilizing the set of repeated observed measures to estimate “an unobserved trajectory that gave rise to the repeated measures” (Bollen and Curran, 2006, p. 34). The primary interest is not in the repeated measures themselves but rather in the unobserved path of change, which is referred to as latent trajectory (MacCallum et al., 1997). To that extent LCM resembles

the traditional latent variable SEM approach where indicators of a latent construct are used to understand the unobserved construct.

LCM models estimate random intercepts and random slopes (linear or higher order) for each case (i.e., subject) in the sample so that trajectories over time for each case can be constructed. To illustrate, a hypothetical situation is shown in Figure 1. Each individual in this organization may potentially have a different trajectory of usage of a particular technology. Employee ‘F’ adopts technology early and uses it as much as 26 hours a month

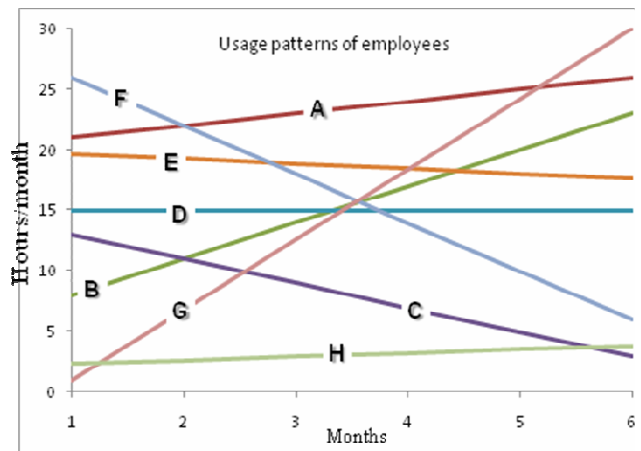


Figure 1- Linear trajectories of technology usage

but his usage drops down to 6 hours/month at the end of six months, whereas employee ‘G’ adopts the same technology cautiously (1 hour/month) but she gradually becomes the most frequent user of the technology at the end of six months (30 hours/month). Employee ‘D’ uses technology consistently for 15 hours/month for entire period shown in Figure 1. Other users show various linear patterns of usage.

However, technology usage need not be a linear trajectory. Figure 2 presents an example of non-linear trajectories for the individuals in Figure 1. Notice that usage levels for the individuals ‘A’ to ‘H’ in month ‘1’ and month ‘6’ are the same as their usage shown in Figure 1. So, if we capture the usage only for these two months we will miss the dynamics of non-linear change. This is the reason why two cross-sectional snapshots cannot substitute for longitudinal design for capturing patterns of change.

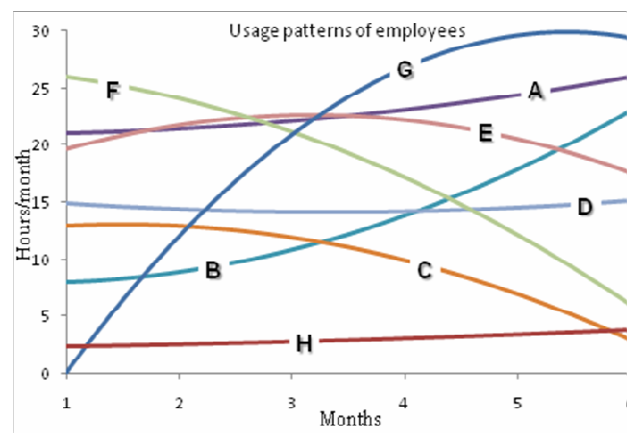


Figure 2 Non-linear trajectories of technology usage

From Figure 1 and Figure 2 it is clear that each individual may have a different intercept (i.e. initial level of usage) and a different slope (i.e. change in usage over time). LCM incorporates these random coefficients (i.e.

random intercepts and random slopes) through a structural equation modeling framework (Bollen and Curran, 2006). These coefficients are operationalized as latent variables. Figures 3 and 4 illustrate simple linear and quadratic LCM. These are simple in LCM terms because only one phenomenon is modeled and no predictors of this phenomenon are included. Once we have discussed the simple LCM, we will provide an overview of complexities that can be added to these models.

Figure 3 shows an example of an LCM that has six waves of usage data. The trajectory is modelled with two latent variables: intercept (Int) and linear slope (Lin). Use1, ..., Use6 are usage at time T1, ..., T6. For simplicity they are shown as observed measures; however, they could be latent constructs themselves measured by multiple observed measures¹. Each one of Use1, ..., Use6 is associated with an error term (not shown). Covariance between the two latent variables is marked as 'Cov'. The observed repeated measures (Use1, ..., Use6) are related to unobserved latent factors,

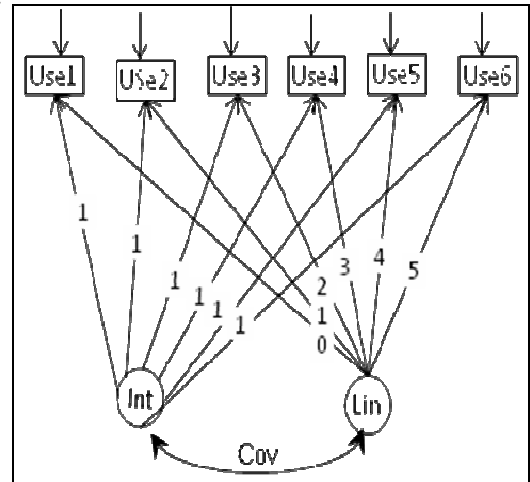


Figure 3- Simple linear model (LCM-1)

i.e. 'Int' and 'Lin', through factor loadings. These factor loadings are generally fixed based on the expected shape of the trajectories. All the loadings for intercept latent variable (i.e. 'Int' in Figure 3) are fixed at '1'. This means 'Int' affects all the repeated measures equally across all the waves (Duncan et al., 2006). This latent variable captures the initial level of the phenomenon under study. If the variance of this latent variable is significantly different from zero then we conclude that individuals differ in their initial levels

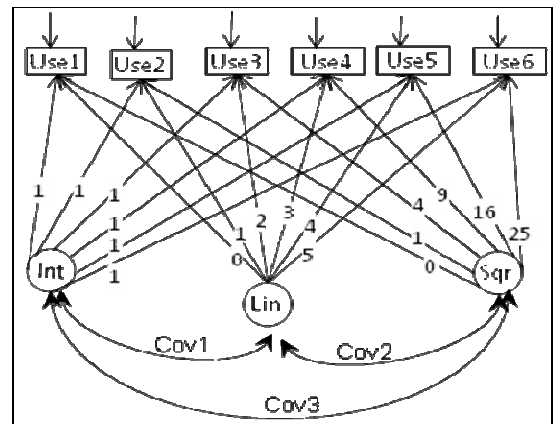


Figure 4- Simple quadratic model (LCM-2)

¹ Use of latent repeated measures represents one the strengths of LCM that is not available with other techniques of modeling trajectories (Bollen and Curran, 2006)

of the phenomenon (i.e. in this example their usage of technology). The differences in intercepts and slopes can then be explained by predictors. We will later explain how predictors can be used to answer some of the questions such as whether individuals from different cultures have different initial levels of usage of a technology.

For linear trajectories, i.e. linear LCM models (LCM-1), the slope of the trajectory is captured by a linear latent variable (Lin). As shown in Figure 3, loadings for Lin are 0, 1, 2, ... 6 for Use1, Use2, Use3, ... Use6 respectively. The first loading is fixed to zero in order to capture the mean value of usage in the first wave (Bollen and Curran, 2006). The unit interval between loading values reflects the fact that use is measured at equal intervals of time. If this is not the case then suitable modifications can be made to represent the actual interval. For example if usage was measured in the first week each of January, April, May, August, October and December that factor loadings for linear latent variable would be 0 (for January), 3 (April), 4 (May), 7 (August), 9 (October) and 11 (December).

However, if the expected trajectory is non-linear then, as shown in Figure 4, a quadratic latent variable ‘Sqr’ can be added to the intercept and linear latent variables to create simple quadratic model (LCM-2). The loadings for the Sqr latent variable are squares of corresponding

loadings of the linear latent variable. Similarly, a cubic or higher order non-linear latent variable can be added to LCM-2 to represent more complex trajectories. Another way to estimate non-linear trajectories, as shown in Figure 5, is to keep the intercept latent variable as is but modify the slope latent variable in such a way that only ‘0’ (for time T1) and ‘1’ (for Time T2) are fixed loadings while others are freely

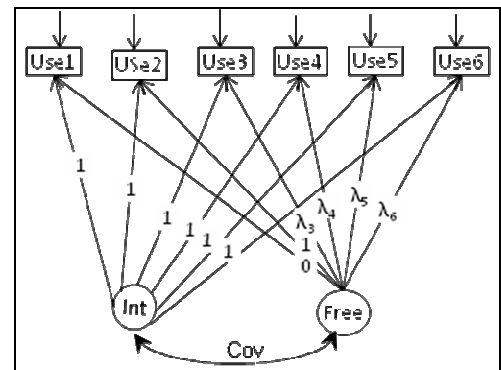


Figure 5- Simple free (non-linear) model (LCM-3)

estimated. In this model (LCM-3), freely estimated values of λ_3 , λ_4 , λ_5 , and λ_6 determine the nature of trajectories. For example, if the estimated values of λ_3 , λ_4 , λ_5 , and λ_6 are 1.8, 2.4, 2.8 and 3.0 then it would indicate that change observed between T1 and T3 is 1.8 times the change observed between time T1 and T2. Similarly, changes observed between T1 and T4, T1 and T5, and T1 and T6 are respectively 2.4, 2.8, and 3.0 times the change between T1 and T2. This would indicate a gradually saturated usage pattern which is typical of logarithmic trajectory.

This section provided an overview of how simple LCM models can be implemented. These models are helpful in estimating the growth pattern in single phenomena. However, their importance increases multi-fold if we consider multiple processes (MLCM) or include time invariant covariates. These two procedures are explained below.

Multivariate latent growth models (MLCM)

MLCM is a term used when two or more latent curve processes are estimated simultaneously (Figure 6). It may be insightful to see how the latent trajectory of one process might influence the trajectory of another co-evolving process. For example, Figure 6 shows two co-evolving non-linear latent processes, use by an individual (with random latent variables Int and Free) and use by his or her peers (with random latent variables Pint and PFree). The covariances amongst Int, Free, Pint and PFree are labelled as C1, ..., C6. With this model, the influence of one process on another can be tested through significance of these covariances. For example, a positive and significant C3 indicates that initial level of peers' usage influences initial level of focal individual's usage, or vice versa. Similarly, a positive and significant C5 would suggest that initial level of peers' usage

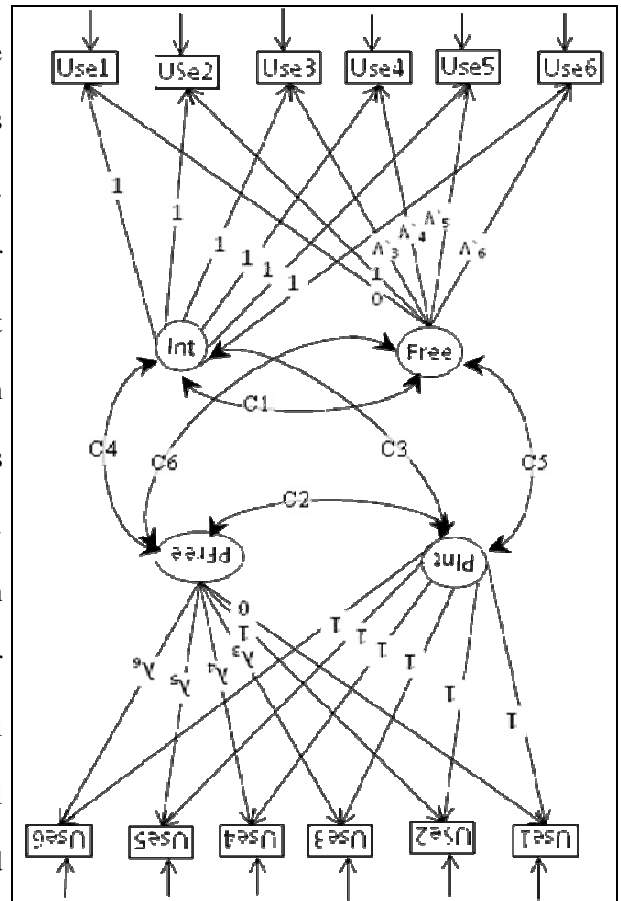


Figure 6-Multivariate free latent curve model (MLCM)

would affect the slope (change) of focal individual. Here, the ordering is more clear as Pint reflects initial use and Free reflects later use.

It is important to note that Figure 6 used usage patterns for both the latent trajectories. However, in order to construct a MLCM, it is not necessary to have identical growth processes. One could choose two very different but theoretically related processes. For example, one could model the dynamic inter relationships between

technology self-efficacy and usage to examine the nature of self-efficacy spirals (Lindsley et al., 1995; Shea and Howell, 2000)

Time invariant covariates

LCM provides the necessary tools for modeling trajectories and statistically testing the difference between individual trajectories. In the above description of LCM we have not yet mentioned predictors of these growth patterns or trajectories and yet we frequently want to know what predicts differences in usage patterns. Is there a gender effect in growth trajectories? Is usage across the organizational hierarchy different? Is there a cultural/ country effect in usage patterns? Covariates such as gender and culture that do not change over time are referred to as time invariant covariates (TIC) and LCM that incorporates these covariates is referred to as LCM-TIC. Figure 7 presents an example of LCM-TIC.

In this example four cultural dimensions, power distance (PDI), individualism (IDV), masculinity (MAS), and uncertainty avoidance (UAI) (Hofstede et al., 1990), represent time invariant covariates. This model tests whether cultural dimensions significantly explain the variance in intercept or slope (or both) of system usage trajectory of the individuals.

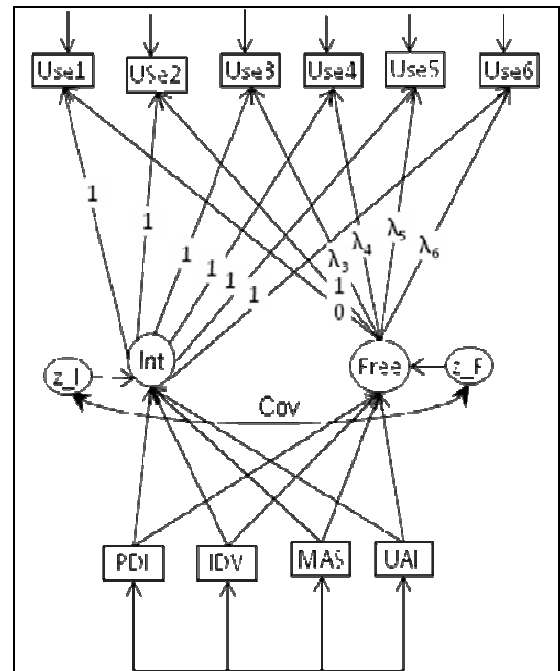


Figure 7-LCM with time invariant covariate (LCM-TIC)

LCM implementation

The preceding sections have highlighted the different models of LCM and their potential value for analyzing data. We turn now to a discussion of the implementation (usage) of LCM, and then to a demonstration of its application in a particular research context. Figure 8 provides the major steps to be followed in LCM implementation. As with any other statistical technique, researchers should check their data for normality, and make appropriate modifications as outlined in the Figure.

As a second step the researcher should establish, either theoretically or empirically, the shape of trajectory i.e. whether the process or processes under study follows linear, quadratic or other non-linear trajectories (i.e. LCM1, LCM2 or LCM3 model). If shape is determined theoretically then the researcher can test the shape based on the how theoretical model fits the data. On the other hand if the shape of the trajectory is determined empirically then the researcher tests various models and the best fit model is chosen to represent the trajectories. If there is more than one process then LCM for each process should be estimated separately to establish shape of their trajectories before combining them in MLCM.

The next step is to establish whether each of these processes have variability in their intercept and slope latent variables. If there is no variability then we can conclude all the individuals in the sample follow same trajectory. For example, if LCM model for technology usage has no variation in intercept and slope latent variable, then individuals in our sample have adopted technology at the same time, and their usage over time is similar. However, if either intercept or slope latent variable has significant

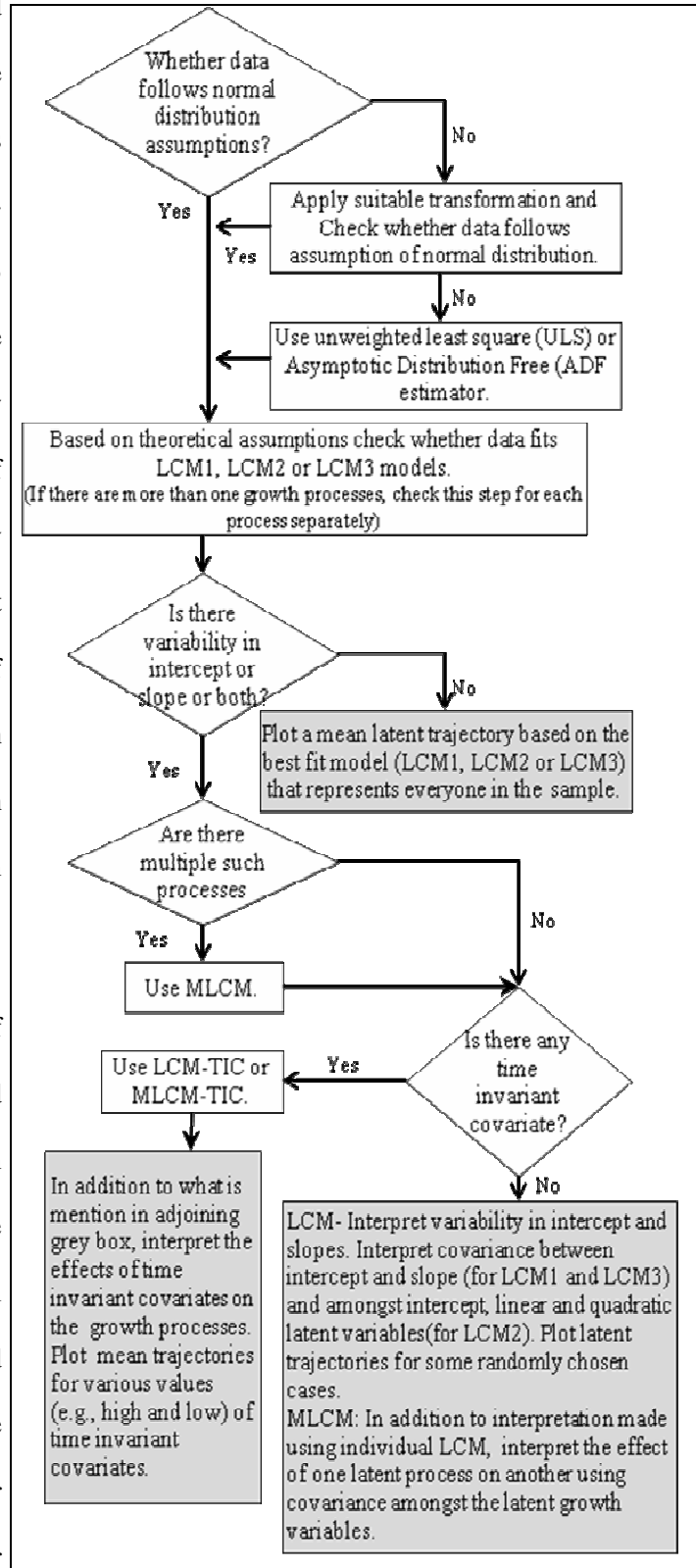


Figure 8-Flowchart for LCM implementation

variation then this variation can be used to plot different trajectories for each individuals. In addition, other growth processes MLCM) or TIC (LCM-TIC) or both (MLCM-TIC) can be used to explain these variations.

Empirical example

Our empirical example using LCM utilizes data that were collected from a major international management consulting firm headquartered in the United States. In 2005, this firm implemented a company-wide

Table 1: Descriptive statistics for system usage and cultural dimensions											
		Use1	Use2	Use3	Use4	Use5	Use6	PDI	IDV	MAS	UAI
Analyst	Mean	2.55	3.01	3.32	3.30	3.30	3.45	58.13	61.57	57.40	55.21
	SD	21.82	66.31	57.63	22.92	17.66	46.23	20.21	22.18	14.73	19.95
	Skewness	40.70	168.21	118.40	46.43	33.65	151.52	0.33	-0.02	-0.37	0.65
	Kurtosis	2008.15	30429.42	15477.48	3413.12	1866.30	26330.36	-1.01	-1.22	3.95	-0.81
Consultant	Mean	5.42	4.85	5.10	5.21	5.27	5.40	50.27	70.23	57.83	54.86
	SD	46.88	31.00	33.46	25.30	24.26	26.05	17.41	22.43	14.89	19.42
	Skewness	27.97	24.18	26.57	20.73	19.34	19.08	1.01	-0.75	-0.96	0.70
	Kurtosis	939.53	748.84	925.45	610.22	512.59	507.21	0.12	-0.69	3.50	-0.53
Manager	Mean	8.73	7.18	7.19	8.32	8.72	9.02	47.10	73.65	57.83	54.55
	SD	59.29	28.82	30.06	29.13	30.88	53.71	15.86	21.46	15.22	19.19
	Skewness	21.00	15.81	19.41	14.06	15.95	62.08	1.34	-1.13	-1.26	0.68
	Kurtosis	512.38	353.23	608.77	282.18	380.84	5295.59	1.31	0.19	3.50	-0.41
Sr. M'ger	Mean	8.97	8.41	8.36	9.57	9.79	9.52	45.53	75.99	58.92	53.23
	SD	48.26	33.02	30.33	25.87	26.13	25.84	14.30	21.01	14.16	17.97
	Skewness	27.93	38.57	30.14	11.08	14.21	11.90	1.66	-1.31	-1.34	0.94
	Kurtosis	1032.35	2277.55	1528.12	202.48	383.74	240.46	2.74	0.60	4.70	0.14
Sr. Exec	Mean	5.45	5.65	5.20	6.13	6.53	6.20	44.18	78.52	58.85	53.68
	SD	12.57	14.37	12.08	13.79	16.60	13.01	12.50	18.52	14.15	18.11
	Skewness	7.22	10.51	5.06	6.53	14.86	5.19	1.75	-1.57	-1.48	0.89
	Kurtosis	90.26	242.71	40.56	87.67	429.35	46.40	3.71	1.66	4.68	0.01
Total	Mean	4.95	4.72	4.91	5.24	5.35	5.46	52.55	67.83	57.78	54.77
	SD	39.48	49.24	44.63	24.63	22.79	40.23	18.79	22.67	14.78	19.45
	Skewness	31.19	182.84	116.31	27.36	21.49	123.85	0.80	-0.51	-0.80	0.70
	Kurtosis	1197.09	43837.85	18934.06	1413.34	734.17	22553.43	-0.39	-1.02	3.79	-0.58

knowledge management system as part of the effort to facilitate knowledge storage and sharing. This system included knowledge repositories that contained reports, proposals, memos etc. as well as knowledge directories that could connect people to experts in various areas. We were able to gain access to 6 months of usage data of

this system (the first six following its implementation). From system logs, we obtained the monthly system usage information of over 80,000 users who were located in 54 countries and specialized in 21 different areas (e.g., technology consulting and finance), with various organizational statuses ranging from entry-level employees to senior management. For each user, monthly usage was measured by the number of times he or she visited the system in a given month². This data fits the purpose to examine the performance of latent growth modeling very well as the time period it covers represent the critical duration in which new adopters accumulated experience, developed understanding and formed use patterns.

Table 1 provides descriptive statistics for monthly usage (Use1, Use2, ..., Use6) and culture dimensions for each category of users (e.g. analyst) as well as for entire organization (i.e. total). The culture dimensions were obtained by using Hofstede's country scores and applying them based on the location of the individual. It may be noted that monthly usage data was highly skewed and kurtotic. We transformed usage using natural log transformation (Ln). The skewness and kurtosis for transformed variables were within acceptable limits. We used these log transformed variables for all of our analysis. We will demonstrate two LCM examples using this dataset. First we will present a step-by-step account of LCM-TIC models and then we will demonstrate use of MLCM.

LCM-TIC

We expect that various groups of employees (e.g. analysts, consultants and other levels) will have different initial level of usage and different growth patterns because employees at different levels may have different responsibilities for knowledge management and thus use the system differently. For instance, first line employees usually struggle with daily work and are likely to seek knowledge only, while middle level managers need to attend to daily work and knowledge management at the same time, making them use both the seeking and contributing functions of the system. In addition, we expect that country culture will have effect on the usage trajectory. For example, seeking knowledge from people may be deemed as more embarrassing in some countries and as a result people in those countries are more likely to turn to the non-relational system when they need

² While this data does not tell us differences in the total time used, it offers a reasonable assessment of usage that can be reliably differentiated among users.

knowledge, leading to a different use pattern from those of others. Thus, we decided to estimate LCM-TIC for each group of users.

Following the steps outlined above (Figure 8) we first estimated LCM1, LCM2 and LCM3 for each groups: analysts, consultants, managers, senior managers, and senior executives. The results of the analysis are

presented in Table 2. All of these models have very good fit statistics and pass the most conservative cut-off level of .96 for CFI and NFI, and .06 for RMSEA (Hu and Bentler, 1999). Only χ^2 test was problematic for a few of these models. It is not unusual in LCM (similar to SEM) research to include models that do not pass χ^2 test, as this test is very sensitive to sample size and we had sample sizes in the range of 36,394 (analysts) to 3,854 (senior executives). For analysts, the best model based on χ^2 test is LCM2 ($\chi^2 = 4.85$, $df=1$, $p=.028$). Thus, the latent trajectories for analysts follow a quadratic shape. The last two columns in the Table 2 provide information on the variance in intercept and slope. For analysts, LCM2 model indicates that there is significant variance in intercept (.38, $p<.01$), linear (.16 $p<.01$) and quadratic (.004, $p<.01$) latent variables. Thus,

Table 2: LCM Models for various groups of employees								
	χ^2	df	p	CFI	NFI	RMSEA	Variance	
							Int	Slope
Analysts								
LCM1	23.25	1	.000	.999	.999	.025	.33**	.03**
LCM2	4.85	1	.028	.999	.999	.010	.38**	.16** .004**
LCM3	30.13	1	.000	.999	.999	.028	.27**	.03**
Consultants								
LCM1	8.83	4	.066	.999	.999	.007	.57**	.03**
LCM2	1.49	2	.475	1	1	.000	.61**	.18** .006**
LCM3	2.19	1	.139	1	1	.007	.49**	.02*
Managers								
LCM1	6.43	3	.093	.999	.999	.010	.80**	.04**
LCM2	15.05	3	.002	.999	.999	.018	.88**	.27** .009**
LCM3	.08	1	.783	1	1	0	.72**	.005
Senior Managers								
LCM1	10.86	5	.054	.999	.999	.013	.89**	.04**
LCM2	15.44	5	.009	.999	.999	.017	.93**	.25** .009**
LCM3	.88	2	.645	1	1	0	.80**	.011
Senior Executives								
LCM1	4.03	7	.776	1	1	0	.57**	.02**
LCM2	1.68	4	.795	1	1	0	.59**	.14** .005**
LCM3	20.8	4	.001	.997	.996	.033	.54**	.001
LCM1, LCM2, LCM3 represent linear, quadratic, and higher order non linear LCM models. For LCM2 first value in the cell in slope column represents variance in linear latent variable and second value represents variance in quadratic latent variable. For intercept and slope: ** $p<.01$, * $p<.05$. Row with bold numbers indicates the best fit model for that group. For example, LCM2 is the best fit model for Analysts.								

individual analysts differ in their initial level of usage and their growth patterns even though they broadly follow the quadratic trajectories.

For consultants, all the three models pass χ^2 test. In addition, LCM2 and LCM3 models pass the test of $\chi^2/df < 2$, which is normally reliable for large sample size (for consultants sample size was 23781). Since both the models fit the data adequately, LCM3 was chosen over LCM2 for its parsimony (LCM2 has three latent variables to model the trajectory whereas LCM3 models the trajectory with only two latent variables). For consultants, the LCM3 model indicates that there is significant variance in intercept (.49, $p < .01$) and non-linear (.02, $p < .05$) latent variables. Thus, individual consultants differ in their initial level of usage and their growth patterns. Similarly,

Table 2 indicates that LCM3 is the best fit model for managers and senior managers, and LCM1 is the best fit model for senior executives. For managers and senior managers there are significant variations in intercept but no significant variations in slope. For senior executives there is significant variation in intercept as well as linear slope. Average trajectories for various groups have been

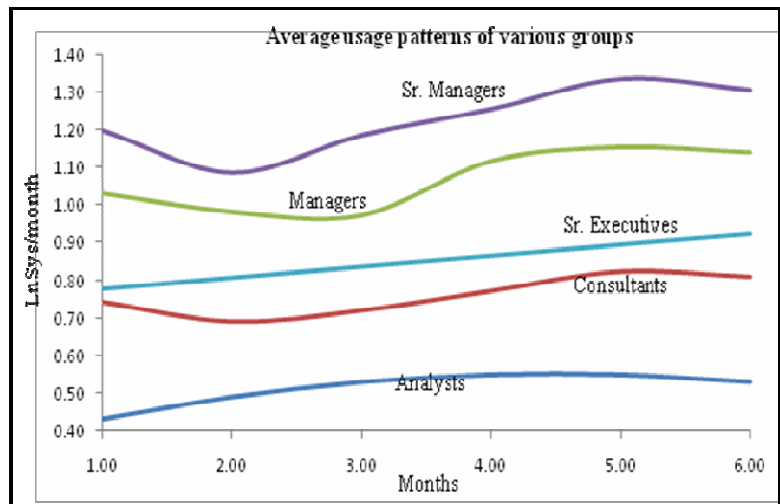


Figure 9- Average usage patterns of various groups

plotted in the Figure 9. However, there are significant differences in slope and intercepts of the members within each group. Therefore, average trajectory for each group does not represent each trajectory for each group member.

In the first step we established the significant variations in intercept and/or slope in the trajectories. Then we used the time-invariant covariates to predict variations in slope and intercept. Figure 10 shows a LCM2-TIC model for analysts. LCM2 was chosen as this is the best fit LCM for analysts (Table 2). The time invariant covariates (TIC) are

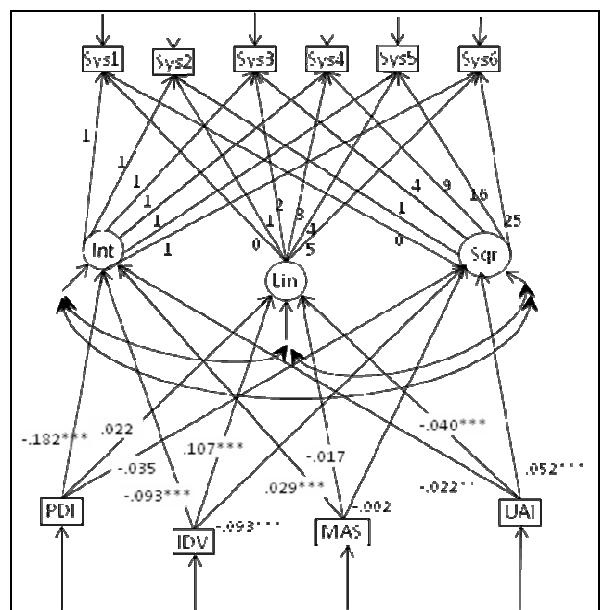


Figure 10-LCM2-TIC results for analysts

Hofstede's four cultural dimensions: Power Distance (PDI), Individualism (IDV), Masculinity (MAS) and

Uncertainty Avoidance (UAI) (Hofstede et al., 1990). The model has reasonable fit. Goodness of fit indices for the model (CFI=.998, NFI=.998, RMSEA=.018) were all better than the recommended levels (CFI, NFI >.96 and RMSEA < .06). However, the χ^2 value was high (167, df=13,p<.001).

All four cultural dimensions were predictors of variation in either intercept or slope of the trajectories. Power distance predicted variations in the intercepts. In Figure 11-A, the curves for Low and High power distance are parallel but widely separated. There is a clear difference in initial usage between individuals with high and low power distance but there is no statistical difference between their slopes. Similarly, masculinity also had

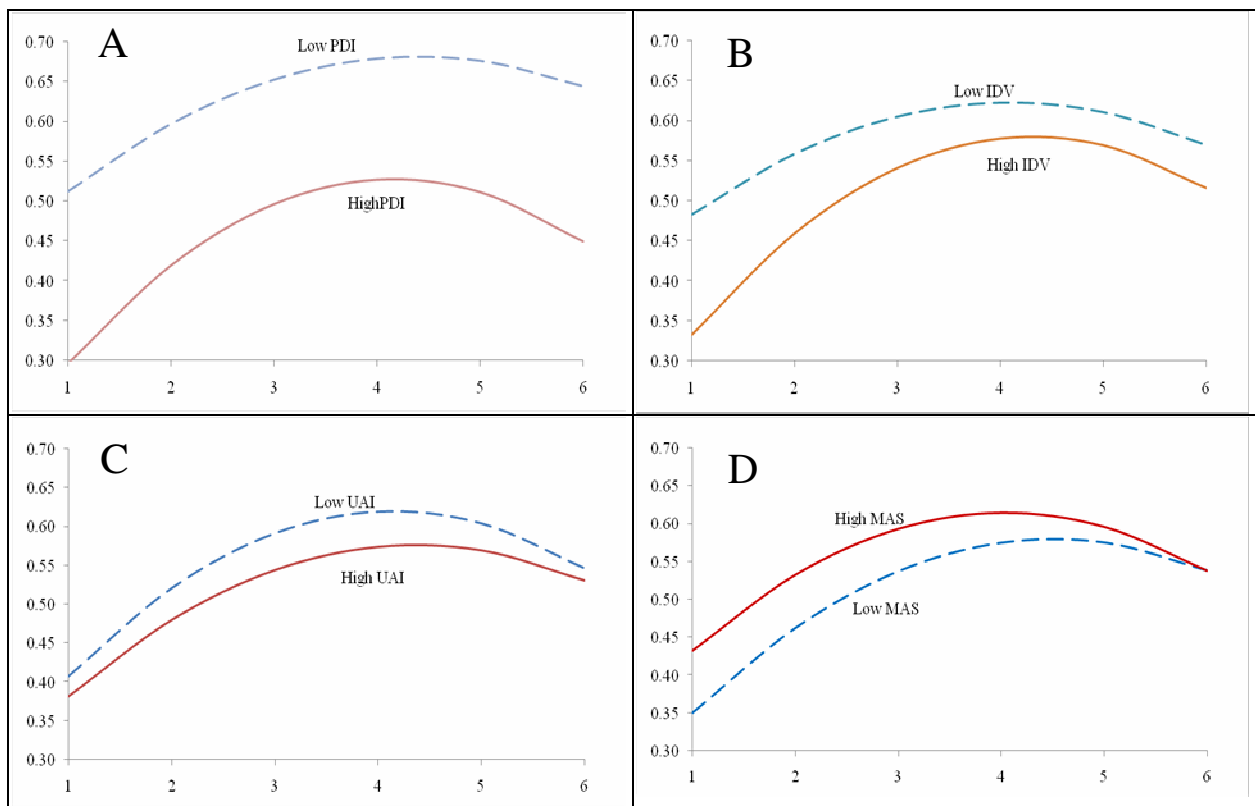


Figure 11- Cultural dimensions and latent trajectories for analysts.

significant but small effect on intercept and this can be observed from Figure 11-D. Individualism and uncertainty avoidance predicted variations in slope as well as intercepts. To observe the effects on non linear slope, two things should be considered: 1) linear change, observed by overall general linear trend from T1 to T6 (roughly connecting usage at T1 and T6) and 2) rate of change of slope i.e. change in slope at each time point. Figure 11-B, indicates that those with low individualism score adopts systems early compared to those high on individualism. This represents effect of individualism on intercept. This Figure also shows that the linear trajectory for high

individualism is steeper than low individualism, representing its effect on the linear component of the slope. The rate of change in the slope for high individualism is faster than that of low individualism, a quadratic trend. Analysts in countries that have high power distance, high individuality, and high uncertainty avoidance tended to adopt the system slowly. The effect of masculinity was opposite i.e. analysts in the countries that have cultures characterised by high masculinity tended to adopt the system more quickly. In addition, the effects of individualism and uncertainty avoidance on linear and quadratic slope component were opposite. Higher individuality was associated with higher linear growth in system access but the rate of growth was lower in the early time periods, whereas higher uncertainty avoidance was associated with lower linear growth in systems access but rate of growth was higher in the early time periods. Figure 11 presents the statistical results graphically. For each of these curves the values for other dimensions were held at mean levels. It can be observed from Figure 10 that the effect of power distance is strongest on the intercept ($\beta = -.182$, $p < .001$), as represented by the large separation in the curves of HighPDI and LowPDI in the Figure 11. For individualism, there is a large separation between the Low IDV and High IDV curves at $T=1$ as IDV also affect the intercept ($\beta = -.093$, $p < .001$); however, this separation reduces gradually up until $T=5$ after which it starts increasing again. This change in separation of the two curves indicates the effect of IDV on the linear ($\beta = .107$, $p < .001$), and quadratic ($\beta = -.093$, $p < .001$) latent variables. The effects of masculinity and uncertainty avoidance can also be observed from Figure 11.

Figure 12 shows the results of LCM3-TIC for consultants. It may be recalled from Table 2 that the LCM3 model fits best for consultants and there is significant variation in intercept and slope. Thus, cultural dimensions were used as TIC to account for these variations. This model has reasonable fit. Goodness of fit indices for model (CFI=.999, NFI=.999, RMSEA=.016) were all better than recommended level (CFI, NFI $> .96$ and RMSEA $< .06$), though the χ^2 value was high (85, $df=12$, $p < .001$).

For LCM3, λ_3 , λ_4 , λ_5 , and λ_6 are freely estimated. A table embedded in Figure 12 provides the estimated values of these loadings. This pattern of loadings can be interpreted in terms of change between time T1 and T2. Here values of λ_3 , λ_4 , λ_5 , and λ_6 are -2.29, -.316, .58 and .152 respectively. This pattern indicates that change in system access observed between T1 and T3 is 2.29 times the change observed between time T1 and T2 and it is in the opposite direction. Similarly, the change observed between T1 and T4 is .316 times change observed in T1 and T2 and is in opposite direction. Changes observed between T1 and T5, and T1 and T6 are respectively .58 and .152, times the change between T1 and T2 and are in the same direction. This trajectory changes its direction two times, thus the overall shape of the trajectory is cubic. Power distance, individuality, and masculinity have significant negative effects on the intercept latent variable, indicating that consultants in countries with high power distance, high individualism, and high masculinity have slower adoption. MAS and UAI also affect the growth of the trajectory (graphical results not shown).

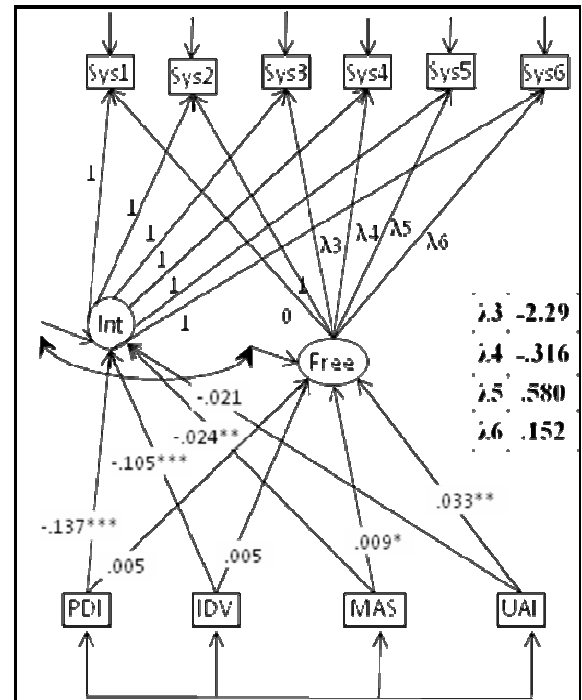


Figure 12-LCM3-TIC results for consultants

Power distance, individuality, and masculinity have significant negative effects on the intercept latent variable, indicating that consultants in countries with high power distance, high individualism, and high masculinity have slower adoption. MAS and UAI also affect the growth of the trajectory (graphical results not shown).

LCM3-TIC results for Managers and Senior Managers are shown in the Figure 13. that the results in table 2 indicated the the LCM3 model was the best fit for Managers and Senior Managers and in both the cases there was no significant variance in the slope latent variable. Thus, for both these groups TIC was used only for the intercept latent variable. For Managers (CFI=.995, NFI=.995, RMSEA=.024) and Senior Managers (CFI=.997, NFI=.996, RMSEA=.021) model fit indices were all better than recommended levels (CFI,

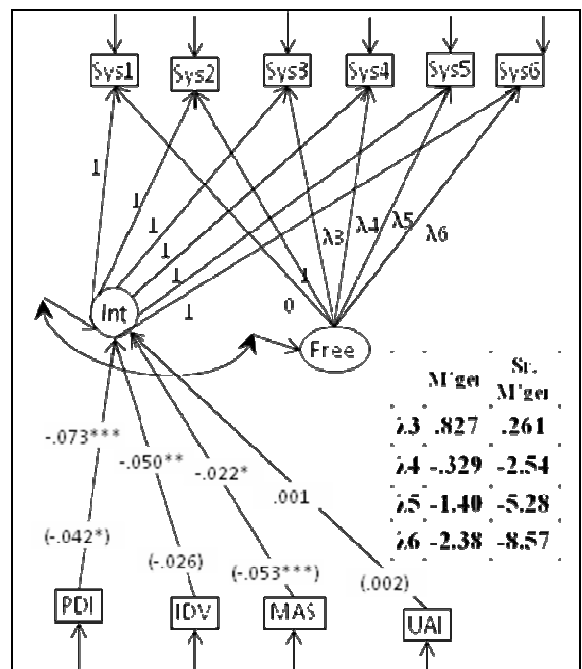


Figure 13-LCM3-TIC results for managers and senior managers (coefficients in parentheses)

NFI >.96 and RMSEA < .06). χ^2 values, however, were high (managers - 164, df=20, p<.001; senior managers - 88, df=22, p<.001). Free loadings for Managers are shown in column 2 of the embedded table and those for Senior Managers are in column 3. For both groups power distance and masculinity have a negative effect on the intercept latent variable.

For senior executives, Table 2 suggested a linear trajectory (LCM1) and both the intercept and linear slope latent variables had significant variance. Thus, TICs were used to predict both these latent variables. Model fit indices were good (CFI=.997, NFI=.995, RMSEA=.017) though χ^2 value was high (49, df=23, p=.002). In this case, none of the cultural dimensions had any effect either on intercept or on linear slope latent variables.

Figures 10, 12, 13 and 14 present an interesting story. As one moves upward in the hierarchy (i.e. from analyst to consultant ... to senior executive), the effect of cultural dimensions on technology adoption decreases. The adoption trajectories of analysts are most affected by the culture of their countries whereas the adoption patterns of senior executives are least affected. One possible interpretation of this result is that senior executives reflect more of a common culture (dominated by the firm’s culture) having had more international experience and exposure than junior staff.

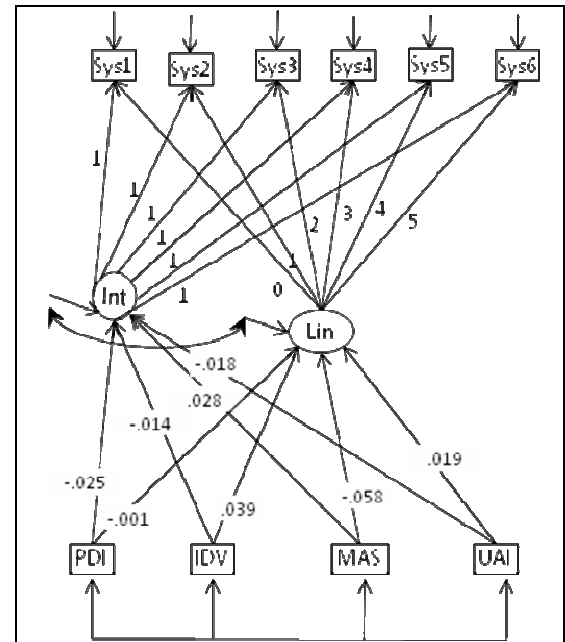


Figure 14-LCM1-TIC results for Sr executives

MLCM

Figure 15 demonstrates MLCM results examining usage patterns. In Figure 15, there are four boxes marked ‘A’, ‘B’, ‘C’ and ‘D’. Each of these boxes represents a growth process that affects a focal individual. Box ‘A’ represents his/ her own usage trajectory. Box ‘B’, ‘C’ and ‘D’ respectively represent his/ her subordinates’, supervisors’ and peers’ usage trajectories. The usage of an individual’s peers was calculated as the average usage of all the people in the same unit (same workgroup and same region) who had the same organizational status,

while superiors' and subordinates' usage were calculated as the average usage of all the people in the same unit who had higher and lower organizational status respectively.

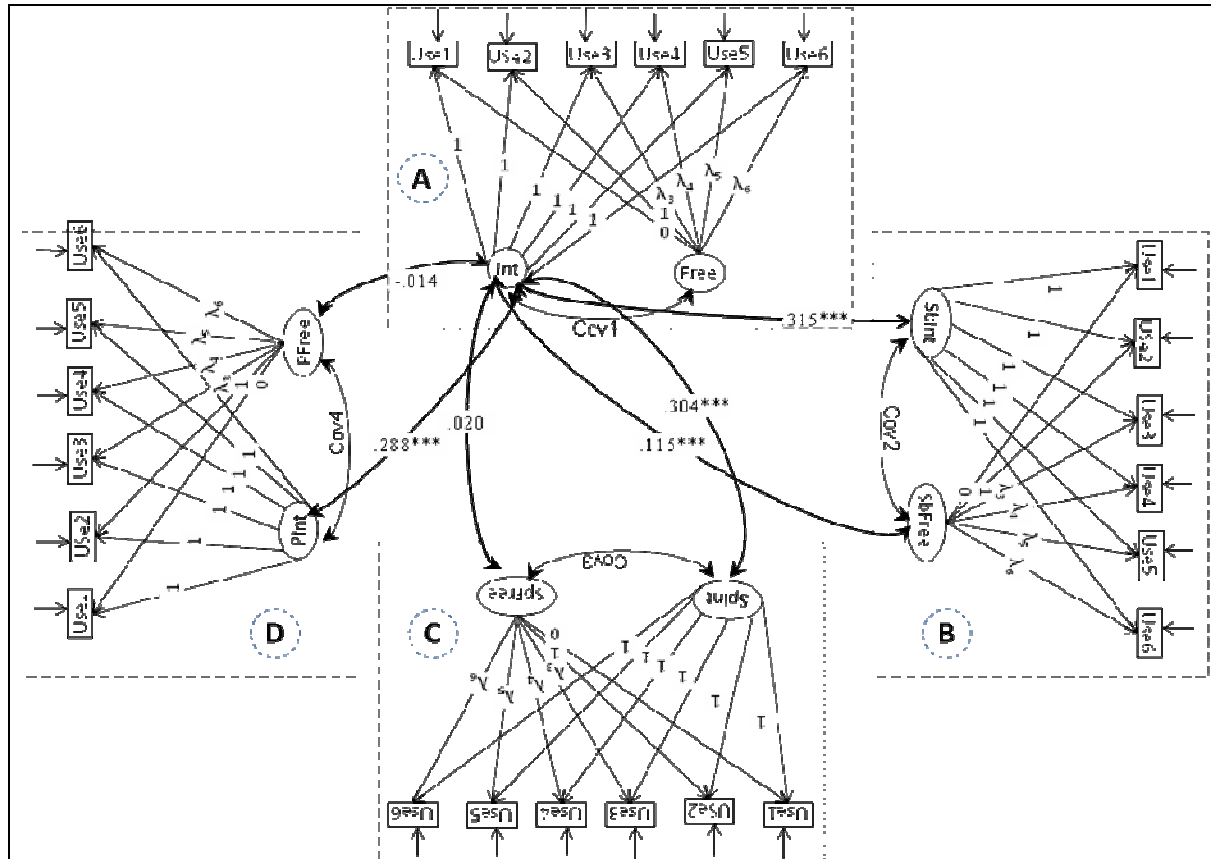


Figure 15-Multivariate latent curve model (MLCM)

We chose managers as the focal group because for them subordinates' usage and supervisors' usage both were meaningful growth processes (for analysts there would not be any subordinates and for senior executives there wouldn't be any supervisors). Each of these processes was separately and individually estimated to see whether LCM1, LCM2 or LCM3 fits for each of them. We found that for all of them LCM3 either had the best fit or was more parsimonious when more than one model fit equally well. For managers, there was significant variance only in the intercept latent variable and hence covariance between intercept (Int) for managers' usage and latent coefficients for their subordinates (SbInt, SbFree), their supervisors (SpInt, SpFree) and their peers (PInt and PFree) were estimated.

This model had moderate fit (CFI=.943, NFI=.943 and RMSEA=.103; $\chi^2=2433$, $df=189$, $p<.001$). The covariance indicates that the initial level of managers' usage is correlated to that of their subordinates ($r = .315$,

$p < .001$), their supervisors ($r = .304$, $p < .001$) and their peers ($r = .288$, $p < .001$). However, managers' initial usage is not related to growth patterns of their supervisors ($r = .020$, ns) nor to the growth patterns of their peers ($r = -.014$, ns). Managers' initial usage does affect their subordinates growth patterns strongly ($r = .115$, $p < .001$). These results indicate that individuals' initial usage is affected strongly by the initial usage of the individuals around them, whether they are their peers, subordinate or supervisors. However, initial usage of focal individuals (in this case, managers) does not affect growth patterns of others except their subordinates.

Concluding remarks

Longitudinal research is relatively rare in IS research, but is of great importance. To facilitate this kind of research, we have introduced an advanced statistical technique. As we demonstrated, Latent Curve Modeling appears to be a useful tool for IS researchers to detect the effects of latent variables on patterns over time as well as the interrelationships between patterns. It can be applied to a variety of research in the IS field. For instance, as shown in our example, it can be used to understand why there are different usage patterns of an information system. Another example application could be using it to examine IT professionals' performance over time and identify facilitators and/or inhibitors. There is a lot of potential in this technique awaiting IS researchers to explore. Since we have passed the phase of viewing IS as something new and entered an era where IS have become a continuous part of daily life in organizations, we believe Latent Curve Modeling will help research capture this essence of IS and contribute to the IS community greatly.

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