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CHANGES IN EMPLOYEES' JOB CHARACTERISTICS DURING AN ENTERPRISE SYSTEM IMPLEMENTATION: A LATENT GROWTH MODELING PERSPECTIVE

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Appendix A

An Overview of Latent Growth Modeling (LGM) Analysis

LGM has gained widespread acceptance in organizational research in recent years as an integrative approach to measure change (Bentein et al. 2005; Chan 1998; Jokisaari and Nurmi 2009; Lance, Meade, and Williamson 2000; Lance, Vandenberg, and Self 2000; Ployhart and Vandenberg 2010; Van Iddekinge et al. 2009). Unlike traditional techniques that measure change over two periods of time, LGM measures change over three or more periods of time and suggests a true change pattern and variations over time. Chan (1998) suggested that there are inherent limitations in a two-wave design because it cannot precisely indicate a change in a phenomenon because a trajectory of change cannot be identified and conceptualized from two waves of data. The most complex functional form that can be fitted is a straight line passing through two data points. A two-wave design essentially represents two snapshots of a phenomenon without allowing the assessment of intra-individual change process as it unfolds over time. In contrast, LGM offers precise information on intra-individual change over time by incorporating measurements from three or more time periods. Readers interested in further details related to LGM analyses are encouraged to consult the following articles and books: Chan (1998, 2002), Duncan et al. (2006), Lance, Meade, and Williamson (2000), Lance, Vandenberg, and Self (2000), Meredith and Tisak (1990), Ployhart and Vandenberg (2010), and Willett and Sayer (1994).

LGM overcomes many of the problems associated with traditional approaches to studying change, such as *t*-tests, ANOVA, lagged regression, and difference scores (Chan 1998; Lance, Meade, and Williamson 2000). For example, given that LGM is an SEM-based approach, it creates a latent change construct incorporating individual ratings for each focal construct over time, thus offering a true score for change that is free of measurement error. The traditional techniques, such as *t*-tests, ANOVA, lagged regression, and difference scores, measure change at the aggregate level and are not able to capture individual differences. LGM captures intra-individual change (i.e., change for each individual) by developing a trajectory of change in a focal construct for each individual over time. It also provides each individual's initial status on the construct. Further, LGM supports multivariate analysis of change to examine the interrelationships among changes in multiple focal constructs over time and the effects of change in one construct on the change in another construct. Finally, LGM provides the ability to model predictors and outcomes of change, thus helping us better understand the nature of change in a phenomenon of interest.

Following Chan (1998, 2002) and exemplars from prior research (Bentein et al. 2005; Jokisaari and Nurmi 2009; Lance, Vandenberg, and Self 2000; Van Iddekinge et al. 2009), we followed a three-step process to conduct the LGM analysis. Figure A1 summarizes these three steps.

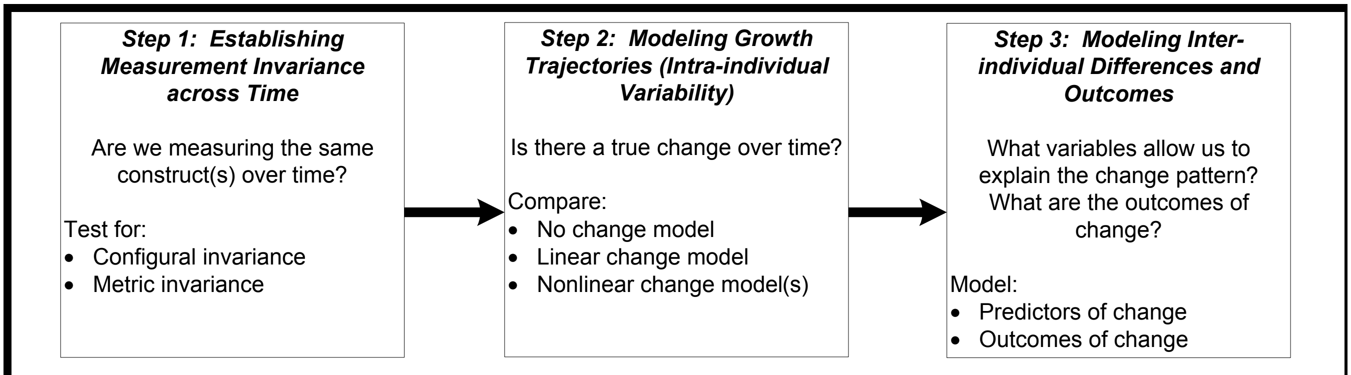

Figure A1. LGM Analysis Steps

Step 1: Establishing Measurement Invariance across Time

Given that the primary purpose of LGM analysis is to measure change in a construct over time, the first step is to establish whether we measured the same constructs over time. Measurement invariance is critical for LGM analysis to ensure unambiguous interpretation of change (Lance, Vandenberg, and Self 2000). Bentein et al. (2005) noted that measurement invariance within an LGM context is said to exist if (1) the nature of the construct that is operationalized by a measured variable remains unchanged across measurement occasions, that is, the measures demonstrate invariant construct validity over time, and (2) the relations between measures and their corresponding constructs are invariant across measurement occasions. These two criteria are called configural invariance and metric or factorial invariance, respectively (Bentein et al. 2005; Chan 1998; Lance, Meade, and Williamson 2000). If we have the same number of factors at each time with the same specific factor loadings on each factor, we have configural invariance (Chan 1998). If the factor loadings corresponding to the identical items are equal across time, we can establish metric invariance (Chan 1998).

We strictly followed the procedures outlined in Chan (1998) to test for configural and metric invariance. In particular, we undertook a series of SEM-based confirmatory factor analysis (CFA) nested model comparisons to evaluate various aspects of measurement invariance separately for job demands and job control. We used a k-item × three-occasion variance-covariance matrix, with indicator means as input data. We compared five nested models to establish measurement invariance across time and identify boundaries for possible functional forms of change trajectories in job demands and job control. Model 1 was a three-factor model in which (1) factors corresponded to measurement occasions; (2) items were constrained to load only on the respective measurement occasion factor—for example, T_0 items loaded only on the Time 0 factor; (3) the intercept for the first item within each measurement occasion was fixed equal to 0 (zero) to identify the mean of the respective factor; (4) same-item residuals were allowed to covary across measurement occasions to control for correlated specificities—for example, the residual for JDEM1 (T_0) was allowed to covary with item JDEM1 (T_2); and (5) factor loadings, error variances, factor means, and factor variances were freely estimated. An acceptable fit of Model 1 would indicate the unidimensional factor structure for job demands and job control over time—hence, configural invariance would be established (Chan 1998; Horn and McArdle 1992; Lance, Vandenberg, and Self 2000).

Model 2 was identical to Model 1 except that factor loadings for the same items were constrained to be equal across measurement occasions—for example, factor loading of JDEM1 (T_0) = factor loading of JDEM1 (T_2) = factor loading of JDEM1 (T_3). Given that Model 2 was nested within Model 1, the difference in chi-square values was used to test if there was any statistically significant change (i.e., reduction) in model fit from Model 1 to Model 2. If Model 2 did not differ significantly from Model 1, metric invariance was established because a significant worsening in fit would indicate inequivalence of factor loadings over time. Although Models 1 and 2 helped us establish configural and metric invariance, we tested three other models to identify the functional forms of change trajectories that would help us in steps 2 and 3 of the LGM analysis.

Given that Model 2 was a more constrained (parsimonious) model, it was preferred over Model 1 and the subsequent models were compared against it. Model 3 was equivalent to Model 2 except for error variances for the same items that were constrained to be equal across measurement occasions—for example, error variance for JDEM1 (T_0) = error variance for JDEM1 (T_2) = error variance for JDEM1 (T_3). Model 4 was equivalent to Model 2 except that it constrained all factor means to be equal across time. If Model 4 did not have a significant reduction in fit, it would indicate that there are no changes in factor means (i.e., no growth) for job demands and job control over time. Finally, Model 5 was equivalent to Model 2 except that Model 5 constrained the three factor variances to be equal across measurement occasions. Equal factor variances would indicate that individuals did not differ systematically in their individual slopes. Chan (1998, p. 434) noted that Models

Table A1. Tests of Measurement Invariance for Job Characteristics

Models	Job Chars.	X^2	df	Model Comparison	ΔX^2	Δdf	NNFI	CFI	RMSEA	SRMR
Model 1: Free factor loadings, error variances, factor means, factor variances	JDEM	32.7	39	–	–	–	.99	.99	.01	.02
	JCON	46.42	39	–	–	–	.99	.99	.02	.04
Model 2: Equal factor loadings, free error variances, factor means, factor variances	JDEM	39.21	45	1 vs. 2	6.51	6	.99	.99	.00	.02
	JCON	50.68	45	1 vs. 2	4.26	6	.99	.99	.02	.04
Model 3: Equal factor loadings, error variances, free factor means, factor variances	JDEM	579.48***	53	2 vs. 3	540.27***	8	.92	.93	.15	.04
	JCON	415.51***	53	2 vs. 3	364.83***	8	.94	.95	.13	.06
Model 4: Equal factor loadings, factor means, free error variances, factor variances	JDEM	322.12***	47	2 vs. 4	282.91***	2	.95	.97	.12	.10
	JCON	134.27***	47	2 vs. 4	83.59**	2	.98	.99	.07	.09
Model 5: Equal factor loadings, factor variances, free error variances, factor means	JDEM	42.40	47	2 vs. 5	3.19	2	.99	.99	.00	.02
	JCON	54.96	47	2 vs. 5	4.28	2	.99	.99	.02	.04

Notes: *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$. JDEM = Job Demands; JCON = Job Control.

1 and 2 were sufficient to establish measurement invariance in LGM, and the other models have more stringent requirements for measurement invariance which are "extremely demanding, and most researchers recognize that it is unrealistic to expect such extreme invariance to hold in actual data."

Table A1 presents the results of the tests of longitudinal measurement invariance for job demands and job control. The table shows five models corresponding to those discussed earlier. Consistent with Chan (1998), we used the chi-square difference test (ΔX^2) to compare the fit of two nested models. If the difference is not significant (i.e., there is no significant reduction in fit), the nested model is accepted because it is more parsimonious. Models 1 and 2 had acceptable fit for both job demands and job control—hence, configural and metric invariance were established for both job characteristics. Model 5 was the most parsimonious model—hence, the constraints in Model 5 were kept in place for the next step of LGM analysis.

Step 2: Modeling Growth Trajectories

Step 1 of the analysis provided us a basic growth model that adequately and parsimoniously described the form of change over time. In step 2, we conducted a multivariate LGM analysis in which we simultaneously modeled growth trajectories for job demands and job control.[1] Given that job demands and job control are from a single theoretical model (i.e., JSM), a multivariate LGM analysis was deemed appropriate as opposed to a univariate analysis in which growth trajectories for job demands and job control would be modeled separately. We created four second-order latent variables—two for each of the job characteristics. These second-order factors (SOFs) represented two important attributes of a variable's change trajectory: the intercept and the slope (Chan 1998). The intercept corresponded to the initial status of job demands and job control at T_0 (i.e., the true score of job demands and job control before the implementation of the SAP modules), and the slope corresponded to the changes in job demands and job control (i.e., the rate of increase or decrease of job demands and job control over time). We created six first-order factors (FOFs) representing the repeated latent variables (i.e., job demands and job control) over three periods of time. These were the factors used in step 1 for assessing measurement invariance.

Following Chan (1998) and Lance, Vandenberg, and Self (2000), we estimated models for four change functions (i.e., no-growth, linear growth, quadratic growth, and optimal growth) to determine for the nature of growth trajectories in job demands and job control (see Table 6 in the

[1]We also conducted univariate LGM analysis for job demands and job control separately and found virtually identical results, suggesting that there were no anomalies in the results when univariate models were combined (Bentein et al. 2005).

"Results" section). Here, the no-growth model is nested under the linear growth model, the linear growth model is nested under the quadratic and optimal growth model, and the optimal growth model is nested under the quadratic growth model. We also examined two FOF residual structures: (1) homoscedastic (i.e., error variances associate with FOFs are homogeneous over time), and (2) heteroscedastic. The homoscedastic structure models are nested under the heteroscedastic structure models. Model G1a and G2a indicated there were no changes in job demands and job control over time (no-growth model). In these models, the intercept had a fixed value of 1 for factor loadings across the measurement occasions because it is a constant for any given individual across time. The rest of the model was identical to the Model 5 that we developed in step 1. Per Table 6, Model G1a (no growth, heteroscedastic residual structure) had a better fit because there was significant reduction in fit for Model G1b (no growth, homoscedastic residual structure).

Models G2a and G2b were positive linear growth models. These models were equivalent to Models G1a and G1b respectively except that the slope factors were added for job demands and job control, and the factor loadings for the slopes were fixed as 0, 1, and 2, representing three equally spaced measurement occasions. This provided us a linear change trajectory. As shown in Table 6, the chi-square difference between Models G1a and G2a was significant, suggesting that the linear growth model (G2a) had a better fit, and there were at least linear growth trajectories in job demands and job control. Between Models G2a (linear growth, heteroscedastic residual structure) and G2b (linear growth and homoscedastic residual structure), Model G2a had a slightly better fit ($\Delta X^2 = 9.81$, $\Delta df = 4$, $p < .05$). However, fit indexes were identical (see Table 6). Given that Figure 3 shows curvilinearity in both plots, we continued our analysis to model nonlinear growths in job demands and job control.

Models G3a and G3b were quadratic growth models. In these models, two factors corresponding to the quadratic term were added for job demands and job control and the factor loadings for these quadratic factors were fixed as 0, 1, and 4 (squaring the slope factor loadings) to find a positively accelerated quadratic trajectory. These models were unidentified because adding the quadratic term increased the number of parameters to be estimated and the models did not have enough degrees of freedom because of three measurement occasions. Following Duncan et al. (2006), it was possible to have a perfectly identified model by constraining the FOF error variances to be zero. However, this would create an unrealistic growth model because it would be unlikely that there were no variances in individuals' assessment of job demands and job control. Further, we found in step 1 that error variances associated with job demands and job control were indeed significant ($p < .001$) across time.

In fact, polynomials (with squared or other higher-order terms) are not the only way to model nonlinear growth functions (Chan 1998; Duncan et al. 2006; Lance, Vandenberg, and Self 2000). It is possible to create an optimal growth model by freely estimating the slope factor loadings for the latter measurement occasions. This will allow us to determine the nature of the growth based on the empirical data. For instance, for three waves of data collection, the FOF's loadings for the first two measurement occasions on the slope factor can be set to 0 and 1 and the loadings for the third measurement occasion on the slope factor can be freely estimated (see Figure A2). The first two measurement occasions' FOF loadings need to be fixed as reference points to identify the proportionality of measurement intervals (Lance, Vandenberg, and Self 2000). If this model fits well and is better than the linear growth model, the freely estimated loading is used as a weight of the slope to determine the overall change in the latent variable during the study duration (Duncan et al. 2006; McArdle and Nesselroade 2003). More details about the optimal growth model can be found in prior exemplars: Bentein et al. (2005), Jokisaari and Nurmi (2009), Lance, Vandenberg, and Self (2000), and Van Iddekinge et al. (2009).

Models G4a and G4b were optimal growth models in which the first two factor loadings on the slope factors for job demands and job control were fixed at 0 and 1 (for the first two time periods) and the third one (for the third time period) was freely estimated (L1 and L2 in Figure A2). Model G4a (optimal growth, heteroscedastic residual structure) failed to converge to an admissible solution. Hence, we compared Models G4b (optimal growth, homoscedastic residual structure) and G2b (linear growth, homoscedastic residual structure) and found that Model G4b had the overall best fit, suggesting a nonlinear growth trajectory for both job demands and job control. These findings are further discussed in the "Results" section.

Step 3: Modeling Predictors and Outcomes of Growth Trajectories

In step 3, we added the predictors and outcomes of the latent change constructs to the optimal growth model created in step 2. In particular, we added (1) technology characteristics and pre-implementation process characteristics as predictors of post-implementation work process characteristics, (2) pre-implementation process characteristics and post-implementation process characteristics as predictors of changes in job demands and job control, and (3) pre-implementation job satisfaction and changes in job demands and job control as predictors of post-implementation job satisfaction. A pre-implementation measure of perceived process radicalness was not included because perceived process radicalness was measured only post-implementation to capture the degree of newness of post-implementation work processes. The rest of the model and constraints was identical to the model developed in step 2. Findings from step 3 are reported in the "Results" section.

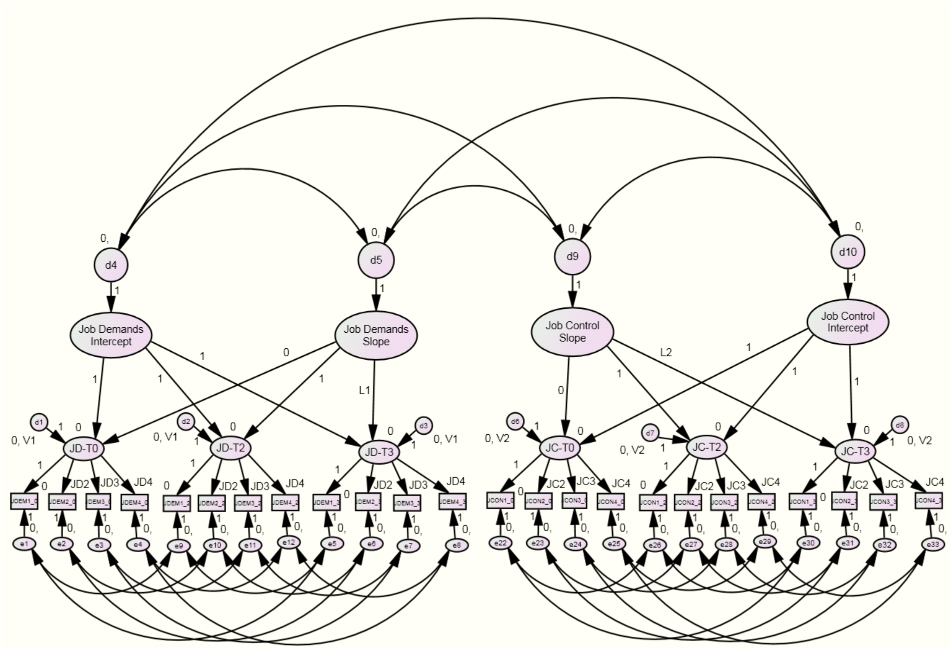

Figure A2. Optimal Growth Model Estimation in LGM

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Appendix B

Item Loadings

Construct	Items	T_0			T_1			T_2			T_3		
		Org. A (N = 281)	Org. B (N = 141)	Pooled (N = 422)	Org. A (N= = 281)	Org. B (N = 141)	Pooled (N = 422)	Org. A (N = 281)	Org. B (N = 141)	Pooled (N = 422)	Org. A (N = 281)	Org. B (N = 141)	Pooled (N = 422)
Perceived technology complexity (TCOMP)	TCOMP1	–	–	–	.91	.85	.89	–	–	–	–	–	–
	TCOMP2	–	–	–	.89	.95	.91	–	–	–	–	–	–
	TCOMP3	–	–	–	.86	.84	.87	–	–	–	–	–	–
	TCOMP4	–	–	–	.90	.82	.88	–	–	–	–	–	–
Perceived technology reconfigurability (TRCNF)	TRCNF1	–	–	–	.89	.92	.90	–	–	–	–	–	–
	TRCNF2	–	–	–	.86	.91	.88	–	–	–	–	–	–
	TRCNF3	–	–	–	.84	.90	.87	–	–	–	–	–	–
	TRCNF4	–	–	–	.89	.83	.87	–	–	–	–	–	–
Perceived technology customization (TCUST)	TCUST1	–	–	–	.92	.88	.91	–	–	–	–	–	–
	TCUST2	–	–	–	.89	.84	.88	–	–	–	–	–	–
	TCUST3	–	–	–	.89	.88	.91	–	–	–	–	–	–
	TCUST4	–	–	–	.86	.87	.85	–	–	–	–	–	–
Perceived process complexity (PCOMP)	PCOM1	.95	.92	.94	.92	.89	.91	–	–	–	–	–	–
	PCOM2	.91	.90	.91	.88	.87	.88	–	–	–	–	–	–
	PCOM3	.92	.89	.92	.87	.88	.88	–	–	–	–	–	–
	PCOM4	.90	.84	.88	.76	.72	.75	–	–	–	–	–	–
Perceived process rigidity (PRGDT)	PRGDT1	.93	.93	.94	.84	.87	.85	–	–	–	–	–	–
	PRGDT2	.94	.92	.94	.86	.83	.83	–	–	–	–	–	–
	PRGDT3	.94	.91	.93	.90	.90	.90	–	–	–	–	–	–
	PRGDT4	.93	.92	.93	.89	.92	.91	–	–	–	–	–	–
Perceived process radicalness (PRDCL)	PRDCL1	–	–	–	.91	.92	.92	–	–	–	–	–	–
	PRDCL2	–	–	–	.85	.95	.87	–	–	–	–	–	–
	PRDCL3	–	–	–	.89	.84	.86	–	–	–	–	–	–
	PRDCL4	–	–	–	.88	.88	.88	–	–	–	–	–	–
Job demands (JDEM)	JDEM1	.91	.91	.93	–	–	–	.88	.88	.87	.92	.91	.92
	JDEM2	.92	.94	.95	–	–	–	.90	.91	.90	.95	.93	.93
	JDEM3	.90	.95	.94	–	–	–	.88	.90	.89	.93	.92	.93
	JDEM4	.89	.94	.95	–	–	–	.89	.90	.89	.93	.93	.92
Job control (JCON)	JCON1	.95	.96	.93	–	–	–	.93	.94	.94	.95	.95	.92
	JCON2	.97	.96	.96	–	–	–	.93	.92	.93	.94	.94	.95
	JCON3	.94	.94	.94	–	–	–	.93	.93	.93	.94	.93	.94
	JCON4	.96	.97	.96	–	–	–	.92	.93	.93	.96	.95	.95
Job satisfaction (JSAT)	JSAT1	.86	.83	.84	–	–	–	–	–	–	.86	.85	.85
	JSAT2	.84	.84	.85	–	–	–	–	–	–	.88	.84	.86
	JSAT3	.85	.86	.86	–	–	–	–	–	–	.89	.86	.88

Note: All cross loadings were less than .35.

Appendix C

Controlling Common Method Biases

Techniques	Actions Taken
Procedural Remedies	
Temporal, proximal, psychological, or methodological separation of measurement	We measured the key dependent variables (i.e., job characteristics) separately from the independent variables. For instance, job characteristics were measured at T_0, T_2, and T_3, and technology and work process characteristics were measured at T_1.
Protecting respondent anonymity and reducing evaluation apprehension	We informed the participants that their responses would be confidential, assured them that there were no right or wrong answers, and requested that they answer questions as honestly as possible.
Counterbalancing question order	We counterbalanced the items by randomizing them within each survey block. We also randomized the survey blocks. For example, items within technology characteristics were randomized, and the blocks for technology characteristics and work process characteristics were randomized.
Improving scale items	We used pre-validated reliable items (see discussion of measurement) and provided definitions and examples for potentially unfamiliar terms.
Statistical Remedies	
Harman's single factor test	The Harman's single factor test indicated that there was no single factor that explained most of the variance. The first factor explained only 26% of the variance.
Partial correlation procedure (e.g., marker variable technique)	Given that we did not include any constructs that were completely theoretically unrelated to one or more constructs in our model to reduce the survey length, we, following Pavlou et al. (2007), used a construct that was not part of our model and was weakly related to other constructs in the model—namely, *organizational tenure*. We compared the correlation between organizational tenure and other constructs in the study and did not find any significant correlations. The average correlation was .09, thus indicating that there was no evidence of common method bias.
Controlling for the effects of an unmeasured latent methods factor (i.e., single-common-method-factor approach; Podsakoff et al. 2003)	We did not find a good fit for the models when we used the single-common-method-factor approach. For example, the model fit indexes at T_0 were: $\chi^2 = 441.64$, $p < .001$, CFI = .82, NNFI = .72, SRMR = .18, RMSEA = .22.

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