An overview of longitudinal data analysis (LDA)



Dr. Mahmoud Danaee

Longitudinal study

- A longitudinal study is a research strategy in which the same variables (e.g., *individuals*) are observed repeatedly over a short or long period of time (i.e., uses longitudinal data).
- It's usually an observational research, although it may also take the form of a longitudinal randomized experiment

 In a longitudinal study, researchers repeatedly examine the same individuals to detect any changes that might occur over a period of time.



EFFECTS OF ECCENTRIC CYCLING PERFORMED AT LONG VS. SHORT MUSCLE LENGTHS ON HEART RATE, RATE PERCEIVED EFFORT, AND MUSCLE DAMAGE MARKERS

LUIS PEÑAILILLO,¹ CAROLINA AEDO,¹ MAYARI CARTAGENA,¹ ALEJANDRA CONTRERAS,¹ Alvaro Reyes,² Rodrigo Ramirez-Campillo,³ Jacob E. Earp,⁴ and Hermann Zbinden-Foncea¹



Organisational Stressors, Coping, and Coping Effectiveness: A Longitudinal Study with an Elite Coach

Andrew Levy¹, Adam Nicholls², David Marchant³ and Remco Polman⁴



Figure 3. Coping Effectiveness Reported Over 28-Day Period

Longitudinal 2-Year Follow-up on the Effect of a Non-Randomised School-Based Physical Activity Intervention on Reducing Overweight and Obesity of Czech Children Aged 10–12 Years

Erik Sigmund †,* and Dagmar Sigmundová †



Longitudinal and Time-Series Analysis



Longitudinal analysis is concerned with studying the progression of the values of a variable over time for the members of a population.



If time is defined as a **categorical variable**, longitudinal analysis is closely related to multivariate analysis, studying **vectors of outcomes**.



When time is a **continuous variable**, longitudinal analysis studies the <mark>subjects' curves</mark> (trajectories), and random coefficient models are well suited for this purpose

Data analysis approaches





T test & One way ANOVA (method 1)



Department of Social and Preventive Medicine

-2.842

5.158

.809

.886

4.803

.153

276

.134

.180

4742

Analysis of Covariance (Method 2)

 ANCOVA is commonly used for analysis of pretestposttest designs in which groups are compared at posttest, using pretest scores as the covariate to control for pre-existing differences on the dependent variable



- ANCOVA is sometimes recommended with experimental research (e.g., Huitema, 2011; Maxwell & Delaney, 1990), where inclusion of covariates can have the effect of reducing the mean square error and
- thus increasing the power of the analysis
- Among the methods, ANCOVA-POST is generally regarded as the preferred approach, given that it typically leads to unbiased treatment effect estimate with the lowest variance relative to <u>ANOVA-POST or ANOVA-CHANGE</u>

Assumption of ANCOVA

- linearity of regression
- Homogeneity of error variances
- Independence of error terms
- Normality of error terms
- Homogeneity of regression slopes (when you have more than 1 group)





b. Computed using alpha = .05

Test of Regression Slopes



Violation of the homogeneity of regression slopes assumption in ANCOVA for two-group pre-post designs: Tutorial on a modified Johnson-Neyman procedure

Teresa R. Johnson^{a, 20} ^aJohns Hopkins University School of Medicine, Baltimore

https://www.tqmp.org/RegularArticles/vol12-3/p253/p253.pdf

Drawing of Regression Slopes



Repeated Measures ANOVA (Method 3)

Repeated Measures ANOVA – one-way ANOVA but the same subjects are measured in each group.

In repeated measures subjects serve as their own controls.own controls.

- Differences in means must be due to:
- Treatment variations
- Within subject's variations
- within subject's error (unexplained variation)error

Repeated measures designs are more powerful than independent groups designs.



One-way RM-ANOVA/ MANOVA

Two-way RM-ANOVA /MANOVA

Three-way RM-ANOVA / MANOVA



Comparison to One-Way ANOVA

- Other assumptions hold (e.g., normality, equal variance), but sphericity is an added assumption.
 - Sphericity means data are uncorrelated.
- Counterbalancing may be needed.
- η^2 is interpreted the same way as for one-way ANOVA.
- Post-hoc t-tests need to be for paired samples, not independent groups.

Assumptions

The following assumptions are made when using the F-test.

- 1. The response variable is continuous.
- 2. The eijk follow the normal probability distribution with mean equal to zero.
- 3. The variances of the eijk are equal for all values of i, j, and k.
- 4. The individuals are independent

RM-ANOVA using SPSS



Repeated Measur	es: Model	Profile Plots				
Specify Model		Eactors:		Horizontal Axis:		
Eull factorial	© <u>B</u> uild terms	Group		TIME		
Retween-Subjects	Between	Casaling		Separate Lines:		
u ^t Group	Detween			Group		
			2	Segarate Plots:		
1	Build Term(s)	Plots:	Add Ch	ange Remove		
	Interaction 🔻	TIME*Group				
		- Chad Tupe'				
+	By* (Within)	Line Char	t			
Build Term	ta Repeated Measures: Estimated	d Marginal Me	tans	×		
	Estimated Marginal Means					
	Estimated Marginal Means	ins:	Display <u>M</u> eans fo	r		
	Estimated Marginal Means Eactor(s) and Factor Interaction	ins:	Display <u>M</u> eans fo Group	r		
	Estimated Marginal Means Eactor(s) and Factor Interactio (OVERALL) Group	ins:	Display <u>M</u> eans fo Group TIME	r.		
	Estimated Marginal Means — Eactor(s) and Factor Interaction (OVERALL) Group TIME CroupsTIME	ins:	Display <u>M</u> eans fo Group TIME Group*TIME	r.		
	Estimated Marginal Means Eactor(s) and Factor Interaction (OVERALL) Group TIME Group*TIME	ins:	Display <u>M</u> eans fo Group TIME Group*TIME	r.		
	Estimated Marginal Means		Display <u>Means</u> fo Group TIME Group*TIME	r. n effects		
	Estimated Marginal Means		Display <u>Means</u> fo Group TIME Group*TIME ✓ Compare mai	r. n effects		
	Estimated Marginal Means	ns:	Display <u>Means</u> fo Group TIME Group*TIME ✓ Compare mai Confidence interv	r: n effects ral adjustment.		
	Estimated Marginal Means Eactor(s) and Factor Interaction (OVERALL) Group TIME Group*TIME	ons:	Display <u>Means</u> fo Group TIME Group*TIME ✓ Compare mai Confidence interv LSD(none)	r. n effects ral adjustment		
	Estimated Marginal Means Eactor(s) and Factor Interaction (OVERALL) Group TIME Group*TIME	ons:	Display <u>Means</u> fo Group TIME Group*TIME ✓ Compare mai Confidence interv LSD(none) LSD(none) Bonferroni	r. n effects ral adjustment.		

- 1. You can specify and customize the model
- 2. Defining the graph (line & bar)
- 3. EM Mean calculation and comparison

Modified syntax for pairwise comparison

- DATASET ACTIVATE DataSet1.
- GLM PRE.KN.T POST.KN.T FLW1.KN.T FLW2.KN.T BY Group
- /WSFACTOR=TIME 4 Polynomial
- /METHOD=SSTYPE(3)
- /PLOT=PROFILE(TIME*Group) TYPE=LINE ERRORBAR=NO MEANREFERENCE=NO YAXIS=AUTO
- /EMMEANS=TABLES(Group*TIME) COMPARE (Group) ADJ(LSD)
- /EMMEANS=TABLES(Group*TIME) COMPARE (Time) ADJ(LSD)
- /EMMEANS=TABLES(Group*TIME)
- /PRINT=DESCRIPTIVE ETASQ OPOWER HOMOGENEITY
- /CRITERIA=ALPHA(.05)
- /WSDESIGN=TIME
- /DESIGN=Group.

Pairwise Comparisons

Measure: MEASURE_1

			Mean			95% Confidence Interval for Difference ^b			
TIME	(I) Group	(J) Group	J) JImerence	Std. Error	Sig. ^b	Lower Bound	Upper Bound		
1	1.0	2.0	.037	.258	.887	474	.548		
	2.0	1.0	037	.258	.887	548	.474		
2	1.0	2.0	7.064	.338	.000	6.394	7.734		
	2.0	1.0	-7.064	.338	.000	-7.734	-6.394		
3	1.0	2.0	7.139	.245	.000	6.654	7.624		
	2.0	1.0	-7.139	.245	.000	-7.624	-6.654		
4	1.0	2.0	6.914	.256	.000	6.408	7.420		
	2.0	1.0	-6.914	.256	.000	-7.420	-6.408		

Baseli on estimated marginal means

*. The mean difference is significant at the .05 level.

b. Adjustment for multiple comparisons: Least Significant Difference (equivalent to no adjustments).

Univariate Tests

Measure: MEASURE_1											
TIME	Sum TIME Squa		df Mean Square F Sig. Partial Eta Squared		Noncent. Parameter	Dbserved Power ^a					
1	Contrast	.042	1	.042	.020	.887	.000	.020	.052		
	Error	256.406	123	2.085							
2	Contrast	1559.280	1	1559.280	436.016	.000	.780	436.016	1.000		
	Error	439.872	123	3.576							
3	Contrast	1592.458	1	1592.458	848.114	.000	.873	848.114	1.000		
	Error	230.950	123	1.878							
4	Contrast	1493.751	1	1493.751	731.715	.000	.856	731.715	1.000		
	Error	251.097	123	2.041							

Each F tests the simple effects of Group within each level combination of the other effects shown. These tests are based on the linearly independent pairwise comparisons among the estimated marginal means.

a. Computed using alpha = .05

ſ				Pairwis	e Compari	sons			
	Meas	ure: MEAS	URE_1						
				Mean Difference (I-			95% Confidence Interval for Difference ^b		
П	Grou	p (I) TIME	(J) TIME	J)	Std. Error	Sig. ^b	Lower Bound	Upper Bound	
Ш	1.0	1	2	-7.710	.273	.000	-8.250	-7.169	
Ш			3	-7.419	.235	.000	-7.885	-6.953	
4			4	-7.258	.247	.000	-7.748	-6.768	
		2	1	7.710	.273	.000	7.169	8.250	
			3	.290	.256	.259	216	.797	
			4	.452	.271	.098	085	.988	
		3	1	7.419	.235	.000	6.953	7.885	
			2	290	.256	.259	797	.216	
			4	.161	.120	.182	077	.399	
		4	1	7.258	.247	.000	6.768	7.748	
	_		2	452	.271	.098	988	.085	
			3	161	.120	.182	399	.077	
	2.0	1	2	683	.271	.013	-1.219	146	
Ц			3	317	.234	.177	780	.145	
			4	381	.245	.123	867	.105	
		2	1	.683	.271	.013	.146	1.219	
			3	.365	.254	.153	137	.868	
			4	.302	.269	.264	231	.834	
		3	1	.317	.234	.177	145	.780	
			2	365	.254	.153	868	.137	
			4	063	.119	.595	299	.172	
		4	1	.381	.245	.123	105	.867	
			2	302	.269	.264	834	.231	
			3	.063	.119	.595	172	.299	

Based on estimated marginal means

*. The mean difference is significant at the .05 level.

b. Adjustment for multiple comparisons: Least Significant Difference (equivalent to no adjustments).

Group		Value	F	Hypothesis df	Error df	Sig.	Fartial Eta Squared	Noncent. Parameter	Observed Power ^b
1.0	Pillai's trace	.908	395.946 ^a	3.000	121.000	.000	.908	1187.837	1.000
	Wilks' lambda	.092	395.946 ^a	3.000	121.000	.000	.908	1187.837	1.000
	Hotelling's trace	9.817	395.946 ^a	3.000	121.000	.000	.908	1187.837	1.000
	Roy's largest root	9.817	395.946ª	3.000	121.000	.000	.908	1187.837	1.000
2.0	Pillai's trace	.052	2.223 ^a	3.000	121.000	.089	.052	6.669	.552
	Wilks' lambda	.948	2.223 ^a	3.000	121.000	.089	.052	6.669	.552
	Hotelling's trace	.055	2.223ª	3.000	121.000	.089	.052	6.669	.552
	Roy's largest root	.055	2.223ª	3.000	121.000	.089	.052	6.669	.552



- ANCOVA /MANCOVA
- RM ANOVA /MANOVA /ANCOVA/MANCOVA

Data analysis approaches



Comparison of traditional and new methods

Table 1. Comparison of Traditional and Mixed-Effects Approaches for the Analysis of Repeated-Measures Data

	End-Point Analysis	rANOVA	rMANOVA	Mixed-Effects Analysis
Complete data required on every subject	Yes	No*	Yes	No
Possible effect of omitting subjects with missing values	Sample bias	Sample bias	Sample bias	Not applicable†
Possible effects of imputation of missing data	Estimation bias	Estimation bias	Estimation bias	Not applicable†
Subjects measured at different time points	Yes	No	No	Yes
Description of time effect	Simple	Flexible	Flexible	Flexible
Estimation of individual trends	No	No	No	Yes
Restrictive assumptions about correlation pattern	Not applicable	Yes	No	No
Time-dependent covariates	No	Yes	No	Yes
Ease of implementation	Very easy	Easy	Easy	Hard
Computational complexity	Low	Low	Medium	High

Abbreviations: rANOVA, univariate repeated-measures analysis of variance; rMANOVA, multivariate repeated-measures analysis of variance. *Subjects with missing data are often omitted from the analysis.

†It is not necessary to omit subjects with missing values from the analysis or to impute missing values.

FROM:

Ralitza Gueorguieva, PhD; John H. Krystal, MD Move Over ANOVA : Progress in Analyzing Repeated-Measures Data and Its Reflection in Papers Published in the Archives of General Psychiatry. Arch Gen Psychiatry. 2004;61:310-317.



Generalized Estimating Equations

Introduction to randomised controlled trial (RCT) design

Generalized Linear Models

- The generalized linear model expands the general linear model so that the dependent variable is linearly related to the factors and covariates via a specified link function. Moreover, the model allows for the dependent variable **to have a non-normal distribution**
- It covers widely used statistical models, such as linear regression for normally distributed responses, logistic models for binary data, loglinear models for count data, complementary log-log models for interval-censored survival data, plus many other statistical models through its very general model formulation.\

Introduction to randomised controlled trial (RCT) design

The general linear model make the 5 assumptions below. When these assumptions are met, OLS regression coefficients are MVUE (Minimum Variance Unbiased Estimators) and BLUE (Best Linear Unbiased Estimators).

1. Exact X: The IVs are assumed to be known exactly (i.e., without measurement error)

<u>1. Independence</u>: Residuals are independently distributed (prob. of obtaining a specific observation does not depend on other observations)
 <u>3. Normality</u>: All residual distributions are normally distributed

<u>4. Constant variance</u>: All residual distributions have a constant variance, SEE²

<u>5. Linearity</u>: All residual distributions (i.e., for each Y') are assumed to have means equal to zero

Introduction to randomised controlled trial (RCT) design

Problems and Solutions

<u>Normality</u>: Inefficient (with large N). Use power transformations, generalized linear models

<u>Constant variance</u>: Inefficient and inaccurate standard errors. Use power transformations, SE corrections, weighted least squares , generalized linear models

Linearity: Biased parameter estimates. Use power transformations, polynomial regression, generalized linear models

- The generalized linear model expands the general linear model so that the dependent variable is linearly related to the factors and covariates via a specified link function.
- The link function is a transformation of the dependent variable that allows estimation of the model. The following functions are available

- Identity. f(x)=x. The dependent variable is not transformed. This link can be used with any distribution.
- Complementary log-log. f(x)=log(-log(1-x)). This is appropriate only with the binomial distribution.
- Cumulative complementary log-log. f(x)=ln(-ln(1-x)), applied to the cumulative probability of each category of the response. This is appropriate only with the multinomial distribution.
- Cumulative logit. f(x)=ln(x / (1-x)), applied to the cumulative probability of each category of the response. This is appropriate only with the multinomial distribution.

- Cumulative negative log-log. f(x)=-ln(-ln(x)), applied to the cumulative probability of each category of the response. This is appropriate only with the multinomial distribution.
- Cumulative probit. f(x)=Φ-1(x), applied to the cumulative probability of each category of the response, where Φ-1 is the inverse standard normal cumulative distribution function. This is appropriate only with the multinomial distribution.
- Log. f(x)=log(x). This link can be used with any distribution.
- Log complement, f(x)=log(1-x). This is appropriate only with the binomial distribution.
- Logit. f(x)=log(x / (1-x)). This is appropriate only with the binomial distribution.

- Negative binomial. f(x)=log(x / (x+k −1)), where k is the ancillary parameter of the negative binomial distribution. This is appropriate only with the negative binomial distribution.
- Negative log-log. f(x)=-log(-log(x)). This is appropriate only with the binomial distribution.
- Odds power. f(x)=[(x/(1-x))α-1]/α, if α ≠ 0. f(x)=log(x), if α=0. α is the required number specification and must be a real number. This is appropriate only with the binomial distribution.
- Probit. f(x)=Φ-1(x), where Φ-1 is the inverse standard normal cumulative distribution function. This is appropriate only with the binomial distribution.
- Power. f(x)=x α, if α ≠ 0. f(x)=log(x), if α=0. α is the required number specification and must be a real number. This link can be used with any distribution.

Types of outcome/DV in GEE

- Scale Response. The following options are available:
- Linear. Specifies Normal as the distribution and Identity as the link function.
- Gamma with log link. Specifies Gamma as the distribution and Log as the link function.
- **Ordinal Response.** The following options are available:
- **Ordinal logistic.** Specifies Multinomial (ordinal) as the distribution and Cumulative logit as the link function.
- **Ordinal probit.** Specifies Multinomial (ordinal) as the distribution and Cumulative probit as the link function.
- **Counts.** The following options are available:
- **Poisson loglinear.** Specifies Poisson as the distribution and Log as the link function.
- **Negative binomial with log link.** Specifies Negative binomial (with a value of 1 for the ancillary parameter) as the distribution and Log as the link function. To have the procedure estimate the value of the ancillary parameter, specify a custom model with Negative binomial distribution and select **Estimate value** in the Parameter group.
- **Binary Response or Events/Trials Data.** The following options are available:
- **Binary logistic.** Specifies Binomial as the distribution and Logit as the link function.
- **Binary probit.** Specifies Binomial as the distribution and Probit as the link function.
- Interval censored survival. Specifies Binomial as the distribution and Complementary log-log as the link function.
- **Mixture.** The following options are available:
- **Tweedie with log link.** Specifies Tweedie as the distribution and Log as the link function.
- **Tweedie with identity link.** Specifies Tweedie as the distribution and Identity as the link function.

GEE

m	<u>A</u> nalyze	<u>G</u> raphs	<u>U</u> tilities	Extensions	Windo	w <u>H</u>	elp			
-	Repo	rts		•			A (
	D <u>e</u> sc	riptive Stati	stics	•			1			
	<u>B</u> aye:	sian Statist	ics	•						
G	Ta <u>b</u> le	S		•		Mar	ried A	. No C	hildr	
	Co <u>m</u>	oare Means	3	•	**			49		
	<u>G</u> ene	ral Linear N	lodel	•			ye	ei		
	Gene	Generalized Linear Models				neralize	ed Linear I	Models		
	Mi <u>x</u> eo	Mi <u>x</u> ed Models ▶			Generalized Estimating Equations					
	<u>C</u> orre	late		*			2 00		00	

Repeated Type of Model	Response Predictors Model Estimation Statistics EM Means Save Export	^
Variables: Group Age Edu Married Age Mo. Children Ø DV. PRE Ø NXI.PRE	Subject variables:	
	Magimum iterations: 100 W Updatg matrix Iterations between updates: Convergence Criteria	

Introduction to randomised controlled trial (RCT) design

Working Correlation Matrix

- This correlation matrix represents the within-subject dependencies.
- Its size is determined by the number of measurements and thus the combination of values of within-subject variables.

Repeated measurements have a first-order **autoregressive relationship**. The correlation between any two elements is equal to rho for adjacent elements, rho2 for elements that are separated by a third, and so on.



ta Generalized Estimating Equations

Repeated Type of Model Re	esponse Predictors Model Estimation Statistics EM Means Save Export
<u>V</u> ariables:	<u>S</u> ubject variables:
 ♣ Group ♠ Age ♠ Edu ♠ Married.Age ♠ No Childrep 	▶ ● ● ● ● ●
DV PRE	Within-subject variables:
ANXI.PRE	✓ time ✓ time ✓ time
	Sort cases by subject and within-subject variables
	Covariance Matrix
	Robust estimator Image: Constraint of the section o
	Working Correlation Matrix Structure: Independent M: Adjust es Independent AR(1) Maximum ite Exchangeable
	Update n M-dependent Unstructured Unstructured
	At least one convergence criterion must be specified with a minimum greater than zero.
	Minimum: Type: Change in parameter estimates 1E-006 Hessian convergence Absolute
	OK Paste Reset Cancel Help

1 : Enter your subject's ID

2- Within subject variable (Time)

3 : define the type of correlation matrix

 \times

The response can be scale, counts, binary, or events-in-trials. Factors are assumed to be categorical. The covariates, scale weight, and offset are assumed to be scale.

Generalized Linear Models											×	
	Type of Model	Response	Predictors	Model	Estimation	Statistics	EM Means	Save	Export			
	Choose one of	f the model ty	pes listed be	low or sp	ecify a custo	m combinat	tion of distrib	ution ar	id link fund	ction.		
	🔗 Scale Resp	oonse			d	Ordinal R	esponse —					
	Linear					© <u>O</u> rdinal I	ogistic					
	© <u>G</u> amma w	vith log link				© Or <u>d</u> inal µ	probit					
	∦í Counts —				o	Binary Re	sponse or E	/ents/Tr	ials Data			
	© Poi <u>s</u> son loglinear © <u>B</u> inary logistic											
	© Negative binomial with log link © Binary probit											
Mixture O Interval censored survival												
	O Tweedie v	with log link										
	⊂ © T <u>w</u> eedie v	with identity lin	nk									
	Street Custom											
	© Custom											
	<u>o</u> ustani											
	Distribu	tion: Norn	nal	T	Link <u>f</u> unctio	n: Identif	ty			T		
	Par	rameter			Powe	r:						
	۲	Specify value			_							
	Va	alue: 1										
	0	Esti <u>m</u> ate valu	le									
			(ОК	Paste R	eset Car	ncel Help					

✓ ID Dependent Variable ✓ Group Age ✓ Edu ✓ Anxi.PRE ✓ Married.Age Category order (multinomial only): ✓ No.Children ✓ Ine ✓ DV.PRE Ø Binary ✓ Reference Category ⑧ Number of events occurring in a set of trials ✓ Variable: ✓ Trials ✓ Vumber of Trials: ✓ Trials ✓ Scale Weight Scale Weight
Scale Weight Variable:

taile Generalized Estimating Equations



Х



Goodness of Fit^a

Pairwise Comparisons

Independence Model Outward Outward Sol Error Operation	Quasi Likeliho	od under 11	alue 0.552				Mean Difference (I			Sequential	95% Wald Confidence Interval for Difference ^b	
Circuited uais (algebrain during budgebraine is deal (algebrain during budgebraine is deal (algebraine is deal (algebraine) is deal (Independence Criterion (OIC)	Model			(I) Group*time	(J) Group*time	J) Jillerence	Std. Error	df	Sig.	Lower	Upper
List moduling (highendame Multiple Criticin (Group) 10.932 10.932 10.932 10.932 10.932 Independame Multiple Criticin (Group) [Group-1.00]time=1.00 (Group-2.00]time=1.00 (Group-2.00]time=1.00 1.952 1 1.000 -2223 4.848 Dependent Viralize AND PRE model: (Indersph), Group, time, Group (Group-2.00]time=1.00 1.9720 1.4256 1 0.000 -2252 4.848 Dependent Viralize AND PRE model: (Indersph), Group, time, Group (Group-2.00]time=1.00 -4720 1.4381 1 0.000 -2252 4.848 Disprint Micro Disprin Micro Disprint Micro Disprint Micro Disprint Micro Dis	Corrected Oue		0.550		[Group=1.00]*[time=1.00]	[Group=1.00]*[time=2.00]	.8750 ^a	.14038	1	.000	.4630	1.2870
Independence Model Image of the second	Likelihood und	ier 11	0.552			[Group=1.00]*[time=3.00]	.6622ª	.13303	1	.000	.2746	1.0498
Characterization Construction Construc	Independence	Model				[Group=2.00]*[time=1.00]	.0972	.15267	1	1.000	2422	.4366
index index <t< td=""><td>Dependent Va</td><td>riable: ANVI PDE</td><td></td><td></td><td></td><td>[Group=2.00]*[time=2.00]</td><td>.2081</td><td>.14256</td><td>1</td><td>1.000</td><td>1754</td><td>.5915</td></t<>	Dependent Va	riable: ANVI PDE				[Group=2.00]*[time=2.00]	.2081	.14256	1	1.000	1754	.5915
**ime 0 0.100pm100(r0tm210) 0.4030 1.4030 1.4030 0.1030 0.12870 0.4030 8. Information citrain are insmalter is better form 0.000pm100(r0tm210) 0.7778 0.1030 0.10 0.1030 0.12870 0.1030 9 quasitier is better form 0.000pm100(r0tm210) 0.7778 0.1030 0.10 0.11870	Model: (Interce	ept), Group, time, G	Foup			[Group=2.00]*[time=3.00]	.1203	.14443	1	1.000	2151	.4556
a information criteria are in smallers-better form: 0.0000	* time				[Group=1.00]*[time=2.00]	[Group=1.00]*[time=1.00]	8750 ^a	.14038	1	.000	-1.2870	4630
b. Computed using the full log quasiting the full set of function of funce of function of function of function of funce	a. Informatio	on criteria are in s-better form				[Group=1.00]*[time=3.00]	2128	.16381	1	1.000	6365	.2109
	h Compute	d using the full log	-			[Group=2.00]*[time=1.00]	7778 ^a	.17401	1	.000	-1.2764	2792
Val Chi- Source val Source Val Chi- Source val Source <	quasi-like	elihood function.	9	This is same as		[Group=2.00]*[time=2.00]	6669 ^a	.16521	1	.001	-1.1357	1982
First of Model Implication effect are source Implication effec				ANOVA table , both		[Group=2.00]*[time=3.00]	7547ª	.16683	1	.000	-1.2369	2725
$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$	т	acts of Madal	Effecto	interaction effect are	[Group=1.00]*[time=3.00]	[Group=1.00]*[time=1.00]	6622ª	.13303	1	.000	-1.0498	2746
Waid chi SourceSig. Sig.Image: SourceSig. SourceSig.Sig. SourceSig.Sig. SourceSig.		ests of Model	Ellects	tested using Wald test		[Group=1.00]*[time=2.00]	.2128	.16381	1	1.000	2109	.6365
Source Source (intercept)dfSig.(Group=2.00)*(time=2.00)-4542 ^a 1.578110.03288670227(intercept)3199.33810.00.5419 ^a 1.595110.0099970942Group14.80110.006119 ^a 0.09721526711.00043662422Group=2.00*(time=2.00)6Group=1.00*(time=0.00)99721.516710.0043662422Group=1.00*(time=2.00)	Type III Wald Chi-			\sim		[Group=2.00]*[time=1.00]	5650ª	.16700	1	.007	-1.0309	0991
Concept 3199.338 1 0.00 Circup 14.801 1 0.00 Circup 14.801 1 0.00 Circup 14.801 1 0.00 Circup 14.801 1 0.00 Circup 24.327 2 0.00 Group *time 16.517 2 0.00 Dependent Variable: ANXI.PRE Group=2.001/time=3.00 6.560* 1.670 1 0.00 2.542 Model: (intercer), Group, time, Group, time, Group, time, Group=2.001/time=3.00 0.660* 1.660 1 0.00 2.542 4.759 Model: (intercer), Group, time, Group, time, Group=2.001/time=3.00 0.021 1.4256 1 0.00 2.542 3.754 Model: (intercer), Group=2.001/time=3.00 Coope 1.650* 1.650 1 0.00 2.542 3.754 Model: (intercer), Group=2.001/time=3.00 Coope 1.650* 1.650* 1 0.00 2.542 3.754 Group=2.001/time=3.00 Group=2.001/time=3.00 Coope	Source	Vvaid Chi- Square	df	Sig.		[Group=2.00]*[time=2.00]	4542 ^a	.15781	1	.032	8857	0227
Group14.80110.00time24.32720.00Group *time16.51720.00Dependent variable: ANXLPRE 3.000 3.000 Dependent variable: ANXLPRE 5.000 3.000 Model: (inter=2.00)*time=3.00) 5.650^3 3.070 1.000 3.020 Dependent variable: ANXLPRE 5.000^2 3.000 3.000 3.000 3.000 3.000 Dependent variable: ANXLPRE 5.000^2 3.000 3.000^2 3.000^2 3.000^2 3.000^2 3.000^2 3.000^2 Dependent variable: ANXLPRE 5.000^2 3.000^2	(Intercept)	3199.338	1	.000		[Group=2.00]*[time=3.00]	5419 ^a	.15951	1	.007	9897	0942
time24.32720.00Group *time16.51720.00Group *time16.51720.00Dependent V-INERInstanceInstance1.6001.6001.6001.600Dependent V-INERInstanceInstanceInstance1.6001.6101.6101.0001.620Dependent V-INERInstanceInstanceInstanceInstanceInstanceInstanceInstanceInstanceModel:(InstanceInstanceInstanceInstanceInstanceInstanceInstanceInstanceInstanceModel:InstanceInstanceInstanceInstanceInstanceInstanceInstanceInstanceInstanceModel:InstanceInstanceInstanceInstanceInstanceInstanceInstanceInstanceInstanceModel:InstanceInstanceInstanceInstanceInstanceInstanceInstanceInstanceInstanceModel:Instance <t< td=""><td>Group</td><td>14.801</td><td>1</td><td>.000</td><td>[Group=2.00]*[time=1.00]</td><td>[Group=1.00]*[time=1.00]</td><td>0972</td><td>.15267</td><td>1</td><td>1.000</td><td>4366</td><td>.2422</td></t<>	Group	14.801	1	.000	[Group=2.00]*[time=1.00]	[Group=1.00]*[time=1.00]	0972	.15267	1	1.000	4366	.2422
Group *time16.5172.000Dependent Variable: ANXLPRE Model: (Interest), Group, time, Justice ANXLPRE Model: (Interest), Group, Lime, Justice ANXLPRE (Group,	time	24.327	2	.000		[Group=1.00]*[time=2.00]	.7778 ^a	.17401	1	.000	.2792	1.2764
Dependent Variable: ANXLIPRE Model: (Intercept), Group, time, Group * time) [Group=2.00]*(time=2.00] 0.1108 1.6260 1 1.000 2542 .4759 Model: (Intercept), Group, time, Group * time) (Group=2.00]*(time=2.00) (Group=2.00]*(time=3.00) .0231 1.1611 1 1.000 .2912 .3373 [Group=2.00]*(time=2.00] (Group=1.00)*(time=2.00) .2081 .14256 1 1.000 .5915 .1754 [Group=2.00]*(time=2.00] (Group=1.00)*(time=2.00) .6669 ³ .16521 1 .0001 .1982 .1357 [Group=2.00]*(time=3.00) .4542 ³ .15781 1 .001 .4593 .2642 [Group=2.00]*(time=3.00) .4542 ³ .17201 1 .0001 .2444 [Group=2.00]*(time=3.00) .6669 ³ .17201 1 .0001 .2459 .2844 [Group=2.00]*(time=3.00) .6791 .1443 1 .000 .2459 .2151 [Group=2.00]*(time=3.00) .6791 ³ .16683 .1 .000 .2456 .2151	Group * time	16.517	2	.000		[Group=1.00]*[time=3.00]	.5650ª	.16700	1	.007	.0991	1.0309
Model: (Intercept), Group, time, Group * time Image: Group = 2.00]*(time=3.00] Image: Gro	Dependent Var	riable: ANXI.PRE				[Group=2.00]*[time=2.00]	.1108	.16260	1	1.000	2542	.4759
[Group=2.00]*[time=2.00][Group=1.00]*[time=1.00]2081.1425611.0005915.1754[Group=1.00]*[time=2.00].6669³.1652111.001.1982.1.357[Group=2.00]*[time=3.00].4542°.1578111.002.0227.8857[Group=2.00]*[time=3.00].1108.1626011.000.4759.2542[Group=2.00]*[time=3.00].0878.1720111.000.4559.2844[Group=2.00]*[time=3.00].1608.17203.144431.1000.4556.2151[Group=1.00]*[time=2.00].7547°.166831.000.2725.12369[Group=2.00]*[time=3.00].5419°.5419°.156111.007.0942.9897[Group=2.00]*[time=1.00].0231.156111.000.3373.2912[Group=2.00]*[time=2.00].0878.1720111.000.2844.4599	Model: (Interce	ept), Group, time, G	Froup * time			[Group=2.00]*[time=3.00]	.0231	.15611	1	1.000	2912	.3373
[Group=1.00]*[time=2.00] 6669 ^a 16521 1 001 1982 1357 [Group=1.00]*[time=3.00] 4542 ^a 15781 1 032 2272 8857 [Group=2.00]*[time=3.00] 1008 1620 1 1.000 4599 2542 [Group=2.00]*[time=3.00] [Group=2.00]*[time=3.00] 8788 7201 1 1.000 4599 2844 [Group=2.00]*[time=3.00] [Group=1.00]*[time=2.00] 4143 1 1.000 4556 1536 [Group=2.00]*[time=3.00] [Group=1.00]*[time=3.00] 5419 ^a 6683 1 000 2725 12369 [Group=2.00]*[time=3.00] [Group=2.00]*[time=3.00] 5419 ^a 5191 1 001 3373 2912 [Group=2.00]*[time=2.00] 0878 7201 1 1.000 2844 4599					[Group=2.00]*[time=2.00]	[Group=1.00]*[time=1.00]	2081	.14256	1	1.000	5915	.1754
[Group=1.00]*[time=3.00] .4542 ^a .15781 1 .032 .0227 .8857 [Group=2.00]*[time=1.00] 1108 1.6260 1 1.000 4759 .2542 [Group=2.00]*[time=3.00] 0878 1.7201 1 1.000 4599 .2844 [Group=2.00]*[time=3.00] (Group=1.00)*[time=2.00] 1203 1.1443 1 1.000 4556 .2151 [Group=1.00]*[time=3.00] .7547 ^a 1.6683 1 0.000 .2725 1.2369 [Group=2.00]*[time=3.00] .6419 ^a .15951 1 0.007 .0942 .9897 [Group=2.00]*[time=2.00] .0078 .1611 1 1.000 3373 .2912 [Group=2.00]*[time=2.00] .0878 .17201 1 1.000 .2844 .4599						[Group=1.00]*[time=2.00]	.6669 ^a	.16521	1	.001	.1982	1.1357
[Group=2.00]*[time=1.00] 1108 .16260 1 1.000 4759 .2542 [Group=2.00]*[time=3.00] 0878 1.7201 1 1.000 4559 .2844 [Group=2.00]*[time=3.00] 1003 1.1443 1 1.000 4559 .2151 [Group=1.00]*[time=2.00] .7547* 1.16683 1 0.000 .2725 1.2369 [Group=2.00]*[time=3.00] .5419* .15951 1 0.007 .0942 .9897 [Group=2.00]*[time=1.00] 0231 1.5611 1 1.000 3373 .2912 [Group=2.00]*[time=2.00] .0878 .17201 1 1.000 2844 .4599						[Group=1.00]*[time=3.00]	.4542 ^a	.15781	1	.032	.0227	.8857
[Group=2.00]*[time=3.00] 0878 .17201 1 1.000 2849 [Group=2.00]*[time=3.00] [Group=1.00]*[time=1.00] 1203 1.1443 1 1.000 4556 .2151 [Group=1.00]*[time=3.00] .7547 ^a 1.1683 1 0.000 .2725 1.2369 [Group=1.00]*[time=3.00] .5419 ^a .15951 1 0.007 .0942 .9897 [Group=2.00]*[time=1.00] .0231 .15611 1 1.000 .3373 .2912 [Group=2.00]*[time=2.00] .0878 .17201 1 1.000 .2844 .4599						[Group=2.00]*[time=1.00]	1108	.16260	1	1.000	4759	.2542
[Group=2.00]*[time=3.00] [Group=1.00]*[time=1.00] 1203 .14443 1 1.000 4556 .2151 [Group=1.00]*[time=2.00] .7547 ^a .16683 1 .000 .2725 1.2369 [Group=1.00]*[time=3.00] .5419 ^a .15951 1 .007 .0942 .9897 [Group=2.00]*[time=1.00] .0231 .15611 1 1.000 .3373 .2912 [Group=2.00]*[time=2.00] .0878 .17201 1 1.000 .2844 .4599						[Group=2.00]*[time=3.00]	0878	.17201	1	1.000	4599	.2844
[Group=1.00]*[time=2.00] .7547 ^a .16683 1 .000 .2725 1.2369 [Group=1.00]*[time=3.00] .5419 ^a .15951 1 .007 .0942 .9897 [Group=2.00]*[time=1.00] .0231 .15611 1 1.000 .3373 .2912 [Group=2.00]*[time=2.00] .0878 .17201 1 1.000 .2844 .4599					[Group=2.00]*[time=3.00]	[Group=1.00]*[time=1.00]	1203	.14443	1	1.000	4556	.2151
[Group=1.00]*[time=3.00] 5419 ^a 5515 1 007 9942 9897 [Group=2.00]*[time=1.00] 0231 1.15611 1 1.000 3373 2912 [Group=2.00]*[time=2.00] 878 7201 1 1.000 2844 4599						[Group=1.00]*[time=2.00]	.7547 ^a	.16683	1	.000	.2725	1.2369
[Group=2.00]*[time=1.00] 0231 1.15611 1 1.000 3373 .2912 [Group=2.00]*[time=2.00] .0878 .17201 1 1.000 2844 .4599						[Group=1.00]*[time=3.00]	.5419 ^a	.15951	1	.007	.0942	.9897
[Group=2.00]*[time=2.00] .0878 .17201 1 1.0002844 .4599						[Group=2.00]*[time=1.00]	0231	.15611	1	1.000	3373	.2912
						[Group=2.00]*[time=2.00]	.0878	.17201	1	1.000	2844	.4599

a. The mean difference is significant at the .05 level.

Cluster design

- A cluster randomised controlled trial is a type of randomised controlled trial in which groups of subjects (as opposed to individual subjects) are randomised.
- Cluster randomised controlled trials are also known as cluster randomised trials, group-randomised trials and place-randomized trials.
- Cluster trials originated from educational research. Intact classes or schools were randomised to an intervention or no intervention.

Introduction to randomised controlled trial (RCT) design



Introduction to randomised controlled trial (RCT) design

.

The responses from individuals within a cluster are likely to be more similar than those from different clusters. This is because individuals within a cluster may share similar characteristics or be exposed to the same external factors associated with membership to a particular cluster.

Observations on participants in the <u>same</u> <u>cluster tend to be correlated</u> (nonindependent). • <u>Degree of correlation</u> within clusters is known as intracluster correlation coefficient (ρ). Published by Oxford University Press on behalf of the International Epidemiological Association International Journal of Epidemiology 2006;35:1292–1300 © The Author 2006; all rights reserved. Advance Access publication 30 August 2006 doi:10.1093/ije/dyl129

METHODOLOGY

Sample size for cluster randomized trials: effect of coefficient of variation of cluster size and analysis method

Sandra M Eldridge,¹* Deborah Ashby² and Sally Kerry³

design effect can be calculated as was calculated as:

$DE = 1 + \rho (m-1)$

Where m = number of subjects in a cluster and ρ = intra cluster correlation coefficient

ICC= 0.01 which usually, values of between 0.01 and 0.02 in human studies

Introduction to randomised controlled trial (RCT) design

Cluster allocation

- Need to use some form of stratification.
 - Pairing is often used match clusters on an important co-variate and randomly allocate a member of each pair to the intervention.
 - Stratification using blocking or the use of minimisation is an alternative.

Introduction to randomised controlled trial (RCT) design

geepack: Generalized Estimating Equation Package

Package 'geepack'

December 18, 2020

Version 1.3-2

Title Generalized Estimating Equation Package

Maintainer Søren Højsgaard <sorenh@math.aau.dk>

Description Generalized estimating equations solver for parameters in mean, scale, and correlation structures, through mean link, scale link, and correlation link. Can also handle clustered categorical responses.

Encoding UTF-8

LazyData true

License GPL (>= 3)

NeedsCompilation yes

Depends R (>= 3.5.0), methods

Imports MASS, broom, magrittr

RoxygenNote 7.1.1

Author Søren Højsgaard [aut, cre, cph], Ulrich Halekoh [aut, cph], Jun Yan [aut, cph], Claus Ekstrøm [ctb]

Repository CRAN

Date/Publication 2020-12-18 06:20:11 UTC

ouTube ^{MY}	Search	Q V					
1 Data Description	Lab 11: Analyzing Longitud	linal Data (Part					
2 Methods for Non-normal Distributions	2): GEE						
3 Models	Ehsan Karim and Derek Ouyang						
4 Compare with Random Effects	06 November 2020						
Reference							
	1 Data Description						
	 In addition to BtheB dataset in part 1, we used respiratory data from HS with non-normal responses: The response variable in this dataset is status (the respiratory statement) 	AUR2 package to demonstrate the analysis atus), which is a binary response					
	• Other covariates are: treatment, age, gender, the study center						
	• The response has been measured at 0, 1, 2, 3, 4 mths for each subject						
	<pre>data("respiratory", package = "HSAUR2") head(respiratory)</pre>						
	<pre>## centre treatment gender age status month subject ## 1 1 placebo female 46 poor 0 1</pre>						
	## 112 1 placebo female 46 poor 1 1						

Lab 11 (part B) gee::gee vs geepack::geegIm, compare via QIC & QICu, marginal vs conditional

572 views • Nov 7, 2020

https://www.youtube.com/watch?v=rF8pgvfMqo0

Data analysis approaches



GLMM (Mixed model)

- Mixed effects models are useful when we have data with more than one source of random variability.
- For example, an outcome may be measured more than once on the same person (repeated measures taken over time).
- When we do that we have to account for both within-person and across-person variability.



Predictor Variable x

Predictor Variable x

2		None		<i>«</i> 20010
>		{1.00 PhD		
-		News	Fixed Effects	
Linear Mixed Mod	lels	>	Build nested terms	
	Dependent Varial	ble:	Factors and Covariates: Model:	
🛷 ID	ANXI.PRE	Fi <u>x</u> ed	Group	
Age	Eactor(s):	Ra <u>n</u> dom	time time	
Married Age	Group	Estimation		
No.Children	💙 🐼 time	Statistics	Main Effects 🔻	
IV.PRE	Covariate(s):	E <u>M</u> Means		
		Sa <u>v</u> e		
		<u>B</u> ootstrap		
	Residual Weight			
	+ Residual <u>w</u> eight.		<u>By</u> (Within) Clear Ferm Add <u>Remove</u>	
	K Paste Reset Concel	Help	Build Term:	
		Пеір		
			✓ Include intercept Sum of squares: Type III ▼	
			Continue Cancel Help	
			Linear Mixed Models: Random Effects	×
			Random Effect 1 of 1	
			Previous	Ne <u>x</u> t
			Covariance Type: Variance Components	T
			Random Effects	tercept
			Eactors and Covariates: <u>M</u> odel:	lo copt
			time	
			Factorial	
			- → By* (Within) Clear Term Add Remove	
			Build Term:	
			Build Term:	
			Build Term: Subject Groupings Subjects: Combinations:	
			Build Term: Subject Groupings Subjects: Combinations: D D	
			Build Term: Subject Groupings Subjects: D D D	
			Build Term: Subject Groupings Subjects: D D D D D	
			Build Term: Subject Groupings Subjects: D D D D D D D	

Continue Cancel

Help

Latent growth curve modeling (LGC)

- Latent growth curve modeling is currently one of the most popular approaches used to study longitudinal patterns of change over time
- LGM is a methodology that uses structural equation modeling techniques to model individual change, assess treatment effects and the relationship between multiple outcomes simultaneously, and model measurement error.
- The growth curve model (GCM), or latent curve model (<u>Meredith & Tisak, 1990</u>), has been one of the most widely adopted statistical techniques in longitudinal studies to investigate progression over time

Mediators of Intervention Effects on Depressive Symptoms Among People Living With HIV: Secondary Analysis of a Mobile Health Randomized Controlled Trial Using Latent Growth Curve Modeling

Mengting Zhu¹⁽¹⁾; Weiping Cai²⁽¹⁾; Linghua Li²⁽¹⁾; Yan Guo^{1,3,4}⁽¹⁾; Aliza Monroe-Wise⁵⁽¹⁾; Yiran Li¹⁽¹⁾; Chengbo Zeng^{6,7}⁽¹⁾; Jiaying Qiao¹⁽¹⁾; Zhimeng Xu¹⁽¹⁾; Hanxi Zhang⁸⁽²⁾; Yu Zeng¹⁽¹⁾; Cong Liu²⁽²⁾



	Mean			Variance		
	Estimate	SE	þ	Estimate	SE	Þ
Perceived social supp	port					
Intercept	28.00	0.52	<0.001	32.00	3.80	<0.001
Slope T1-T3	1.05	0.29	<0.001	6.25	1.27	<0.001
Slope T3-T5	0.42	0.24	0.077	0	-	

Posttraumatic stress symptoms

Intercept	27.01	0.61	<0.001	58.22	5.30	<0.001
Slope T1-T3	-6.52	0.48	<0.001	25.14	3.41	<0.001
Slope T3-T5	-1.11	0.46	0.016	0	-	

Note: T1 = pretreatment, T3 = post-treatment, T5 = 18 months after post-treatment measure.

	Perceived so	ocial supp	ort	Posttraumatic stress symptoms			
	Estimate	SE	Þ	Estimate	SE	Þ	
$Treatment^a \rightarrow intercept$	-0.03	0.10	0.742	-0.06	0.09	0.509	
$Treatment^a \rightarrow slope$	-0.18	0.10	0.197	0.23	0.10	0.025	
$Caregiver^b \rightarrow intercept$	0.04	0.10	0.694	-0.09	0.10	0.334	
$Caregiver^b \rightarrow slope$	0.01	0.13	0.942	-0.11	0.11	0.326	
$Sex^c \rightarrow intercept$	-0.14	0.10	0.742	0.14	0.08	0.091	
Sex ^c → slope	0.13	0.10	0.197	0.06	0.10	0.557	
Age → intercept	-0.01	0.01	0.900	0.04	0.09	0.648	
Age→ slope	-0.11	0.13	0.445	0.09	0.10	0.334	



B Unnamed project : Group number 1 : Input

File	Edit V	iew D	iagram Analyze Tools	Nugins Help	
		111		Plugins Alt+F8	
	$\overline{}$	o		Clean Estimates Table	
←	\leftrightarrow	2		Common Latent Factor Connector	
			Group number 1	Draw Covariances	
Title	-			Erase All	
լիդ	_m	rum)		Erase Selected	
~	\bigcirc	$\overline{}$		Growth Curve Model	
E SPY		X	VV: Default model	HTMT Analysis	
542	\cap	***	AX. Default model	Indirect Effects	
2.4.2	O	~		J-N Plot Analysis	
\bigcirc		0		MagiClean	
				Model Fit Measures	
			Unstandardized estimates	Multigroup	
			Standardized estimates	Name Parameters	
**				Name Unobserved Variables	
	"E	₹ ₩ ₽		Pattern Matrix Model Builder	
	́д,	Å		Resize Observed Variables	
Ľ	Ţ	$ \leq $		Specific bias test	
\bigcirc	* *	28C)		Standardized RMR	
	<u>*</u>	~		Validity and Reliability Test (MasterValidity V2.dll)	
	x-x Ø=Ø	Ŷ		Validity and Reliability Test (MasterValidity(noHTMT).dll)	
5	~	Å Å.		Validity and Reliability Test (MasterValidity.dll)	
~ /			CFA ACE		
1	11	11	CFA 1		
			cfa AMOS		
			TEST		
				Path diagram Tables	
Not es	timating	any us	er-defined estimand.		





Coral protection from seastars (Culcita) by symbionts (McKeon et al., 2012)

Thank you

- Dr. Mahmoud Danaee
- <u>mdanaee@um.edu.my</u>

Research method and statistical consultation service (RMC)

- Department of Social and Preventive Medicine,
- Faculty of Medicine, University of Malaya, 50603 Kuala Lumpur,
- MALAYSIA.

Introduction to randomised controlled trial (RCT) design