Longitudinal Data Analysis (PSY 5939)

Spring 2022 Syllabus

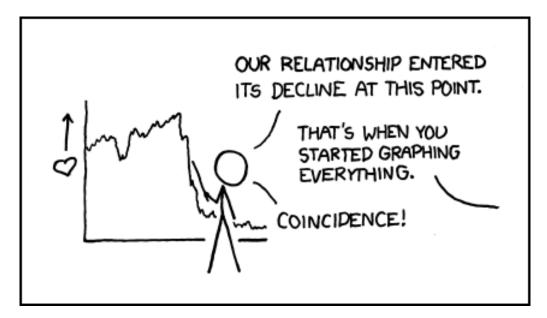


Figure 1: https://xkcd.com/523/

Instructor Information

- Stefany Coxe, Ph.D.
- Email: stefany.coxe@fiu.edu this is the best way to contact me!
- Office Hours: By appointment via Zoom send me an email to schedule a time

Course Information

- PSY 5939: Longitudinal Data Analysis
- Thursday, 9:30am 10:45am
- Zoom (link in Canvas or here)

This course covers topics related to statistical analysis of longitudinal data, focusing on methods used in the social sciences and health research. Topics include analysis of covariance (ANCOVA), difference scores, statistical mediation, mixed models (with correlated residuals

and/or with random effects), and latent growth modeling. You will be able to analyze, interpret, and write up results using these methods.

This course takes place using the Online LIVE modality. We will meet synchronously via Zoom for 1 hour 15 minutes each week; you will be responsible for completing course assignments such as readings, videos, and quizzes to be prepared to participate in the live meeting.

Prerequisites

Graduate coursework in analysis of variance and linear regression, such as PSY 5939: Quant 1 and PSY 5939: Quant 2. We will cover a variety of topics in this course, but all of them build on a basic ANOVA and regression (general linear model) framework. A course covering multivariate statistics (such as PSY 5246C) is also required.

Learning objectives

- Explain how longitudinal data, research questions, and statistical models differ from cross-sectional data, research questions, and statistical models
- Develop longitudinal research questions
- Choose the appropriate analysis approach for the longitudinal research question
- Analyze longitudinal data with statistical methods and software appropriate to the research question
- Create a written report of your findings
- Draw conclusions about your research question(s) based on those results
- Create a presentation to verbally report your findings and conclusions

Software and Technology

All course materials will be posted on Canvas. All assignments will be submitted via Canvas.

We will use Zoom for synchronous course meetings.

We will use **SPSS and R** for the first part of the course. I expect you to be able to use **at least one of these software packages** to do things like open datasets, transform variables, conduct simple analyses, etc. I will provide information about the specific procedures you will need to know for this course, including key data re-structuring techniques.

We will use Mplus for latent growth models. I do not expect you to know anything about Mplus; I will provide information on what you need to know about Mplus for this course.

Course Structure

This course takes place using the Online LIVE modality. We will meet synchronously via Zoom for 1 hour 15 minutes each week; you will be responsible for completing course assignments such as readings, videos, and quizzes to be prepared to participate in the live meeting.

Each week will follow a similar structure:

- Monday: Lecture and related materials posted by end of the day
- Wednesday: Watch lecture and complete embedded quiz by 8pm
- Thursday: Synchronous meeting via Zoom to review material and work on applications
- Sunday: Assignment (homework or article discussion) due by 8pm

Assignments

Your work in this course will be assessed using a variety of methods.

• Lecture quizzes (10%)

Quiz questions will be embedded within the lecture video. These questions will assess whether you understand some key points in the lecture.

• Homework (40%)

Four homework assignments covering: (1) models for 2 waves, (2) mixed models, (3) latent growth models, and (4) statistical mediation. The assignments involve running several analyses, making some decisions based on the analyses, interpreting output, and presenting the results in tables/figures and text.

• Article discussions (15%)

We will use **Perusall** to conduct group article discussions. I will provide prompts / direction; you will annotate the article with questions and comments. These are designed to give you some experience reading and understanding quantitative methods articles and to get you to think about the topics in more detail. You will also write up a short (~150 word) reflection on the article.

• Final project

You will propose and conduct a project using your own dataset or a publicly available dataset, culminating in a short paper. I want you to focus on **developing longitudinal research questions** and **mapping them on to appropriate longitudinal analyses**.

• Proposal (5%)

You will turn in a 1 to 2 page proposal for your project. The purpose of the proposal is to get you to **select a dataset**, start to **solidify your ideas**, and **get feedback** and additional resources from me. You can change the direction of the project later in the semester as you learn more.

• Presentation (10%)

A short presentation about your final project. I expect that your analyses should be complete (or nearly so) at this point; preparing the presentation should help you organize your thoughts. The main purpose of this presentation is to give you **practice presenting your analysis findings in a group setting**. Approximately 15 to 20 minutes per person, including questions.

• Presentation discussion (5%)

Each student should ask a question of at least 2 other students about their presentations. The original student should attempt to answer the questions. (Feel free to have further discussion as well!)

• Paper (15%)

The final written record of your project. This should be in the style of a journal article, with Introduction, Methods, Results, and Discussion sections.

Tentative Schedule

Date	Topic	Assignment
Jan 10	Introduction	Article 1
Jan 17	Two waves	Article 2
Jan 24	Mixed models (G)	Homework 1
Jan 31	Mixed models (G)	Article 3
Feb 07	Mixed models (G)	Article 4
Feb 14	Mplus	Homework 2
Feb 21	Latent growth models	Article 5
Feb 28	SPRING BREAK	No assignment
${\rm Mar}~07$	Latent growth models	Proposal
Mar 14	Latent growth models	Article 6
Mar 21	Mediation	Homework 3
Mar 28	Mediation	Article 7
Apr 04	Growth mixture	Homework 4
Apr 11	Mixed models (\mathbf{R})	Article 8
Apr 18	Office hours	Presentation
Apr 25	FINALS WEEK	Final paper

Due dates subject to change due to hurricane, emergency, scheduling changes, etc.

Quizzes are due by Wednesday at 8pm.

Assignments are due by the end of Sunday (midnight).

Presentation due by end of the day on Sunday, April 24, 2022.

Presentation discussion due by end of day on Wednesday, April 27, 2022.

Final project due by the end of the day on Friday, April 29, 2022.

Grades

Grade	Percentage
A	>=93
A-	90 - 92.99
B+	87 - 89.99
В	83 - 86.99
B-	80 - 82.99
C+	77 - 79.99
С	70 - 76.99
F	<= 69.99

Course and University Policies

Online Course Policies

https://online.fiu.edu/html/canvas/policies/

Academic Misconduct

Students at Florida International University are expected to adhere to the highest standards of integrity in every aspect of their lives. Honesty in academic matters is part of this obligation. Academic integrity is the adherence to those special values regarding life and work in an academic community. Any act or omission by a student which violates this concept of academic integrity shall be defined as academic misconduct and shall be subject to the procedures and penalties set forth herein. All students are expected to adhere to a standard of academic conduct, which demonstrates respect for themselves, their fellow students, and the educational mission of the University. All students are deemed by the University to understand that if they are found responsible for academic misconduct, they will be subject to the Academic Misconduct procedures and sanctions, as outlined in the Student Handbook.

https://dasa.fiu.edu/all-departments/student-conduct-and-academic-integrity/

Academic Dishonesty

Please refer to your student handbook for a description of what constitutes academic dishonesty. I expect all students to complete and turn in their own work.

Accessibility / Accomodation

Any student with a disability or other need that may require special accommodations for this course should make this known to the instructor during the first week of class. You can contact the Disability Resource Center at

- http://drc.fiu.edu
- drcupgl@fiu.edu
- 305-348-3532
- Graham Center 190

Attendance

Attendance is not explicitly part of your grade in this course, but activities completed during the synchronous portion of the course will be **extremely** helpful.

If you need to miss class (such as for illness, religious event, professional activity, or universitysanctioned event), please contact me as soon as possible to make any necessary arrangements.

References

General longitudinal

Fitzmaurice, G. M., Laird, N. M., and Ware, J. H. (2011). Applied longitudinal analysis (2nd ed.). Hoboken, NJ: John Wiley & Sons.

Gelman, A., & Hill, J. (2007). Data analysis using regression and multilevel/hierarchical models. Cambridge: Cambridge University Press.

Hamaker, E. L., Kuiper, R. M., & Grasman, R. P. (2015). A critique of the cross-lagged panel model. Psychological methods, 20(1), 102.

Hedeker, D., & Gibbons, R. D. (2006). Longitudinal data analysis. New Jersey: Wiley.

Hoffman, L. (2015). Longitudinal analysis: Modeling within-person fluctuation and change. New York, NY: Routledge Academic.

MacCallum, R. C., Kim, C., Malarkey, W. B., & Kiecolt-Glaser, J. K. (1997). Studying multivariate change using multilevel models and latent curve models. Multivariate Behavioral Research, 32(3), 215 - 253.

McNeish, D., & Matta, T. (2018). Differentiating between mixed-effects and latent-curve approaches to growth modeling. Behavior research methods, 50(4), 1398-1414.

Newsom, J., Jones, R. N., & Hofer, S. M. (Eds.). (2013). Longitudinal data analysis: A practical guide for researchers in aging, health, and social sciences (Vol. 18). Routledge.

Ployhart, R. E., & Vandenberg, R. J. (2010). Longitudinal research: The theory, design, and analysis of change. Journal of Management, 36, 94 - 120.

Preacher, K. J., & Hancock, G. R. (2015). Meaningful aspects of change as novel random coefficients: A general method for reparameterizing longitudinal models. Psychological methods, 20(1), 84.

Raudenbush, S. W., and Bryk, A. S. (2002). Hierarchical linear models: Applications and data analysis methods (2nd ed.). Thousand Oaks, CA: Sage Publications.

Singer J. D. & Willett J. B. (2003). Applied longitudinal data analysis. New York: Oxford University Press.

Snijders, T. A. B., and Bosker, R. (2012). Multilevel analysis: An introduction to basic and advanced multilevel modeling (2nd ed.). Sage Publications, Ltd.

Stroup, W. W. (2012) Generalized linear mixed models: Modern concepts, methods, and applications. Chapman & Hall/ CRC.

Usami, S., Murayama, K., & Hamaker, E. L. (2019). A unified framework of longitudinal models to examine reciprocal relations. Psychological methods, 24(5), 637.

Ye, A., & Bollen, K. A. (2021). Can we distinguish between different longitudinal models for estimating nonlinear trajectories?. Structural Equation Modeling: A Multidisciplinary Journal, 1-13.

Two wave models

Aiken, L. S., West, S. G., & Reno, R. R. (1991). Multiple regression: Testing and interpreting interactions. SAGE.

Allison, P. D. (2005). Fixed effects regression methods for longitudinal data using SAS. SAS Institute.

Cohen, J., Cohen, P., West, S. G., & Aiken, L. S. (2003). Applied multiple regression/correlation analysis for the behavioral sciences. Routledge.

Jaccard, J., Wan, C. K., & Turrisi, R. (1990). The detection and interpretation of interaction effects between continuous variables in multiple regression. Multivariate behavioral research, 25(4), 467-478.

Kisbu-Sakarya, Y., MacKinnon, D. P., & Aiken, L. S. (2013). A Monte Carlo comparison study of the power of the analysis of covariance, simple difference, and residual change scores in testing two-wave data. Educational and Psychological Measurement, 73(1), 47 - 62.

Lin, H., & Larzelere, R. E. (2020). Dual-centered ANCOVA: Resolving contradictory results from Lord's paradox with implications for reducing bias in longitudinal analyses. Journal of Adolescence, 85, 135-147.

Lord, F. (1967). A paradox in the interpretation of group comparisons. Psychological Bulletin, 68(5), 304 - 305.

Pike, G. R. (2004). Lord's paradox and the assessment of change during college. Journal of College Student Development, 45(3), 348 - 353.

Rogosa, D., Brandt, D., & Zimowski, M. (1982). A growth curve approach to the measurement of change. Psychological bulletin, 92(3), 726.

Rogosa, D. R., & Willett, J. B. (1983). Demonstrating the reliability of the difference score in the measurement of change. Journal of educational measurement, 335-343.

Tu, Y.-K., Gunnell, D., & Gilthorpe, M. S. (2008). Simpson's paradox, Lord's paradox, and suppression effects are the same phenomenon: The reversal paradox. Emerging Themes in Epidemiology, 5:2.

Westfall, J., & Yarkoni, T. (2016). Statistically controlling for confounding constructs is harder than you think. PloS one, 11(3), e0152719.

Mixed / multilevel / random effects / hierarchical linear models

Baldwin, S. A., Imel, Z. E., Braithwaite, S. R., & Atkins, D. C. (2014). Analyzing multiple outcomes in clinical research using multivariate multilevel models. Journal of consulting and clinical psychology, 82(5), 920.

Bates D, Mächler M, Bolker B, Walker S (2015). Fitting Linear Mixed-Effects Models Using lme4. Journal of Statistical Software, 67(1), 1–48. doi: 10.18637/jss.v067.i01.

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Gelman, A. (2006). Multilevel (Hierarchical) Modeling: What It Can and Cannot Do. Technometrics, 48(3), 432 - 435.

Hoffman, L., & Stawski, R. S. (2009). Persons as contexts: Evaluating between-person and within-person effects in longitudinal analysis. Research in Human Development, 6, 97 - 120.

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Johnson, M. (2002). Individual growth analysis using PROC MIXED. SAS User Group International, 27.

Judd, C. M., Westfall, J., & Kenny, D. A. (2012). Treating stimuli as a random factor in social psychology: A new and comprehensive solution to a pervasive but largely ignored problem. Journal of personality and social psychology, 103(1), 54.

Kincaid, C. (2005). Guidelines for selecting the covariance structure in mixed model analysis. In Proceedings of the Thirtieth Annual SAS Users Group International Conference (No. 198-30). Cary, NC: SAS Institute Inc.

Kwok, O. M., Underhill, A. T., Berry, J. W., Luo, W., Elliott, T. R., & Yoon, M. (2008). Analyzing longitudinal data with multilevel models: An example with individuals living with lower extremity intra-articular fractures. Rehabilitation Psychology, 53(3), 370 - 386.

McCoach, D. B., Rifenbark, G. G., Newton, S. D., Li, X., Kooken, J., Yomtov, J., Yomtov, D., Gambino, A., J., & Bellara, A. (2018). Does the package matter? A comparison of five common multilevel modeling software packages. Journal of Educational and Behavioral Statistics, 43(5), 594-627.

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Peugh, J. L. (2010). A practical guide to multilevel modeling. Journal of School Psychology, 48(1), 85 - 112.

Pinheiro, J., Bates, D., DebRoy, S., Sarkar, D., R Core Team (2021). nlme: Linear and Nonlinear Mixed Effects Models_. R package version 3.1-153, <URL: https://CRAN.R-project.org/package=nlme>.

Wang, L. P., & Maxwell, S. E. (2015). On disaggregating between-person and within-person effects with longitudinal data using multilevel models. Psychological methods, 20(1), 63.

Latent growth models

Bishop, J., Geiser, C., & Cole, D. A. (2015). Modeling latent growth with multiple indicators: A comparison of three approaches. Psychological Methods, 20(1), 43 - 62.

Curran, P. J., & Hussong, A. M. (2003). The use of latent trajectory models in psychopathology research. Journal of Abnormal Psychology, 112(4), 526 - 544.

Curran, P. J., Obeidat, K., & Losardo, D. (2010). Twelve frequently asked questions about growth curve modeling. Journal of cognition and development, 11(2), 121-136.

Duncan, T. E., & Duncan, S. C. (2009). The ABCs of LGM: An Introductory Guide to Latent Variable Growth Curve Modeling. Social and Personality Psychology Compass, 3, 979 - 991.

Li, F., Duncan, T. E., & Acock, A. (2000). Modeling interaction effects in latent growth curve models. Structural Equation Modeling, 7(4), 497-533.

Preacher, K. J., Wichman, A. L., MacCallum, R. C., & Briggs, N. E. (2008). Latent growth curve modeling (No. 157). Sage.

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Widaman, K. F., & Thompson, J. S. (2003). On specifying the null model for incremental fit indices in structural equation modeling. Psychological methods, 8(1), 16.

Wu, W., & Lang, K. M. (2016). Proportionality assumption in latent basis curve models: A cautionary note. Structural Equation Modeling: A Multidisciplinary Journal, 23(1), 140-154.

Mixture (GMM / LCGA)

Jung, T. & Wickrama, K. A. S. (2008). An introduction to latent class growth analysis and growth mixture modeling. Social and Personality Psychology Compass, 2/1, 302 - 317.

Wang, M., & Bodner, T. E. (2007). Growth mixture modeling: Identifying and predicting unobserved subpopulations with longitudinal data. Organizational Research Methods, 10 (4), 635 - 656.

Collins, L. M., & Lanza, S. T. (2010). Latent Class and Latent Transition Analysis. Hoboken, NJ: John Wiley & Sons.

Mediation

Baron, R. M., & Kenny, D. A. (1986). The moderator-mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. Journal of personality and social psychology, 51(6), 1173 - 1182.

Cheong, J., MacKinnon, D. P., & Khoo, S. T. (2003). Investigation of mediational processes using parallel process latent growth curve modeling. Structural Equation Modeling, 10(2), 238-262.

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Meeker, W. Q., Cornwell, L. W., & Aroian, L. A. (1981). The product of two normally distributed random variables (No. 7). American Mathematical Society.

Sobel, M. E. (1982). Asymptotic confidence intervals for indirect effects in structural equation models. Sociological methodology, 13, 290-312.

Sobel, M. E. (1986). Some new results on indirect effects and their standard errors in covariance structure models. Sociological methodology, 16, 159-186.

Thoemmes, F. (2015). Reversing arrows in mediation models does not distinguish plausible models. Basic and Applied Social Psychology, 37(4), 226-234.

Miscellaneous topics

Categorical outcomes

Hu, F. B., Goldberg, J., Hedeker, D., Flay, B. R., & Pentz, M. A. (1998). Comparison of population-averaged and subject-specific approaches for analyzing repeated binary outcomes. American Journal of Epidemiology, 147(7), 694 - 703.

Hubbard, A. E., Ahern, J., Fleischer, N. L., Van der Laan, M., Lippman, S. A., Jewell, N., Bruckner, T., & Satariano, W. A. (2010). To GEE or not to GEE: comparing population average and mixed models for estimating the associations between neighborhood risk factors and health. Epidemiology, 21(4), 467 - 474.

Jaeger, T. F. (2008). Categorical data analysis: Away from ANOVAs (transformation or not) and towards logit mixed models. Journal of memory and language, 59(4), 434 - 446.

Centering

Enders, C. K., & Tofighi, D. (2007). Centering predictor variables in cross-sectional multilevel models: A new look at an old issue. Psychological Methods, 12(2), 121 - 138.

Kreft, I. G., De Leeuw, J., & Aiken, L. S. (1995). The effect of different forms of centering in hierarchical linear models. Multivariate Behavioral Research, 30(1), 1 - 21.

Wang, L., & Maxwell, S. E. (2015). On disaggregating between-person and within-person effects with longitudinal data using multilevel models. Psychological Methods, 20(1), 63 - 83.

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Missing data

Baraldi, A. N., & Enders, C. K. (2010). An introduction to modern missing data analyses. Journal of School Psychology, 48(1), 5-37.

Black, A. C., Harel, O., & Betsy McCoach, D. (2011). Missing data techniques for multilevel data: Implications of model misspecification. Journal of Applied Statistics, 38(9), 1845-1865.

Enders, C. K. (2011). Missing not at random models for latent growth curve analyses. Psychological Methods, 16(1), 1 - 16.

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Non-parametric models

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Power and effect size

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Feingold, A. (2009). Effect sizes for growth-modeling analysis for controlled clinical trials in the same metric as for classical analysis. Psychological methods, 14(1), 43.

Feingold, A. (2013). A regression framework for effect size assessments in longitudinal modeling of group differences. Review of General Psychology, 17(1), 111-121.

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Judd, C. M., Westfall, J., & Kenny, D. A. (2017). Experiments with more than one random factor: Designs, analytic models, and statistical power. Annual review of psychology, 68, 601-625.

Resampling for CIs

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Preacher, K. J., & Hayes, A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. Behavior research methods, 40(3), 879-891.

Time

Cain, M. K., Zhang, Z., & Bergeman, C. S. (2018). Time and other considerations in mediation design. Educational and psychological measurement, 78(6), 952-972.

Collins, L. M., & Graham, J. W. (2002). The effect of the timing and spacing of observations in longitudinal studies of tobacco and other drug use: temporal design considerations. Drug and Alcohol Dependence, 68, S85 - S96.

Timmons, A. C., & Preacher, K. J. (2015). The importance of temporal design: How do measurement intervals affect the accuracy and efficiency of parameter estimates in longitudinal research?. Multivariate behavioral research, 50(1), 41-55.

Example applied articles

Atkins, D. C. (2005). Using multilevel models to analyze couple and family treatment data: Basic and advanced issues. Journal of Family Psychology, 19(1), 98 - 110.

Bianconcini, S. (2012). A general multivariate latent growth model with applications to student achievement. Journal of Educational and Behavioral Statistics, 37(2), 339 - 364.

Duperrouzel, J. C., Hawes, S. W., Lopez-Quintero, C., Pacheco-Colón, I., Coxe, S., Hayes, T., & Gonzalez, R. (2019). Adolescent cannabis use and its associations with decision-making and episodic memory: Preliminary results from a longitudinal study. Neuropsychology.

Guglielmi, R. S. (2012). Math and science achievement in English language learners: Multivariate latent growth modeling of predictors, mediators, and moderators. Journal of Educational Psychology, 104(3), 580 - 602.

Hawes, S. W., Trucco, E. M., Duperrouzel, J. C., Coxe, S., & Gonzalez, R. (2019). Developmental pathways of adolescent cannabis use: Risk factors, outcomes and sex-specific differences. Substance use & misuse, 54(2), 271-281.

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Kieffer, M. J., & Lesaux, N. K. (2012). Development of morphological awareness and vocabulary knowledge in Spanish-speaking language minority learners: A parallel process latent growth curve model. Applied Psycholinguistics, 33(01), 23 - 54.

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