PSY 5246C: Fall 2023 Syllabus
Multivariate Analysis in Applied Psychological Research

Instructor Information

- **Instructor**: Dr. Stefany Coxe
  - Ph.D., Quantitative Psychology from Arizona State University
  - I **evaluate** and **apply** advanced *statistical methods* in *behavioral research*, especially regression models for **categorical outcomes** and **statistical graphics**
  - **Email** (stefany.coxe@fiu.edu) is **always** the best way to contact me! If you don't hear back from me in a couple days, send me another email
  - **Office Hours** are *by appointment* via Zoom (link also on Canvas)
- **Teaching Assistant**: Morgan Jusko
  - Ph.D. student in Clinical Science
  - **Email**: mjusko@fiu.edu
  - **Office Hours** are *Wednesday 1 to 2pm* via Zoom (link also on Canvas)

Course Information

Format and Meetings

This is a hybrid course. We will meet in person each Wednesday from 10:30am to 11:45am in PC 214; you will be responsible for completing course assignments such as **videos** and **readings** prior to class in order to be prepared to participate in the in-person meeting. See Assessments and Schedule below.

Learning Goals

This course covers topics related to **multivariate statistical analysis**, focusing on methods used in the social sciences and health research. You will learn about *matrix algebra, linear regression, logistic regression, Poisson regression, factor analysis, principal components analysis, MANOVA, mixed models, and mediation.* You will be able to **analyze, interpret, and write up results** using these methods. This course will provide you with the background and confidence for *further study in applied statistics.*

Learning Objectives

- **Compare** and **contrast** possible analysis options based on the research question
- **Select** the appropriate analysis approach for the research question
- **Analyze** data with statistical methods appropriate to the research question
- **Create** a written report of your findings
- **Make conclusions** about your research question(s) based on those results
- **Discover** a love of statistics!

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 general linear model (ANOVA and regression) framework.

Software and Technology

- **Canvas**

Course materials will be posted on Canvas. Lecture videos will be posted on **Playposit**, with links in Canvas. You will submit all assignments via Canvas.

- **Statistical software**

We will use **SPSS and R** for this 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.

We will briefly use M*plus* later in the course. I do not expect you to know anything about M*plus*; I will provide input and output files for you for this portion of the course.

Course Structure

This course takes place in a hybrid format. We will meet in person for 1 hour 15 minutes each week. You will be responsible for completing course assignments such as videos and readings prior to class in order to be prepared to participate in the in-person meeting. You will also have assignments to complete outside of class.

Each week will follow a similar structure:

- **Sunday**: Lecture videos posted
- **Tuesday**: Watch lecture and complete embedded questions by 8pm
- **Wednesday**: In-person meeting to review material and work on applications
- **Thursday**: Reflection due by 8pm
- **Sunday**: Homework assignment due by end of day (midnight)

Assessments

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

- **Lecture Questions (10%)**

Questions will be embedded within the lecture video. These questions will assess *whether you understand some key points* in the lecture. You will have **unlimited** attempts to answer each question.

- **Homework (60%)**

There will be eleven (11) homework assignments covering each of the topics we will cover. The assignments generally involve *running analyses in SPSS and/or R*, making some decisions based on the analyses, interpreting output, and presenting the results.

- **Reflections (10%)**

There will be eleven (11) short reflections about the week's work, including responses to in-class questions, connections between the material and your own research, and similar.

- **End-of-module Presentations (20%)**

There will be three (3) in-class presentations, one at the end of each module. See the Tentative Schedule for dates. There will be a presentation (*not by you!*) of a real (likely published) application of one or more of the methods from the section. You will attend the presentation in class and complete a short written assignment related to it. More details to come.

Tentative Schedule

Week	Topic	L	P	R	H
Aug 21	Intro, matrix algebra	1		1	1
Aug 28	Linear regression	2		2	2
Sep 4	Linear regression	3		3	3
Sep 11	Logistic regression	4		4	4
Sep 18	Poisson regression	5		5	5
Sep 25	Presentation		1		
Oct 2	Matrix algebra	6		6	6
Oct 9	Principal components analysis	7		7	7
Oct 16	Factor analysis	8		8	8
Oct 23	Latent class analysis	9		9	9
Oct 30	Presentation		2		
Nov 6	MANOVA / RM ANOVA	10		10	10
Nov 13	Mixed models	11		11	11
Nov 20	HOLIDAY - NO CLASS				
Nov 27	Presentation		3		
Dec 4	Finals week - NO CLASS				

Due dates subject to change due to hurricane, emergency, scheduling changes, etc. (Let's be real – that's going to happen.)

L: Watch lecture videos by **Tuesday at 8pm**.

P: Presentations take place in class on **Wednesday morning**. You will have a short written assignment due by the **end of Sunday (midnight)**.

R: Reflections are due by **Thursday at 8pm**.

H: Homework assignments are due by the **end of Sunday (midnight)**.

Grades

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

Grade	Percentage
F	<= 69.99

Course and University 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. While you may work with other students on your homework assignments, **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 in-person portion of the course will be **extremely** helpful.

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

References

General Multivariate Statistics

Hair, J. F., Black, W. C., Babin, B. J., Anderson, R. E., & Tatham, R. L. (2006). Multivariate data analysis. Upper Saddle River, NJ: Pearson Prentice Hall.

Harlow, L. L. (2014). The essence of multivariate thinking: Basic themes and methods. Routledge.

Tabachnick, B. G., & Fidell, L. S. (2012). Using Multivariate Statistics, 6th Edition. Pearson.

Matrix Algebra

Basilevsky, A. (2013). Applied matrix algebra in the statistical sciences. Courier Corporation.

Fieller, N. (2015). Basics of Matrix Algebra for Statistics with R. CRC Press.

Searle, S. R., & Khuri, A. I. (2017). Matrix algebra useful for statistics. John Wiley & Sons.

Linear Regression / General(ized) Linear Model

Ai, C. & Norton, E. C. (2003). Interaction terms in logit and probit models. Economics Letters, 80 (1), 123–129. doi:10.1016/S0165-1765(03)00032-6

Agresti, A. (2003). Categorical data analysis (Vol. 482). John Wiley & Sons.

Agresti, A. (2018). An introduction to categorical data analysis. John Wiley & Sons.

Cohen, J., Cohen, P., West, S.G. & Aiken, L.S. (2003). Applied Multiple Regression/Correlation Analysis for the Behavioral Sciences. L. Erlbaum Associates, Mahwah, N.J.

Fox, J. (2015). Applied regression analysis and generalized linear models. Sage Publications.

Gelman, A., & Hill, J. (2006). Data analysis using regression and multilevel/hierarchical models. Cambridge University Press.

Long, J. S. (1997). Regression models for categorical and limited dependent variables (Vol. 7). Advanced quantitative techniques in the social sciences, 219.

McCabe, C., Halvorson, M. A., King, K. M., Cao, X., & Kim, D. S. (2020, April 8). Estimating and interpreting interaction effects in generalized linear models of binary and count data. https://doi.org/10.31234/osf.io/th94c

Norton, E. C., Wang, H., & Ai, C. (2004). Computing interaction effects and standard errors in logit and probit models. The Stata Journal, 4 (2), 154–167.

Logistic Regression

Allison, P. D. (2012). Logistic regression using SAS: Theory and application. SAS Institute.

Bürkner, P. C., & Vuorre, M. (2019). Ordinal regression models in psychology: A tutorial. Advances in Methods and Practices in Psychological Science, 2(1), 77-101.

Chen, K., Cheng, Y., Berkout, O., & Lindhiem, O. (2016). Analyzing Proportion Scores as Outcomes for Prevention Trials: A Statistical Primer. Prevention Science, 1-10.

DeMaris, A. (2002). Explained variance in logistic regression: A Monte Carlo study of proposed measures. Sociological Methods & Research, 31(1), 27-74.

Hayes, A. F., & Matthes, J. (2009). Computational procedures for probing interactions in OLS and logistic regression: SPSS and SAS implementations. Behavior research methods, 41(3), 924-936.

Hosmer Jr, D. W., Lemeshow, S., & Sturdivant, R. X. (2013). Applied logistic regression (Vol. 398). John Wiley & Sons.

Menard, S. (2002). Applied logistic regression analysis (No. 106). Sage.

Poisson Regression

Atkins, D. C., & Gallop, R. J. (2007). Rethinking how family researchers model infrequent outcomes: a tutorial on count regression and zero-inflated models. Journal of Family Psychology, 21(4), 726.

Blevins, D. P., Tsang, E. W., & Spain, S. M. (2015). Count-Based Research in Management Suggestions for Improvement. Organizational Research Methods, 18(1), 47-69.

Cameron, A. C., & Trivedi, P. K. (2013). Regression analysis of count data (Vol. 53). Cambridge university press.

Coxe, S., West, S. G., & Aiken, L. S. (2009). The analysis of count data: A gentle introduction to Poisson regression and its alternatives. Journal of personality assessment, 91(2), 121-136.

Gardner, W., Mulvey, E. P., & Shaw, E. C. (1995). Regression analyses of counts and rates: Poisson, overdispersed Poisson, and negative binomial models. Psychological bulletin, 118(3), 392.

Green, J. (2020). A tutorial on modelling health behaviour as count data with Poisson and negative binomial regression.

Land, K. C., McCall, P. L., & Nagin, D. S. (1996). A comparison of Poisson, negative binomial, and semiparametric mixed Poisson regression models with empirical applications to criminal careers data. Sociological Methods & Research, 24(4), 387-442.

Principal Components Analysis (PCA) and Factor Analysis (FA)

Hayton, J. C., Allen, D. G., & Scarpello, V. (2004). Factor retention decisions in exploratory factor analysis: A tutorial on parallel analysis. Organizational research methods, 7(2), 191-205.

Joliffe, I. T., & Morgan, B. J. T. (1992). Principal component analysis and exploratory factor analysis. Statistical methods in medical research, 1(1), 69 - 95.

O'Connor, B. P. (2000). SPSS and SAS programs for determining the number of components using parallel analysis and Velicers MAP test. Behavior research methods, instruments, & computers, 32(3), 396 - 402.

Suhr, D. D. (2005). Principal component analysis vs. exploratory factor analysis. SUGI 30 proceedings, 203, 230.

Velicer, W. F., & Jackson, D. N. (1990). Component analysis versus common factor analysis: Some issues in selecting an appropriate procedure. Multivariate behavioral research, 25(1), 1 - 28.

Latent Class / Profile Analysis

Bray, B. C., Lanza, S. T., & Tan, X. (2015). Eliminating bias in classify-analyze approaches for latent class analysis. Structural equation modeling: a multidisciplinary journal, 22(1), 1-11.

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

Lanza, S. T., & Cooper, B. R. (2016). Latent class analysis for developmental research. Child Development Perspectives, 10(1), 59-64.

Lanza, S. T., Tan, X., & Bray, B. C. (2013). Latent class analysis with distal outcomes: A flexible model-based approach. Structural equation modeling: a multidisciplinary journal, 20(1), 1-26.

Magidson, J., Vermunt, J. K., & Madura, J. P. (2020). Latent class analysis. Thousand Oaks, CA, USA:: SAGE Publications Limited.

Masyn, K. E. (2013). Latent class analysis and finite mixture modeling. The Oxford handbook of quantitative methods, 2, 551.

Nylund-Gibson, K., & Choi, A. Y. (2018). Ten frequently asked questions about latent class analysis. Translational Issues in Psychological Science, 4(4), 440.

MANOVA

Hummel, T. J., & Sligo, J. R. (1971). Empirical comparison of univariate and multivariate analysis of variance procedures. Psychological Bulletin, 76(1), 49 - 57.

Keppel, G., & Wickens, T. D. (2004). Design and Analysis: A Researchers Handbook, 4th ed. Upper Saddle River: Prentice Hall, 2-11.

Olson, C. L. (1976). On choosing a test statistic in multivariate analysis of variance. Psychological Bulletin, 83(4), 579 - 586.

Stevens, J. P. (1980). Power of the multivariate analysis of variance tests. Psychological Bulletin, 88(3), 728 - 737.

Repeated Measures ANOVA

Gueorguieva, R., & Krystal, J. H. (2004). Move over anova: progress in analyzing repeated-measures data andits reflection in papers published in the archives of general psychiatry. Archives of general psychiatry, 61(3), 310-317.

Huck, S. W., & McLean, R. A. (1975). Using a repeated measures ANOVA to analyze the data from a pretest-posttest design: a potentially confusing task. Psychological bulletin, 82(4), 511.

McCulloch, C. E. (2005). Repeated Measures Anova, RIP?. Chance, 18(3), 29-33.

Misangyi, V. F., LePine, J. A., Algina, J., & Goeddeke Jr, F. (2006). The adequacy of repeated-measures regression for multilevel research: Comparisons with repeated-measures ANOVA, multivariate repeated-measures ANOVA, and multilevel modeling across various multilevel research designs. Organizational Research Methods, 9(1), 5-28.

Muller, K. E., & Barton, C. N. (1989). Approximate power for repeated-measures ANOVA lacking sphericity. Journal of the American Statistical Association, 84(406), 549 - 555.

Mixed / Multilevel 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 - 930.

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.

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.

Ferron, J. M., Hogarty, K. Y., Dedrick, R. F., Hess, M. R., Niles, J. D., & Kromrey, J. D. (2008). Reporting results from multilevel analyses. Multilevel modeling of educational data, 391-426.

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., & Kaniskan, B. (2010). Using time-varying covariates in multilevel growth models. Frontiers in psychology, 1, 1 - 12.

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.

McNeish, D., Stapleton, L. M., & Silverman, R. D. (2017). On the unnecessary ubiquity of hierarchical linear modeling. Psychological methods, 22(1), 114.

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

Snijders, T. A. B., & 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. CRC press.

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.

Geldhof, G. J., Anthony, K. P., Selig, J. P., & Mendez-Luck, C. A. (2018). Accommodating binary and count variables in mediation: A case for conditional indirect effects. International Journal of Behavioral Development, 42(2), 300-308.

Hayes, A. F. (2013). Introduction to mediation, moderation, and conditional process analysis: A regression-based approach. Guilford Press.

Hayes, A. F., & Preacher, K. J. (2010). Quantifying and testing indirect effects in simple mediation models when the constituent paths are nonlinear. Multivariate behavioral research, 45(4), 627-660.

Imai, K., Keele, L., & Tingley, D. (2010). A general approach to causal mediation analysis. Psychological methods, 15(4), 309.

Judd, C. M., & Kenny, D. A. (1981). Process analysis estimating mediation in treatment evaluations. Evaluation Review, 5(5), 602 - 619.

MacKinnon, D. P. (2008). Introduction to statistical mediation analysis. Routledge.

MacKinnon, D. P., Fritz, M. S., Williams, J., & Lockwood, C. M. (2007). Distribution of the product confidence limits for the indirect effect: Program PRODCLIN. Behavior Research Methods, 39(3), 384 - 389.

Maxwell, S. E., & Cole, D. A. (2007). Bias in cross-sectional analyses of longitudinal mediation. Psychological Methods, 12(1), 23 - 44.

Maxwell, S. E., Cole, D. A., & Mitchell, M. A. (2011). Bias in cross-sectional analyses of longitudinal mediation: Partial and complete mediation under an autoregressive model. Multivariate Behavioral Research, 46(5), 816 - 841.

Preacher, K. J., & Kelley, K. (2011). Effect size measures for mediation models: quantitative strategies for communicating indirect effects. Psychological methods, 16(2), 93.

Preacher, K. J., Rucker, D. D., & Hayes, A. F. (2007). Addressing moderated mediation hypotheses: Theory, methods, and prescriptions. Multivariate behavioral research, 42(1), 185-227.

Selig, J. P., & Preacher, K. J. (2009). Mediation models for longitudinal data in developmental research. Research in human development, 6(2-3), 144-164.

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

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