Multilevel Regression Modeling as a Complement to Traditional Repeated Measures Analysis of Variance in Sports Biomechanics Research

Kyle Wasserberger1,2, William Murrah3, Kevin Giordano4, and Gretchen Oliver2 1Research & Development; Driveline Baseball

2School of Kinesiology; Auburn University

3Department of Educational Foundations, Leadership, & Technology; Auburn University

4Department of Physical Therapy; Creighton University

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1 **Abstract**

2 With the increasing availability and decreasing costs of sport science technologies, longitudinal data

3 are becoming increasingly available to the biomechanics and adjacent sport science communities. To

4 take advantage of this emerging wealth of data and best understand how biomechanics influence health

5 and performance over time, consideration regarding the appropriate handling of longitudinal data is

6 warranted. Traditionally, longitudinal data in the sport sciences have most often been analyzed using

7 repeated measures analysis of variance . However, typical analysis of variance is limited in its ability

8 to handle missing data and unbalanced observations, two scenarios common in longitudinal designs.

9 Alternatively, multilevel regression modeling is a flexible analysis method capable of handling these

10 scenarios. In this paper, we hope to draw increased attention to multilevel regression modeling and

11 lobby for its increased adaptation when examining repeated measures biomechanics data. First, we

12 introduce the rationale and approach underlying multilevel regression models. We then present examples

13 using simulated and real-world data to illustrate their potential application and limitations in sports

14 biomechanics research. Lastly, we provide some recommendations, words of caution, and additional

15 resources.

# 16 1 Introduction

17 Quantifying change over time is a central tenet for those working working with athletes of all levels.

18 Identifying factors that influence longitudinal athletic performance is vital for evaluating the effectiveness

19 of athlete training programs. For the biomechanist, measuring technique changes over time and elucidating

20 the relationships between those technique changes, athlete performance, and injury risk is of particular

21 importance. However, despite the importance placed on longitudinal athletic development in the applied

22 sport science domain, many researchers are forced to conduct cross-sectional studies due to limited time,

23 labor, or funding. Fortunately, technological advances continue to decrease the burdens associated with

24 collecting longitudinal data. Given these advances, we feel increased consideration is needed regarding the

25 appropriate means by which we analyze and draw inferences from longitudinal data.

26 Calls for improved statistical methodology in the sport sciences have grown in recent years [[5,](#_bookmark13) [10,](#_bookmark18) [11,](#_bookmark19)

27 [14,](#_bookmark22) [15,](#_bookmark23) [19,](#_bookmark27) [20,](#_bookmark28) [24].](#_bookmark32) Informal skimming of recent *Sport Biomechanics* publications indicates repeated measures

28 analysis of variance (RM*·*ANOVA) remains a popular choice for dealing with longitudinal biomechanics

29 data [[16,](#_bookmark24)[17,](#_bookmark25)[21,](#_bookmark29)[28].](#_bookmark36) Beyond *Sport Biomechanics*, Google Scholar returns over 4,200 hits over the last ten years

30 for “ANOVA” in journals associated with biomechanics compared to approximately 600 hits for “multilevel

31 regression”, “mixed-effects”, or “mixed-model”[i](#_bookmark0). Despite the greater apparent popularity of ANOVA-based

32 methods, RM*·*ANOVA carries with it several important assumptions which limit its utility in applied

33 longitudinal settings. Most notably, RM*·*ANOVA assumes balanced designs (equal number of repeated

34 measures across individuals), complete cases (no missing observations within individuals), and temporal

35 equivalence (repeated measures across individuals are equally spaced in time). While these conditions can

36 usually be met in tightly-controlled, laboratory-based studies, applied longitudinal work often suffers from

37 study imbalances, unforeseen disruptions to data collection schedules, and participant attrition; all of which,

38 depending on their severity, may threaten RM*·*ANOVA’s validity.

39 The assumptions surrounding RM*·*ANOVA present salient challenges to those working in the

40 observational or quasi-experimental settings common in sport biomechanics research. Conversely, multilevel

41 regression modeling is capable of handling both imbalanced designs and partially missing data, positioning it

42 as a useful complement to more traditional repeated measures methods. Regretfully, multilevel models have

43 yet to make significant headway into sport biomechanics despite being present in other sport performance

44 domains, such as sport psychology [[2,](#_bookmark10) [3,](#_bookmark11) [6].](#_bookmark14) If fact, to our knowledge, the use of multilevel modeling in

iANOVA search: ["ANOVA" or "repeated measures" source:biomechanics], multilevel modeling search: ["multilevel regression" OR "mixed-effects" OR "mixed-model" source:biomechancis]. Date range limited between 2012 and 2022. Disregarding patents and citations. Performed February 2022.

45 sport biomechanics is limited to three papers, all published since 2019 [[13,](#_bookmark21) [26,](#_bookmark34) [27].](#_bookmark35) While studying the

46 baseball pitching motion Slowik et. al. [[26]](#_bookmark34) and Solomito et al [[27]](#_bookmark35) used a multilevel framework to examine

47 the associations between various kinematic factors and pitching arm joint loads. Additionally, Iglesias et.

48 al. examined between-participant differences in the within-participant load-velocity relationship during

49 several weightlifting exercises [[13].](#_bookmark21) Although these papers provide important insight into their respective

50 research areas, we feel a formal introduction of the advantages, disadvantages, and limitations of multilevel

51 modeling would benefit those in sport biomechanics working alongside athletes in longitudinal settings

52 and who frequently encounter repeated measures study designs. Therefore, our purpose is to introduce

53 multilevel regression modeling to a sports biomechanics audience and offer a brief tutorial on model

54 notation, construction, and interpretation. We also outline the advantages and disadvantages of multilevel

55 modeling over traditional repeated measures designs and offer recommendations for those interested in

56 further exploration of multilevel techniques.

# 57 2 The Traditional Regression Model

58 Before examining the multilevel regression model, let us first consider a simple linear regression predicting

59 some outcome measure, *y*, from one predictor variable, *x*, given by Equation [1:](#_bookmark1)

*y*ˆ*i* = *β*0 + *β*1*xi* + *ϵi* (1)

60 In Equation [1,](#_bookmark1) *β*0 represents the model intercept and *β*1 represents the model slope. Recall that a model

61 intercept can be thought of as the predicted value of *y* when *x* equals zero and a model slope can be thought

62 of as the predicted increase (or decrease, if negative) in *y* for a 1-unit increase in *x*. If our predictor, *x*,

63 is centered around its mean, then the intercept represents the predicted value of *y* for an average value

64 of *x*. *ϵi* represents the residual error between the *i*-th model prediction and the *i*-th observation (*yi − y*ˆ*i*)

65 (Figure [1).](#_bookmark2) The one-predictor linear regression model can be extended to multiple regression by adding

66 additional predictor variables (i.e. *x*2, *x*3*...xn*) or nonlinear[ii](#_bookmark0) regression by adding polynomial (i.e. *x*2*, x*3*...xn*),

67 exponential (*ex*), or logarithmic (*ln*(*x*)) terms. Additionally, how predictor variables’ effects depend on one

68 another can be examined by introducing their product terms (i.e. *x*1 *∗ x*2) and analyzing their interactions.

iiMore formal writings will use *linear vs. nonlinear* in terms of the role of the regression coefficients (i.e. *β*0, *β*1, etc...). However, here we use *nonlinear* in terms of the relationships between *x* and *y*. For more details we refer the reader to the works of Curran-Everett [[7]](#_bookmark15)

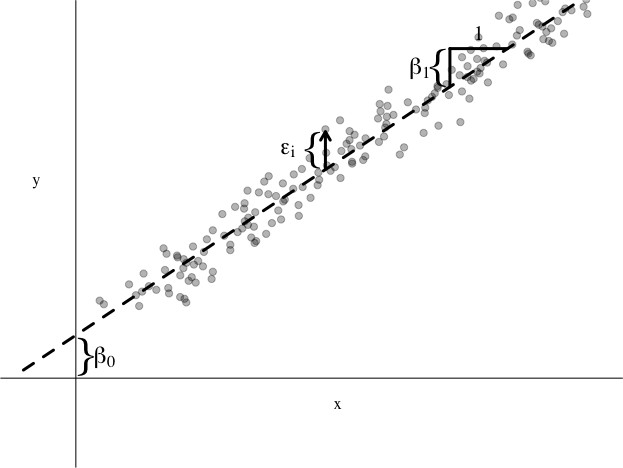


Figure 1: Hypothetical Simple Regression

# 69 3 Nested Data and the Multilevel Regression Model for Repeated Measures

70 Collecting multiple observations from a single participant results in what is sometimes referred to in other

71 fields as ‘nested’, ‘hierarchical’, or ‘multilevel’ data [[1,](#_bookmark9) [4,](#_bookmark12) [23,](#_bookmark31) [25,](#_bookmark33) [29].](#_bookmark37) In repeated measures designs, we

72 consider observations to be nested within individuals. In other applications, individuals may be nested

73 within some grouping structure such as classrooms, congressional districts, or treatment arms. Regardless

74 of the grouping structure in question, nested data violate the assumption of observational independence

75 required by traditional regression [[8,](#_bookmark16) [12,](#_bookmark20) [23].](#_bookmark31) That is, two observations from the same individual will be more

76 closely related to each other compared to two observations from two different individuals.

77 The degree to which nested data are more closely related than independent data is sometimes referred

78 to as the *intraclass correlation* and is computed as the variance in a model’s outcome accounted for by the

79 data’s nested structure divided by the outcome’s total variance [[12,](#_bookmark20) p. 15][iii](#_bookmark0).

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*σ*

*ICC* = *u*0 2

0

(2)

80 Where *σ*2

*u*0

and *σ*2

*e*

*σu*2 + *σe*

represent the between-group and within-group variances, respectively. Under highly

81 dependent data conditions (where most variance is accounted for by the nested data structure), the ICC will

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*σ*

82 approach 1.0 since Equation [2](#_bookmark3) simplifies to *u*0 as *σ*2 trends towards zero. Conversely, the ICC will approach

2 *e*

*σ*

*u*0

iiiFor those more familiar with the ANOVA-based framework, an analog to the ICC is the between sum of squares divided by the total sum of squares ( *SSbtwn* ).

*tot*

*SS*

83 zero under highly independent data since Equation [2](#_bookmark3) simplifies to 0 as *σ*2 trends towards zero.

2 *u*0

*σ*

*e*

84 In practice, the ICC will lay somewhere between 0 and 1. Most important for the applied researcher,

85 even apparently small deviations from 0 can drastically inflate type 1 error rates if ordinary least squares

86 methods are used [[18].](#_bookmark26)

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88 Similar to traditional regression, we can start with a simple multilevel model predicting some outcome

89 measure, *y*, from one predictor variable, *x*. For this paper we will be following Hox’s [[12]](#_bookmark20) notation[iv](#_bookmark0).

*y*ˆ*ij* = *β*0*j* + *β*1*jxij* + *ϵij* (3)

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Equation [3](#_bookmark4) is often referred to as the *level-one* or *first-level* model since it deals with the first level of nesting in our data.

Equation [3](#_bookmark4) is identical to Equation [1](#_bookmark1) except we now have a second subscript, *j*, denoting the nested nature of the data. *xij* now represents observation *i* from individual *j* while *β*0*j* and *β*1*j* represent the model intercept and slope for individual *j*. *y*ˆ*ij* represents the model prediction for observation *i* from individual *j* and *ϵij* represents the residual error between each observed outcome and its corresponding predicted value (*yij − y*ˆ*ij*). The inclusion of a second subscript, *j*, thereby allowing model intercepts and slopes to vary between individuals is the fundamental difference between traditional and multilevel regression.

By allowing model intercepts and slopes to vary between individuals, the multilevel model for repeated measures parses each individual’s intercept and slope into a combination of the average model intercept/slope plus some individual-specific deviation from the average. Equations [4](#_bookmark5) and [5](#_bookmark6) represent the regression equations predicting each individual’s model intercept (Equation [4)](#_bookmark5) and slope (Equation [5)](#_bookmark6) and make up the second-level model. In Equations [4](#_bookmark5) and [5,](#_bookmark6) the first term on the right side (*γ*00 and *γ*10) represent the *average* model intercept and slope, respectively, across all individuals. These average model parameters are known as *fixed*-effects since they do not vary between individuals (notice there is no *j* subscript). The second terms on the right side (*µ*0*j* and *µ*1*j*) represent the individual-specific deviations from the average model intercept and slope, respectively. Because *µ*0*j* and *µ*1*j* vary between individuals, they are known as *random*-effects. Modeling parameter variability as a combination of fixed and random-effects is why multilevel models are sometimes referred to as *mixed*-effects models (a mixture of fixed and random effects).

ivIt should be known that other authors have used slightly (or sometimes very) different notations. Admittedly, this is one

of the higher barriers to entry for those without strong analytical training. We encourage readers to take considerable time learning model notation as it will accelerate the remaining stages of the learning process

*β*0*j* = *γ*00 + *µ*0*j* (4)

*β*1*j* = *γ*10 + *µ*1*j* (5)

109 The multilevel model can then use second-level parameters (*zj*) to account for variance in the predicted

110 intercepts and slopes. With the inclusion of second-level parameters, *µ*0*j* and *µ*1*j* represent the residual

111 variation in the predicted intercept and slope after accounting for *zj*.

*β*0*j* = *γ*00 + *γ*01*zj* + *µ*0*j* (6)

*β*1*j* = *γ*10 + *γ*11*zj* + *µ*1*j* (7)

112 Substituting the right side of Equations [6](#_bookmark7) and [7](#_bookmark8) for *β*0*j* and *β*1*j* from Equation [3](#_bookmark4) yields the complete multilevel

113 model predicting one outcome from one first-level and one second-level variable:

*intercept*

*slope*

*y*ˆ*ij* = *γ*00 + *γ*0 1 *zj* + *µ*0 *j* + (*γ*10 + *γ*1 1 *zj* + *µ*1*j* ) *xij* + *ϵij* (8)

114 Distributing *xij* and arranging like terms helps delineate the fixed and random parts of the model:

*fixed random*

*y*ˆ*ij* = *γ* 00 + *γ*01*zj* + *γ* 1 0*xij* + *γ*11*xijz* *j* + *µ* 1*jxij* + *µ*0*j* + *ϵi* *j* (9)

115 As with traditional regression models, the multilevel regression model can be generalized to multiple

116 multilevelv regression with *m* first-level and *n* second-level predictors:

*m*

*y*ˆ*ij* =*β*0*j* + *βmjxmij* + *ϵij* (10)

*m*=1 *n*

*β*0*j* =*γ*00 + *γ*0*nznj* + *µ*0*j* (11)

*n*=1 *n*

*βmj* =*γm*0 + *γ*1*nznj* + *µnj* (12)

*n*=1

vyeah, "multiple multilevel", I know. Yikes

# 117 4 Benefits and Drawbacks of Multilevel Models over Traditional Repeated

118 **Measures ANOVA**

119 The three assumptions made by repeated measures ANOVA that are most relevant to sport biomechanics:

120 temporal equivalence, design balance, and case completeness.

Repeated Measures ANOVA Multilevel Regression

Temporal equivalencea Assumes repeated measures are equally

spaced in time

Balanced design Assumes participants have same number of repeated measures

Case completeness Assumes no missing data; incomplete cases

are handled through listwise deletion

Repeated measures may be unequally

spaced in time

Participants may have different number of

repeated measures

Missing data may be accounted for under

certain circumstancesb

a "Temporal" equivalence does not only apply to growth models, where time is placed on the x-axis. It may be extended to "whatever is on the x-axis of your scatterplot".

b Missing data analysis is an extremely rich stand-alone area of research that we cannot do justice in this article alone. Readers are directed to works of Enders [[9]](#_bookmark17) for a more thorough exploration of the topic

121 **4.1 When ANOVA will do just fine**

122 Simple pre-post designs with no missing data

# 123 5 Other Figures to incorporate

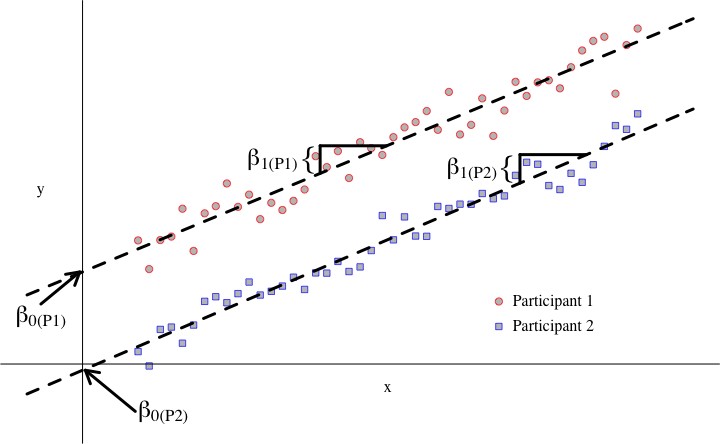


Figure 2: Fictional multilevel model with random intercepts. Individual regression lines are parallel (equal slopes) but differ in their respective intercepts

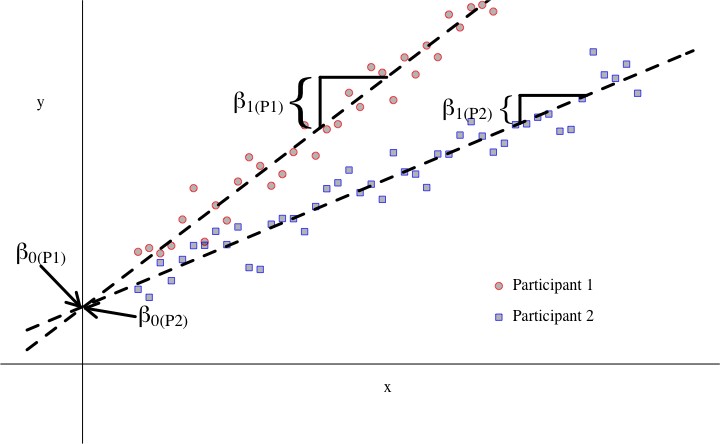


Figure 3: Fictional multilevel model with random slopes. Individual regression lines are not parallel (unequal slopes) but share a mutual intercept

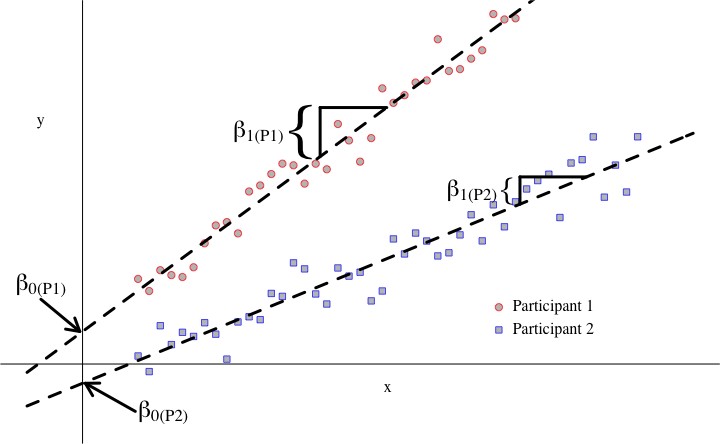


Figure 4: Fictional multilevel model with random intercepts and slopes. Individual regression lines are not parallel and do not share a mutual intercept

124 **6 Discard Pile**

125 We biomechanists like to throw away lots of data. Our cameras capture the positions of dozens of reflective

126 markers with sub-millimeter accuracy hundreds of times each second while our participants perform several,

127 sometimes dozens, of movement trials during data collection. Each new trial brings additional data that

128 could increase statistical power and be used to better understand our research questions. Yet, far too often,

129 choices related to experimental design or statistical analysis greatly reduce the volume of data we work

130 with. Reduced data volume negatively impacts inferential power when conducting statistical analyses and

131 can potentially indicate inefficient use of data collection resources and research labor.

132 Two research practices common in sports biomechanics that reduce data volume are discretization and

133 ensemble averaging. Discretization occurs when researchers extract one value, such as a maxima, minima, or

134 average value, from a continuous time series of data. Ensemble averaging occurs when researchers combine

135 several trials from the same participant into one *representative* trial. Discretization and ensemble averaging

136 can also be combined to further reduce the available data by averaging discrete values from multiple trials

137 or taking discrete values from ensemble averaged time series. Although sometimes appropriate depending

138 on the research question, discretization and ensemble averaging reduce the dimensionality and variability in

139 time series data, reducing statistical power.

140 While discretization can be ameliorated though emerging techniques such as statistical parametric

141 mapping [[22],](#_bookmark30) researchers may still wish to examine certain discrete measures if warranted by their domain

142 expertise and research question of interest. One such scenario is the repeated measure of biomechanic

143 or performance values over time. Typically, repeated measures data in sports biomechanics are examined

144 using univariate or multivariate repeated measures analysis of (co)variance. While these statistical tools

145 are appropriate under certain conditions, they make several assumptions that may often be problematic

146 in the observational or quasi-experimental settings common in sport biomechanics research. In such cases,

147 multilevel regression modeling may complement or replace more traditional repeated measures analyses.

148 Although multilevel techniques are present in other sport performance domains such as sport

149 psychology [[2,](#_bookmark10) [3,](#_bookmark11) [6],](#_bookmark14) they have yet to make significant headway into sport biomechanics. If fact, to our

150 knowledge, the use of multilevel modeling in sport biomechanics is limited to two papers, both published

151 since 2019 [[13,](#_bookmark21) [26].](#_bookmark34) Slowik et. al. used a multilevel framework to contrast the strong within and weak

152 between-participant relationships between elbow joint loading and baseball pitching speed [[26]](#_bookmark34) while Iglesias

153 et. al. examined between-participant differences in the within-participant load-velocity relationship during

154 several weightlifting exercises [[13].](#_bookmark21) Although these two papers provide important insight into their respective

155 research areas, we feel a formal introduction of the advantages, disadvantages, and limitations of multilevel

156 modeling would benefit those in sport biomechanics working with repeated measures designs. Therefore,

157 our purpose is to introduce multilevel regression modeling to a sports biomechanics audience and offer a

158 brief tutorial on model notation, construction, and interpretation. We also outline the advantages and

159 disadvantages of multilevel modeling over traditional repeated measures designs and offer recommendations

160 for those interested in further exploration of multilevel techniques.

161 Some of the more notable assumptions that can cause problems for sport biomechanists dealing with

162 repeated measures include temporal equivalence (i.e. time between data points must be the same for all

163 participants), balanced study designs (i.e. must have the same number of data points for each individual)

164 and case completeness (i.e. must have no missing data).

165 Compared with traditional univariate or multivariate analysis of (co)variance, multilevel modeling

166 allows more researcher flexibility through fewer statistical assumptions and the ability to handle missing

167 data, non-linear relationships, and time-varying covariates [[12].](#_bookmark20)

168 In addition to its assumptions regarding data symmetry and structure, RM*·*ANOVA is restricted to

169 testing for the presence of linear relationships between variables and, while the ANOVA framework can

170 handle time-invariant covariates, modeling covariates which change over the duration of a longitudinal study

171 is not possible in RM*·*ANOVA.

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