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Original research

The applied impact of *'naïve'* statistical modelling of clustered observations of motion data in injury biomechanics research

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A B S T R A C T

Objectives: Appropriate statistical analysis of clustered data necessitates accounting for within-participant effects to ensure results are repeatable and translatable to real-world applications. This study aimed to compare statistical output and injury risk interpretation differences from two statistical regression models built from a clinical movement sidestepping database. A "naïve" regression model, which does not account for within-participant effects, was compared with an appropriately applied mixed effects model.
Design: Comparative study.
Methods: Three-dimensional unplanned sidestepping joint angle data (trunk, hip, and knee) from 35 males (112 observations) were used to model peak knee valgus moments and anterior cruciate ligament injury risk during the impact phase of stance. Both statistical models were cross-validated using a k-fold analysis.
Results: The naïve regression returned inflated goodness of fit statistics ($R^2 = 0.50$), which was evident following cross-validation (predicted $R^2 = 0.43$). Following cross-validation, the mixed effects model (predicted $R^2 = 0.40$) explained a similar amount of variance, despite containing three less predictors. The naïve model produced inaccurate parameter estimates, overestimating the effects of certain kinematic parameters by as much as 79 %.
Conclusions: A regression model naïvely applied to clustered observations of sidestepping data resulted in erroneous parameter estimates and goodness of fit statistics which have the potential to mislead future research and real-world applications. It is important for sport and clinical scientists to use statistically appropriate mixed effects models when modelling clustered motion capture data for injury biomechanics research to protect the translatability of the findings.

1. Introduction

Statistics are a vital component of the philosophy and application of the scientific method. The primary purpose of statistics within science is to test *a-priori* hypotheses of pre-defined test-populations.[1] The results from these analyses are estimates, often generalised beyond the sample of data used within the original statistical model. To ensure results are both repeatable and generalisable at the population level, statistical models must be appropriate for the test-population investigated, the research question posed, and the study design in which they are applied.

Within the fields of biomechanics and sports medicine, dynamic movement patterns and postures are often linked to joint and tissue loading along with musculoskeletal and ligament injury risk. Regression models are a useful form of statistical analysis which model how multiple independent variables relate to a dependent variable. These statistical models have been utilised within biomechanical anterior cruciate ligament (ACL) injury research to model associations of multiple injury risk factors (e.g., joint and segment kinematics) with a surrogate measure of injury risk (e.g., peak tissue loading).[2–4] These injury risk associations are then used to inform injury interventions.[5] It is therefore important that sound statistical methods are used to promote efficacy when generalising findings to the wider community.

Clustered datasets contain multiple observations for each participant and maximise the effective power of the sample used in a study.[6] However, when analysing clustered datasets, care should

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be taken to account for correlations that exist between multiple observations from an individual.[7] Examples where regression models have been implemented inappropriately for injury biomechanics data containing clustered observations can be found in the literature. For example, a limitation of a previous study, which associated sidestepping technique with ACL injury risk, was the use of a regression analysis which incorrectly assumed clustered observations were independent.[2] Other ACL injury studies have reported collecting multiple observations of movement from each participant, without clearly specifying whether clustered observations were considered independent within the analyses.[3,4] Analyses that don't account for within-participant effects present in clustered data, limit the ability to apply reported injury risk associations to individuals or populations external to the participants included in the analyses.[8]

Mixed effects models contain both random and fixed effects, and are useful in settings where measurements are made on clusters of related observations.[8] These models can include random effects to account for inherent correlations between clustered data. Moen and colleagues[8] tested the effect of statistically modelling within-subject effects for the treatment of neurons in mice. They found that "naïve statistical models", which incorrectly modelled clustered observations as independent, produce incorrect model parameter estimates when compared with an appropriately applied mixed effects model.[8] Additionally, a study comparing a variety of analyses for clustered data found a higher probability of recording a false-positive finding when analyses did not correctly account for correlations between clustered observations.[9] It is known that clustered observations, which are incorrectly assumed to be independent, lead to erroneous statistical outputs.[8,9] However, it remains unclear what effect incorrect statistical modelling assumptions have on the clinical interpretation of biomechanical injury research findings, and by extension, their future scientific and real-world applications.

The purpose of this study was to compare statistics and inferences from results of a naïve and an appropriately applied regression model applied to a sample of clustered unplanned sidestepping data. Joint and segment kinematics previously linked to ACL injury risk[3,10,11] will be used to predict peak knee valgus moments (PKVM) during weight acceptance. We hypothesise that a naïve statistical model,[8] in the form of a backwards multiple regression, will return parameter estimates that differ to the appropriately applied model. Where differences in the included model parameters are found between the two statistical approaches, we discuss the potential effects these differences may have on clinical interpretations and real-world applications. Secondly, we hypothesise that a naïve statistical model will overestimate model goodness of fit statistics. This will be determined by comparing goodness of fit measures of the naïve model within the sample population to its performance following cross-validation. Lastly, it is hypothesised that following cross-validation the mixed-effects approach will have superior goodness of fit statistics to the cross-validated naïve model.

2. Methods

Three-dimensional kinematic and kinetic data from 35 right-leg dominant male participants (age 22 ± 5 years, height 1.8 ± 0.3 m, and body mass 79.8 ± 9.4 kg) were used in the current analysis. This sample comprises previously published data,[12] and additional unpublished data using the same data collection protocols. Ethics approval was obtained from the Human Research Ethics Committee at the University of Western Australia (RA/4/1/5333 and RA/4/1/5713).

Participants completed a series of randomised planned and unplanned straight-line runs, sidesteps and crossovers which is detailed in a previous study.[12] For the current analysis, only the unplanned sidesteps were analysed. Retro-reflective kinematic markers were placed according to an established full-body anatomical joint model.[13,14] Functional methods were used to identify hip and knee joint centres.[13] A three-dimensional camera system consisting of 12 Vicon® MX cameras (Oxford Metrics, Oxford, UK) recorded kinematic markers at 250 Hz. An AMTI force plate (Advanced Mechanical Technology Inc., Watertown, USA) synchronously recorded ground reaction force (GRF) at 2000 Hz. Vicon Nexus® (version 1.85) was used for the signal processing of the kinematic and analogue data and to custom model the biomechanical data. Both marker trajectory and GRF data were filtered at 15 Hz using a zero-lag fourth-order Butterworth filter.[12] The impact or weight acceptance phase of stance was defined as when the vertical ground reaction force exceeded 10 N through to the first trough, which is typically observed in the first 20–30% of stance.[15]

Joint/segment angles were calculated for the trunk, hip, and knee at foot contact (vertical GRF >10 N). All angles were calculated as the angle of the child segment relative to the parent segment, except for transverse-plane trunk rotation which was relative to the global three-dimensional coordinate system. Transverse-plane trunk rotation towards the change of direction, and lateral trunk flexion towards the stance limb were reported as positive angles. Inverse dynamics was used to calculate externally applied knee valgus moments during weight acceptance, which were normalised to each participant's height (m) and weight (N) and the peak was recorded.

Analysis of clustered data was performed in SPSS Statistics® (version 24) ($p < 0.05$). For each statistical model; trunk, hip and knee angles were entered as model parameters before performing a backwards stepwise elimination process. A total of 113 unplanned sidestepping observations, from 35 participants, were entered into SPSS. Examination of the data found one trial containing an unrealistic PKVM measure (0.42) as per a systematic review of knee kinematics and kinetics.[16] This trial was removed, resulting in a final participant sample of 35, with 112 observations.

Using the final sample, a backwards multiple regression was performed. This regression analysis does not account for within-participant effects present in the clustered data. The criterion to remove parameters was set to $F \leq 0.1$. R^2, adjusted R^2, root mean squared error (RMSE), F and p values were reported. Non-standardised parameter estimates, confidence intervals and p-values were reported for each parameter.

Using the final sample, an appropriately applied linear mixed model was performed. Maximum likelihood estimation was chosen to allow the comparison of nested models. A random intercept was calculated with participants entered as random effects. Three-dimensional trunk, hip, and knee angles were entered as fixed effects and the relative log-likelihood for the model was recorded. Backwards elimination was performed by sequentially removing non-significant predictors. When a predictor was removed, Wilk's likelihood ratio[17] was used to test that the model before removing a predictor did not explain a significantly greater distribution of PKVM than the model after parameter elimination. The last model which did not report significance in Wilk's likelihood ratio test was used as the final model. The linear mixed model does not output the R^2 statistic, however, the goodness of fit measure can be found by testing against withheld data or through cross-validation.[18]

The backwards multiple regression model and the linear mixed model were tested using a k-fold cross-validation, where k was set to 10. This approach uses each observation once as a test variable and nine times in the training sets to create model parameter estimates.[19] During each k-fold, fixed model parameter estimates from the training set were applied to make marginal predictions

Table 1
Mean and standard deviation of joint angles at foot contact and normalised peak knee valgus moments during weight acceptance.

Segment/Joint	Variable	Mean	Standard deviation
Trunk	Flexion	−10.2°	7.1°
	Lateral flexion	8.9°	4.2°
	Rotation	−6.4°	9.8°
Hip	Flexion	47.3°	7.5°
	Abduction	17.5°	8.2°
	Internal rotation	3.1°	8.2°
Knee	Flexion	17.4°	8.2°
	Abduction	2.4°	3.7°
	Internal rotation	2.0°	9.4°
	PKVM	0.79[a]	0.53[a]

[a] Peak knee valgus moments (PKVM) are presented in scientific notation $\times 10^{-1}$ and normalised to participant height (m) and body weight (N).

of PKVM from observations in the test set. Paired samples t-tests were used to test for significant correlations between the estimated PKVM and measured PKVM. The R^2 statistic reported from the cross-validations is a predicted R^2, which indicates the ability of the model to be extrapolated to homogeneous populations outside of the current sample.[19]

For both models, changes to each model parameter by one standard deviation were performed to assess the influence of each parameter on the modelled dependent variable (PKVM).[2] For each parameter, the standard deviation of the measurement was multiplied with the relative parameter estimate and was reported as a percentage of the mean predicted PKVM (where all parameters are set to the mean value from the sample).

3. Results

The mean and standard deviation of joint kinematic measurements at foot contact and PKVM during weight acceptance are reported in Table 1. Knee kinematics and kinetics fall within expected ranges reported in previous sidestepping biomechanics literature.[16] Trunk and hip angles were also similar to measures reported previously.[2,15]

In the backwards multiple regression model; trunk lateral flexion, trunk rotation, knee flexion and knee internal rotation at foot contact were removed, $F(7,104) = 14.644$, $p < 0.001$, $R^2 = 0.50$, adjusted $R^2 = 0.46$, RMSE = 0.27. Trunk lateral flexion, trunk rotation, hip internal rotation, knee flexion and knee internal rotation were removed from the linear mixed model (log-likelihood = −445.462, degrees of freedom = 6). There was no significant difference in the variance of PKVM explained when compared with the preceding model (log-likelihood = −446.446, degrees of freedom = 7). Knee abduction angle was a significant parameter in the naïve model but not in the linear mixed model. Hip internal rotation was a significant predictor in the naïve model but was removed from the linear mixed model. Estimates of parameters common to both models differed, with the naïve model underestimating the trunk flexion estimate (−15.0 %) and overestimating the estimates for hip flexion (16.5 %), hip abduction (21.5 %) and knee abduction (79.4 %) when compared to the linear mixed model. For both models, parameter estimates, confidence intervals and the effect of a one standard deviation change on predicted PKVM are reported in Table 2.

When cross-validated, the PKVM predicted from both the naïve backwards multiple regression (predicted $R^2 = 0.43$, RMSE = 0.29, $p < 0.001$) and the appropriately applied linear mixed model (predicted $R^2 = 0.40$, RMSE = 0.30, $p < 0.001$) were significantly correlated with measured PKVM (Fig. 1).

4. Discussion

This study compared the statistics and clinical interpretations of outputs derived from a naïvely applied regression model and an appropriately applied linear mixed model, applied to a sample of clustered three-dimensional sidestepping data. These analyses confirm our primary hypotheses. A model naïvely applied to clustered biomechanical data produced errors in the estimation of parameter estimates. Secondly, the naïve model also inflated the goodness of fit measures, which was proven by a lower predicted R^2 estimate following cross-validation (0.50 vs 0.43). Secondary hypotheses of this study were not supported by the findings, with both models explaining a similar level of variance in measured PKVM. However, these findings may be attributable to the greater number of parameters included in the naive model predictor set after backwards elimination. The inclusion of extra parameters is an example of the naïvely applied models' susceptibility to Type 1 error. Overall, the current results highlight concern for the effects of inappropriate statistical approaches when analysing clustered observations of biomechanical data. Differences in parameters and estimates produced within each model leads to potential compounding error in inferred injury risk recommendations and has the apparent potential to bias follow-on injury prevention and rehabilitation research along with real-world applications.

Inappropriate analysis techniques that do not account for correlations between clustered observations, leads to erroneous statistical outputs. Our concern is that this creates the potential for incorrect interpretation of biomechanical data in the context of ACL injury risk. In the current study the naïve backwards multiple regression model overestimated goodness of fit statistics, which was evident when the naïve model ($R^2 = 0.50$, RMSE = 0.27) was compared with its performance following cross-validation (predicted $R^2 = 0.43$, RMSE = 0.29). These results align with research published in the neuroscience literature, which have shown that incorrectly assuming independence between multiple observations of the same participant biases model statistics.[8] Results from this research demonstrates that incorrect statistical treatment of clustered data can have a significant bearing on the interpretation and conclusions derived from a statistical model. Moving forward, or looking back to the rules set within the field of statistics, the authors recommend reporting two items when applying regression analysis to clustered datasets: (1) sample sizes for the number of participants and number of observations, and (2) clear detail as to how analysis procedures treat clustered observations (i.e., independent vs dependent). This will provide adequate information for readers to critically evaluate the validity of the statistical methods and the suitability for future applications.

Testing regression parameters against withheld data indicates the applicability of the results outside of the study's sample population and improves the generalisability of the findings.[20] Though the naïve model was inappropriate for the statistical analysis of clustered observations,[8,9] it returned similar goodness of fit statistics to the appropriately applied model when cross-validated (predicted R^2: 0.43 vs 0.40, RMSE: 0.29 vs 0.30, respectively). Reported goodness of fit statistics from a published ACL injury prediction algorithm,[4] which does not detail how clustered observations were treated, may be unaffected by any potential use of naïve statistical methods as the regression equation was validated against withheld data. It may be best practice for injury prevention research to test regression parameters outside of the sample used to train the statistical model, further safeguarding the generalisability of findings.

Statistical modelling of ACL injury risk factors which does not account for correlations between clustered observations is more susceptible to Type 1 error.[9] In the current study, the linear regression model contained three predictors not found within the

Table 2
Model parameters, parameter estimates and percentage change in modelled peak knee valgus moments for different regression methods.

Model	Parameters	Parameter Estimates (Confidence intervals)	One SD change (%)
Backwards linear regression (naïve model)	Constant	−0.660* (−1.245, −0.069)	
	Trunk flexion°	0.021** (0.008, 0.034)	18.9
	Trunk rotation°	−0.012 (−0.026, 0.001)	15.3
	Hip flexion°	0.013 (0.000, 0.025)	12.1
	Hip abduction°	0.047*** (0.032, 0.062)	48.9
	Hip internal rotation°	0.016** (0.006, 0.064)	16.2
	Knee abduction°	0.039** (0.014, 0.064)	18.4
	Knee rotation°	0.008 (0.001, 0.018)	9.8
Linear mixed model (appropriately applied model)	Constant	−0.201 (−0.832, 0.431)	
	Trunk flexion°	0.025** (0.010, 0.039)	22.2
	Hip flexion°	0.011 (−.001, 0.023)	10.4
	Hip abduction°	0.039*** (0.030, 0.048)	40.3
	Knee abduction°	0.022 (−0.002, 0.046)	10.3

Parameter estimates are non-standardised. One SD change is the percentage change in predicted peak knee valgus moments from changing the parameter by one standard deviation and indicates the influence of an independent variable within a regression.

* Indicates $p < 0.05$.
** Indicates $p < 0.01$.
*** Indicates $p < 0.001$.

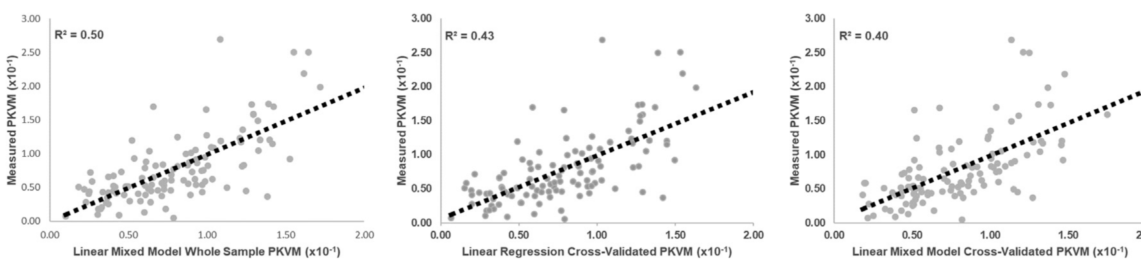

Fig. 1. Scatterplots of the estimated peak knee valgus moments (PKVM) from the linear regression applied to the whole sample (left), the cross-validated linear regression (middle) and cross-validated linear mixed model (right). PKVM are normalized to height (m) and weight (N) and reported in scientific notation $\times 10^{-1}$.

appropriately applied model, which may have been incorrectly included due to inappropriate modelling of within-participant effects present in the clustered data. Additionally, hip internal rotation and knee abduction were significant parameters in the naïve model but not in the linear mixed model. Despite inappropriate statistical modelling, the inclusion of transverse trunk rotation and hip internal rotation as predictors does align with previously published ACL injury research.[10,21] However, the inclusion of knee internal rotation contradicts previous research, which has shown there is no effect on PKVM when this posture was imposed on an individual's sidestepping technique.[15] Despite some agreement with previous findings, the associations unique to the naïve model should be treated with caution, as failing to account for correlated observations within clustered data increases susceptibility to Type 1 error[9] — a result which cannot be ruled out in the present study.

Differences in the number of parameters within the two statistical models mean the naïve model is less suitable for informing targeted ACL injury prevention research. The mixed effects model was more parsimonious while explaining a similar amount of variance in PKVM. The three additional variables reported in the naïve model convolute the importance of the predictors found within the appropriately applied model. Interestingly, the parameters unique to the naïve model were all transverse-plane joint angles which may shift the focus away from the frontal and sagittal-plane joint angles returned by the linear mixed model. Real-world interventions based on naïve statistical models may lead to the formation of a sub-optimal prevention programs which spend resources and time targeting superfluous risk factors. In comparison, the lower number of degrees of freedom in the mixed effects model means it is more suitable for creating focused ACL injury prevention strategies, which may translate more effectively to time-poor sports and clinical settings.

Disparity in the estimates of parameters common to both models (trunk flexion, hip flexion, hip abduction and knee abduction) suggest there is meaningful difference in the association of these common parameters with PKVM. Compared to the linear mixed model, the naïve model underestimated the trunk flexion estimate (−15 %) and overestimated the estimates for hip flexion (16 %), hip abduction (22 %) and knee abduction (79 %). Within the naïve model knee abduction had the third highest one standard deviation change on predicted PKVM, however, within the linear mixed model it had the lowest one standard deviation influence of any kinematic parameter. Therefore, the naïve analysis changed the perceived practical importance of parameters when explaining variance in PKVM. Errors in the estimates are likely attributable to modelling correlated participant data as independent.[8] These errors highlight concern in the future reproducibility of naïvely applied regression models. Additionally, future research may be ill-informed if guided by estimates attained through inappropriate modelling of clustered biomechanical data.

There are limitations to the current study. It is not possible to identify the practical impact of differing technique recommendations from each model without testing informed interventions in randomised control trials. However, the findings that naïve regressions overestimate model goodness of fit and include variant parameters and parameter estimates when compared to an appropriately applied model, highlights a need to ensure statistical standards are observed when analysing clustered data. Specifically, it is important for researchers to treat clustered observations as dependent. There are other statistical methods of accounting for within-participant effects in clustered datasets (e.g. generalised linear models) that were not tested in this study. However, it was not the aim of the current study to compare these approaches, but rather to establish the applied impact to injury prevention research when clustered biomechanical observations are incorrectly treated as independent. A linear mixed model was used as the appropriately applied model, as Galbraith, Daniel and Vissel[9] reported that they perform best when clustered data is normally distributed.

5. Conclusion

The inappropriate statistical modelling of clustered biomechanical data results in overestimating goodness of fit measures and produces erroneous parameter estimates and significant associations influenced by Type 1 error. The downstream effect is that naïvely applied models change the relative importance of different kinematic parameters, potentially creating divergence in injury prevention recommendations within the literature. It is recommended for researchers in sports medicine to heed advice from the statistical literature by appropriately accounting for inherent correlations in clustered data, and clearly communicate how correlated observations are treated within analyses. Additionally, cross-validation of regressions is recommended to indicate the generalisability of the model and protect the repeatability and potential impact of future applications influenced by findings in the fields of sports medicine and biomechanics.

Practical implications

- Inappropriate statistical analysis of data containing multiple observations per participant leads to inflated model goodness of fit statistics.
- Inappropriately applied statistical models have the potential to identify alternate sets of predictor variables, due to increased susceptibility to Type I error.
- Failing to account for within-participant effects generates incorrect parameter estimates and alters the relative importance of kinematic variables.
- Cross-validation of regression models is recommended to protect the translatability of the findings to real-world settings.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.jsams.2018.10.006.

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