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Thirty-year Trends of Study Design and Statistics in Applied Sports and Exercise Biomechanics Research

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ABSTRACT

International Journal of Exercise Science 11(1): 239-259, 2018. This study documented the change in study design and statistics employed in applied sports and exercise biomechanics research from 1985 to 2014. The sample comprised 676 data based original research reports published in the Journal of Applied Biomechanics (JAB) from 1985 to 2014. Eight design and 10 statistical criteria were extracted from each study. Descriptive statistics were calculated and change in study criteria over time were documented. Design criteria that did not change over time, remaining at relatively low levels of rigor, were widespread (71%) use of small (2-20) sample sizes and examination of numerous dependent variables (26.6% with >13). The number of experimental groups and independent variables also did not change with typically 1 to 2 reported. There was a significant 61% linear increase in randomization of participants into groups, however by 2014 still a minority (39%) of studies were not reporting randomized assignment. Types of statistical analysis showed positive changes over time with a 48% quadratic decrease in descriptive analyses, a 3% linear increase in nonparametric statistics, and a 45% linear increase in reporting parametric statistical analysis. Changes in specific statistical methods included a 9% linear decrease in bivariate correlation and a 73% linear increase in ANOVA. Reporting of assumptions had a 35% linear increase, yet in 2014 sixty-five percent still did not report on meeting statistical assumptions. Changes in test statistics included a linear 56% increase of reporting observed P values and a quadratic 29% increase in reporting effect sizes beginning in the late 1990s. It was concluded there was evidence of small improvements in research design and statistics in JAB over the last 30 years; however, there is still room for improvement to meet higher levels of research rigor and current recommendations on statistical analysis and reporting.

KEY WORDS: Assumptions, bias, effect size, sample size, P values, quality, rigor

INTRODUCTION

Scientific research strives to provide better models of reality and eventually apply that knowledge to improve human wellbeing. The quality of research design and statistical analysis in research directly affects this advancement of knowledge. Despite impressive developments in human knowledge and its application in technology, there have been growing concerns about

errors and bias in research reports in many disciplines that undermine repeatability and advancement of knowledge (24, 35, 64, 55, 13, 32, 7). To what extent have these problems influenced advancements in the field of kinesiology/sport and exercise science? This field, hereafter referred to as kinesiology, is an expanding discipline with research on all aspects of human physical activity that also might have a body of knowledge threatened by accumulation of erroneous results.

Several studies that have examined the methodological rigor of research reports in kinesiology sub-disciplines have been published. Reports investigated the rigor of the research designs and the statistics in adapted physical activity, biomechanics, medicine, nutrition, pedagogy, and psychology. Observations on the quality of kinesiology published reports include weaknesses in reporting statistical assumptions and statistical analysis (15, 16, 49, 57, 63, 74) and weaknesses in experimental designs (27, 49, 57, 74). In sports medicine, there appears to be improvement in research rigor over time (12), however randomized control trials remain rare (10). Despite advancements in statistical analysis, substantial percentages of published kinesiology research have weak designs, small samples, and errors in statistical analysis and interpretation. The kinesiology sub-discipline of applied sports and exercise biomechanics, however, is a highly quantitative field with little qualitative research, that has a history of several articles calling for improvements in research design and statistical analysis.

Early biomechanics articles and commentary discussed methodological problems like uncorrected statistical testing of multiple dependent variables (53) and greater use of within-subject rather than between-subject designs in biomechanics research (3, 4, 38). Subsequent studies continued to point out that these methodological and statistical problems were still apparent in biomechanics research reports (54, 40, 41, 42, 45, 66). Recently, studies of applied biomechanics reports indicated that despite significant increases in coauthorship over twenty years there have been no changes in sample size (43, 44). Both these observations have been reported in other kinesiology sub-disciplines (44). Continued errors in design and statistical analysis in applied biomechanics reports may pose a confidence crisis in knowledge development in this field (45).

The present review builds upon this recent work to confirm the rigor of design and statistical analyses of applied biomechanics research reports over a 30-year period. It was hypothesized that the design and statistical rigor of applied biomechanics research reports would not have significantly changed over the last 30 years. The study provided evidence on potential improvements in research design and analysis in applied research in biomechanics over time. According to Ioannidis (37) "the study of the trajectory of the credibility of scientific findings and of ways to improve it is an important scientific field on its own."

METHODS

Protocol

Applied sports and exercise biomechanics research is published in several multidisciplinary kinesiology journals, however in limited numbers compared to biomechanics and other

scientific journals. The journal selected for this study was the Journal of Applied Biomechanics (JAB) because it represents the longest continuously published source of applied biomechanics research related to kinesiology, beginning publication in 1985 as the International Journal of Sport Biomechanics. Thus, the initial source of sports and exercise biomechanics papers comprised the 866 papers published in JAB during the first three decades of its circulation (1985 to 2014). After excluding editorials, letters to the editor, technical notes, case studies, modeling, and reviews, a final sample of 676 data based original research reports was retained for analysis. No attempt was made to exclude reports relationship to kinesiology when authors chose to submit under clinical, neuroscience, or ergonomics review areas of JAB beginning in 1993.

Each retained research report was analyzed using eight design specific (Table 1) and five statistical analyses specific (Table 2) criteria. A sub-analysis was performed by classifying the statistical analysis used into five groups (Table 3). The frequency (f) and proportion (%) of studies for the eighteen criteria were calculated annually and for the 30-year sample.

Statistical Analysis

The progression of each variable across the 30 years studied was statistically tested using polynomial trend analysis via GLM-ANOVA. We, thus, conducted 18 tests in two sets (families): (i) eight tests for the study design criteria and (ii) ten tests for the study statistics criteria. Multiplicity implied protection against inflation of the type I error rate (i.e. 8, 59). Thus, to keep the family-wise alpha level for each of the two sets of analyses at 0.05, we tested the significance of each conducted statistical test at the Šidàk-Bonferroni (61) adjusted probability of $1-(1-0.05)^{1/8} = 0.006391$ for the design variables, and $1-(1-0.05)^{1/10} = 0.005116$ for the statistics variables.

To assess the size of each analyzed variable's percent (%) value and change (Δ%) overall and at specific points in the 30-year span studied, Batterham and Hopkins (6) extension of Cohen's (19) scale of assessing outcome statistics on frequencies were employed: 0-10% (very low), 11-30% (low), 31-50% (medium), 51-70% (high), 71-90 (very high), 91-100% (excellent). All statistical analyses were performed with SPSS version 23.

RESULTS

Study Design: Almost all reviewed studies (99.6%) used nonrandom samples, typically (71%) comprising 2-20 participants (Table 1). Most all (91%) studies examined 1-2 groups, with more fixed (69.5%) than randomized group assignment (30.5%). About half of the studies (54%) collected data using 1-3 trials per participant, with 15% of the studies collecting 9 or more trials per participant. Most of the studies examined 1-2 independent variables (76%). Studies often examined numerous dependent variables (DVs), 45% reporting 3-8 dependent variables and 27% of studies reporting 13 or more DVs. In 57% and 64% of the studies, the text included some information on limitations or recommendations, respectively.

Study Design Trends Over Time: All design variables met assumptions for polynomial trend analysis. Four of eight study design criteria in JAB research reports had statistically significant modest to large linear increases over the last 30 years (Figures 1 to 4). The number of trials tested

per participant increased significantly by 3.7 trials across years (Figure 3, $R^2 = 0.36$, $P < 0.001$). Randomization (of participants to groups/treatments) increased significantly by 61% across years (Figure 1, $R^2 = 0.56$; $P < 0.001$). The number of studies reporting limitations and recommendations increased 66% (Figure 4, $R^2 = 0.44$, $P < 0.001$) and 36%, respectively over 30 years (Figure 4, linear $R^2 = 0.60$, $P < 0.001$). Sample size, number of groups of participants, number of independent variables (IVs), and the number of DVs showed no significant trend over time.

Table 1. Categories and counts (f, %) for the study design criteria (N=676 data-based studies).

Criterion	Ordered Categories						
	1st	2nd	3rd	4th	5th	6th	7th
Size (N) of Sample [a]	2-10 242, 35.8%	11-20 237, 35.1%	21-30 87, 12.9%	31-40 43, 6.4%	41-50 15, 2.2%	51-60 19, 2.8%	≥ 61 33, 4.9%
Randomization (of partic. to groups)	No 470, 69.5%	Yes 206, 30.5%					
Num. of Groups (of participants)	1 414, 61.2%	2 200, 29.6%	3 19, 2.8%	4 32, 4.7%	≥ 5 11, 1.6%		
Num. of Independ. Variables (IVs)	0 37, 5.5%	1 292, 43.2%	2 222, 32.8%	3 83, 12.3%	4 18, 2.7%	≥ 5 24, 3.6%	
Num. of Dependent Variables (DVs)	1-2 83, 12.3%	3-4 121, 17.9%	5-6 99, 14.6%	7-8 83, 12.3%	9-10 63, 9.3%	11-12 47, 7%	≥ 13 180, 26.6%
Num. of Trials (per participant)	1 125, 18.5%	2 74, 10.9%	3 163, 24.1%	4 46, 6.8%	5 106, 15.7%	6-8 60, 8.9%	≥ 9 102, 15.1%
Study Limitations	Not Reported 288 , 42.6%	Reported 388, 57.4%					
Recommendations (for future research)	Not Reported 244, 36.1%	Reported 432, 63.9%					

[a] Sampling Type: Non-random 674 (99.6%), Random 3 (0.4%).

Table 2. Categories and counts (f, %) for the study statistics criteria (N=676 data-based studies).

Criterion	Ordered Categories				
	1st	2nd	3rd	4th	5th
Statistical Assumptions	Not reported 447, 66.1%	Reported 229, 33.9%			
Type of Statistics	Descriptive 59, 8.7%	Non-Param. 37, 5.5%	Parametric 580, 85.8%		
Statistical Method	Descriptive 59, 8.7%	Bivariate Correlation 59, 8.7%	Two-Group Comparison 150, 22.2%	ANOVA 335, 49.6%	Multivariate 73, 10.8%
Effect Size [a] (ES)	Not Reported 496, 88.9%	Reported 62, 11.1%			
Observed [b] Signif. (P)	Not Reported 325, 52.7%	Reported 292, 47.3%			

[a] based on the 558 studies that used other than descriptive analysis (8.7%) or bivariate correlation (8.7) as the main statistical method; [b] based on the 617 studies that used other than descriptive analysis (8.7%) as the main statistical method.

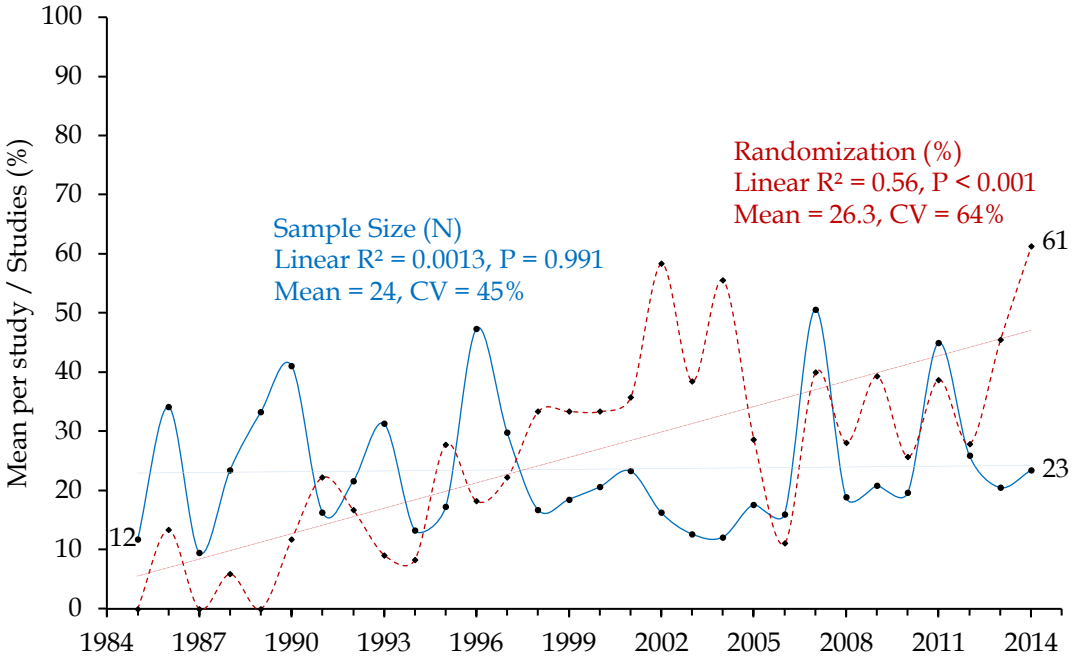

Figure 1. Variation and progress in the size of the samples and in the number of studies using randomization (of participants to groups/treatments).

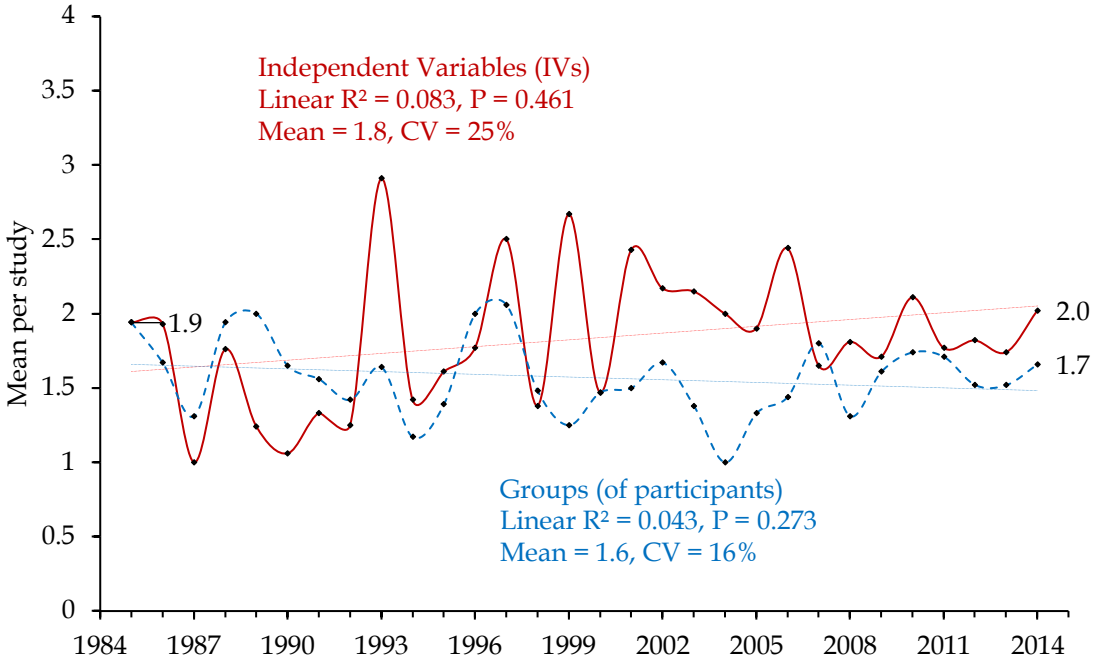

Figure 2. Variation and progress in the number of independent variables (IVs) and in the number of groups (of subjects).

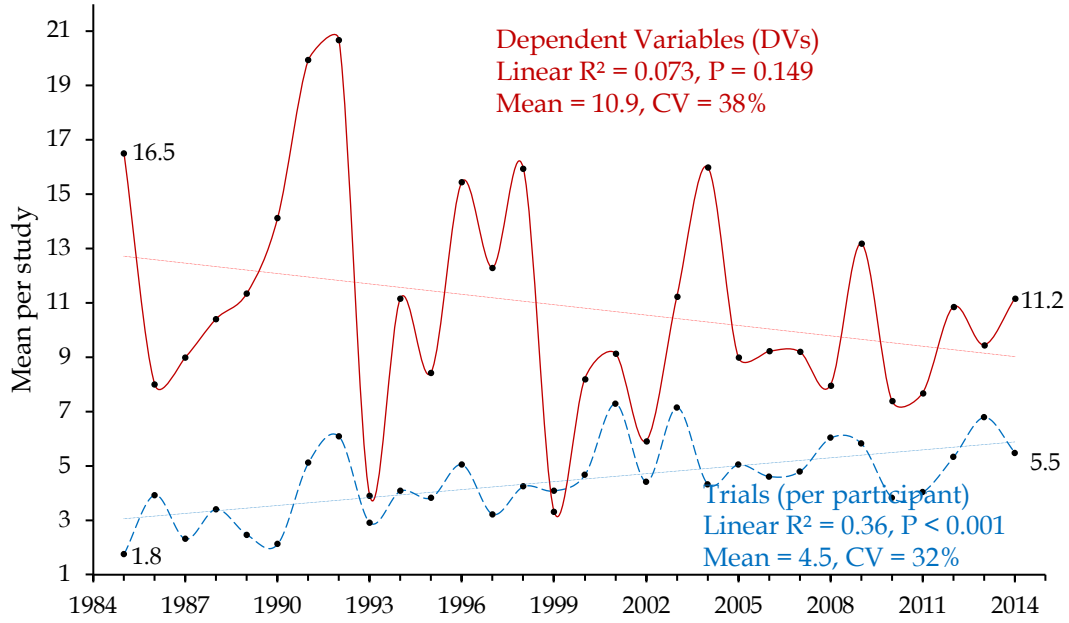

Figure 3. Variation and progress in the number of dependent variables (DVs) and in the number of (repeated) trials (per subject and condition).

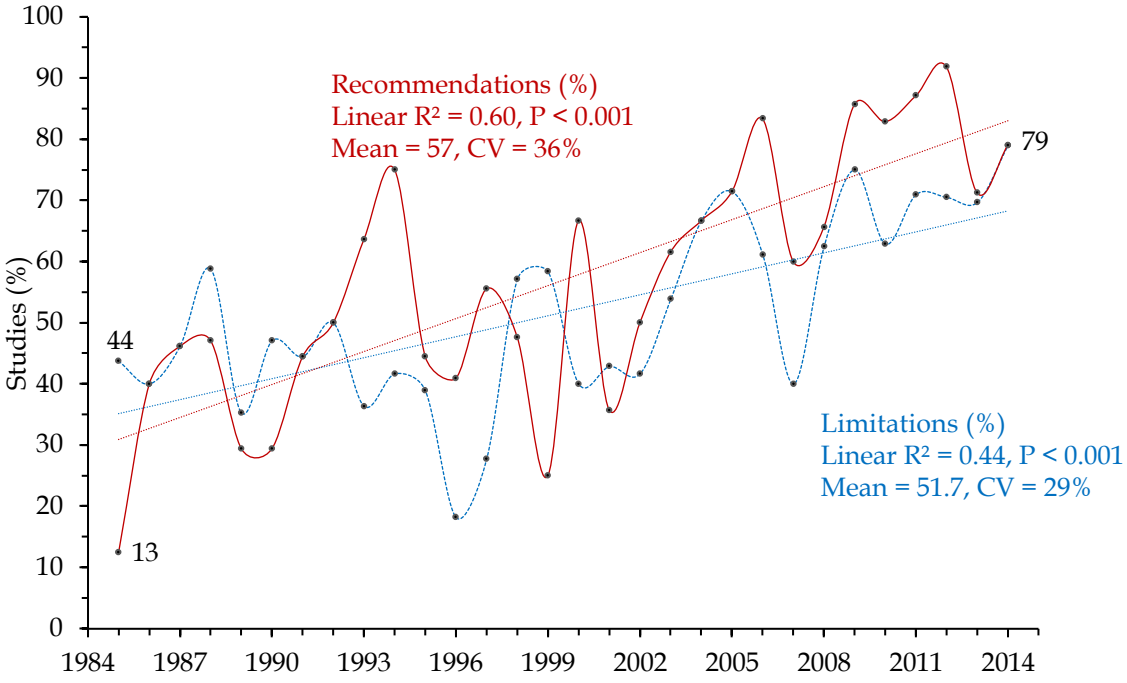

Figure 4. Variation and progress in the number of studies reporting limitations & recommendations.

Study Statistics: A minority (40%) of the reviewed studies reported data on statistical assumptions (Table 2). Most studies used parametric (85.8%) rather than non-parametric (5.5%) or descriptive (8.7%) statistics, and ANOVAs (49.6%) or two-group comparisons (22.2%), rather than bivariate correlations (8.7%) or multivariate methods (10.8%). The most common main statistical method was Pearson (84.7%) for bivariate correlations, t-test (84%) for two-group comparisons, ANOVA (97%) for Analysis of Variance, and MANOVA (50.1%) and Multiple Regression (35.1%) for multivariate methods (Table 3). In parametric ANOVA analyses, the most frequent post hoc tests conducted were Tukey's HSD (37.9%) and t-tests (24.3%). Only 43.2% of the reviewed studies reported observed P-values for test statistics, and only 9.2% reported effect sizes (ES).

Table 3. Subcategories and counts (f, %) for the (main) statistical methods (N=676 data-based studies).

Stat. Method*	f, %	Subcategories						
Bivariate Correlation	59, 8.7%	Pearson 50, 84.7%	Simple Regress. 7, 11.9%	Spearman 2, 3.4%				
Two-group Comparison	150, 22.2%	t-test 126, 84%	Mann-Whitney 9, 6%	Wilcoxon 15, 12%				
Analysis of Variance [a]	335, 49.6%	ANOVA 325, 97%	Kruskall-Wallis 4, 1.2%	Friedman 6, 1.8%				
Multivariate Methods	73, 10.8%	Multiple Regress. 26, 35.1%	MANOVA 37, 50.1%	Factor Analysis 6, 8.1%	Discrim. Analysis 4, 5.4%			
Multiple Comparisons [a]	103, 15.2%	Scheffé 13, 12.6%	Tukey 39, 37.9%	Bonferroni 8, 7.8%	Newman-Keuls 9, 8.7%	Duncan /Dunnett 3, 2.9%	LSD 6, 5.8%	t-test 25, 24.3%

* From Table 2: [a] In order of rigor of control of the family-wise error rate: Scheffé, Tukey, Bonferroni (high control); Newman-Keuls, Duncan (moderate to low control); Dunnett, LSD, t-test (no control); Šidàk-Bonferonni, Holm, and Hochberg tests are lacking.

Study Statistics Trends Over Time: All study statistics variables met assumptions for polynomial trend analysis. Eight of ten study statistics criteria in JAB research reports had statistically significant changes of different directions and shapes over the last 30 years (Figures 5 to 8). There were significant linear increases in studies statistical assumptions (Figure 5; $R^2 = 0.54$, $P < 0.001$) and use of parametric statistics (Figure 5, $R^2 = 0.40$; $P < 0.0164$). There was very small (3%) linear increase is use of non-parametric statistics (Figure 6, $R^2 = 0.20$, $P < 0.001$), however, there was a large (48%) quadratic decrease in the reporting of descriptive statistics (Figure 6, $R^2 = 0.81$, $P < 0.001$).

Regarding primary statistical tests there was no significant change in use of two group comparisons over time. Use of simple bivariate correlations has a significant (Figure 7a, $R^2 = 0.30$; $P = 0.00166$) 9% linear decrease. The use of multivariate statistics did not change over time, however use of ANOVA increased significantly (Figure 7b, $R^2 = 0.69$; $P < 0.001$) in a linear fashion. Reporting observed P-values for test statistics had a significant (Figure 8; $R^2 = 0.77$, $P <$

0.001) linear increase of 59%, while reporting effect sizes increased significantly (Figure 8; R^2 = 0.73, P < 0.001) in a quadratic fashion 29% beginning in the late 1990s.

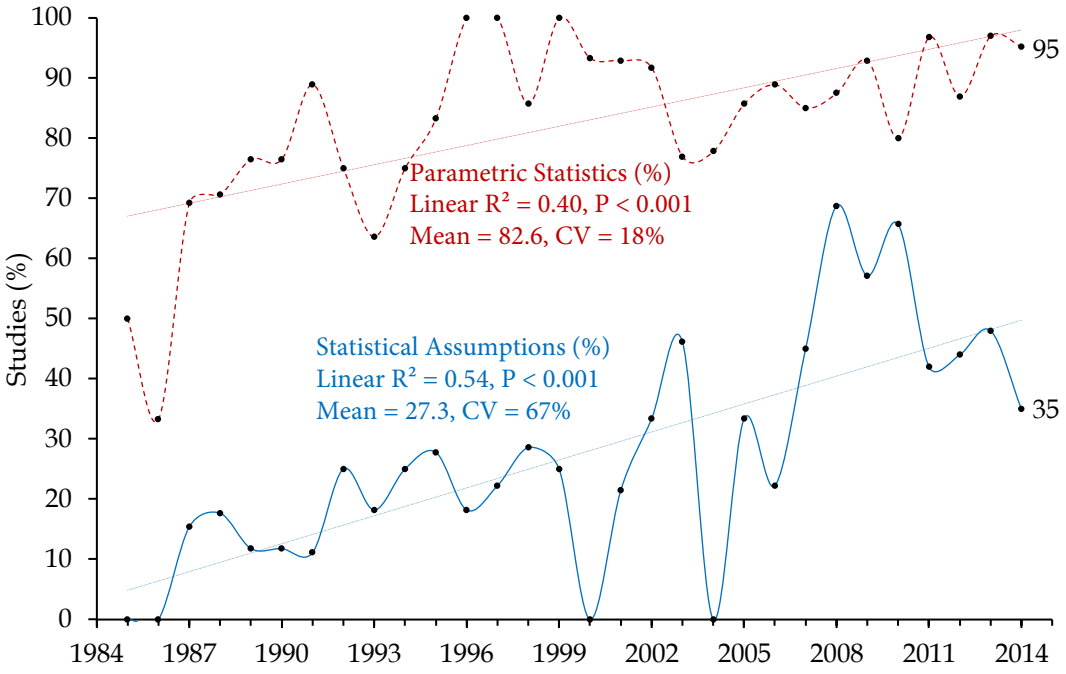

Figure 5. Variation and progress in the number of studies using parametric statistics and reporting statistical assumptions.

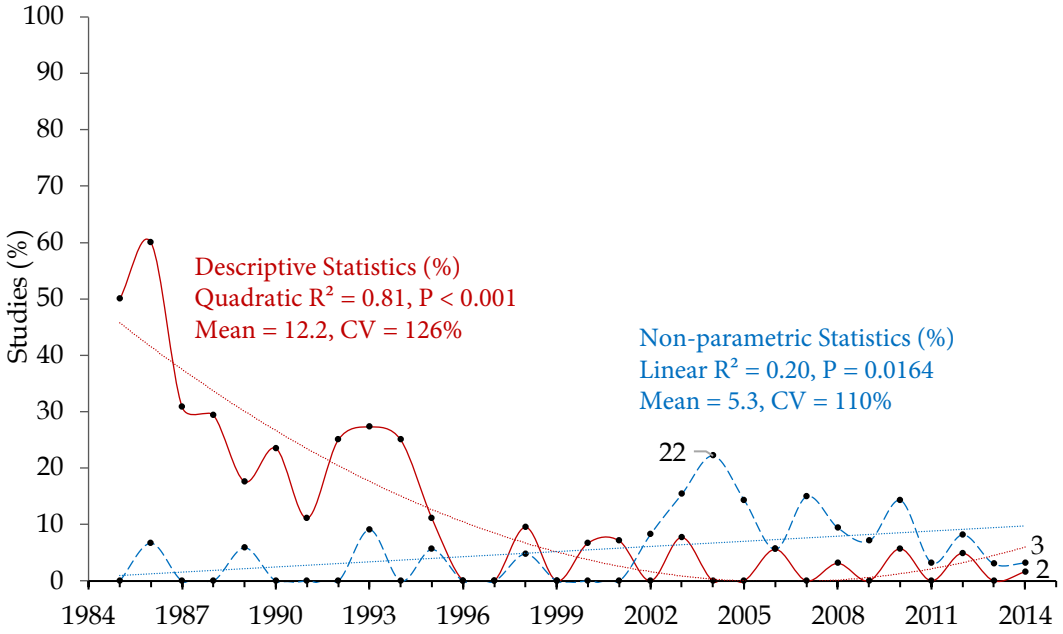

Figure 6. Variation and progress in the number of studies using descriptive or non-parametric statistics.

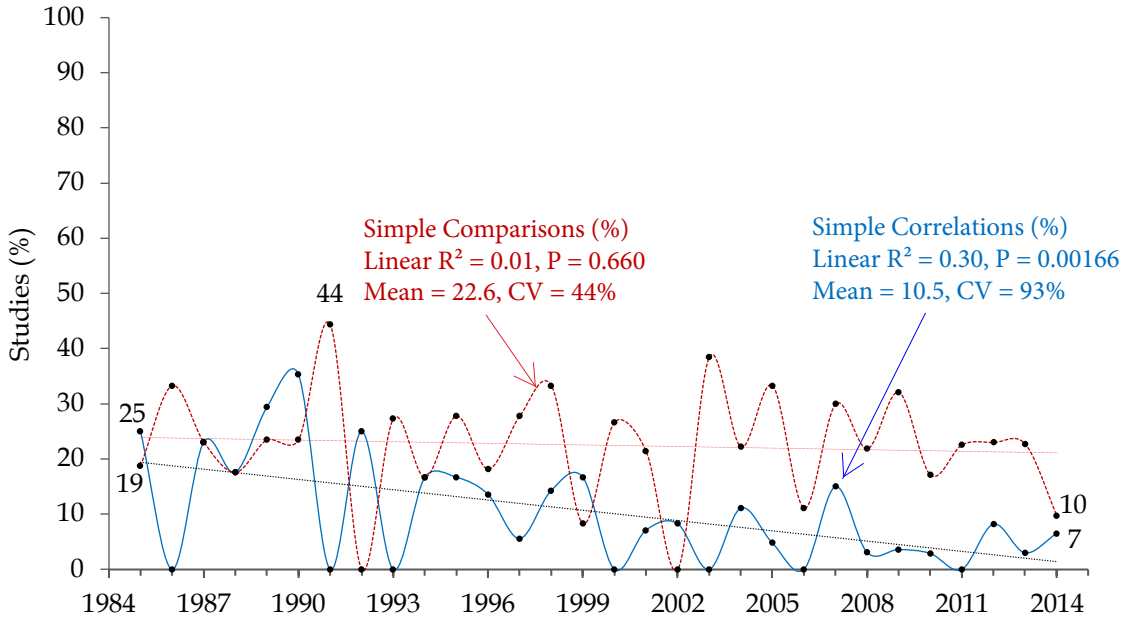

Figure 7a. Variation and progress in the number of studies using simple (two-group) comparison and simple (bivariate) correlation.

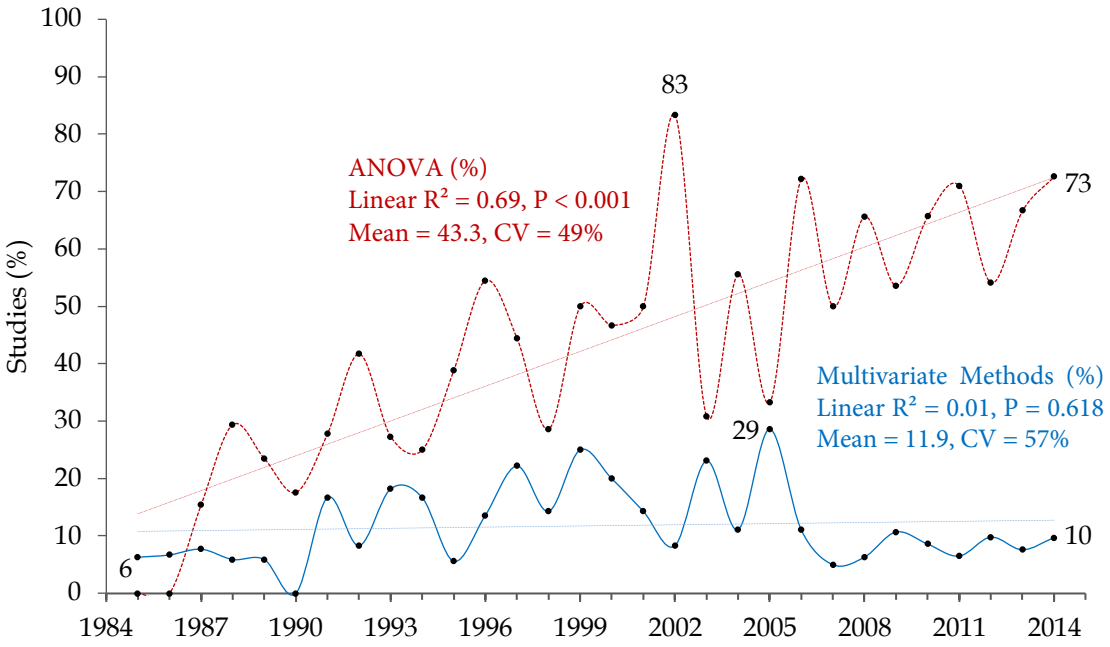

Figure 7b. Variation and progress in the number of studies using ANOVA and multivariate method.

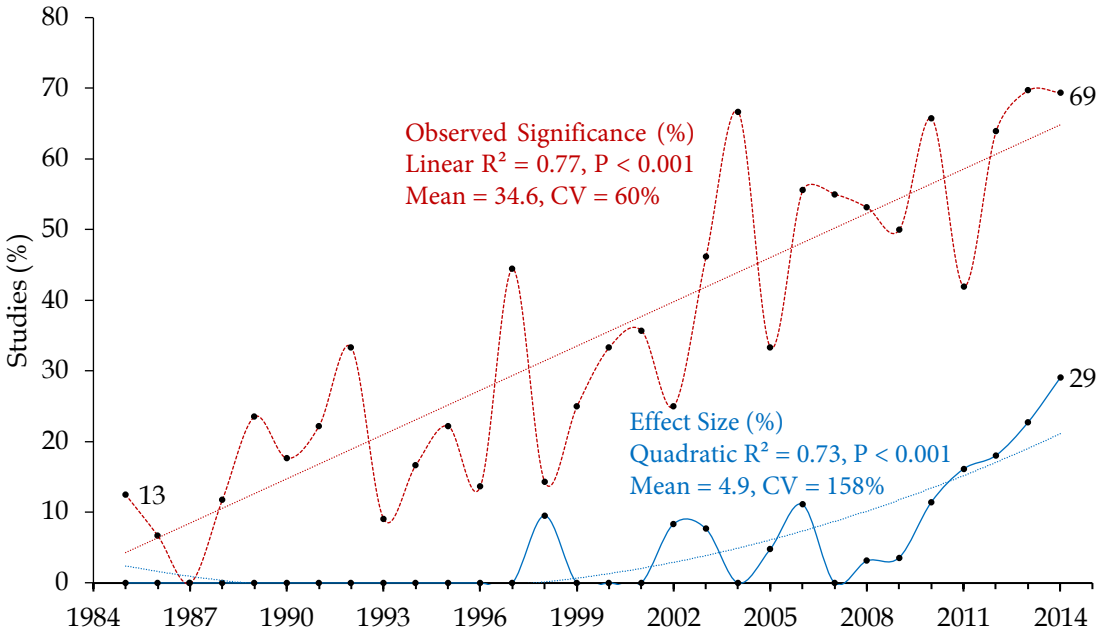

Figure 8. Variation and progress in the number of studies reporting observed statistical significance (P-value) and effect size (ES).

DISCUSSION

The hypothesis of unchanging design and statistical analysis in applied research reports in JAB was not supported, with 12 of 18 research design and statistics criteria having significant linear or curvilinear changes over the last 30 years. While there was substantial evidence of changes in research design and statistical analysis in research reports published in JAB over time, several of the changing and stable criteria were not considered as evidence toward improvements in rigor or quality of applied biomechanics research reports. The importance of the present results to knowledge development in kinesiology from the applied sub-discipline of biomechanics are discussed in eight areas: sampling, number of trials analyzed, study variables, statistical assumptions, type of statistical analysis, statistical methods and multiplicity, reporting observed P-values and effect sizes and reporting of limitations and recommendations.

Sampling: There was no significant change in sample sizes over the 30-years, with a large positive skew and most (71%) studies with small (2-20 participants) samples. This is comparable to previous findings showing that many sports biomechanics studies recruit less than 20 participants (40, 42, 44) and these small samples have not changed over the last 20 and 25-years (43, 44, 46). This lack of improvements in sample size over time is also apparent in other sub-disciplines of kinesiology (44).

Rigorous study designs require well justified sample size estimation before data collection (39). However, in the reviewed biomechanics reports the present study this design criterion was lacking. This shortcoming limits the generalizability of the findings in this sub-discipline (58). Thus, future applied biomechanics research would support sample size estimation and

justification of how it affects the size of the effects reported, although there are important research questions in the field that cannot access sufficiently large samples (47).

Ideally, before estimating sample size, researchers should consider not only the importance and impact of the expected effect, but also the burden the study puts on the participants (2). Thus, a sample can be "unethically" small or large (e.g., underpowered or overpower study) depending on the pragmatic difference of the expected effect. Recent guidelines to prospective authors of sports medicine papers suggest that a small sample might be ethical if the participant burden is low and the study findings are practically or clinically important, irrespective of their statistical significance (29). Study importance should outweigh participant burden and risk, but samples must be large enough for the identification of practically useful effects with high probability (56). The dangers of small samples common in biomechanics and other kinesiology sub-disciplines (44) to valid estimates of effects has recently been summarized by Knudson (45).

Almost all (99.6%) studies in JAB employed convenience or purposive sampling rather than random sampling, which is often unfeasible in human research (20). Assuming sample representativeness is an ideal state of statistical methods (50) and implies that samples in empirical research adequately reflect strata and traits of the target population of interest (39). Much biomechanics and kinesiology research involves convenience samples of participants of unknown compliance to the strata and the traits of the target populations, introducing the risk of bias when inferring from non-random samples (39). Nevertheless, when random sampling is unfeasible, as is the case in most kinesiology sub-disciplines, the potential for improving future research in this respect is rather limited. Future studies should acknowledge these limitations and limit attempts at generalization to the population. Kinesiology journals should also consider publishing more replication studies to improve the generalizability of important results and sizes of effects given the small, non-random samples in most published studies. It is not uncommon for authors of biomechanics and kinesiology in the discussion section of research reports to erroneously claim application and generalization of their results from small samples to unspecified populations (47).

Most (69.5%) JAB studies did not even randomize participants into experimental groups or conditions. Since overall about two thirds of the studies did not randomize group assignment, there is even greater risk of sampling bias beyond the small, nonrandomized convenience sampling noted above. Though randomization is not always possible, random assignment of participants into groups/treatments eliminates systematic error due to inter-participant variation (39). Randomization "prevents selection bias, produces the comparable groups, eliminates the source of bias in treatment assignments, and permits the use of probability theory to express the likelihood of chance as a source for the difference of end outcome" (69). Random assignment, however, did increase to a high level (61%) in 2014 (Figure 1), however this level and the very low levels of randomized control trials (RCT) needs to increase in the future. The high cost of RCTs means they are even at very low levels (10% or less) in better funded fields like sports medicine (10, 12).

Repeated Trials Per Participant: Much of the research undertaken in applied sports and exercise biomechanics will un-avoidably rely on rather small samples of participants. In these cases, biomechanics experts suggest that the results of small samples may be greatly enhanced by increasing the number of tested trials (5, 54), as, for example, in single-group designs (4). While the number of repeated trials of participants per group/condition in the reviewed studies increased in a linear fashion (Figure 3) in JAB, the 2014 mean level of 5.5 trails per condition are just now becoming adequate for good reliability in many biomechanical variables. Aside from the usual practice of recording more trials than those finally retained for analysis in biomechanics research (54), there a need for collecting more trials per participant/condition to obtain representative and reliable data. Bates et al. (5) commented on the need for more repeated trials in sports biomechanics and determined that approximately 10, 5, and 3 trials are preferable for samples consisting of 5, 10, and 20 participants, respectively, to achieve a statistical power of 90%. Similarly, Salo, Grimshaw, and Vitasalo (60) estimated that a relative reliability of 0.90 is attainable in many kinematics variables with at least eight trials. Thus, improvement in more accurate effects from small samples can be enhanced if the number of trials required to obtain valid results is determined before data collection (54).

Study Variables: A critical issue in scientific research is determining the proper variables to represent the phenomenon under study. Ideally, the DVs must be valid, reliable, and sensitive enough to respond proportionally to the underlying effects of the IVs. This study confirmed recent reports of statistical analysis of numerous DVs in applied biomechanics research (40, 41), with many (27%) studies statistically testing more than 13 DVs (27%). There was no significant trend in the use of DVs over time (Figure 3).

The complexity biomechanical models and advances in the biomechanical measurement systems allow researchers to analyze more variables than those needed to test a pre-specified theoretical or deterministic model (17). Except of purely descriptive studies (8-9%), the design and statistical flaws of multiple univariate statistical tests of numerous dependent variables inflate the experiment-wise type I error rates (41), biasing and complicating the interpretations of the results and size of effects (54). The mean values of 11 DVs tested from a sample size of 23 for the 2014 year does not argue for the accuracy of the results reported in JAB. If kinesiology re-searchers prospectively reduce DVs statistically tested based on theory or previous research result, future research will have improved accuracy of effects identified and interpretability of those findings.

There was also no significant change in the mean number of IVs examined over time in JAB (Figure 2). Most studies in the journal examined one to three IVs. Experimental economy and the advantage of examination of interactions in factorial designs are benefits of research designs with numerous independent variables (39). It appears that most research reports in JAB are not taking advantage of examination of multiple IVs. Apparently, the explicit justification for the choice of both the DVs and IVs s (34) is not always the case in this research field.

Statistical Assumptions: Reporting statistical assumptions increased in a linear fashion (Figure 5), however still a majority (65%) of 2014 reports did not address meeting assumptions of the

statistical tests used. This was consistent with the low levels reported by Knudson (40) but was nominally better than very low levels (7-10%) of studies reporting assumptions in other kinesiology sub-disciplines (15, 16, 49). It appears there is need for improvement in this area of research reporting in kinesiology. Assumptions are important conditions under which statistical models give valid results (25). All these conditions must have been met before the hypothesized model is fitted to the variables under analysis, while investigators should mention any shortcomings regarding these assumptions (21). Assumptions can also be stated regarding experimental methodology (e.g. instruments, designs, experiments) and if not carefully addressed may affect research quality (28).

Type of Statistical Analysis: Over time there were large changes in types of statistical analyses in JAB, with a 48% quadratic decrease in descriptive analyses, a 45% linear increase of parametric statistics, and a 3% linear increase in use of nonparametric statistics. The increase in parametric statistical analysis is consistent with the quantitative nature and high levels of measurement of biomechanics data. The choice of parametric or nonparametric statistics in a study depends primarily on the type of raw data; whether it is nominal, ordinal, interval, or ratio (67). Nominal and ordinal data are qualitative and therefore appropriate only for nonparametric analysis. Interval and ratio data are quantitative, but their analysis via parametric statistics is conditional to their degree of departure from the basic distributional assumptions (62). The central limit theorem makes many parametric tests robust to moderate violations of normality, but when the underlying distribution is too asymmetric, and the samples are unequal, the actual type I error rates deviate excessively from their nominal values, and the tests of directional hypotheses become inaccurate. In these cases, the analysis is untrustworthy even after optimal data transformation (34), and non-parametric tests (i.e. Kruskal-Wallis, Friedman) become more powerful than their standard parametric counterparts (i.e. ANOVA; 39).

Since the results showed that 84% of the studies used convenience samples with 30 or fewer participants, the low levels of reporting assumptions may be due to the small sample sizes. When samples are small ($N < 30$) it is impractical to test distributional normality and we instead rely on the small sample theory which allows for an optimal choice of robust test statistics in cases of distributional non-normality (51). When data are qualitative or deviate from normality or homoscedasticity, nonparametric tests are preferable than their parametric counterparts (62). In JAB, nonparametric test statistics were uncommon (Figure 6), and, when chosen, were mostly two-sample comparisons (i.e. Mann-Whitney and Wilcoxon) as oppose to multi-sample comparisons (i.e. Kruskal-Wallis or Friedman ANOVA), respectively (Table 3). Together, these results indicate that many JAB studies may have incorrectly used parametric statistics.

Statistical Methods and Multiplicity: The most common (49.6%) statistical method used in JAB was some type of parametric ANOVA (Table 2) that tended to increase (73%) in a linear fashion. There was also a linear 9% decrease in the use of bivariate correlations. On the other hand, the studies using multivariate statistical methods had no change, remaining at low (10.8%) levels. Of the studies using MANOVA, most incorrectly applied numerous univariate post hoc comparisons, rather than follow-up discriminant analysis or the stricter step-down F-tests (70).

When numerous DVs show moderate to high inter-correlations, a MANOVA is more powerful than multiple univariate models, and provides the means of a more comprehensive interpretation of the results (70). Multivariate methods are complex but unveil meaningful combinations of DVs, thus enhancing the interpretation of multifactorial phenomena. The relative contributions of the variables involved in multivariate models can then be determined by step-down F-tests or discriminant function analysis in the context of dealing with redundancy and multidimensionality in multivariate structure (65).

In choosing the optimal number of DVs for theoretically sound statistical models, statistical parsimony along with internal validity are most important. Parsimony is considered during the planning of the research and helps to explain the problem under study with the fewer possible DVs (11). Less parsimonious models unavoidably measure interrelated variables, and this makes interpretation of the shared variance problematic (72). When the DVs possess low inter-correlations (i.e. < 0.50, depending sample size) then ANOVA is more powerful, but conducting as many ANOVAs as the DVs requires adjusting for the resulting inflation of type I error rate. A similar adjustment of the probability of type I error is also applied in all multiple comparison analyses associated with significant F ratios. In these cases, appropriate multiple comparison testing may involve either the rigorous post hoc tests of Scheffé or Tukey for between-subjects designs or some variation of the Bonferroni adjustment (i.e., Bonferroni, Šidàk-Bonferroni) for within-subjects designs (39). Multiplicity adjustments should be ac-companied by proper control of the experiment-wise error rate, especially when the results of multiple tests are connected and summarized in one conclusion (8, 59).

There are two simultaneous and two sequential multiplicity adjustment methods. Simultaneous adjustments assume no priority among the DVs (i.e., of equal importance). Oppositely, sequential adjustments require prior hierarchy of the DVs. The simultaneous adjustment methods are Bonferroni or Dunn (23) and Šidàk-Bonferroni (61), and the sequential adjustment methods are Holm (31) and Hochberg (30). With c comparisons and α_{FW} the familywise error rate the per comparison alpha level (α_{PC}) becomes α_{FW}/c with Bonferroni and $1-(1-\alpha_{FW})^{1/c}$ with Šidàk-Bonferroni. In sequential adjustments of k progressive comparisons from 1 to c, the per comparison alpha level at each of the k steps becomes $\alpha/(c-k+1)$ in Holm's step-down method and α/k in Hochberg's step-up method. There is also the false discovery rate (number of Type I errors divided by the number of significant tests), a tool to ensure a less stringent multiplicity adjustment (9). The Bonferroni and Šidàk-Bonferonni approaches are strict when the comparisons are many and non-orthogonal. The sequential methods of Holm's and Hochberg's are more powerful but always at the expense of type I error (1). Interestingly, the relatively easy Holm's and Hochberg's methods have not yet been adopted by contemporary researchers, although, for example, SPSS Statistics 23 Algorithms provide both simultaneous and sequential Bonferroni and Šidàk-Bonferroni adjustments, as well as a version of Hochberg's range (GT2).

On the other hand, multiple comparisons can be either planned or post hoc. The present data confirmed previous results that planned comparisons in applied biomechanics are lacking. Instead, multiple comparison tests comprised 68% real post hoc tests, 24% t tests, and 8% Bonferroni adjusted (Table 3). Tukey tests were most frequent (38%) followed Scheffé (13%),

Newman-Keuls (9%), Bonferroni's (8%), and LSD (6%). Except for Scheffé, Tukey, and Bonferroni, which provide good protection for type I error rate inflation, all other tests (about 31%) are unadjusted. The common erroneous statistical analyses based on numerous univariate tests uncorrected for inflation of type I errors observed in this study was consistent with previous studies of applied biomechanics (40, 41) and physical education pedagogy (15). It is likely these problems exist in other sub-disciplines of kinesiology, posting a threat to the credibility of knowledge generated in the field.

Reporting Observed P values and Effect Sizes: Research reports in JAB had a 56% linear increase in reporting of observed P values for statistical tests and a 29% quadratic increase in reporting effect sizes beginning in the late 1990s. This is evidence of recent adoption of advances in statistical analysis and reporting in research reports in the journal and, perhaps, the field of applied biomechanics. How these trends influence research quality is unclear, given the weaknesses observer earlier in sample sizes and uncorrected testing of numerous DVs, as well as the debate between traditional statistical testing and magnitude-based statistical testing (14, 34, 6).

Setting this debate aside, observed P values of test statistics and effect sizes are both essential metrics for a comprehensive evaluation of statistical evidence for the observed experimental effects in the context of sample size, number of tests, and study design (59). The rejection of a null hypothesis based on a statistical test, however, does not alone indicate a substantial or meaningful effect (52). The need to focus on all issues of design and statistical testing has led to replacing the arbitrary levels of statistical significance (e.g. 0.05, 0.01) with observed P values (22) and likely sizes of effects. Cohen (18) concluded, "what it matters best is the importance of power analysis, and the determination of just how large (rather than how statistically significant) are the effects that we study."

The numerous recommendations to increase reporting of effect sizes in kinesiology and biomechanics (33, 71, 41) may have begun to increase reporting of these important statistics in JAB in the late 1990s, similar to the increase in sport and exercise biomechanics beginning in 1991 noted by Mullineaux et al. (54). Despite these positive trends, however, still 71% of JAB reports published in 2014 did not report any size of effects. Not reporting sizes of effects is also frequent in research in other sub-disciplines of kinesiology (49, 15), in psychology (26), and in medicine (68). There is still a clear need of improvement in reporting sizes of effects in applied biomechanics using standardized effect sizes like Cohen's d and Glass' Δ or also variance accounted for effect sizes (41).

Limitations and Recommendations: Reporting of limitations and recommendations increased in a linear fashion 66% and 36%, respectively. By 2014, 70 to 80 percent of studies in JAB criteria. reported this important considerably (Figure 4). Limitations are methodological weaknesses that can reduce both the validity of the study and the credibility of the conclusions; they should be clearly stated beyond estimating the magnitude and direction of random and systematic errors (36). Limitations in applied biomechanics are not only design specific, but also model, algorithm, procedure, and instrument specific (73). There is room for improvement in JAB author's ethical

responsibility to report study limitations and recommendations to improve future research (36). Recommendations may include important next steps in seeking higher levels of evidence to refute, confirm, or extend the current consensus of research on a study topic (47).

Limitations of the Present Study: The present study was limited to the 676 empirical studies in JAB and did not analyze the subfields of biomechanics identified by the journal beginning in 1993. Second, there could be investigator errors in reviewing and identifying all studies with inflated type I error rate, as often studies using numerous ANOVAs or t tests did not report enough information to confirm use or lack of control for alpha inflation. The results are influenced by the hierarchal research design and statistical criteria used and the inability to include all issues that affect research rigor and potential bias. Some research questions and logistical factors do not allow for the most rigorous quantitative designs and statistical analyses. Given these limitations of the data we did not employ logistic or non-linear regression for testing the association between year of publication and design or statistics criteria.

Conclusions: It was concluded there was evidence of small improvements in research design and statistics in JAB over the last 30 years, however there is still room for improvement to meet higher levels of research rigor and current recommendations on statistical analysis and reporting. Even with improvements, a large portion of the research reported in JAB by 2014 was not free of problems in several design and statistical analysis criteria. Most important to study rigor, there continues to be problems with small sample sizes, a small number of repeated trials tested per participant and condition, and errors in statistical analysis, particularly uncorrected univariate testing of numerous DVs. Remediation of these problems in future research are critical to the accuracy of research results. Given the evidence of continued weaknesses in peer review in kinesiology (48) and the slow nature of self-correction in science in general (37), this should be a call to action for all biomechanics and kinesiology researchers, reviewers, and journal editors to hold each other to contemporary standards of research design and statistical analysis.

Recommendations: This action for future sports and exercise biomechanics research, and in research in other quantitative sub-disciplines of kinesiology, should involve directly addressing the major methodological shortcomings noted in previous articles and supported by this study of the JAB. Design improvements include use of larger samples sizes, with sample size justification prior to data collection, more randomization of participants to treatments/groups, and more repeated trials per participant.

Given most studies employ multiple ANOVAs or other univariate statistical tests of numerous DVs that inflate the experiment-wise type I error rate, there should be justification of the biomechanical variables chosen for analysis and statistical analyses addressing multiplicity adjustments (8). Authors should also report the interrelations between the DVs under analysis, along with a summary of statistical diagnostics that address the assumptions of the statistical model used. In addition, authors should report how inflation of type I error is addressed when using multiple univariate statistical analyses. When studies focus on a combination of numerous DVs, authors should provide a theory based multivariate hypothesis and perform a suitable

multivariate analysis. There should also be adequate justification for the use of parametric or nonparametric statistical tests. Reporting of observed P values of statistical tests is common, however there needs to be greater reporting of the practical importance through effect sizes of the findings.

Future research in biomechanics could focus on patterns of specific biomechanics research methods (e.g., force plate, motion analysis, muscle testing), as well as more study of misuse of research design statistical analyses and their likely effect on erroneous results in the field. Additional longitudinal studies on research design and statistical testing should also be conducted on journal reports from other sub-disciplines of kinesiology.

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