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Confirmatory Factor Analysis as a Biomechanical Tool: A Novel Approach to Investigating Different Fatigue Aspects in Baseball Pitching

TU Delft

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By

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Abstract—**BACKGROUND: Rising UCL injury rates at both amateur and professional levels have been linked to fatigue in baseball pitchers. Repeated pitching has been associated with changes to kinematics, kinetics, and perceived fatigue, but no statistical model exists which incorporates all the most common aspects of fatigue into one framework. Confirmatory factor analysis (CFA) can be used to investigate possible fatigue frameworks and their plausibility in explaining the multivariate nature of observed changes occurring with repeated pitching. AIM: To investigate how multiple fatigue manifestations could be associated with a shared factor in baseball pitching. METHOD: Two CFA models were proposed; one a priori model based solely on previous findings and literature linking commonly found variables which change with repeated pitching, and one a posteriori model with added correlation factors between maximum external shoulder rotation (MER) with perceived fatigue and MER with triceps EMG activity. RESULTS: Model fitness test performed on the first a priori model proved plausible, with it passing some of the tests but failing others. The a posteriori model showed to be an excellent model for explaining the covariance of the data, passing all model fitness tests. CONCLUSIONS: Confirmatory factor analysis can serve to provide a plausible framework for explaining the covariance measured in kinematic, kinetic, and other fatigue related changes to baseball pitching data. Both models would suggest that the shared latent variable represents an underlying aspect of physiological fatigue. Changes to MER were determined to not be directly caused by fatigue. A proper understanding of different fatigue manifestations can potentially reduce the amount of fatigue related UCL injuries plaguing baseball pitchers by providing a more accurate proxy for measuring physiological fatigue.**

Index Terms—**Fatigue, Baseball, Pitching, Confirmatory factor analysis, UCL, Injury**

PREFACE

This study serves as a follow-up to a previous study titled *Potential Injury Mechanisms In UCL Injuries; The Influence Of Repetitive Pitching On Within-individual Elbow Load Magnitude And Variability And Elbow Muscle Activation During Baseball Pitching*[1]. In that study we have investigated the effects of repeated pitching on kinematics, kinetics, and elbow muscle activation during baseball pitching. We found that while there is little change to elbow valgus torque at a group level, there is a group level decrease in elbow muscle activation and an increase in self perceived fatigue with repeated pitching. This led to the question of whether these changes we observed were due to the accumulation of fatigue during the extended bout. The following study uses data obtained during the previous research to address this gap in knowledge, and to propose a new way of researching fatigue in baseball pitchers.

I. INTRODUCTION

Through 2011 and 2016, baseball pitchers accounted for 39.1% of all injuries at major and minor league levels [2]. Their over-representation on the disabled list can be attributed to the high loading experienced on the throwing arm while pitching [3], as well as the increased workload a pitcher undergoes relative to other players on the field. One of the most impactful injuries a pitcher can sustain is an ulnar collateral ligament (UCL) rupture, occurring in 16% of professional pitchers [4]. While the chances of a complete recovery from ulnar collateral ligament reconstruction are estimated to be between 67 % and 90 % [5], a rehabilitation period of 12 to 15 months is often necessary for pitchers [6].

UCL injuries are becoming more common across both professional and amateur levels of play. A cross-sectional study performed by Leland et al.[7] found a significant rise in the occurrence of UCL injuries at both the MLB and MiLB levels of professional play from 2012 to 2018. Furthermore, between 2003 and 2014, an increase of 343% in the number of UCL repair surgeries was observed, with a disproportionate percentage of this growth belonging to youth pitchers (15 – 19 years old) [8].

A possible cause for the rise in UCL injury rates is fatigue. Several epidemiological studies have been performed which highlighted the association between fatigue and injuries in youth [9] and high school players [10], finding that increased fatigue is associated with increase UCL injury rates. Most youth baseball pitchers experience arm muscular fatigue and arm pain during regular play, and are even encouraged to continue playing through it [9]. In this case, fatigue is defined as the physical and mental weariness resulting from repeated pitching, which eventually results in an a deterioration in performance or inability to continue pitching with the same level of intensity.

Two of the typical aspects of fatigue seen in baseball pitchers are perceived fatigue and physiological fatigue. Perceived fatigue describes the self reported perceived difficulty of performing a task. It can be experienced as as a sense of tiredness, lack of energy, or feeling of exhaustion. It differs from physiological fatigue in which the focus is on the muscle and it's ability to generate and maintain force

[11], instead focusing on how the subject experiences their perceived difficulty performing a task. Physiological fatigue can be split into contributions based on their position along the neuromuscular chain. Neurological aspects which include the cortex and spinal cord are also known as central fatigue, while the processes distal to the spinal cord are called peripheral fatigue. The peripheral processes include contributions from the peripheral nerve, the neuromuscular junction, and the crossbridge functionality itself [12]. Repeated muscle activation reduces the effectiveness of future muscle activation by acting on crossbridge functionality and Ca^{2+} release, and is considered muscular fatigue.

A systematic review regarding the manifestations of fatigue in baseball pitchers performed by Birfer and Sonne[13] found that kinematic changes due to fatigue occurred even at the highest level of play. Murray et al. observed a decrease in maximum external rotation of the shoulder during pitching, while Erikson et al. observed an increase in shoulder external range of motion post pitching. While investigating the effects of extended pitching bouts on elbow loading and elbow muscle activity, we found that repeated pitching is associated with both a decrease in elbow muscle activity, and an increase in self-reported fatigue [1]. Together, these findings suggest that pitchers experience multiple of the typical aspects of fatigue. The increase in self-reported fatigue we observed indicates that pitchers experience perceived fatigue, while the kinematic and muscle activation changes summarized by Birfer et al. and our research suggest an increase in physiological fatigue.

A proposed method for researching multiple aspects of fatigue is the use of a confirmatory factor analysis (CFA), sometimes referred to as a common factor model. CFAs are a form of structural equation modelling stemming from the psychology field that allow for the analysis of latent variables by measuring multivariate data present in observed variables. The latent variables represent immeasurable constructs which act as a common factor shared between the observed variables. The observed variables are assumed to be influenced by the latent variable, and as such are assumed to covary together with changes to the latent variable.

An example of a CFA used in the diagnosis of major depression can be seen in Figure 1. CFA models typically represent latent variables as ellipses, observed variables as rectangles, and factors such as correlations connecting two variables as directional arrows, where arrow direction implies a cause-effect relationship. In the example CFA, the observed variables such as depressed mood and loss of interest are measured or determined by experts. The covariance matrix of the observed variables can then be analysed to determine whether the variance could be attributed to a shared common factor “major depression”.

A hypothesized similar model could be constructed which describes the multifaceted relationship between fatigue and the multiple manifestations thereof in baseball pitching. Such a model would allow for investigating which of the typically reported manifestations of pitching fatigue could share a common latent change, and which manifestations appear to develop independently. A better understanding of how different fatigue manifestations develop in baseball pitchers could play an important role in identifying which fatigue aspects influence UCL injury risk. Therefore, the aim of this study is to investigate how multiple fatigue manifestations could be associated with a shared factor in baseball pitching.

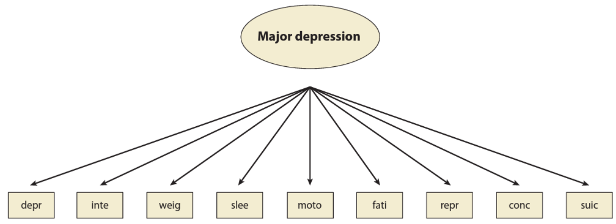

Fig. 1: An example of a confirmatory factor analysis used in the diagnosis of major depression. Arrows point in the direction of influence, indicating that the latent variable ”Major Depression” causes the covariance measured in the observed variables [14].

II. Methodology

Kinematics, self reported fatigue, and EMG data were collected as part of a previous study investigating the effect of repeated pitching on elbow valgus torque and arm muscle activity [1]. The sections *Participants*, *Procedure*, and *Data acquisition* describe characteristics of the data set and brief descriptions of how the data were acquired. The section *Additional data processing* describes additional data processing steps taken as part of this study.

Participants

All tested participants were male baseball pitchers with no recent (past 6 months) injuries and no history of elbow surgery. Data were collected and shared in accordance with the Declaration of Helsinki and was approved by the Ethics Committee of the Delft University of Technology (HREC). Participants were informed of the procedure before the start of the data collections. Informed consent was obtained before the involvement of the study. Table I gives an overview of participant demographic data.

Demographic	Mean	Standard Dev.	Range
Age [years]	24.5	7.5	17 - 44
Weight [kg]	79.4	9.2	62.7 - 102.5
Height [cm]	191	5	183 - 199
Level [1 = highest]	4.1	2	1 - 8

TABLE I: Participant demographics. N = 13

Procedure

Fourteen reflective markers were placed on the anatomical bony landmarks as described in Appendix A, Section *Data analysis*. EMG electrodes were affixed on the shaved skin of the throwing arm, and an accelerometer was attached to the thorax near the incisura jugularis. Maximum voluntary contractions were performed prior to pitching. After their normal warm-up, pitchers were asked to throw maximal effort fastballs in blocks of 10 pitches at a regulation distance (18.44 m) and strike zone, simulating a game environment. After each block of 10 pitches, participants were asked to place a mark on a VAS scale indicating how fatigued they felt. The VAS scale ranged from totally not fatigued (0%) to as fatigued as possible (100%). Pitchers threw until either 110 pitches were thrown, or a VAS score of 80 was reached as further fatiguing the subjects was seen as dangerous (max pitch count : $\mu = 85, \sigma = \pm 18, R = [60 - 110]$).

Data acquisition and processing

All data processing was performed in Python [15]. The inverse dynamic model and EMG analysis software is available at https://github.com/ThomasBTHL/BTHL_public.

Kinematics: Marker trajectories were recorded with a twelve-camera Optitrack motion capture system [16] with a sampling frequency of 120 Hz. The Optitrack system was calibrated to define camera position and orientation, and to construct a global coordinate system. A right-handed global coordinate system consisted of an X_{Global}, Y_{Global} and Z_{Global} axis. The Z_{Global} axis pointed upwards, the Y_{Global} axis was directed forward, from the pitching mound towards the strike zone, and the X_{Global} axis was perpendicular to the Y_{Global} and Z_{Global} axis.

Shoulder angles were determined following an intrinsic $Y_{local} \rightarrow X_{local} \rightarrow Y_{local}$ decomposition order [17]. External rotation was defined as the first rotation about the local y-axis. Maximum external rotation (MER) was taken at the moment the shoulder was most externally rotated during the pitch.

EMG: Muscle activity was measured using bipolar surface Electromyography (EMG) using a plux system with a sampling frequency of 1000 Hz. The flexor pronator mass (FPM), biceps brachii (BIC), and triceps brachii (TRI) were measured using electrodes placed based on SENIAM guidelines [18].

Biceps, triceps, and FPM EMG data were analysed according to guidelines established in the European Recommendations for Surface ElectroMyoGraphy [19]. Data were first rectified, then filtered with a low-pass 20Hz 2nd order bi-directional Butterworth filter. The MVC EMG value was determined by taking the peak value from a 0.2s rolling mean window applied over the MVC contraction data. This value was then used to normalise trial data for each muscle.

Due to their role in shielding the UCL during the acceleration phase, muscle activity of the biceps, triceps, and flexor pronator mass was analysed over the whole phase. In order to represent muscle activity during the whole acceleration phase, the area under the curve (AUC) of the EMG signal was calculated for each muscle. The AUC was defined as the integral of the pre-processed EMG signal from foot contact (approximated as 0.1s before ball release) until ball release.

Additional data processing

It was chosen to take any changes measured in the observed variables between the first pitches thrown in an unfatigued state, and the last pitches thrown once fully fatigued as the input for the CFA models. To ensure the most fatigued pitches were used for the analysis, the average values for the observed variables were taken over a five-pitch window, as it was assumed that the small amount of rest given between pitching blocks would allow for a slight amount of recovery. Taking the last five pitches of the last pitching block ensured that the most fatigued pitches were used in the analysis. The average values measured during the first five pitches were taken to represent an unfatigued state. For any set of pitches with max pitch count N, the input variables (OBS) therefore adhered to the following definition:

$$\Delta OBS = \sum_{i=1}^{5} \frac{OBS_{N-i}}{5} - \sum_{j=1}^{5} \frac{OBS_j}{5} \quad (1)$$

CFA models

Two CFA models were constructed for this study. An a priori CFA model was hypothesized to explain the covariance seen during pitching fatigue based on previously identified factors relating repeated pitching to changes in observed variables. After initial results of the first fatigue model were obtained, an a posteriori model was constructed based on recommended respecifications.

Model 1: pitching fatigue model: The pitching fatigue model (Figure 2) included the observed variables: ΔVAS, ΔMER, ΔTRI, ΔBIC, and ΔFPM. ΔVAS was included in the model to represent the change in perceived fatigue, while the other observed variables were included in order to capture physiological fatigue. Only direct correlations between the latent shared variable and the observed variables were included in the model. Residual error terms were included for all observed variables. The correlation between the shared variable and ΔVAS was fixed to 1. The choice to set the nonstandardized correlation of ΔVAS to 1 determined the scale of the model so that nonstandardized model results could be more easily interpreted.

Model 2: adapted pitching fatigue model: The adapted pitching fatigue model was constructed after analysis of the first models' residual covariance matrix (Table III), model-fit tests, and proposed modification indices. The model (Figure 3) includes all the factors of the first model, but with additional correlation factors between ΔMER with ΔVAS and ΔMER with ΔTRI EMG. These additional factors were added after initial observation of Model 1 results, where a low CFI and high SRMR score indicated that covariance between the observed variables was reducing model fitness.

Statistical analysis

The observed variables were tested for normality using a visual inspection and Shaprio-Wilk normality test in R. A P-value larger than 0.05 was held as a threshold to indicate a normally distributed variable.

Model analyses were performed in the structural equation modelling tool Mplus [20]. An MLR (robust maximum likelihood) estimator was used due to its ability to handle non-normally distributed data. The model ran until either the convergence criterion ($5.0{*}10^{-5}$) was met, or 20 random starts failed to do so within 1000 iterations. Standardized model

	ΔVAS	ΔBIC	ΔTRI	ΔFPM	ΔMER	M	SD	W	P-Value
Self Reported Fatigue on a Visual Analog Scale (ΔVAS)	458.1					51.20	22.27	0.957	0.706
Biceps EMG AUC (ΔBIC)	-0.153	0.001				-0.002	0.031	0.886	0.085
Triceps EMG AUC (ΔTRI)	-0.113	0.001	0.005			-0.037	0.070	0.835	**0.018***
Flexor Pronator Mass EMG AUC (ΔFPM)	-0.265	0.001	0.001	0.002		0.006	0.047	0.932	0.366
Maximum External Rotation (ΔMER)	-100.4	0.004	0.335	0.045	197.224	-4.126	14.62	0.721	**9E-4***

TABLE II: Covariance matrix of the dataset used by the CFA models. Normality testing threshold of 0.05 showed two sources of non-normal data (*).

results and their standard deviations were estimated for all parameters.

The following model-fit information was estimated for all models following guidelines established by Kline and Rex in *Principles and Practice of Structural Equation Modelling* [21]:

- χ^2 Test of Model Fit
- Steiger-Lind Root Mean Square Error of Approximation (RMSEA)
- Bentler Comparative Fit Index (CFI)
- Standardized root mean square residual (SRMR)

Four model-fit tests were performed to determine whether the proposed models were plausible explanations for the multivariate data. An exact-fit test checked P-Values from the χ^2 test together with the lower bound from RMSEA testing to determine if the model could be an exact fit for the measured data. A less demanding close-fit test checked RMSEA P-Values to determine if the total error of fit could be less than 5%. The upper bound of the RMSEA 90% confidence interval was checked to see whether the poor-fit hypothesis could be rejected, and a goodness-of-fit test checked the SRMR to determine how much residual covariance was not explained by the proposed model. Individually none of these model-fit tests can determine the plausibility of a model, but together they can give insight into model performance. Passing none of the four tests would indicate a poorly performing model which does not do a sufficient job at modelling the multivariate data, while passing all four could indicate a very good model. Passing just some of the model fit tests can still indicate a plausible model, as some of the tests can be quite strict and only serve to strength model plausibility.

III. Results

Data Descriptives

The covariance matrix of the dataset, along with means, standard deviations, and the results of normality testing can be found in Table II. Normality testing results from the visual inspection and the Shapiro-Wilk test showed that the ΔMER and ΔTRI variables failed to show normal distribution, and thus a more robust maximum likelihood estimator was required.

Model 1: pitching fatigue model (Figure 2)

All variables correlated highly with their preassigned factors with the exception of an insignificant correlation (-0.18) for ΔMER.

It was inconclusive if the model could be deemed a plausible framework for explaining the covariance of the measurements, as the model passed the exact-fit test ($p_\chi > 0.05$ and $\varepsilon_{LB} = 0$) and the close-fit test ($p_{\varepsilon \leq 0.05} > 0.05$). However, approximate fit indexes (Table V) indicate a mixed picture. The value of SRMR (0.092) is close to passing the goodness-of-fit test threshold of 0.8, but the upper bound of the RMSEA 90% confidence interval of 0.431 is so high that the poor-fit hypothesis can not be rejected. The CFI of .772 could indicate that high co-variances between the observed variables could be responsible for lower model fitness scores, as covariance between observed variables can decrease CFI scores if the covariance can not be associated to the latent variable [21].

Model 2: adapted pitching fatigue model (Figure 3)

The a posteriori pitching fatigue model with added correlations between ΔMER with ΔVAS, and ΔMER with ΔTRI showed to be a plausible model for explaining the covariance of the data. It passed both the previously passed tests: the exact-fit test ($p_\chi > 0.05$ and $\varepsilon_{LB} = 0$) and the close-fit test ($p_{\varepsilon \leq 0.05} > 0.05$), as well as the two previously failed tests: the poor-fit test ($\varepsilon_{UB} < 0.1$) and the goodness-of-fit test ($SRMR < 0.08$). The previously already weak correlation determined between the latent Fatigue variable and ΔMER correlated even weaker in the adapted model (-0.044). However the two newly added correlations between ΔMER with ΔVAS (-0.366), and ΔMER with ΔTRI (0.394) showed to be of moderate strength.

Model Fit Statistics

Model fit statistics for both models are summarized in Table V. While both models could be seen as plausible frameworks to explain the covariation of fatigue aspects in baseball pitching, having both passed some model-fit tests, the adapted pitching fatigue model showed a better global fit to the measured data. Residual covariance Tables III and IV show that after addition of the additional factors, the high residual covariances seen with ΔMER were reduced in the adapted model. This can further be seen in the reduction of SRMR and increase in CFI seen when comparing the two model fitness tests.

IV. Discussion

Model interpretation

The first confirmatory factor analysis model was constructed using only observed changes that occurred with repeated pitching. It served to cross validate previous findings which suggested that the latent cause of observed kinematic / EMG

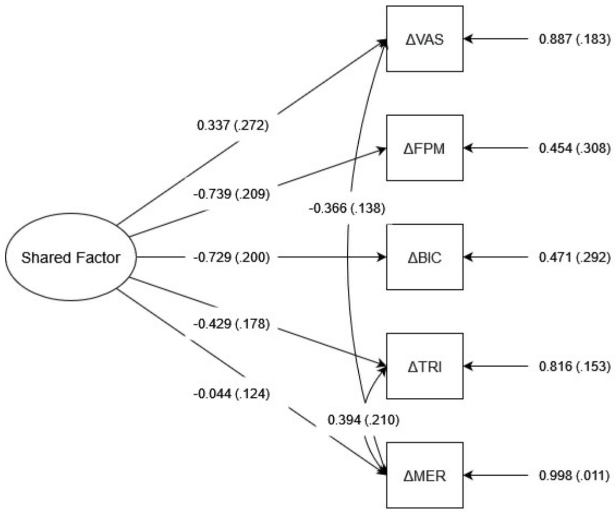

Fig. 2: Model 1: The pitching fatigue model. Standardized parameter estimates are shown for each unknown factor along with their corresponding standard deviations (between parenthesis). Standardized parameter estimates range between fully negatively correlated (-1) and fully correlated (1).
Notes: $\chi^2 = 6.33$, DoF = 5, P-Value = 0.2754

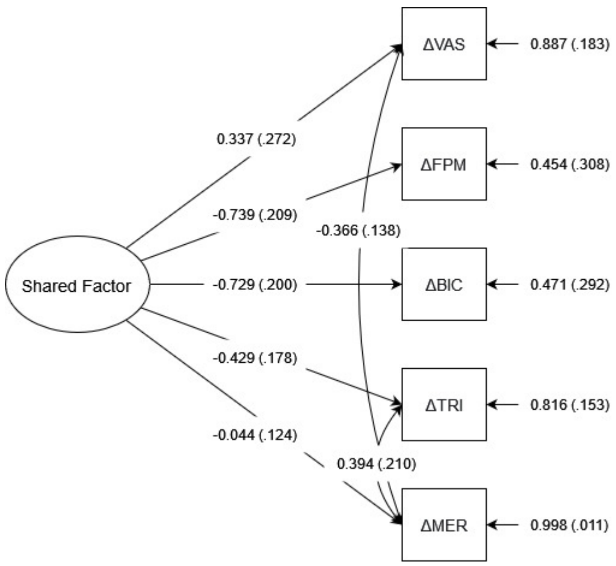

Fig. 3: Model 2: the adapted pitching fatigue model. Standardized parameter estimates are shown for each unknown factor along with their corresponding standard deviations (between parenthesis). Standardized parameter estimates range between fully negatively correlated (-1) and fully correlated (1).
$\chi^2 = 0.252$, DoF = 3, P-Value = 0.9687

changes were in fact due to a shared factor. Model fit testing could not conclude whether it was a plausible model for explaining the covariance of measured variables, as it failed to pass all applied model fit tests. However, passing both the exact-fit and the close-fit tests would indicate that the models' plausibility should not be rejected. The model indicated a range of latent factor correlations ranging from weak negative correlations with ΔMER (-0.181) to strong negative correlations with ΔFPM (-0.754) and ΔBIC (-0.689).

	ΔVAS	ΔBIC	ΔTRI	ΔFPM	ΔMER
ΔVAS	0				
ΔBIC	0.03	0			
ΔTRI	0.347	0	0		
ΔFPM	-0.022	0.046	-0.06	0	
ΔMER	-1.568	-1.014	0.696	-1.211	0

TABLE III: Residual covariance matrix of the pitching fatigue model. High residuals are seen between ΔMER with ΔVAS, and ΔMER with the three EMG variables.

	ΔVAS	ΔBIC	ΔTRI	ΔFPM	ΔMER
ΔVAS	0				
ΔBIC	0.021	0			
ΔTRI	0.272	0	0		
ΔFPM	-0.121	0	0.06	0	
ΔMER	0.171	-0.21	-0.067	0.707	-0.035

TABLE IV: Residual covariance matrix of the adapted pitching fatigue model. Previously high residuals have been reduced with the introduction of additional factors.

The inclusion of the additional correlation factors in the adapted model resulted in a large decrease in the measured correlation between the shared factor and ΔMER, and a slight increase in correlation with the other observed variables. This would suggest that the weak correlation previously present between the shared factor and ΔMER is no longer estimated via a direct correlation. Instead the variance in ΔMER can be achieved using the newly added correlation factors. Allowing for ΔMER to be associated with these other variables has ”freed up” the latent variable to better correlate with the remaining observed variables, hence the higher correlations with the remaining factors.

The weak correlation between the shared factor and ΔMER highlight an ongoing topic in baseball fatigue research. Many studies have attempted to find kinematic and kinetic changes occurring in baseball pitchers with fatigue; oftentimes finding inconclusive or little changes occurring [22][23]. ΔMER was included in the model based on findings by Murray et al. who found a change of -9°in MER among major league pitchers during the course of a normal game [24]. Many other studies investigating fatigue related kinematic changes have failed to measure such a significant change to MER [13], suggesting that the relationship between fatigue and changes to MER may be weak or non-existent.

It is possible that the changes in MER observed by Murray et al. were not in fact caused by a rise in fatigue, and instead were caused by a different source. The other fatigue studies highlighted by Birfer's review [13] performed their data collections in laboratory environments and on lower level athletes (Table VI), where real game pitching situations do not arise. These studies all failed to confirm the changes to MER that Murray observed, suggesting that the changes in MER observed by Murray et al. were in fact not due to fatigue, but may have been caused by changes to the game state which called for a change in pitch delivery. Confirmatory factor analysis might prove useful in isolating fatigue from other

Model	χ^2 Test of Model Fit			RMSEA			CFI	χ^2 Test of Baseline Model Fit			SRMR
	Value	DoF	P-Value	Estimate	90% CI	P-RMSEA <= .05		Value	DoF	P-Value	Value
P. Fatigue	6.330	5	0.2754	0.143	[0, 0.431]	0.294	0.772	15.837	10	0.1044	0.092
Adapted P. Fatigue	0.252	3	0.9687	0	[0, 0]	0.970	1	15.837	10	0.1044	0.021

TABLE V: Model fit statistics of the two models. DoF: Degrees of freedom. CI: Confidence interval

such sources of kinematic change in real game situations.

Despite the lack of conclusive kinematic changes observed in baseball pitchers, it may be possible that there is still physiological fatigue occurring. The strong correlations found between the shared factor and the various included EMG sources suggest that even in what appear to be constant kinematics, there are muscle activation changes occurring. These changes suggest an increase in an underlying fatigue mechanism which acts as a precursor to the kinematic changes associated with extreme physiological fatigue. Further analysis utilizing oxygen uptake (VO_2) measurements could support the theory that physiological fatigue is occurring with repeated pitching, but has yet to effect pitching kinematics. Proper understanding of the development of this pre-kinematic-change physiological fatigue could help determine safe pitching limits and rehabilitation periods for pitchers and coaches.

The muscle activation changes could also be significant in altering the internal load distribution at the ligament level, without altering segment kinematics. Within the context of UCL loading in baseball pitchers, this could mean that previous studies have concluded that there are no kinematic, and therefore no kinetic, changes occurring in the elbow due to fatigue. These studies then wrongfully conclude that there is no change in loading to the UCL. However, the strong negative correlations between the shared factor and arm muscle EMG suggest otherwise. As fatigue increase and arm muscle activity decreases, the UCL may be subjected to higher loads as the effect of stress shielding by the muscles is diminished. The constant kinematics and reduced stress shielding effect could result in increased UCL loading with increased fatigue.

Model selection

The inclusion of the additional correlations factors in the adapted model served to improve the model fit substantially. The decrease in SRMR value from 0.092 to 0.021 indicates that there is very little residual covariance which the adapted model does not describe. Additionally, the RMSEA 90 % confidence interval upper bound of 0 would suggest a very close fit to the multivariate data. Thus, the adapted model can therefore be declared a excellent model for explaining the covariance seen in the data set. However, with the inclusion of additional correlation factors in the adapted model, overfitting may be an issue.

The additional factors added to the adapted model were based on modification indices which represent the amount a χ^2 test value would improve if an additional factor were to be added to a model. It follows that adding respecifications which have high modification indices will create a better model fit for a particular data set. However, the proposed modifications may only serve to improve the model fit so significantly for the exact data set they were calculated with. If the first model had been tested with a different data set, then it is likely that entirely different respecifications would have been suggested.

The original hypothesized model already did a good job of explaining the covariance of the data set, while still being entirely based on theorized fatigue aspects and associations. The SRMR value of 0.092 only slightly exceeded the desired threshold of 0.08, indicating that the original model, while technically failing the goodness-of-fit test, still accounted for more than 90% of the measured covariance. To avoid the issue of using an overfit model with unexplained factors, future studies should move forward and build upon the original pitching fatigue model. Additional hypothesized fatigue aspects such as performance fatigue or psychological fatigue could be included to further improve the model, and help identify the most critical aspects of fatigue relevant to baseball pitching.

Limitations and recommendations

Previous studies have often used self reported fatigue or rate of perceived fatigue as a proxy measurement for physiological fatigue [22][25]. However, the only moderate correlation between ΔVAS and the shared factor suggest that it does not develop together with the physiological factors, and is therefore an inadequate proxy for physiological fatigue factors. This is further supported by analyzing the individual VAS development plots (Figure 4), which show that some subjects perceive their physiological fatigue very differently from other subjects. Despite that no single subject exhibited the significant kinematic changes which come with extreme fatigue, several subjects reported multiple pitch blocks of high fatigue (VAS of 60+). A much more accurate representation of the buildup of physiological fatigue can be derived from the EMG changes observed among the subjects. Future studies should strive to incorporate multiple aspects of fatigue into their quantification of subject physiological fatigue, and should no longer solely use perceived fatigue as a proxy for physiological fatigue. As there is a known association between fatigue and injury likelihood, it remains unethical to fully fatigue subjects to the point of kinematic changes. Future studies can use VO_2 analysis to validate the buildup of neurological fatigue as a proxy for physiological fatigue.

A large limitation of this CFA study is the limited sample size of our obtained data. Complete data was only available for 13 subjects. In relation to other fatigue studies performed on baseball pitchers (Table VI), 13 pitchers is adequate. However, CFA guidelines suggest a recommended sample size of 250 to 300 observations [21]. A smaller sample size is much more heavily influenced by outliers, and may not be a true representation of a general population. Confirmatory factor analysis as a statistical tool is often used in social fields

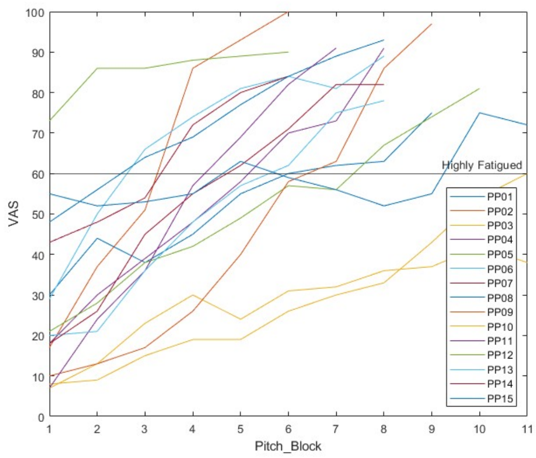

Fig. 4: VAS development per pitch block. Subjects were asked after each block of 10 pitches to place a mark on the VAS scale ranging from totally not fatigued (0%) to as fatigued as possible (100%)

such as psychology where observations are easily obtained via questionnaire. Until recently, biomechanical data has been much more difficult to obtain, and has made such sample sizes impossible. With the rise of markerless motion capture technology and wearable EMG markers, quality biomechanical data has become more obtainable. Future studies which use CFA as a tool to analyse fatigue should consider the use of such developing technologies in order to obtain a more desirable sample size, and improve the quality of their findings.

Study	Sample Population	Sample Size
Escamilla et al. (2007) [22]	Collegiate	10
Murray et al. (2001) [24]	Major league	7
Erickson et al. (2016) [26]	Adolescent	28
Mullaney et al. (2005) [27]	University	13
Keeley, Barber & Oliver (2010) [28]	Collegiate	10
Chou et al. (2015) [29]	High School	16
Oliver and Plummer (2009) [30]	High School	14
Oliver, Weimar & Henning (2016) [31]	Youth	23
van Trigt & van Hogerwou (2022) [1]	Collegiate	13

TABLE VI: Various studies investigating the effect of fatigue on baseball pitchers.

A possible bias exists in both of the proposed models. Of the five observed variables used in the construction of the models, three are from EMG sources. The relative over representation of EMG sources may bias the model towards measuring the shared covariance of a latent neurological variable instead of a general fatigue variable. This possible bias can be addressed with the inclusion of other aspects of fatigue seen in baseball pitchers. One of the most interesting aspects of fatigue not included in the two proposed models is performance fatigue. Much work has been done investigating the effect of fatigue on performance indicators such as ball velocity or strike percentage. However, as we were unable to conclude any significant change to ball velocity in the previous study, it was chosen to not be included in the two proposed models. Previous studies [28][24][26] have found a reduction in ball velocity with repeated pitching, and the inclusion of such factors would help address the issue of bias. Future research could use CFA to provide the framework necessary for determining whether performance changes observed in extended bouts are in fact due to fatigue, or if they are caused by some other latent variable such as ”game state”.

V. Conclusion

Confirmatory factor analysis can identify suitable frameworks for measuring the multivariate nature of fatigue in baseball pitchers. It can provide plausible models which incorporate multiple aspects of fatigue, and it can help identify which aspects do not develop simultaneously. With the incorporation of additional fatigue aspects such as performance, psychological, or muscular fatigue, an even better representation of pitching fatigue can be achieved. Future research should avoid using VAS or other measures of perceived fatigue as a proxy for physiological fatigue, and should instead attempt to incorporate aspects such as neurological fatigue in their analysis.

The hypothesized a priori pitching fatigue model was a plausible fit to the data set, and can function as an example on how to incorporate multiple aspects of fatigue into an analysis. With the addition of two respecifications, the a posteriori adapted pitching fatigue model was capable of fitting the data excellently, but the original model may be preferred due to the fact that it is constructed using only theorized associations with fatigue. Both models would suggest that the shared factor at the center of the CFA models represents an underlying aspect of physiological fatigue.

Changes to MER were determined to not be directly caused by fatigue. Previous findings which reported on fatigue related changes to MER may have misinterpreted the sources of measured changes. The effect of another latent variable such as ”game state” could be influencing measured kinematics in real game situations, and would be an interesting topic for continued CFA studies.

The strong association between fatigue and arm muscle activity indicates that while kinematics may remain consistent throughout extended pitching bouts, there is still a chance of increased UCL load due to a reduced effect of stress shielding during the acceleration phase of the pitch. A proper understanding of different fatigue manifestations can potentially reduce the amount of fatigue related UCL injuries plaguing baseball pitchers.

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APPENDIX