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Prediction of Maximal Vertical Jumps during the Entire Season in NCAA Division 1 Women Basketball Players

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ABSTRACT

Purpose: The purpose of this study was to develop a prediction model of weekly maximum jump height (JHmax) performance as a measure of readiness from external workload measures during practice and games, measures of volume-load during resistance training, and self-reported sleep quality, stress, and recovery in NCAA Division 1, women basketball players during the entire season. **Methods:** Twelve female participants (age = 21.3 ± 1.6 yrs; ht = 171.6 ± 7.1 cm; wt = 67.9 ± 5.3 kg) who were cleared for full participation were recruited to participate in the study. Workload (WL) and work intensity (WI) were measured during every practice and game during the entire official season. The following independent variables were entered into a multivariate regression model to predict JH_{max} performance across each week in the season using a 7-day period prior to assessment: WL, WI, and Work Density (WD) (WL x WI), self-reported sleep quality (SL), stress (STR), and recovery (REC), total resistance training volume-load (RTV), prior week's JH_{max} (Sign), week of the season (Week), and pre-season vs in-season (Season). JH_{max} was the dependent measure assessed prior to the season and every Monday. **Results:** The resultant model was statistically significant with an r^2 of 71 %. All variables were significant predictors of JH_{max} except SL and REC. **Conclusions:** A trend of lower WL and RTV and greater WI and STR had a positive effect on the following JH_{max}. Analyzing the 7-day period prior to JH_{max} assessment, high WD scores by manipulation of WL and WI six days prior had a positive influence on JH_{max} while lower scores were warranted the day before the test. High WL with low WI were indicated three days prior. Finally, controlling for the other variables, JH_{max} tended to decrease across the in-season indicating a need to reduce external loads in the following week when JH_{max} decreased to enhance recovery.

Keywords: College Basketball, Load Management, Resistance Training, Readiness.

INTRODUCTION

The primary goals of training elite athletes are to improve their mental and physical preparedness for competition and to reduce their risk of injury and illness. Research-based evidence is essential in obtaining the knowledge, skill, and ability to achieve these goals. Monitoring an athlete's external workloads can be used to optimize training volumes, intensities, and recovery (Fox, Scanlan, and Stanton 2017; Nunes et al. 2014). However, fatigue experienced by athletes varies depending on the type of athlete and can be detrimental to performance while potentially leading to injury with an inadequate or excessive level of training stimuli and/or recovery (Fry and Kraemer 1997). Sleep quality and stress are also factors causing fatigue that is essential to consider. Arguably, it is the interaction of many factors that cause fatigue in an athlete. In determining the effect of multiple factors on fatigue and recovery, correlation between predictors in regression models can cause problems in coefficient interpretation (Yeatts et. al. 2017). Currently, research has focused on male subjects and weekly or monthly external loads with associated recovery in elite, female basketball athletes (Power et al. 2022), which limits the practitioner's ability to prescribe appropriate daily loads within a week to optimize recovery for upcoming events (Sansone, Tschan, et al. 2020). Given the physiological and biomechanical differences and responses to exercise found between males and females (Ansdell et al. 2020), further studies are needed to better understand the effect of external training demands, sleep, and stress on recovery in elite, female basketball players.

The efficacy of monitoring external workload data in practice and games is currently unclear due to the lack of research, differences in technology used to measure loads, and differences in the research procedures. Inertial measurement units (IMU) are most commonly used to measure external workloads during indoor sports such as basketball due to the sensitivity of IMU technology in measuring repeated, short bursts of accelerations with valid and reliable findings (Roell et al. 2018), but few studies exist in women's collegiate basketball (Peterson and Quiggle 2017; Brown et al. 2022; Philipp et al. 2024; Ransdell et al. 2020). External workloads of volume and intensity can significantly differ based on research procedures (Askow et al. 2022; Brown et al. 2022; Garcia, Fernandez, and Martín 2022; Kutson et al. 2024; Philipp et al. 2024; Ransdell et al. 2020) that have been inconsistent across studies. Specifically, this technology typically allows the user to pause data collection during periods of inactivity unrelated to active time on the court such as time outs, between drills, and other periods when athletes are sitting on the bench. Inconsistent procedures across studies limit the ability to compare data across studies. In addition, two studies limited the analysis of external workloads and performance during only games in male, high school and professional players (Askow et al. 2022; Garcia, Fernandez, and Martin 2022). Thus, studies are needed analyzing external loads from games and practices for the entire season using ecological and valid measures in collegiate female basketball players.

Workloads in the weight room are often monitored using volume-load (sum of repetitions × load) to effectively design a resistance training program. It is common practice for female basketball players to train in the weight room; however, studies have yet to analyze the effect of total workloads from practice and games and the volume-loads in the weight room on recovery. Adding resistance training during the entire season may increase the workload above a threshold that may affect recovery in female collegiate basketball players warranting further investigation.

Sleep and stress have also been investigated to determine the effect on mental and physical performance (Brink et al. 2010; Lastella et al. 2020). High chronic levels of stress and both mental and physical fatigue can modify the pre-frontal cortex that decreases neuron connectivity and firing (McEwen, Nasca, and Gray 2016) while sufficient sleep improves neural plasticity and motor patterns (Stickgold and Walker 2007). In addition, Daub et al. 2022 found that increased mental fatigue from increased academic stress reduced basketball shooting performance, and in contrast, improved basketball performance was found during several weeks of greater levels of sleep during the season in collegiate, male players (Mah et al. 2011). A lack of data demonstrating the impact of sleep and stress currently exists in female, collegiate basketball players (Sansone, Rago, et al. 2023).

Training athletes for maximum performance is a comprehensive approach requiring consideration of the many factors noted in addition to designing the optimum resistance training program. Along with physical preparedness, the athlete's mental preparedness must be considered. A lack of sleep and high stress are factors that have been implicated as causes of mental and physical fatigue (Lastella et al. 2020; Mah et al. 2011). The accumulation of workloads in practice and games are also factors that may affect future performance (Coyne et al. 2021). Recent studies have investigated these factors independently (Brown et al. 2022; Evans et al. 2023; Peterson and Quiggle 2017; Piedra et al. 2020; Philipp et al. 2024). In addition, previous studies have attempted to determine weekly and long-term (monthly) external load totals to predict measures of recovery with mixed results (Brown et al. 2022; Kutson et al. 2024; Philipp et al. 2024). However, analysis of daily external loads influencing recovery within the 7-day week prior to recovery assessment during the entire season requires further investigation. Therefore, the purpose of this study was to analyze the impact of external workload measures during practice and games, measures of volume-load during resistance training, and self-reports of sleep, stress, and recovery on change in weekly maximum jump height (JH_{max}) performance in NCAA D1, female basketball players during the entire season.

METHODS

Study Design

This was a longitudinal, cohort prospective study designed to analyze several factors that predict recovery in NCAA Division 1, female basketball players across the entire season starting the last week of September through February. JH_{max} was assessed and included in a multivariate regression model as the dependent variable representing recovery that took place on every Monday (20 measurements). The independent variables used to make the prediction models were the following: workload (WL), work intensity (WI), work density (WD) during practice and games, resistance training volume (RTV), athlete reported outcomes of sleep (SL), stress (STR), and recovery (REC). WL, WI, and WD were determined daily (7-day period every week) while RTV and athlete reported outcome measures were aggregated weekly prior to JH_{max} assessment. In addition, the prior week's JH_{max} (Sign), weeks 1-20 of the season (Week), and pre- vs in-season (Season) were investigated as independent variables.

Subjects

Twelve participants (age = 21.3 ± 1.6 yrs; ht = 173.9 ± 9.4 cm; wt = 71.0 ± 7.8 kg) from a NCAA Division 1, female basketball team were recruited to participate in the study. All members on the team who were fully released for competition by the team physician and volunteered to be a part of the study were included. WL, WI and WD were recorded from five participants at any given practice or game, which was limited by the number of sensors. These participants were the starters who played most of the game minutes. Due to injury or illness of a starter for a significant period in the season, a sixth participant was added and provided WL, WI and WD data throughout the season. At any time during study the participant was taken out of full participation for practice or games by the athletic trainer or team physician, data was not collected for the participant. When fully released after illness or injury, data collection resumed. Informed consent forms, approved by the university's Internal Review Board, were signed by all participants prior to participation.

Procedures

Vertical Jump Assessment. JH_{max} was assessed via a Vertec device. Baseline measurements took place prior to the first practice session and were used to calculate the change in JH_{max} from all following vertical jump measures (ΔJH_{max}). All jump testing took place on Monday prior to practice and after a standardized 10-min warm up. Monday was used as the start of the new week of training to determine the effect of all variables from the previous week (Monday-Sunday) on recovery represented by the JH_{max}. To control for any inconsistency and variability in the JH_{max} results, a mark was placed on the floor to ensure the feet were placed in the same position prior to each jump. Technique was monitored to ensure no step or shifting of the feet took place prior to the jump. A self-selected depth was allowed with instructions to start with the arms raised above the head prior to the arm swing and countermovement, which preceded the jump for maximum height. Instructions for proper arm-swing and reaching to contact the Vertec markers at the peak of the jump were also provided. Any trial that did not meet these requirements was discarded and a new trial took place. The participants completed two trials of a maximum vertical jump with a 30-sec rest between each jump. The highest JH_{max} was used for analysis. Data was transferred directly to a laptop for storage and analysis.

Resistance Training Volume Data Collection

The participants completed resistance training sessions under supervision of the university's strength and conditioning coaches. A resistance training session included a warm-up on days when the session did not occur immediately after practice. The resistance training occurred one to three times per week starting at three times per week in the pre-season and one to two times per week during the in-season. The primary goal of the program was to maintain strength and power gained during the off-season. Most sessions included a multi-joint, lower- and upper-body exercise for strength completed for 2-4 sets at 60-85% of the participant's 1RM. Upper body exercises included rows, bench press, and shoulder presses. Squats, lunges, rear-foot-elevated split squats were typical lower body exercises. Olympic lifts or derivatives at 40-75% 1RM for 2-3 sets for 3-6 repetitions were included for power along with medicine ball throws. Other trunk exercises were included in most sessions ranging from high volume repetitions (10-20) and low loads intended for improved or maintenance of core stabilization. RTV was calculated as the sum of the load multiplied by the number of repetitions for all exercises. The weekly total was used for analysis.

Inertial Measurement Unit Data Collection

WL and WI were measured using IMUs using Clearsky T6 technology (Catapult, Melbourne, Australia). The device detected 3-dimensional accelerations for every movement and calculates a measure of WL using a proprietary algorithm. WL/min was used as the measure of WI. WD was a derived variable from the multiplication of WL and WI. Means for each day of the week prior to the vertical jump assessment were included in the model as independent variables. The IMU was worn in a sport vest with a pocket that secured the sensor between the scapula. Data were collected for all full practice sessions and games. To ensure that the measure of intensity was an ecologically valid measure of WI, the data collected was monitored live and when the player was not active on the court (breaks, between drills, extended periods of coaching, time-outs, benched in a game, and between quarters), data collection was paused. The data were recorded remotely and downloaded to a secure cloud database.

Athlete Reported Outcome Assessment

A questionnaire was administered prior to each practice to determine the level of SL, STR, REC between sessions. This questionnaire was adopted from the perceived recovery status scale previously validated (Laurent et al. 2011). The participants rated each factor by marking the number on a scale from 0- 10 with 0 = very poorly recovered/extremely tired and 10 = very well recovered/highly energetic with descriptors for numbers 2,4,5,6, and 8. The scales were retained but the descriptors were modified for sleep and stress. For each variable, the average score was recorded for each week. The data were recorded on paper and transferred to an excel worksheet for calculation. These weekly scores were included as independent variables in the statistical models.

Statistical Analyses

Multivariate regression models were created to predict readiness based on JH_{max} performance. Post analysis of these models made the identification of independent variables plausible that were used to make these inferences. We expected WL and WI to show multi-collinearity and therefore created the interaction variable WD via multiplication of the two.

In addition to WD, *Sign*1 at a given week (t) was a derived variable that took the value -1, 0 or 1 depending on whether the JH_{max} at week $t-1$ was lower, same or higher, respectively than the first JH_{max} recorded for the athlete. If for week t, *Sign*1 had the value 1, this revealed that the athlete had at week $t-1$ a JH_{max} that was higher than the first JH_{max} recorded for the athlete. In the regression output, the reference value for *Sign*1 was −1, the athlete having a decrease in JH_{max} value relative to the first recorded JH_{max} in the previous week.

For each practice and game, WL and WI were calculated per available player between 9/25/2023 and 02/27/2024. If no session took place or if the player was not available, the value of the day for the variable was entered as 0. This approach allowed for a more detailed set of independent variables for a more complete picture compared to aggregating weekly totals. Each of the independent variables mentioned above was standardized to z scores due to large differences in their units.

When missing values were taken into account, there were a total of 55 usable ΔJH_{max}s. For each ΔJH_{max} the previous 7-day history of WL, WI, and WD were used as predictors and these independent variables were referred to as WL_t, WI_t, and WD_t.

These procedures lead to a feature set of 26 variables including the intercept. Using all of the features, one cannot be expected to create a reasonable model for inference or prediction as the data most certainly would overfit the model. Therefore, a search algorithm became necessary to identify a model which took into account the tradeoff between the increased fit of the data to the model and the number of estimated parameters. In addition, the week number (Week) and whether the JH_{max} was recorded before the competition season started (Season) were also included in the model as independent variables. A baseline model was constructed from all the available independent variables.

The R R Core Team 2024 and the software package Venables and Ripley 2002 were used to do stepwise regression, which employed a backwards and forwards search algorithm and Akaike's Information

Criterion (AIC). As reported by Cavanaugh and Neath 2019, the AIC measure penalized the likelihood of the model with two times the number of estimated parameters and asymptotically, using AIC tends to select the model with minimized prediction errors out of the sample. The model presented had the smallest AIC value.

RESULTS

Figure 1 shows the Δ JH_{max} across 20 weeks for each participant. Injuries, illness, and other interruptions to training occurred through this time period resulting in a differing number of JH_{max} for each participant. Table 1 shows the descriptive statistics of these variables.

WL, IL and RTV are the three objectively measured data. Perceptions of sleep quality, recovery and stress were the subjective data measured weekly. Table 1 shows the descriptive statistics of these variables.

Workload = (Arbitrary Units-AU); Intensity = Intensity Load WL/min (AU/min); RTV = Resistance Training Load Volume (Reps x Load weekly total); Recovery, Sleep, and Stress = mean 1-10 scale from athlete reported outcome surveys; 1st and 3rd Q = First and third Quartiles.

WL, WI, and WD were utilized as independent variables recorded t days from the day of JH_{max} measurement. These variables are described as WL_t, WI_t and WD_t where t takes values from 1 to 7, indicating the number of days from measurement of the JH_{max}. To correctly interpret how the change in JH_{max} is affected by changing the interaction variable $WD1$, created by multiplying $WL1$ and $WI1$, both of these variables must be present in the model that predicts ΔJH_{max}. The expected ΔJH_{max} compared to the previous week while holding every other variable constant was calculated as the following: $E(\Delta JH_{max}) = -0.51 * WL1 + 0.86 * WI1 - 1.63 * (WL1 * WI1)$.

Figure 2 illustrates the expected Δ JH_{max} relative to the week one when $WL1$ or $IL1$ is fixed to the value -1, 0 or 1 standard deviations while the other variable changes between -3 to 3 standard deviations. The top (bottom) row of the plot has the values of IL

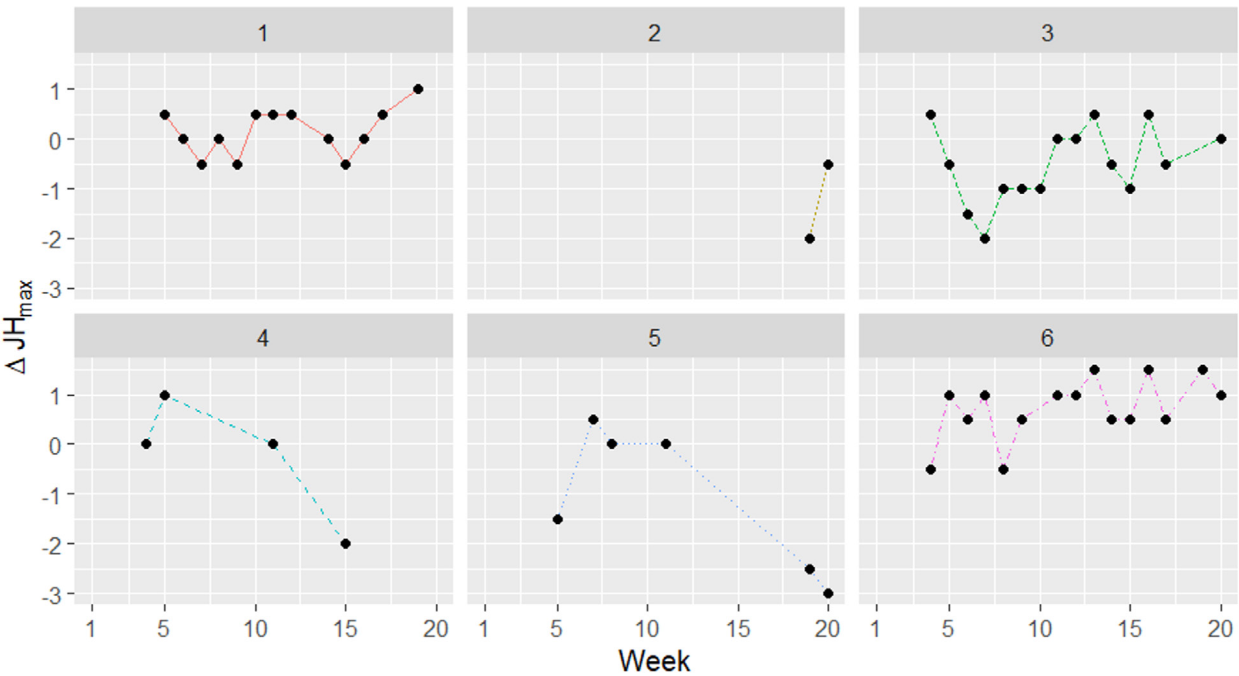

Figure 1. Vertical Jump differences relative to Week 1 across 20 weeks and six players.

Table 1. Summary Statistics of Independent Variables.

	Min	1st Quartile	Median	Mean (SD)	3rd Quartile	Max
WL	0	0	0	253(288.4)	524.5	993
IL	0	0	0	3.4 (4)	5.9	13.9
RTV	0	2318	3573	4364 (3186.7)	4827	13266
Rec	0	5	5.5	5.6 (1.9)	6.3	9
Sl.	0	5	6.6	6.1 (2)	7.3	9.5
Str.	0	1.5	4	4.7 (3.3)	7.8	10

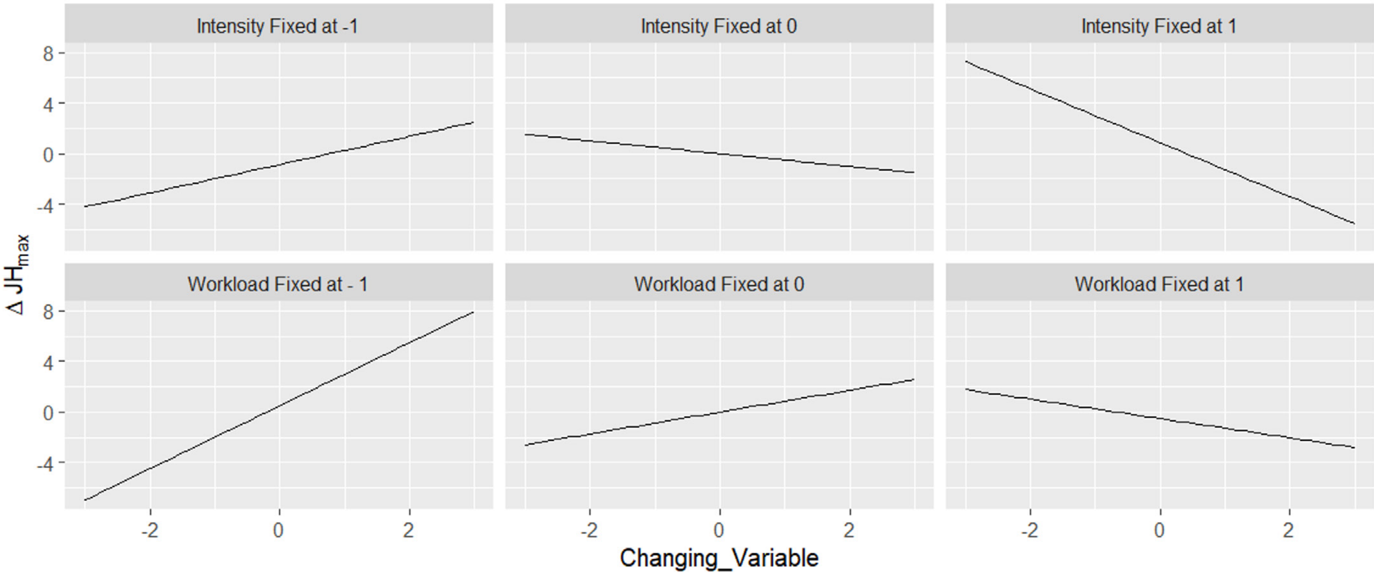

Figure 2. Illustrating the effect on Vertical Jump Difference when Workload and Intensity is changed the day before measurement.

Table 2. Week = Week during the season; WL_{1-7} = Workload day 1-7 prior to JH_{max} assessment; WI_{1-7} = Intensity Load day 1-7 prior to JH_{max} assessment; WD_{1-7} = Density Load day 1-7 prior to JH_{max} assessment; Season = Pre-season vs In-season; Sign 10 = No change in JH_{max} in the previous week compared to baseline; Sign $_{11}$ = Increase in JH_{max} in the previous week compared to baseline; RTV = Resistance Training Load Volume; Stress = Athlete Reported Outcome.

Coefficients	Mean	t value	*p* value
b_0	4.69	3.66	0.00
b_{Week}	-0.22	-3.07	0.00
b_{WL_1}	-0.51	-0.66	0.52
b_{WL_2}	-0.27	-1.43	0.16
b_{WL_3}	1.05	3.07	0.00
b_{WL_5}	-0.70	-1.96	0.06
b_{WL_6}	-0.72	-2.49	0.02
b_{WL_7}	-0.69	-3.72	0.00
b_{WI_1}	0.86	0.93	0.36
b_{WI_3}	-0.75	-2.25	0.03
b_{WI_4}	0.61	3.09	0.00
b_{WI_5}	1.03	3.25	0.00
b_{WI_6}	0.97	2.59	0.01
b_{WD_1}	-1.63	-2.13	0.04
b_{WD_6}	0.48	1.69	0.10
b_{Season}	-1.45	-1.9	0.07
b_{Sign10}	0.10	0.33	0.75
b_{Sign11}	0.92	3.13	0.00
b_{RTV}	-0.75	-2.17	0.04
b_{Stress}	0.25	2.10	0.04
r^2:	0.71,		
Adj. r^2:	0.55		
F-value 19,35 DF:	4.5;	p-value:	0.00

(WL) fixed. Since each variable is standardized, the x-axis is common to all the plots and represents the z-scores of the unfixed variable.

Not all the variables had a p-value that is significant at a p level ≤ 0.1. Of these, WL_1 and WI_1 were added post the step wise model search algorithm after WD_1 was included by the model search algorithm and a significant predictor in the model. Adding these variables was necessary to interpret WD1. Based on the collected data, the summary of the most robust model is provided in table 2. The resultant model was statistically significant with an r^2 of 71.01%

Figure 3 illustrates possible use case scenario how expected $\Delta\ JH_{max}$ can be used via prediction intervals for the six participants under consideration. The inner bands and outer bands show a 90% and 95% prediction interval per week. The unconnected dots are the predicted $\Delta\ JH_{max}$ while the connected dots are the observed values.

In figure 3, the inner ribbon plots 90% and outer ribbon plots 95% confidence intervals. The points are the predicted vertical jumps.

Independent variable importance is obtained via mean absolute SHAP values (Molnar et. al. 2018)

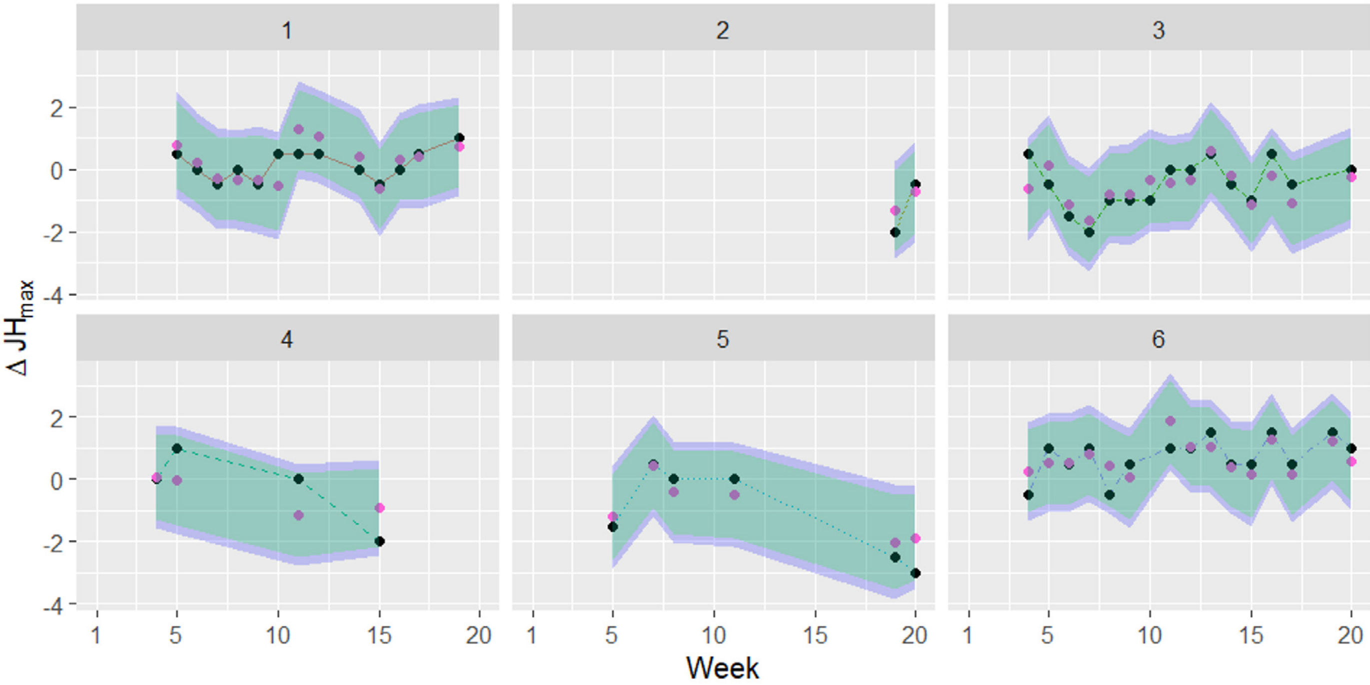

Figure 3. Predicted ΔJH_{max} and prediction intervals through 20 Weeks.

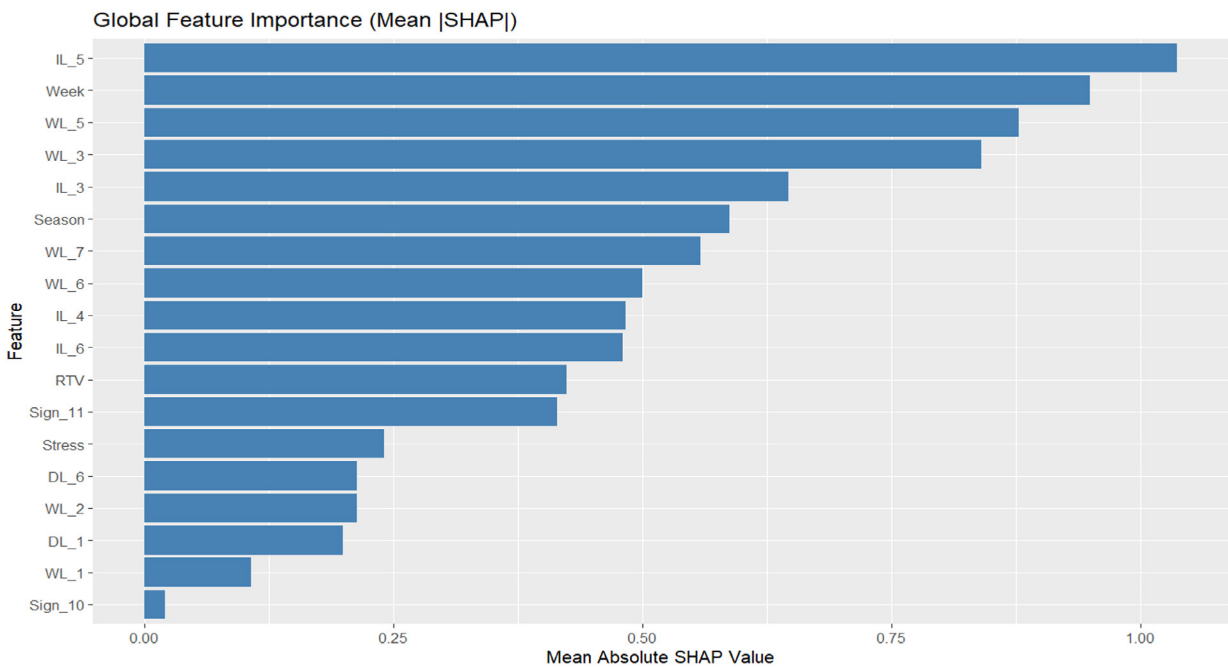

Figure 4. Mean Absolute SHAP values that illustrate the independent variable importance.

from a 10 fold cross validation procedure.

Mean absolute SHAP values in Figure 4 illustrate the feature importance in the dataset, calculated from the average of 10-fold cross validation. SHAP values consider the variance in the variables of the test dataset in addition to the coefficient estimates learned from the training set. The top 5 most important independent variables are listed as IL_5, Week, WL_5, WL_3 and IL_3. The mean absolute error (MAE) value for the 10-fold cross validation is 0.75 inches. The relatively high MAE value is an indicator of how important it will be to continue collecting samples across as many athletes as possible to decrease this uncertainty.

DISCUSSION

The primary finding in this study was that a multivariate regression model was found to be significant as a prediction of weekly JH_{max} performance. WL, WI, WD, RTV, Week, Season, Sign1, and Stress contributed to the prediction. Subjective measures of SL and REC did not significantly improve the prediction, thus were excluded. Daily measures of external loads within the 7-day measures prior to the JH_{max} assessment were found to be significant predictors.

Specifically, the data suggest that WD, the combined effect of WL and WI, one and six days before assessment should also be considered on a weekly basis. The data also indicate that higher WD six days prior to JH_{max} assessment and lower WD one day prior was essential in the endeavor to improve performance (Figure 3). Heishman et al. (2018) found similar results revealing the highest WLs the day before the JH_{max} had the most detrimental effect on performance during the pre-season in NCAA D1, male basketball players. In the current study, WL was a significant predictor on days three, six, and seven prior to JH_{max} assessment and was only excluded in the model on day four. The model suggests that higher WLs can be incorporated day three prior to testing to achieve a greater JH_{max} while reducing WL is warranted on all other days. The model indicates that if WL is increased by about one standard deviation (288 AU) above the mean WL on day three, JH_{max} is going to increase by about one inch relative to Week one. In contrast, along with higher WL on day three, lower WI on day three is suggested to produce greater JH_{max}. Greater WI was indicated on days one, four, five, and six before JH_{max} testing while days two and seven prior to testing were not chosen in the model. Comparison with other studies was not possible as this was the first known study to analyze WL and WI within the previous seven days prior to performance each week across the season.

Figure 2 reveals how vital it is to consider the two factors together (WD). If the goal is to increase JH_{max} in a particular week, increased WI (WL) should be accompanied with decreased WL (WI) the day before the measurement. Early in a given week, for example six days prior to testing JH_{max}, it is likely that high WD6 can occur with manipulation of WL and WI resulting in a relatively high JH_{max} score.

Week was a variable found to have a negative coefficient suggesting that on average the expected decrease in ΔJH_{max} would be approximately a quarter inch per week controlling for the other variables. The variable Season is used to differentiate between the pre-season (six weeks prior to the start of games) and the in-season (14 weeks of games). This variable indicates that once the team starts the season, controlling for the other variables, ΔJH_{max} decreases by nearly 3.8 cm. To summarize, if all the other variables were held at a constant value over the course of the 20 weeks, a constant decrease in JH_{max} would be expected. This finding highlights the importance of long-term planning to manipulate all of the variables within control to enhance recovery.

Using a different IMU system, Howard et al. (2024) found that WL decreased in the in-season while time at ≥85% max heart remained the same and peak oxygen consumption improved suggesting a minimum dose of WL and maintenance of intensity was sufficient to produce cardiovascular improvement. Our study had a similar trend of decreasing WL and an increase in WI across the entire season. Based on limited studies, the data indicate that physical conditioning can improve through the season by decreasing WL and increasing WI as the season progresses and games begin. This data should be considered when planning WL and WI during pre-season and in-season to maximize recovery and performance.

The variable Sign1 revealed the importance for coaches to follow trends of the individual athletes. The Sign11 coefficient indicated that for a given week, JH_{max} was greater than the baseline JH_{max} taken prior to the start of the official season. Using Sign11 from the model, one could expect a JH_{max} of 2.3 cm greater during the following Monday assessment compared to a loss in JH_{max} during the previous week. This would indicate that the previous week's level of readiness based on the ΔJH_{max} can be used to predict readiness in the following week. If the ΔJH_{max} decreases, this may demonstrate a lack of recovery. However, as illustrated in Figure 2, there is no athlete who fell below the lower 90% prediction interval. Analysis of the Sign11 variable underscores the importance of maintaining a continuous positive level of recovery during the entire season.

RTV was a significant predictor in the model. When all variables were controlled, lower levels of RTV were associated with greater JH_{max}. This was the first known study to investigate the impact of weekly total RTV on ΔJH_{max} during a basketball season. Resistance training took place three times per week during the pre-season and two times per week during the in-season. Thus, RTV decreased during the in-season with the primary goal to maintain strength and power. The greatest RTV took place in the last few weeks of the pre-season with a progressive reduction of volume each week as the in-season progressed. Including resistance training during the entire basketball season is likely essential to maintain or improve strength and power. However, the added volume of work in addition to the WL and WI experienced during practice and games may be detrimental to recovery indicated by the negative RTV coefficient in the model. The data indicate that lower RTVs may have provided improved recovery reflected by greater JH_{max} scores produced in this study.

Participant's STR was found to be a significant predictor of ΔJH_{max} in the model. The positive coefficient suggests that greater STR level aggregated during the week is associated with improved JH_{max}, which was surprising. It was expected to find that lower STR levels would impact greater JH_{max} due to existing research demonstrating that high levels of STR reduce shooting performance in male basketball players (Daub et al. 2022) and neuron firing rate (McEwen, Nasca, and Gray 2016). It is possible that the players experienced a level of STR that was below a threshold for negative effects on JH_{max}.

Factors of SL and REC were not chosen to be in the model, which was also not expected. In contrast, perceived REC status was found to be associated with sprint performance in trained men and women in high intensity exercise (Laurent et al. 2011). A fatiguing sprint protocol followed by one, two and three days of rest before repeating the sprint performance took place, which differs from our study by involving a short-term study with one session used to fatigue participants. SL is considered necessary that allows physical recovery to occur. An increase in SL has been shown to enhance nervous system function (Stickgold and Walker 2007) and improve basketball performance (Mah et al. 2011). It is possible that fine motor skill performance may be more sensitive to changes in SL while gross motor patterns involving strength and power such as a JH_{max} are less affected. In a review of 56 studies, Saw, Main, and Gastin (2016) found that athlete reported outcomes as indirect measures of fatigue had strong and better associations than objective measures from the level of previous training loads. More data is needed to determine the impact that subjective measures of STR, SL, and REC can have on changes in JH_{max} during the entire season in elite, women basketball players.

Existing limitations to the study are important to be noted. Two vertical jump assessments were missed due to the participants being unavailable during the Christmas break. Individual participants had missing JH_{max} scores due to illness and injury. Participants had to have a full release for participation in practice on the day of the JH_{max} assessment to complete the test. Surveys were recorded only on practice days. While instructions during the JH_{max} were consistent, maximum effort could not be assessed. Subjective responses on the athlete reported outcome measures were limited by the participants' willingness to accurately report their level of SL, STR, and REC. The study was composed of 55 observations across six individuals and 25 independent variables. The stepwise algorithm allowed us to search across a large number of models; however, additional data need to be collected in order to increase confidence for the illustrated model as well as reducing uncertainty around the coefficients within it. The multiple linear regression model assumes each observation to be independently observed for each athlete. This leads to estimating common coefficients for the effect of independent variables on the JH_{max} for each athlete. Coaches should be aware that individuals might react differently to the same training. Based on the noted limitations, it is warranted to consider a linear mixed-effects model in similar future studies as an appropriate tool to model these differences as random effects, which could provide further data to improve weekly training program decisions based on the individual's jump performance.

CONCLUSION

The presented model is based on daily on- and off-court factors that affect JH_{max} in NCAA D1, female basketball players during the season. The model indicates that the demands of on-court WL and WI and the combined effect (WD) can be monitored on a weekly basis within a 7-day week prior to JH_{max} assessment through the entire season to manage recovery using JH_{max} as the predicted measure. A trend of decreasing WL and increasing WI appears beneficial for jump performance across the season. It is beneficial to maintain JH_{max} performance in the previous week for the following week's JH_{max} performance. Within a 7-day period preceding JH_{max} assessment, high WD implemented six days before the measurement resulted in a positive effect on JH_{max}. High WL on day 3 was also beneficial. In contrast, it was essential to have a low WD the day before the JH_{max} took place. Maintaining lower RTV should be considered within the season while increased STR can be tolerated resulting in improved JH_{max}. Finally, Season impacted JH_{max} with a trend to decrease JH_{max} during the in-season indicating a need to address all factors that could contribute to the potential of overtraining.

CONFLICTS OF INTEREST

The authors had no conflicts of interest.

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ETHICAL APPROVAL

Informed consent forms, approved by the university's Internal Review Board, were signed by all participants prior to participation.

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