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ORIGINAL RESEARCH

Underpinning Performance Metrics Between a Winning and Losing Season in Division 1 Women's Basketball

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Abstract

Athletic success depends on several factors, including measurable factors such as training, sleep, and mental state. The women's Basketball team at Sacred Heart University, USA, has been monitored over two consecutive seasons. The first season, 2021/22, was relatively unsuccessful, followed by a much-improved performance in the 2022/23 season, with a higher win percentage. Six metrics have been measured consistently: Training, sleep, mental state, game workload, jump analysis, and game performance. We compare those metrics over the two seasons, and our findings show the direct relationship between better training, better sleep, and mental health on the team's performance as a group. We analyze the performance of the players common to both seasons and note the improvement of this group's fitness over the two seasons (3.5% better sleep, 8% in recovery, 12% in stress, and 13% in jump height) even before the games started, and the effect of the new players on the team performance.

Keywords Athlete performance · Basketball · Game performance · Sport analytics · Temporal analysis

Introduction

As in all sports, success in competitive basketball requires the development and execution of a finely honed set of technical and tactical skills coupled with requisite athleticism. Although seemingly categorically distinct, technical ability and physicality are inextricably linked, with deficiencies likely limiting individual and team success [1]. The acquisition of sport-specific technical skills is a prolonged and complex experience-driven process primarily directed by the sports coaching staff [2]. Although successful execution may be influenced by acute fatigue [3], once developed, technical ability may become relatively stable [4]. The chronic nature of skill acquisition suggests that player retention may influence team performance, where experienced players demonstrate more remarkable skills, thus having greater influence over team success. However, genetic determinants of talent have also been identified [4]; therefore, adding athletes with

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superior genetic endowment may also influence program success.

In contrast to technical ability, athlete physicality is relatively more dynamic, with acute and chronic athletic fluctuations closely associated with the fitness-fatigue paradigm [5]. **S**ports scientists aim to assist in athlete development and acute preparation for competition by concurrently monitoring workload characteristics related to fatigue, injury, physiological indicators of recovery, athlete subjective responses, and key performance indicators (KPIs) intended to reflect an athlete's physical ability at any given moment. Through acute and chronic monitoring of variables associated with fatigue and recovery and KPIs, sports scientists can evaluate athletes' performance potential and gain insight into the appropriateness of the stimulus provided in sport-specific practice and strength and conditioning sessions. Furthermore, reconciling performance outcomes with data collected through athlete monitoring may assist in the determination of the relative importance of factors influencing individual and team success in competition.

Literature Review

A paucity of research has examined the determinants of successful competition among NCAA Division I women's basketball programs. Russell [6] presents an interesting review of research done to determine the physical demands of basketball and the importance of monitoring players' mental states and training.

Sarlis [7] also presents an excellent study reviewing basketball metrics used in National Basketball Association (NBA) and Euroleague games. They benchmark existing performance analytics used in the literature for evaluating teams and players. They propose utilizing these analytics for team composition athlete career improvement and assessing how this could be materialized for future predictions. Another interesting study by Cabarkapa [8] compares a winning season with a losing season for NBA games over three years. The results are impressive; however, the data taken into consideration is the publicly available game statistics, and other game success factors such as training, sleep, injury occurrence, and mental health were not considered.

Although recent evidence demonstrates the importance of several qualities of athleticism, such as muscular power, strength, and agility [9], the relative contribution of athleticism and technical ability to successful outcomes at higher levels of competition in women's basketball remains unclear. Furthermore, the influence of athlete retention and the addition of new athletes to team success remains to be examined. Therefore, the purpose of the current investigation is to evaluate the relative contributions of athleticism and sport-specific skill in the success of an NCAA Division I women's basketball program by examining team performance, injury occurrence, year-to-year roster changes, and acute and chronic fluctuations in player athleticism across two seasons of competition.

The Sacred Heart University Women's Basketball team (SHU WBB) competes in the North East Conference (NEC) at the Division 1 level within the National Collegiate Athletic Association (NCAA) [10]. While athlete monitoring for the WBB program has been ongoing for nearly a decade, the last few years included more systematic and multimodal data collection strategies, such as heart rate monitoring, assessment of sleep quality and quantity, injury tracking, and determination of workload parameters, along with traditional surveys and countermovement jump performance monitoring. Out of 7 previous seasons, SHU WBB had three winning seasons and four losing seasons (a winning season is defined as a competitive season in which more in-conference games are won than lost). There was a significant shift from the 21/22 to 22/23 season, where the winning percentage improved from 33 to 75%.

In an earlier study, we proposed a holistic approach to performance prediction in collegiate women's basketball, encompassing individual players, teams, and conferences. The study employs machine learning, specifically an Extreme Gradient Boosting (XGB) classifier, to assess player-level metrics using the reactive strength index modified (RSImod), team-level metrics via the game score (GS) metric, and conference-level metrics using Player Efficiency Rating (PER). The data sources include a variety of parameters such as training, stress, sleep, recovery, in-game statistics, and countermovement jumps. The models achieve over 90% accuracy in predicting RSImod and GS and a 0.9 F1 score. The XGB regressor indicates PER with a Mean Squared Error (MSE) of 0.026 and an R-squared (R^2) of 0.680. The paper emphasizes the importance of quantifying and predicting performance at multiple levels, providing coaches with valuable insights into athlete readiness and effective training strategies. Partial Dependence Plots (PDPs) enhance the interpretation of feature impacts on performance variables, doing this valuable research to sports analytics and athlete management [11].

Next, we developed a hybrid approach that outperforms classical regression and decision tree (DT) methods, emphasizing the potential of machine learning in sports analytics. The study uniquely incorporates factor analysis for data characterization and decision tree construction, enhancing interpretability [12]. Following this, we proposed a comprehensive approach to performance prediction in women's Division I basketball employing an Extreme Gradient Boosting (XGB) classifier for player-level metrics, a game score (GS) metric at the team level, and PER for the conference level, integrating diverse data sources such as training, stress, sleep, recovery, injury occurrence, in-game statistics, and countermovement jumps [13].

SHU's Women Basketball Team

In this paper, we studied the performance of SHU WBB in the 21/22 and 22/23 competitive seasons. In the 21/22 season, SHU WBB had 11 returning athletes, while five were new to the program. Seven athletes returned in the 22/23 season, and six joined the program. For this analysis, we stratified the players into four groups, as shown in Table 1. The groups "Common 21/22" and "Common 22/23" represent the athletes who were on the team in both years; we compared the data for these "common" athletes over two consecutive years. The group "21/22 only" is the nine athletes who left the team after the 21/22 season, and the group "22/23 only" is the six athletes who joined the team in the 22/23 season; this group is slightly taller and much lighter than the other groups.

The 21/22 season was challenging for the team, with a win-loss record of 8–17, compared to a much-improved 19–14 in the 22/23 season. The team's home and away performance improved significantly in the latter season (11–6 and 7–7, respectively) compared to the former (4–8 and 4–9). The team's offensive performance improved, scoring an average of 62.3 points per game in 22/23, compared to 60.5 in 21/22. However, shooting efficiency remained below par in both seasons; Field goal percentage rose from 37.6% to 38.1%, but still below league averages of 38.67% and 38.34%. Three-point shooting fell from 30.0% to 26.7%, a decline compared to league averages of 31.71% and 29.23%.

Defensively, the team improved in steals and blocks per game in 22/23 (9.5 and 3.2, respectively) compared to 21/22 (6.5 and 2.5, respectively). The rebound margin improved from -4.2 to -0.3, indicating better control of the boards. Turnovers decreased slightly from 16.5 to 15.5 per game, reflecting improved ball handling. Table 2 summarizes their game performance for both seasons.Our work in this paper is a case study of using data analytics techniques to evaluate the longitudinal trends in performance and recovery in an actual sports environment. This aligns with our general research goal of seeking actionable insights for athlete development. A key difference between our study and most studies in which data analytics and machine learning methods were employed is that data were collected with an active team. In contrast, other researchers commonly use web scraping methods to analyze KPIs for many teams across seasons. A novel aspect of our paper is that we are highlighting a potential use case for data science/analytical techniques that a practitioner might use to identify trends within one athletic program to better inform the decision-making process for the team being monitored.

Table 2 Comparison of team statistics between the 2021–2022 and 2022–2023 seasons. the "-" sign indicates a decline in the performance

Statistic	2021–2022 Season	2022–2023 Season	Difference	Percentage Change (%)
Win-Loss	8–17	19–14	11	137.50
Field Goal %	37.6%	38.1%	0.5%	1.33
Three-Point %	30.0%	26.7%	−3.3%	−11.00
Rebound Margin	−4.2	−0.3	3.9	−92.86
Turnovers	16.5	15.5	−1	−6.06
Steals	6.5	9.5	3	46.15
Blocks	2.5	3.2	0.7	28.00

Methods

Twenty-two Division-1 female basketball players agreed to participate in this study (age: 21 ± 3 yrs; height: 174.21 ± 19.27 cm; body mass: 73.98 ± 11.52 kg). Athletes were monitored from August 2021 through March 2023. Data collected included workload, vertical jump performance, athlete questionnaire responses, sleep data, polar strap data, and game performance metrics. All subjects read and signed informed consent. This project was approved by Sacred Heart University's Institutional Review Board (IRB#170720A).

Data collection for this study was multilayered and complex as multiple sports scientists, staff, and athletes were required to submit and gather data. A challenge intrinsic to collecting 24 h physiological data through individual telemetry devices (Whoop straps) is that athletes will be responsible for operating and maintaining equipment. Furthermore, questionnaires in assessing subjective and psychological aspects related to performance are particularly susceptible

Table 1 Performance and physical attributes of athlete groups across two seasons

Group name	Number of Athletes	Avg. Height (m)	Avg. Weight (kg)	Total minutes played	Avg. minutes per game
21/22 season only	9	1.75	74.22	3085	21.87
Common 21/22	7 (5 return)	1.76	76.79	1965	16.65
Common 22/23	7	1.76	76.93	2569	16.05
22/23 season only	6	1.77	70.97	4031	24.88

to unresponsiveness unless completed in the presence of the sports scientist, strength and conditioning coach, or sports coach. Therefore, collecting 24 h physiological data and assessing subjective and psychological data may contribute to missing, not at random, as in our study. Additionally, a more significant potential for human error is expected when surveying this magnitude, as collected data required extensive cleaning and formatting before more complex analysis.

In this section, we define the metrics used to measure the training workload, recovery data for both sleep and mental health, and the resulting performance metrics from the game statistics and weekly jump testing. This quantifies our research and is the basis for our comparative analysis.

Indicators of Internal and External Workload

Session RPE

Each week, a composite workload score was calculated by summing the total work completed in practice, conditioning, strength training, and competitive matches. Ten minutes following each session, each athlete obtained a session rating of perceived exertion (RPE). From here, we multiplied this by the time in each training modality to create a session RPE (Session RPE). A total workload was calculated by summing all work for the week into one cumulative score.

Game Workload Metrics (Polar Data)

During competitive matches, each athlete was affixed with a heart rate strap and Polar Team Pro unit [14] (Polar Team Pro, Polar Electro, Kempele, FI) sampled at 10 Hz. This allowed for the calculation of heart rate, distance covered, velocity, and acceleration, which was incorporated into the workload metric calculations.

Indicators of Athlete Recovery

Sleep Data (Whoop Data)

During the collection period, all athletes were given Whoop straps and instructed to wear them during sleep and all other activities except for practice and competitive matches. Data was collected daily and analyzed using Whoop's proprietary software. Sleep and recovery metrics examined a player's physiological response to imposed training demands.

Subjective Questionnaire Data (SRSS)

Twice per week, athletes were instructed to complete a short recovery and stress questionnaire (SRSS) consisting of four recovery and four stress questions. Upon waking, they would complete a 0–6 Likert scale question: overall recovery, mental performance capability, physical performance capability, emotional balance, overall stress, muscular stress, lack of activation, and negative emotional state. This survey is valid and reliable for athletes [15].

Key Performance Indicators (KPIs)

Vertical Jump Testing

Finally, once per week, vertical jumps were collected at the first practice. Following a general warm-up, the subject completed two maximal vertical jumps standing on dual force plates (FD Lites, Force decks, Newstead, QLS, AUS) sampling at 1000 Hz. Subjects placed a near-weightless polyvinyl chloride pipe just below the C7 spinous process and were instructed to jump as high as possible on each rep. Passive rest was given between repetitions. Data were collected and analyzed using the proprietary Force Decks software. Jump height, calculated from the duration of time spent off the platform (flight time), and reactive strength index modified (mRSI), calculated as flight time divided by contact time, were used for exploring readiness.

Results

We now compare the workload, recovery, and performance indicators for both seasons and the four groups. Each section covers one of the measurement points defined in the previous section. Data analysis was performed using the R programming language [16].

Session RPE

Session RPE measures dropped considerably starting around week 10, coinciding with the start of the competitive period. Table 3 shows the average session RPE for both seasons. In the 22/23 season, the sessions were less rigorous, and the weekly Trimp Total was 22% less than the previous season. However, sessions were more regular, with fewer athletes missing due to COVID-19 or injury. This was reflected in a lower weekly standard deviation (11.7% less) and consequently less monotony (15% less) and considerably lower Strain (39.7% less), which led to a reduced rate of injury (contact & non-contact injuries) and better overall team performance (30% higher game score).

Game Workload Metrics (Polar Data)

Figure 1 shows the time-series change of the "Total distance" field for both seasons. The x-axis represents the day number since the start of the practice season in early September (Day 1); note that the games started on days 65 and

Table 3 Comparison of average RPE metrics across two seasons (arbitrary units)

	Weekly TRIMP[1] Total (au)	Weekly TRIMP Standard Deviation (au)	Monotony[2] (au)	Strain[3] (au)
All players 21/22	1918.33	329.77	0.7988	1997.48
All players 22/23	1488.93	291.15	0.6792	1204.21
Percentage Change (%)	22.4% less	11.7% less	15% less	39.7% less

[1]TRIMP is an abbreviation of TRaining IMPulse. It is defined as the product of training volume, measured in minutes, and training intensity, measured as average heart rate (beats per minute or bpm)

[2]Monotony was calculated by taking the mean daily load and normalizing it by the weekly SD of the training load

[3]Training Strain was calculated by taking the total weekly load and multiplying it by the monotony score

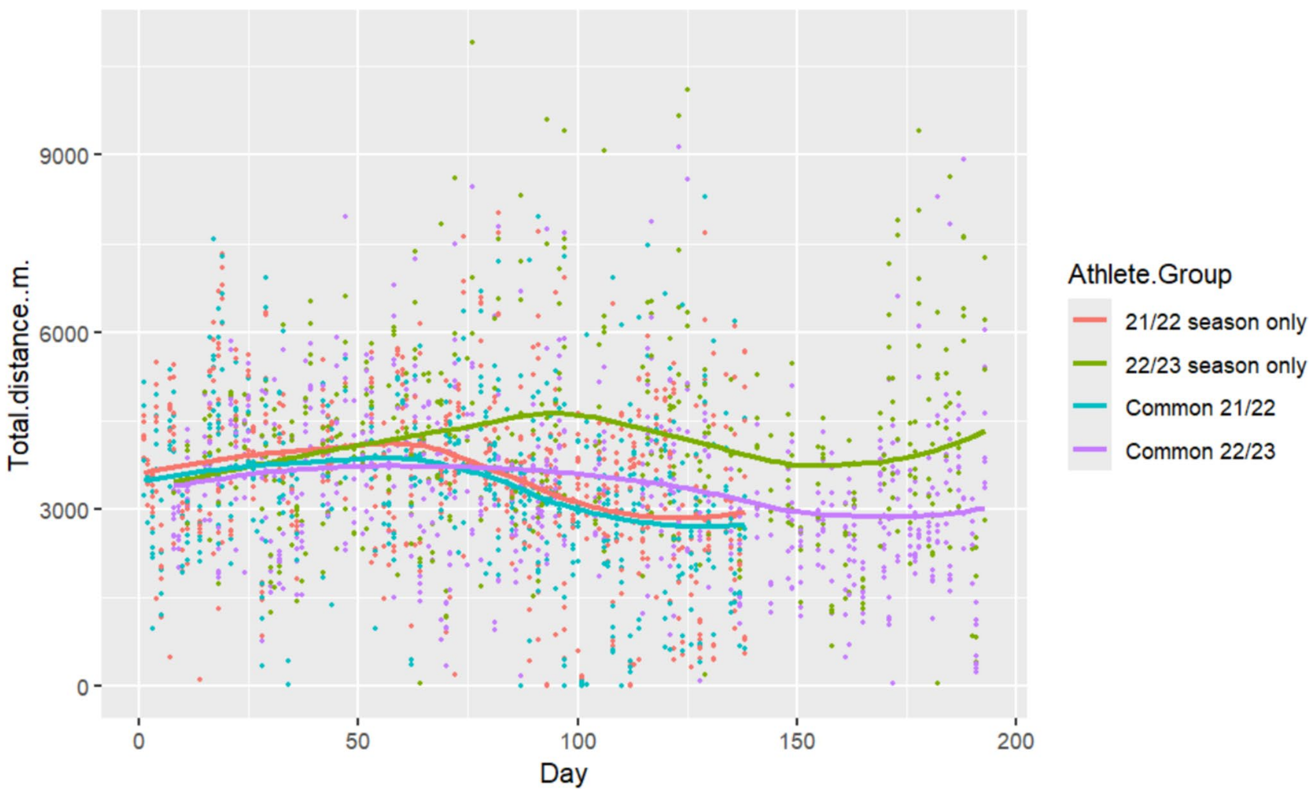


Fig. 1 Total distance versus time by player group

67 for the 21/22 and 22/23 seasons, respectively. The four lines show the trend line for all four groups. Note the drop in performance in early November for the 21/22 season and around early December in the 22/23 season. The data also shows that the new 22/23 players ran much more than all other players, and the common players performed better in 22/23 as well. Table 4 shows the average values for some of the polar strap fields. The players who joined in 22/23 had a higher average distance, max speed, and average speed, pulling up the team average for the season.

An analysis of the polar data for the two seasons shows that common players performed slightly better in the second season. However, the new players performed better than those who left after the 21/22 season, as shown in Figure 1 and Table 4. Table 4 also shows an improvement in the common players' heart rate (HR) metrics.

Both seasons started with similar polar metrics until around day 60-70, when the advantage of the new players in 22/23 became clear. Note the drop in performance around early November (days 60-70) in the 21/22 season; this is due to multiple factors: the strength trainer loss at this time, several athletes getting sick and injured in December and January, and several games being canceled, leading to an irregular game schedule.

Table 4 Comparison of average game workload metrics for athlete groups across seasons

	HR min (bpm)	HR avg (bpm)	HR max (bpm)	Total distance (m)	Distance /min (m/min)	Max speed (km/h)
All players 21/22	74.73	133.05	193.21	3385	28.53	23.47
All players 22/23	64.46 (14% less)	131.48 (1% less)	200.9 (4% more)	3638 (8% more)	28.92 (1% more)	23.99 (1% more)
21/22 only players	74.2	132.1	191.2	2449	29.04	23.32
Common 21/22	75.37	134.2	195.5	3307	27.92	23.65
Common 22/23	67.47	131.76	200.77	3363	26.9	23.43
22/23 only players	59.95	131.06	201.17	**4051**	**31.95**	**24.82**

Whoop Sleep Data

The average Whoop strap measurements are shown in Table 5 for the four groups throughout the season. We observe that the common players had a better sleep performance in their second season, with a 3.5% increase in their sleep score and a 6% drop in their Resting Heart Rate (RHR). The 22/23-only players had a lower RHR than the other groups and were generally better sleepers than the 21/22-only players group. In summary, the 22/23 season players were better rested.

Subjective Questionnaire Data

The subjective questionnaire is used as a measure of the athletes' mental state and how they perceive their physical fitness. The weekly survey started at the beginning of the season in early September and was repeated until the end of February for both seasons. The survey had eight questions about their physical and mental state. The SRSS survey [15] data is collected bi-weekly with a numerical answer in the range 0 (strongly disagree) to 6 (strongly agree):

- PPC: Physical Performance Capability
- MPC: Mental Performance Capability
- EB: Emotional Balance
- OR: Overall Recovery
- MS: Muscular Stress
- LA: Lack of Activation
- NES: Negative Emotional State
- OS: Overall Stress

Table 6 shows the average answers for both seasons and for each group. It shows a 9.2% improvement in the overall recovery and a 20.8% improvement in overall stress, with the 22/23 only players having the lowest stress and highest recovery perception. The common players also showed an improvement in recovery and stress levels.

Vertical Jump Testing

In the 22/23 season, the group's new players were lighter (average 71 kg), dropping the average player weight from 75.5 to 75.1 kg. The common players' weight remained approximately the same in both seasons. Table 7 shows the vertical jump measurements for all groups. Note that the 22/23 only group is much lighter and has more peak power, RSI (Relative Strength Index), and jump height than the other groups. Also notable are the common players who significantly increased jump height from about 10.5 inches to about 12 inches. This is a significant improvement given that their weight did not change. Their peak power also improved by 6.5% in the 22/23 season, when they had better and more regular strength training sessions.

Table 5 Comparison of average whoop strap metrics for athlete groups

	Resting HR (bpm)	Heart Rate Variability (ms?)	Recovery	Sleep Score	Hours of Sleep	Sleep Need	Sleep Efficiency
All 21/22 players	59.57	84.09	59.56	76.44	6.90	8.91	88.92
All 22/23 players	57.01 (4% less)	97.94 (16% more)	60.31 (1% more)	80.45 (5% more)	7.14 (4% more)	8.73 (2% less)	89.90 (1% more)
21/22 only players	57.59	76.61	60.75	73.72	6.66	8.95	87.19
Common 21/22	61.34	90.83	58.49	78.89	7.10	8.87	90.49
Common 22/23	57.60	102.8	60.13	81.68	7.22	8.65	90.57
22/23 only players	55.50	85.70	60.75	77.40	6.96	8.93	88.23

Table 6 Comparison of average survey responses for both seasons across metrics

	PPC	MPC	EB	OR	MS	LA	NES	OS
All players 21/22	3.87	4.19	3.72	3.47	3.37	2.98	3.18	3.36
All players 22/23	4.02 (4% more)	4.17 (0.5% less)	3.91 (5% more)	3.79 **(9% more)**	2.81 (17% less)	2.25 (24% less)	2.27 (29% less)	2.66 **(21%less)**
21/22 only players	3.93	4.05	3.51	3.48	3.51	3.20	3.42	3.51
Common 21/22	3.81	4.32	3.93	3.46	3.24	2.78	2.96	3.20
Common 22/23	3.85	4.01	3.65	3.73	2.75	2.41	2.60	2.83
22/23 only players	4.30	4.42	4.32	3.88	2.92	2.00	1.75	2.28

Table 7 Vertical jump performance metrics for all athlete groups

	Body Weight (kg)	Peak Power (watts)	Peak Power per BM (watts/kg)	RSI (FT/CT)	Jump Height (cm)
All players 21/22	75.5	3414	45.3	0.38	10.64
All players 22/23	75.15 (0.5% less)	3798 (11.2% more)	50.7 (12% more)	0.43 (13% more)	12.55 (18% more)
21/22 only players	74.22	3441	46.5	0.38	10.74
Common 21/22	76.79	3386	44.05	0.37	10.53
Common 22/23	76.93	3606	46.66	0.37	11.91
22/23 only players	70.97	4226	59.83	0.52	13.59

Game Performance

In the 21/22 season, the team played 25 games, eight wins, and 17 losses, and in the 22/23 season, they played 31 games, 18 wins, and 13 losses. Figure 2 shows the sequence of wins and losses for both seasons, with a win denoted as a 1 and a loss a zero. The 21/22 season had mixed results initially, followed by a series of losses. The 22/23 seasons had a bad start with 7 consecutive losses, followed by a series of wins.

Each player had a game score [6] for each game played. The score is calculated based on the player's performance and depends on the minutes played, field goals, blocks, and other game metrics. The score heavily depends on the position embedded within the tactical framework, which favors players involved in scoring points on offensive drives. Figure 3 shows the average game score for all player groups in both seasons.

We observe that the game scores were generally higher in the 22/23 season compared to the 21/22 season and mirror the win/lose trend shown in Fig. 2. The common players typically had low average game scores and stayed the same between seasons despite better strength training 22/23. The players that played in the 21/22 season only consistently had a higher score and were replaced in the 22/23 season with new players with much better game scores right from the beginning. We iterate that the game score heavily depends on the position the player is playing in.

Plus/Minus Effect

Plus/minus is a statistic calculated by taking the number of points the team scored while the player is on the field and subtracting it from the number of points the other team scored while that same player is on the field [17]. When a player has a positive plus/minus, that means the team is scoring more points than the other team when that player is on the field. Since plus/minus is based on the score change while the player is on the field and not how much the player scores, it is heavily affected by the other players.

Figure 4 shows the average plus/minus for each group in each game over the two seasons. The graph shows a negative trend line for all groups who played in the 2021–2022 season and a positive trend line during the 2022–2023 season. The positive trend lines in the 2022–2023 season imply the players who played in both seasons are working with their new teammates better than they did with their old teammates. It also shows that both groups of players in the 2022–2023 season improved their offense and defense skills as the season progressed.

Results

In this section, we evaluate how all the different factors affect the performance and injury levels in both seasons Table 8.

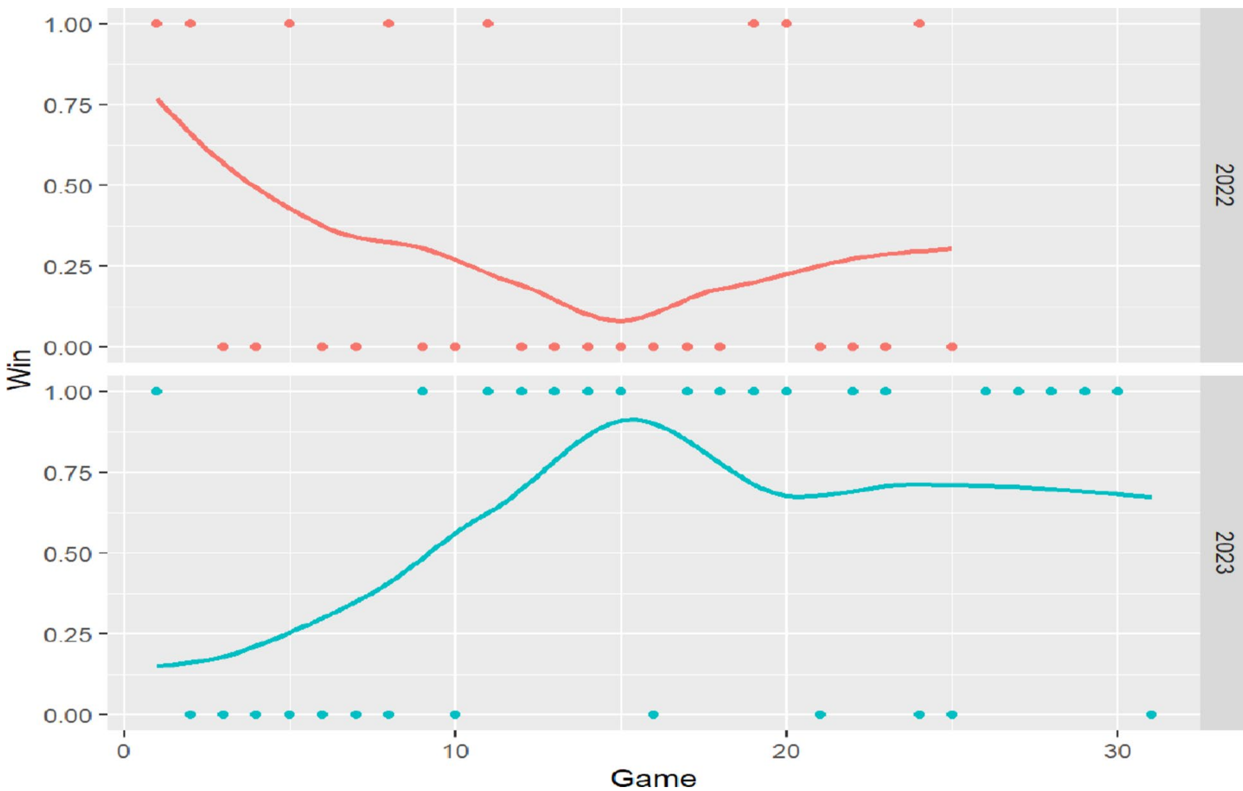
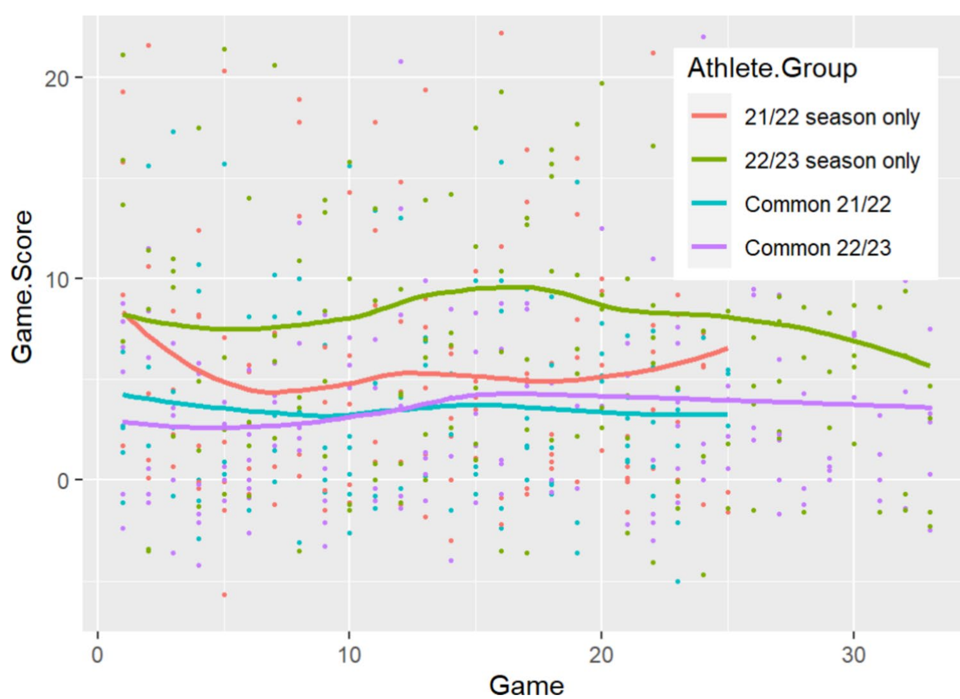


Fig. 2 Time analysis of game results for both seasons

Fig. 3 Average game score for all player groups in both seasons



Effect on Performance

In the previous sections, we analyzed all the different factors separately. This section will examine their effect on the game score, our primary measure of athlete performance, and injury occurrence.

Figure 5 shows the Game Score per minute (normalized as each player played a different amount of minutes, and the

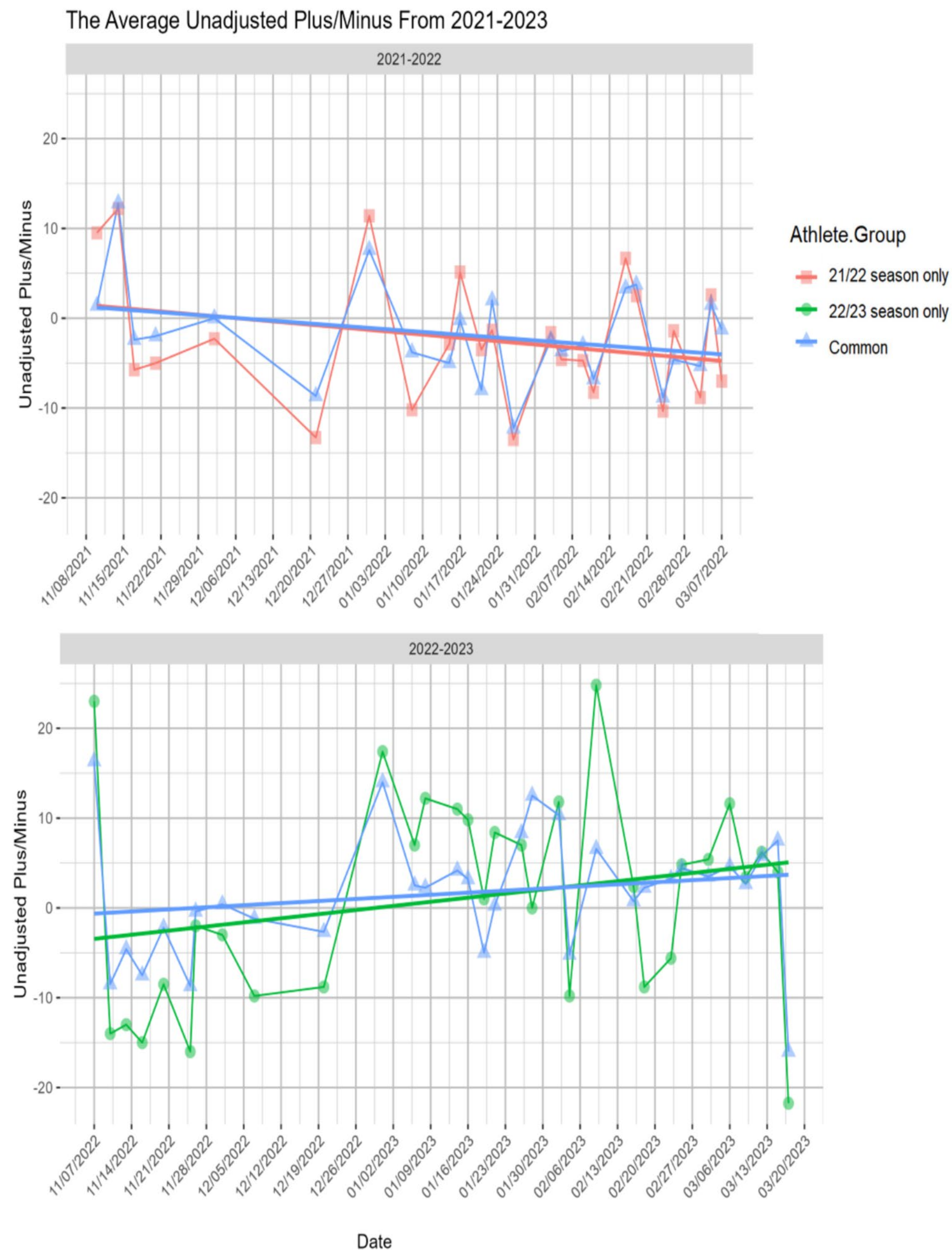


Fig. 4 Unadjusted Plus/Minus for both seasons

Table 8 Average game scores by player group across two seasons

	Average Game Score
All players 21/22	4.43
All players 22/23	5.77 (30% more)
21/22 only players	5.11
Common 21/22	3.59
Common 22/23	3.33
22/23 only players	8.36

game score depends on the minutes played) and the RSI for weeks 8–20 when the games were played. It shows a strong correlation between the RSI and game score.

Figure 6 shows the relationship between the game score and the minutes played by all game players. Note the funnel shape for the figure; the game score increases as the number of minutes played increases, but it varies differently among players who play more than 8 min in a game. We note that the common players had the same game score per minute for both seasons when they played less than 20 min and slightly lower when they played for more than 20 min. In the 22/23 season, only players had a higher game score for any number of minutes played.

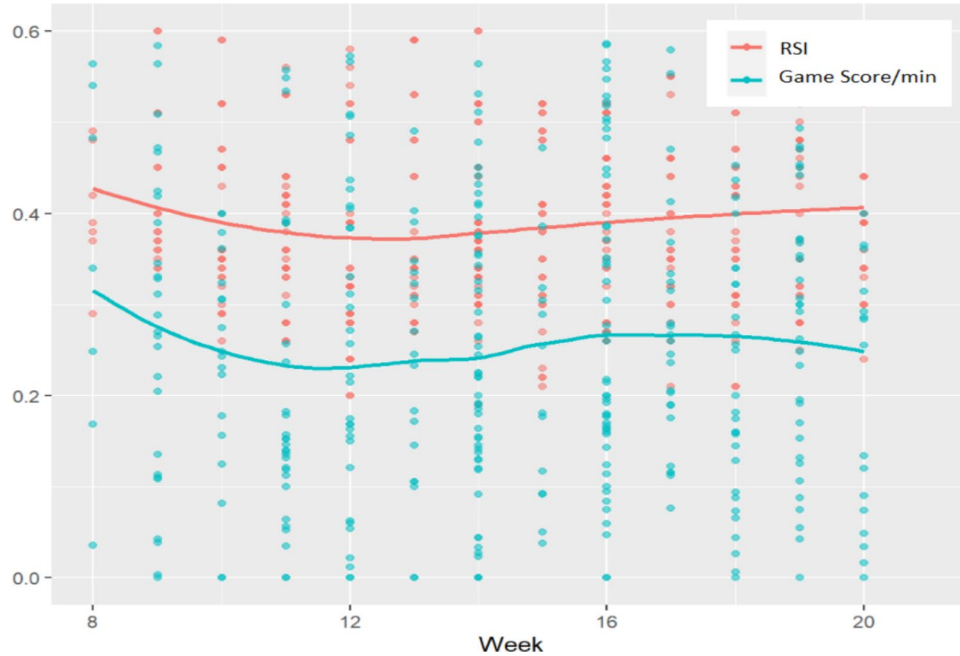


Fig. 5 Correlation between RSI (Relative Strength Index) and Game Score/Min

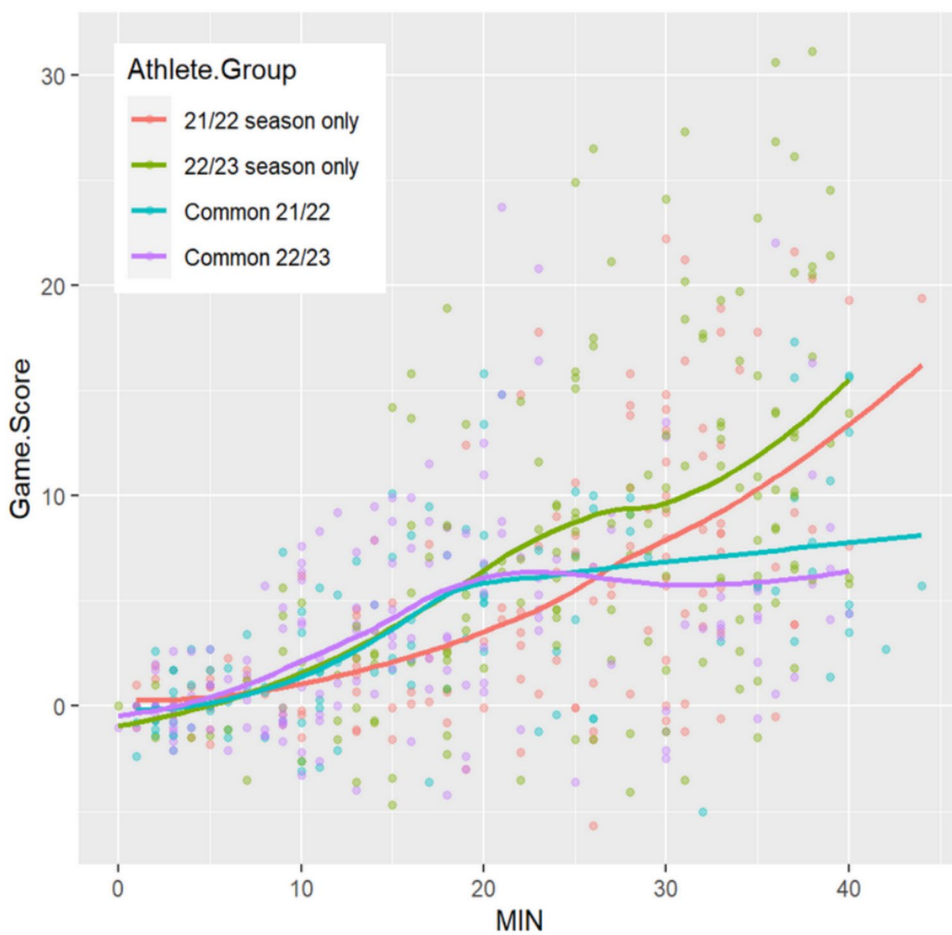


Fig. 6 Effect of playing time on the Game Score

The new players were a factor in the better results; they generally had a better game score. This is in part due to the position they played in the game. As basketball is a team sport, improving the overall game score is more important than individual athletes. So, the better indicator of critical internal and external workload in 22/23 contributed to the season's success.

Table 9 summarizes the effect of the different metrics on the team's performance in both seasons. Due to the small sample size of our study, with one team over two seasons and not multiple teams, it is not a strong reason to establish a causal relationship. However, examining a single team allows for consistent, contextual factors (e.g., coaching style, facilities, and schedules), making our results robust for within-team analysis and comparable across seasons.

Our results show a substantial correlation with performance due to regular training, mental state, athlete general fitness, and less so due to sleep.

Effect on Injury Rates

Just as the individual factors of workload and recovery affected athlete performance, they also affected injury occurrence. While athletic injuries are an inherent risk of sports participation, previous studies have shown that factors such as intensity and structure of training, physical and mental exhaustion, and sleep quality can result in higher injury rates among athletes [11, 18, 19]. Specifically, athletes have been shown to suffer a higher occurrence of overuse injuries and those involving non-contact mechanisms [11, 19]. Moreover, a strong correlation between both physical and mental exhaustion and the occurrence of chronic injuries in female collegiate athletes compared to males has also been shown [19].

A comparison of injury occurrence between the 21/22 and 22/23 seasons is shown in Table 10. Injury reports were obtained from the team's electronic medical records database beginning on July 1st (the beginning of off-season training) and continuing through the conclusion of the respective competitive season. The total number of injuries was further classified by contact and non-contact injuries and by how much missed time resulted from the injury (Level 1 = 0–1 missed days, Level 2 = 2–7 missed days, Level 3 = season-ending). In addition to the contribution of session RPE (Table 3), workload (Table 4), Sleep (Table 5), SRSS (Table 6), and vertical jump (Table 7), the drastic decrease in total injury occurrence in the 22/23 season can also be explained by the return to a more normalized and structured training and competitive schedule. Due to the COVID-19 pandemic, the 21/22 season required significant modifications to the team's regular periodized training schedule, which posed additional injury risk due to frequent shutdown periods, inadequate acclimation upon return, and congested fixture periods [18].

Overall, both performance and injury rates in basketball can be explained by technical skill, tactical execution, and physicality. In the successful seasons, players had greater technical skill and tactical execution. Moreover, they were

Table 9 Causal Relationship between metrics and performance

Metric	Performance outcome	Relationship
Session RPE	Successful season had less rigor, but training sessions were more regular	Regular training leads to more successful outcomes, as opposed to a harder but unregular schedule
Game Workload Metrics (Polar Data)	A successful season had all players performing more (distance, HR, speed)	Players played harder in the winning season, this led to a more successful outcome
Sleep data	Better sleep score (5%) in a successful season	There was not a clear relationship, as the common players had the same sleep patterns
Questionnaire Data	9% better OR 21% less OS	Students felt better about their performance, which could also be because they were winning! (chart?)
Jump Testing	All metrics were better, probably due to better strength training	Fitter players result in less injuries and better game performance

Table 10 Season-wise comparison of injury rates and severity levels

	Total Injuries	Contact Injuries	Non-contact Injuries	Level 1 Injuries	Level 2 Injuries	Level 3 Injuries
All players 21/22	42 (including 8 Covid cases)	10	24	14	6	4
All players 22/23	15(64% less)	1 (90% less)	14 (42% less)	11 (21% less)	3 (50% less)	0(100% less)

in a better physical state through training, sleep, and mental health, which affected the injury rate. This was reflected in the more excellent game score metrics. Underpinning these factors is the overall physical development of the players. New players had greater physical capabilities, allowing them to execute more effectively in each game and throughout the season. Therefore, basketball players need the technical abilities on the court and the physical development to carry out the coaches' tactical aspects. Both acute game settings and chronic season scores must be considered when considering these players' development. To achieve these ends, a long-term plan that follows the established periodization methods to maximize performance should be kept in mind.

Conclusion and Future Directions

This paper examined various aspects affecting team performance monitored across two consecutive seasons. The 21/22 season was relatively unsuccessful, with several injuries and more losses than wins. In contrast, the 22/23 season saw substantial improvements, with a higher win percentage and about half the team returning players.

The athletes were divided into four groups for comparison: athletes who only participated in the 21/22 season, the common athletes in the 21/22 season, the common athletes in the 22/23 season, and the athletes who only participated in the 22/23 season. Eight seperate athlete metrics were compared: Training scores, game workload, Sleep metrics, mental state, jump analysis, injury rate, plus/minus effect, and game scores.

The players trained better in the 22/23 season, with 15% less monotony and 40% less Strain. The game metrics were slightly better as well. Also, the sleep scores were about 5% better in the 22/23 season. The SRSS questionnaire showed a 10% increase in overall recovery and 20% less overall stress. Due to those factors, improvement was evident in both the jump analysis and game score. Our analysis demonstrated that all these factors contributed to the team's success and low injury rate in the 22/23 season. The reactive strength index (RSI) measurement is mirrored in the Game Score/min for the team, and this was a product of better and more consistent training, better sleep, and better mental health.

As our study illustrates, the impact of holistic performance metrics is particularly salient in the success of a collegiate women's basketball program. However, the investigation is limited to one University, and to deepen the impact of our basketball results, we intend to expand our research with other colleges and professional basketball teams to build a more comprehensive dataset. It enables the generalizability of our findings affecting performance and injuries. To partially overcome these logistical and privacy challenges of real-world data collection in basketball, we attempt to create generative models that emulate performance and wellness metrics specific to the sport. While synthetic data is nowhere near adequate, synthetic datasets enable us to test multiple practices in various conditions.

Building on our current metrics (training load, sleep quality, mental state, practices and jump analysis), we want to include data streams of distance covered during practice, high-intensity effort intervals, and in-game positional heat maps. They can further clarify how various roles (e.g., guards vs forward) respond to training and conditions, helping coaches to tailor strategies. Our analysis spread over two consecutive sessions. Extending the evaluation in additional years can reveal the effects of deep trends in the player's development, adaptation of coaching changes, and the effects of recruitment on the dynamics of the team within basketball. Such longitudinal studies enable us to prevent injury, improve skill, and identify patterns in teams that can only emerge in an extended period.

By amassing complete, sport-specific information and leveraging new methods to extend or simulate basketball performance metrics, we propose to deepen our understanding of how training and recovery interact. Ultimately, those steps assist coaches, sports scientists, and athletes make data-based selections that improve performance and reduce the chance of injury.

Author contribution S.S. prepared the manuscript and analyzed the data, N.S.A. provided supervision during data analysis, J.N. contributed to the injury discussion, C.T. and S.A.L. contributed as the sports science experts, S.S. helped analyze the data, M.R. and M.K. worked on the data visualization, M.R., S.D., and T.K. provided insights into the development of the project and data analysis.

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Data availability Data cannot be made available publicly because participants can be identified by cross-referencing the University's athletic website (the game score parameter was obtained from publicly available data). For further inquiries about the data, contact the corresponding author, Dr. Samah Senbel.

Declarations

Conflict of interest The authors have no professional competing interest to disclose.

Informed Consent This project was submitted and approved by Sacred Heart University's Institutional Review Board (IRB#170720A). The methods and procedures of the study were explained to the participants, and signed informed consent was obtained. All procedures were by the Declaration of Helsinki.

Research involving human and animals rights This research involves humans:

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