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UNIVERSIDAD CATÓLICA DE MURCIA

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<u>AUTORIZATION OF THE DIRECTORS OF THE THESIS FOR SUBMISSION</u>

Prof. Dr. Pedro E. Alcaraz Ramón and Prof. Dr. Julio Calleja-González as Directors of the Doctoral Thesis "Do the Eyes tell the Truth? A Novel Approach to Monitoring Fatigue in Professional Basketball Players" by D. Thomas G. Huyghe in the Programa de Doctorado en Ciencias del Deporte, **authorize for submission** since it has the conditions necessary for its defense.

Sign to comply with the Royal Decree 99/2011, 28th of January, in Murcia, June 25th, 2023.

LOS DIRECTORES

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"The eyes are the windows to your soul."
William Shakespeare

This thesis is a compendium of 3 articles already published in peer-reviewed journals. The references for the abovementioned articles are as follows:

Article 1

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Article 2

Huyghe T, Alcaraz PE, Calleja-González J, Bird SP. The underpinning factors of NBA game-play performance: A systematic review (2001–2020). Phys Sportsmed. 2022;50(2):94-122.

Article 3

Huyghe T, Calleja-González J, Bird SP, E. Alcaraz P. Pupillometry as a new window to player fatigue? A glimpse inside the eyes of a Euro Cup Women's Basketball team. Biol Sport. 2024;41(1):3-15.

ABSTRACT

Huyghe, Thomas. (2023). Do the Eyes tell the Truth? A Novel Approach to Monitoring Fatigue in Professional Basketball Players. Murcia: Universidad Católica San Antonio; Unpublished Dissertation.

Introduction: The impact of fatigue on athlete health and performance is of significant interest to the sport science community. Traditional fatigue and recovery monitoring tools have limitations in terms of invasiveness, cost, and time-consuming nature. Therefore, there is a need for alternative, non-invasive methods that provide reliable and valid measures of fatigue and recovery. Pupillometry, a technique that measures various aspects of the pupil in real-time, has emerged as a potential tool for fatigue detection. To explore its potential, the present thesis aimed to explored the underlying factors of NBA game-play performance, and explored the potential of handheld quantitative infrared pupillometers (HQIPs) as a tool for monitoring athlete fatigue and recovery in a professional women's basketball setting. More particularly, the pilot study examined the potential usefulness of a HQIP to monitor game-induced fatigue inside a professional female basketball setting by determining its (1) test-retest repeatability, (2) relationship with other biomarkers of game-induced fatigue, and (3) time-course from rested to fatigued states.. **Method:** A non-ophthalmologic practitioner performed a standardized Pupil Light Reflex (PLR) test using a medically graded HQIP among 9 professional female basketball players (2020–2021 Euro Cup) at baseline, 24-h pre-game (GD-1), 24-h post-game (GD+1) and 48-h post-game (GD+2). This was repeated over four subsequent games, equaling a total of 351 observations per eye. **Results:** The results indicated that (1) jet lag, interrupted sleep schedules, and stress associated with frequent air travel negatively impact the physical and cognitive performance of professional basketball players, (2) a wide variety of factors l influence individual and collective game-play performance in professional basketball, including variables such as the age, gender, height and body mass index of the players as well as other contextual factors such as the playing style and tactical strategies all play a substantial role on NBA game-play performance, (3) Two out of seven pupillometrics displayed good ICCs (0.95–0.99) (MinD and MaxD). Strong significant relationships were found between MaxD, MinD, and all registered biomarkers of game-induced fatigue ($r = 0.69$–0.82, $p < 0.05$), as well as between CV, MCV, and cognitive, lower-extremity muscle, and physiological fatigue markers ($r = 0.74$–0.76, $p < 0.05$). Three pupillometrics were able to detect a significant difference between rested and fatigued states. In particular, PC (right) ($F = 5.173$, $\eta2 = 0.115$ $p = 0.028$) and MCV (right) ($F = 3.976$, $\eta2 = 0.090$ $p = 0.049$) significantly decreased from baseline to GD+2, and LAT (left) ($F = 4.023$, $\eta2 = 0.109$ $p = 0.009$) significantly increased from GD-1 to GD+2. **Discussion:** The findings suggest that a non-ophthalmologic practitioner can effectively monitor pupillometrics in a reliable manner over a 5-week competition period. Five pupillometric measures (NPi, CV, MCV, MD, and MinD) showed promise in monitoring fatigue and recovery following games, with MCV showing the largest and most significant difference from baseline to two days after the game. However, it is important to note that these findings are based on a relatively small and homogenous sample. The study also demonstrated that HQIPs can be used by non-ophthalmologic staff members in a fast, practical, non-invasive, and reliable manner, without interfering with the team's schedule. This is beneficial for professional sports organizations where players often have limited recovery time between games. Future research should explore the applicability of these findings in different sports, teams, and competition formats. **Conclusion:** HQIPs have opened a new window of opportunity for monitoring game-induced fatigue in professional female basketball players. However, future research initiatives across larger and heterogenous samples, and longer investigation periods, are required to expand upon these preliminary findings.

KEYWORDS

Biotechnology; Biooptics; Optometry

RESUMEN

Huyghe, Thomas. (2023). ¿Los ojos dicen la verdad? Un enfoque novedoso para controlar la fatiga en jugadores de baloncesto profesionales. Murcia: Universidad Católica San Antonio; Disertación inédita.

Introducción: El impacto de la fatiga en la salud y el rendimiento de los atletas es de gran interés para la comunidad científica del deporte. Las herramientas tradicionales de seguimiento de la fatiga y la recuperación tienen limitaciones en términos de invasividad, costo y consumo de tiempo. Por lo tanto, existe la necesidad de métodos alternativos no invasivos que proporcionen medidas confiables y válidas de fatiga y recuperación. La pupilometría, una técnica que mide varios aspectos de la pupila en tiempo real, se ha convertido en una herramienta potencial para la detección de fatiga. Para explorar su potencial, la presente tesis tuvo como objetivo explorar los factores subyacentes del rendimiento en el juego de la NBA y exploró el potencial de los pupilómetros infrarrojos cuantitativos portátiles (HQIP) como herramienta para monitorear la fatiga y la recuperación de los atletas en un entorno de baloncesto femenino profesional. Más particularmente, el estudio piloto examinó la utilidad potencial de un HQIP para monitorear la fatiga inducida por el juego dentro de un entorno de baloncesto femenino profesional determinando su (1) repetibilidad de prueba y repetición, (2) relación con otros biomarcadores de fatiga inducida por el juego, y (3) evolución temporal desde estados de reposo a estados de fatiga. **Método:** un médico no oftalmólogo realizó una prueba estandarizada de reflejo luminoso de la pupila (PLR) utilizando un HQIP médicamente calificado entre 9 jugadoras profesionales de baloncesto (Eurocopa 2020-2021) al inicio del estudio. , 24 h previas al juego (GD-1), 24 h posteriores al juego (GD+1) y 48 h posteriores al juego (GD+2). Esto se repitió durante cuatro juegos posteriores, lo que equivale a un total de 351 observaciones por ojo. **Resultados:** Los resultados indicaron que (1) el desfase horario, los horarios de sueño interrumpidos y el estrés asociado con los viajes aéreos frecuentes impactan negativamente el rendimiento físico y cognitivo de los jugadores de baloncesto profesionales, (2) una amplia variedad de factores influyen en el juego individual y colectivo. El rendimiento del juego en el baloncesto profesional, incluidas variables como la edad, el sexo, la altura y el índice de masa corporal de los jugadores, así como otros factores contextuales como el estilo de juego y las estrategias tácticas, juegan un papel sustancial en el rendimiento del juego de la NBA. 3) Dos de siete pupilometrías mostraron buenos ICC (0,95–0,99) (MinD y MaxD). Se encontraron fuertes relaciones significativas entre MaxD, MinD y todos los biomarcadores registrados de fatiga inducida por el juego ($r = 0{,}69$–$0{,}82$, $p < 0{,}05$), así como entre CV, MCV y fatiga cognitiva, muscular de las extremidades inferiores y fisiológica. marcadores ($r = 0{,}74$–$0{,}76$, $p < 0{,}05$). Tres pupilometrías pudieron detectar una diferencia significativa entre los estados de reposo y fatiga. En particular, PC (derecha) ($F = 5{,}173$, $\eta 2 = 0{,}115$ $p = 0{,}028$) y MCV (derecha) ($F = 3{,}976$, $\eta 2 = 0{,}090$ $p = 0{,}049$) disminuyeron significativamente desde el inicio hasta GD+2, y LAT (izquierda) ($F = 4.023$, $\eta 2 = 0.109$ $p = 0.009$) aumentó significativamente de GD-1 a GD+2. **Discusión:** Los hallazgos sugieren que un profesional no oftalmólogo puede monitorear eficazmente la pupilometría de manera confiable durante un período de competencia de 5 semanas. Cinco medidas pupilométricas (NPi, CV, MCV, MD y MinD) resultaron prometedoras en el seguimiento de la fatiga y la recuperación después de los juegos, y MCV mostró la diferencia más grande y significativa desde el inicio hasta dos días después del juego. Sin embargo, es importante señalar que estos hallazgos se basan en una muestra relativamente pequeña y homogénea. El estudio también demostró que los miembros del personal no oftalmológico pueden utilizar los HQIP de una manera rápida, práctica, no invasiva y confiable, sin interferir con el cronograma del equipo. Esto es beneficioso para las organizaciones deportivas profesionales donde los jugadores suelen tener un tiempo de recuperación limitado entre juegos. Las investigaciones futuras deberían explorar la aplicabilidad de estos hallazgos en diferentes deportes, equipos y formatos de competición. **Conclusión:** Los HQIP han abierto una nueva ventana de oportunidades para monitorear la fatiga inducida por el juego en jugadoras profesionales de baloncesto. Sin embargo, se requieren futuras iniciativas de investigación en muestras más grandes y heterogéneas, y períodos de investigación más prolongados, para ampliar estos hallazgos preliminares.

KEYWORDS

Biotecnologia; Biooptica; Optometria

INDEX

ABBREVIATIONS

The abbreviations of the units from the International System Units are not included in the following list as there are internationally accepted standards for their use. In addition, no abbreviations universally used in statistics are presented in this section.

Ach	Acetylcholine
ACL	Anterior cruciate ligament
AMS	Athlete Monitoring Systems
ANS	Autonomic nervous system
ARMS	Applied research model for sport sciences
AT	Away team
BPM	Beats per minute
BPS	Ball possession success
CG	Close games
CLA	Constraints-led approach
CMJ	Countermovement jump
CN	Cranial nerve
CV	Average pupil constriction velocity following light stimulus
DV	Pupil dilation velocity following light stimulus
EFF	Efficiency rating
EL	External load
EI	Exercise-induced
FDP	Factors Determining Production
FG3%	Three-point field goal percentage
FTS	Free throws scored
FTA	Free Throw Attempt
FT	Free throw
GD	Gameday
GGV	Game-to-game variability

GmSc	Game Score
GMLM	General Mixed Linear Models
GPP	Game-play performance
H	Height
HCA	Home Court Advantage
HL	Hand length
HS	Hand size
HRmax	Maximum heart rate
HRV	Heart rate variability
HT	Home team
HQIPs	Handheld quantitative infrared pupillometer
ICU	Intensive care unit
IL	Internal load
LBSP	Lower-body squat power
LA	Left atrium of the heart
LAT	Latency of pupil reaction following light stimulus
L-S	Length-size
LV	Left ventricle of the heart
MCV	Maximum pupil constriction velocity following light stimulus
MBI	Magnitude-based inferences
MinD	Minimum pupil diameter
MM	Mean mass
NBA	National Basketball Association
NMMS	Non-metric multidimensional scaling techniques
NPi	Neurological pupil index
ORB%	Offensive rebound percentage
PNS	Parasympathetic nervous system
PC	Percent change of pupil diameter following light stimulus
PCA	Principal Component Analysis
PCR	Principal Component Regression
PE	Playing experience
PER	Player Efficiency Rating
PIE	Player Impact Estimate

PLR	Pupillary light reflex
PPG	Points per game
PT	Playing time
PQA	Power, quickness, and agility
RA	Right atrium of the heart
Rebs	Rebounds
RPE	Rate of perceived exertion
RV	Right ventricle of the heart
RT	Reaction time
SNS	Sympathetic nervous system
SC	Strength and conditioning
SMHAT-1	Sport Mental Health Assessment Tool 1
SMHRT-1	Sport Mental Health Recognition Tool 1
SR	Standing reach
SRT	Simple reaction time
TO's	Turnovers
TP	Team Pace
TR	Team Ranking
UB	Upper body
UR	Usage Rate
USG%	Usage percentage
VJR	Vertical Jump from running
VJHR	Vertical jump height and reach
VJP	Vertical jump power
VORP	Value over placement player
VTS	Visual tracking speed
WS	Wingspan
WinSc	Win Score
Win-S	Win Shares
Win % CG	Win percentage in close games
W	Weight

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I - INTRODUCTION

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Fatigue is a complex and multifaceted phenomenon, depends on many different factors, emerges from a variety of mechanisms, and has been explored by scientists for many centuries (1, 2). In elite sports, fatigue emerges from a complex and continuous interaction between personal characteristics (e.g., genotype, fitness level, biological age, etc.), task demands (e.g., games, practices, workouts, etc.), and external constraints (e.g., congested fixtures, air travel, game demands, etc.) (1, 3, 4). As a result, fatigue in elite sports can appear in various forms, including non-functional overreaching (fatigue lasting weeks to months), injury, and illness (1). It can also lead to underperformance, such as decreased work rate and fewer high-speed activities (physical) (4, 5), impaired decision-making and unusual mistakes (tactical), changes in movement patterns (technical) (5), and reduced perceptions of vigor or motivation (psychological) (6). In this respect, athlete monitoring systems (AMS; a modern, scientific approach to understanding athletes training responses and competition readiness) have evolved into an integral aspect of player care in many high performance team-sport organizations. Particularly, AMS can help determine whether a player is adapting to the imposed demands and minimize the possible negative consequences associated with fatigue (1). In turn, the use of AMS can bring clarity and confidence pertaining to the possible reasons for changes in player health, well-being, or performance, and minimize the degree of uncertainty associated with these changes (1-4). As stated by Halson et al. (1), when monitoring team-sport athletes, the nature of the monitoring is likely to be very different depending on the sport. Therefore, first and foremost, it is essential to gain a comprehensive understanding of the different factors, mechanisms, and dynamics that contribute to fatigue in the sport of basketball.

Fundamentally, basketball is an intermittent high-intensity sport that requires a combination of aerobic and anaerobic energy systems (7, 8, 9). The aerobic energy system provides the necessary energy for sustained activity, while the anaerobic system is responsible for short bursts of high-intensity efforts, such as sprinting, jumping, landing, shuffling, and rapid changes of direction (7, 8, 9).

Particularly, time-motion analyses revealed that elite basketball players typically change activities or movements every 1-3 seconds (10), complete 21.2 to 56.9 movements per minute (10), jump 35 to 60 times (10), accelerate 43 to 145 times (1 to 15 times at high velocity) (5), decelerate 24 to 95 times (4 to 40 times at high velocity) (5), and cover, on average, a distance of 4,369 m (1,991 to 6,310 m) per game (11). However, it is important to keep in mind that these data may fluctuate based on playing period, playing position, level, geographical location, and sex (5, 9).

From a neuromuscular standpoint, the repetitive nature of the abovementioned movements in basketball, can lead to significant mechanical stress on the muscles, tendons, and joints (12). This mechanical stress can result in altered movement patterns and compensatory strategies as the body attempts to reduce the load on fatigued muscles and joints (13, 14). In turn, this can lead to an increased risk of injury due to the altered loading patterns and movement mechanics (15). For instance, fatigued basketball players may exhibit reduced knee flexion during landing, which has been associated with an increased risk of anterior cruciate ligament (ACL) injuries (16).

From a physiological standpoint, the repeated high-intensity efforts can lead to the accumulation of metabolic by-products, such as lactate and hydrogen ions, in the muscles (5, 9). These metabolic by-products can impair muscle function and contribute to a decrease in force production and power output (17). Moreover, the depletion of muscle glycogen stores, which are the primary source of energy for high-intensity exercise, can also contribute to fatigue (18). Furthermore, basketball players experience significant cardiovascular strain due to the sustained elevated heart rates and increased oxygen consumption required to meet the energy demands of the sport (5, 9). In particular, the maximum heart rate (HR_{max}) during elite level basketball competition typically ranges from 187 to 198 beats per minute (BPM) with a mean of 190 BPM (5). This cardiovascular strain can lead to a reduction in stroke volume and cardiac output, further contributing to fatigue and decreased performance (5).

From a psychological viewpoint, mental fatigue can result from various factors, including sleep deprivation, cognitive workload, and emotional stress (19). This mental fatigue can negatively affect decision-making, reaction time, and attention, which are all critical components of basketball game-play performance

(20). For example, a fatigued player may be more prone to making poor decisions on the court, such as choosing suboptimal offensive or defensive strategies, or being less attentive to the movement of opponents and teammates (20). Moreover, mental fatigue can also have a detrimental effect on motivation, effort, and perceived exertion, making it more challenging for players to maintain their physical performance throughout a game or training session (21). For instance, a mentally fatigued player may perceive a given workload as more strenuous than it would be under normal circumstances, leading to a reduction in effort and an increased perception of exhaustion (21). This interplay between mental and physical fatigue highlights the importance of monitoring and managing both aspects to optimize player health, well-being, and performance in elite basketball.

Within the National Basketball Association (NBA), globally perceived as the world's highest level of basketball competition, players are now dealing with a much higher physical, physiological and psychological demand compared to players from the past few decades due to the rapid expansion and changes in the league's competitive rules and regulations (22-29). More specifically, an increase in the number of games per season (82 regular season, 4-5 preseason, and possible playoffs), higher playing minutes per game, greater training and game volume per week, and the ability to compete for longer at an advanced age have all played a major role in the revolutionary changes of the NBA (22-29). Therefore, a greater emphasis has been placed on player safety and recovery in recent years (22-29). For instance, prior to 2017, NBA teams played eight preseason games across 3–4 weeks (30, 31). Since the 2017–2018 season, the NBA season has consisted of 4-6 preseason games played across 3–4 weeks followed by an 82-game regular season played across 26 weeks (177 days) (22, 23, 31). During the regular season, each team plays two to five games per week (~3.2 games per week) with games lasting an average duration of 2 h and 15 min (31). Furthermore, NBA teams rarely practice during the season and practices that occur are typically less than 1 h (22, 31). On game day, the daily schedule comprises of arriving at the practice facility in the morning for breakfast, working on individual strength and conditioning, followed by an organized practice, press meets, travel back to hotel or home in the afternoon for a break, and then travel back to the stadium for a game (32, 33). Immediately following games, there may be additional press meets, followed by showers, recovery protocols and dinner, additional conditioning activities and then a drive back home or to a hotel (32, 33). If the next game is in another city, especially for back to back games, instead of driving home or to a hotel, players will aboard a chartered flight to get to the city hosting the game and depending on the length of flight may arrive to their hotel rooms between 2 am and 7 am in the morning (32, 33). The travel involves planes, and bus to the hotel, practice, game, and back to the airport (32, 33). On non-game days, there may be scheduled practices as well as walk-throughs which may start later during the day. Timings of arrival at destination and hotels from home and return after a game to hotel typically are around 6 am (32, 33). However, when travelling after games, anywhere from 12:30 am to 3:30 am (32, 33). Additionally, some teams may also choose to travel to the next game city on non-game days. Finally, on any day players may have individual workouts, medical treatments and film sessions. They may also have mandatory charity or public events and personal compromises. This daily schedule of game days interspersed with non-game days continues through the season. Thus, a typical NBA player has non-traditional work hours and is daunted by irregularities and circadian disruption, which makes management of the schedule and the associated inherent variability, an extremely challenging but important venture as its essential for longevity and success in their careers. In response to the strenuous demands of this unique schedule, the NBA extended the duration of the regular season by 7 days with the purpose of scheduling fewer back-to-back games (22, 30).

Despite adjustments to the NBA schedule, air travel demands remain high due to the geographical span of teams across four time zones (eastern, central, mountain, and western) (22, 23, 30, 32, 33). In this regard, NBA players spend more time above 30,000 ft than athletes competing in all other team sports in the United States of America (USA) (22, 33). These air travel requirements are a concern for NBA coaches, players, and owners, as research has demonstrated short-haul flights (≤6 h) increase injury risk (22, 32, 28, 32, 35, 36) and impede performance (22, 32, 33, 34, 35, 36). In particular, frequent air travel can negatively affect hydration status, nutritional behaviors, sleep quality, and sleep quantity, thus extending the time for sufficient recovery between games and/or training in athletes [19]. As a result, the various environmental constraints of the NBA underscores once again the importance for establishing comprehensive AMS in NBA organizations in order to deliver evidence-based player care, and in turn, minimize the potential risks associated with excessive fatigue in NBA players (23).

Despite the increased awareness of AMS by NBA stakeholders (23), to date, research in this area is limited and much of what remains known about AMS in the NBA comes from personal experience and anecdotal information (1, 23) in which much of these data remain protected and unpublished (1, 22, 23). As highlighted by McLean et al. (23), this current lack of public information likely results from multiple factors including limited awareness and understanding of novel basketball-specific technologies, impact of specific league rules, and steps taken to protect players in the age of Big Data (23). Additionally, based on a recent systematic review (37), there appears to be very few AMS that adhere to strong scientific evidence supporting their use in professional basketball overall (37).

According to Halson et al. (1), the external load (EL, the work completed by the athlete) has been the foundation of most AMS in professional team sports, even though the internal load (IL, the relative physiological and psychological stress imposed) is equally as critical in determining the training load and subsequent adaptation. In this sense, it is important to acknowledge that there is yet to be a single, definitive marker described in the literature that captures multiple dimensions of IL simultaneously (e.g., physiological and cognitive stress) (37). Traditional methods for assessing IL have been employed, but many of these approaches possess inherent drawbacks (1, 38-41). For instance, subjective self-report questionnaires (e.g., Borg's scale for Self-Perceived Exertion) rely on the player's ability to accurately perceive and communicate their fatigue levels, which can be influenced by personal biases, mood, or lack of self-awareness (38). On the other hand, maximal performance tests (e.g., Countermovement Jump test) (39), blood and hormonal markers (e.g., blood lactate) (40), and cardiac measures (e.g., morning Heart Rate Variability indices) (41) can provide useful and objective insights, but they often require specialized equipment, invasive procedures, or time-consuming analyses that may not be practical in everyday training or competition settings (1, 23). Additionally, as mentioned before, they might fall short in capturing multiple dimensions of fatigue, as they typically concentrate on either physical or cognitive aspects independently. Consequently, there is a pressing need for alternative IL monitoring techniques that can overcome these limitations.

This critical research gap was also highlighted by a survey in 2017 and 2018 (42) in which 89% of respondents emphasized the importance of IL monitoring tools for fitness improvements, benchmarking different training types and competition, protection against injury, and designing appropriate recovery interventions. However, only a minority of respondents (48%) reported to be using IL monitoring technologies as a method to monitor player workload given it was often perceived as financially unaffordable, logistically challenging, or requires intensive onboarding staff education and training (42). Although the survey reflected a small sample size (N = 44), limited scope, and a relative low response rate, it underscored the need for better tools, systems, and solutions in the context of IL monitoring in elite sports. In professional basketball, and in the NBA in particular, many sport scientists appeared to express the same concerns (23, 37, 42).

Interestingly, the ongoing pursuit for better IL monitoring tools extends far beyond the realm of sports and impacts numerous sectors. For instance, some of the most promising discoveries in IL monitoring technology emerged from collaborative initiatives among engineers, developers, scientists, and practitioners who operate in high-stake professions high-pressure environments (i.e., transatlantic flights, space shuttle missions, military combat, medical surgery, long-haul truck driving, etc.) as a lack of operational readiness in these positions could lead to lethal consequences (42, 43, 44). A prime illustration of these collaborations is the rapidly growing field of pupillometry, which describes the study of the central opening of the iris through which light passes before reaching the lens and being focused onto the retina (43, 44).

Fundamentally, the pupil is considered an extension of the brain, heart, and body since it is directly innervated by the second cranial nerve (CN II) and third cranial nerve (CN III) (45). In this sense, the behavior of the pupils are controlled by the antagonistic actions of the iris sphincter and dilator muscles (46) in which the parasympathetic nervous system (PNS) constricts the iris, while the sympathetic nervous system (PNS) dilates the iris (45, 46) (Figure 1). Therefore, monitoring pupil behavior has emerged as one of the most accessible methods of evaluating the autonomic nervous system (ANS) function (46-53), providing objective insights into the cognitive, emotional, physical, and physiological states of humans in real-time (51-53). Furthermore, different pupillometrics (i.e., parameters of pupillary behavior) can be used as indicators for either SNS or PNS function respectively (45-56).

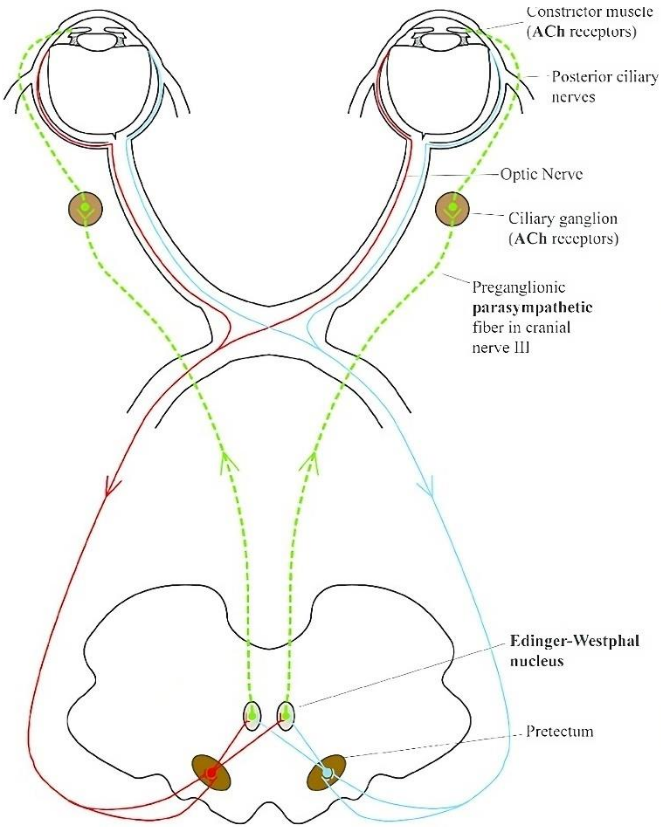

Figure 1. The neurological pathways of the PLR, adapted from Wang et al. (56). Red and blue lines represent the afferent pathway, the ganglion cell axons project to the pretectal region of the midbrain; green line represents the efferent pathway, the signal transmits from preganglionic parasympathetic fiber to ciliary ganglion, finally to the constrictor muscles through the short posterior ciliary nerve.

Historically, the use of pupillometry as a fatigue detection tool was first described by Crawford in 1936 (57), and further pioneered by Lowenstein and colleagues in 1963 (58) who discovered the existence of pupillary fatigue waves (i.e., the continuous slow oscillations in pupil size). Subsequently, in 1969, Yoss et al. (59, 60, 61) measured pupillary activity in total darkness, discovering that pupils become smaller and start to oscillate at a higher amplitude and slower frequency when humans become more sleepy and drowsy (59, 60, 61). However, the traditional methods of pupillary measurement were still exhaustive, time-consuming, and mainly subjective (62). The emergence of solid-state microchips sensitive to infrared light became available in the late 1970s and this created a major breakthrough for researchers as it pioneered the innovation of Handheld

Quantitative Infrared Pupillometers (HQIPs) (62). Specifically, HQIPs have sensors that can detect and quantify pupil oscillations immediately following a light-emitting diode infrared light directed toward the eye (62), which permits fast, continuous, valid, reliable, non-invasive, and objective monitoring of the pupil without altering pupil size and pupil movements at the same time (62).

Most recently, these HQIPs were enhanced by high resolution digital camera systems and computer vision technology to provide more user-friendly automated pupil recording systems (62). Given modern HQIPs are now able to measure the pupil diameter repeatedly (1 measurement every 30 milliseconds) with accuracy levels of <0.03mm (62, 63), they are increasingly being adopted for a wide variety of use cases, such as a "first point of care" solution in Intensive Care Units (ICUs) (63), as well as for the evaluation of cognitive and emotional processing, arousal states, neurological impairments, sleep disturbances, the effects of drugs, exercise-induced exhaustion, traumatic head injuries, progression of specific diseases, etc. (62-71).

One of the most popular and scientifically supported methods for implementing the aforementioned HQIPs is the standard Pupil Light Reflex (PLR) test (45-65). The PLR test measures the constriction and dilation of the pupils in response to a light stimulus (e.g., penlight) directed into one eye (46, 72). The neurological pathway underlying the PLR operates as follows: when light reaches the retina(s), it triggers increased neural activity in the pretectal regions, subsequently stimulating the Edinger-Westphal nucleus (46, 72). This activation prompts the preganglionic parasympathetic neurons, which then innervate the ciliary ganglion. Within the ciliary ganglion and the constrictor muscles, Acetylcholine (ACh) receptors are present (56, 72). These receptors respond to the neurotransmitter ACh, which is the primary transmitter of the PNS. Consequently, the constrictor muscles contract, resulting in pupil constriction (56, 72). As such, the PLR serves as a non-invasive tool for basic neuroscience research and the study of parasympathetic and sympathetic balance (56, 72) (Figure 2 and 3).

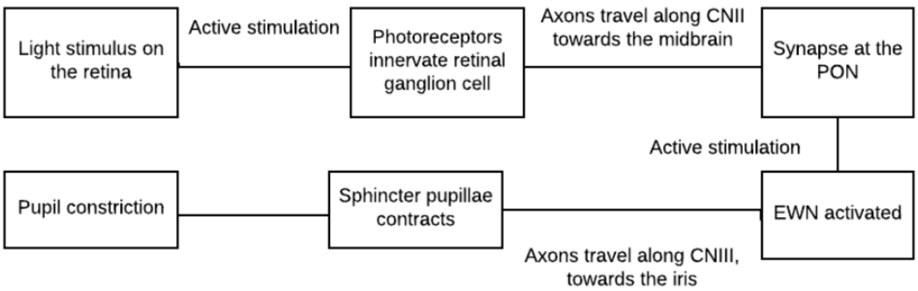

Figure 2. PNS pathway of the PLR, from Capo-Aponte et al. (54).

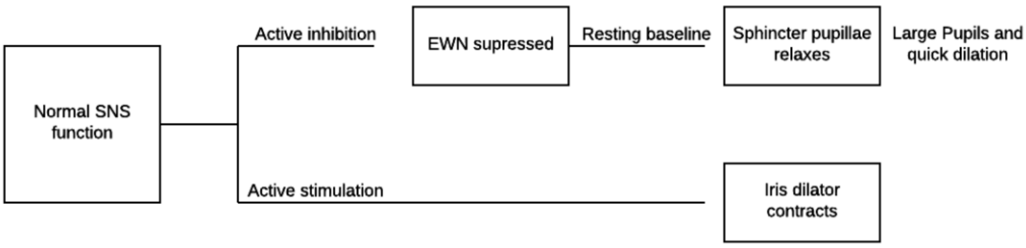

Figure 3. SNS pathway of the PLR, from Capo-Aponte et al. (54).

The PLR can be classified into three phases: 1) a rapid constriction, followed by 2) a swift redilation of the pupil, and finally 3) a gradual redilation where the pupil returns to its initial size (Figure 4). Typically, decreased PNS activity is characterized by a prolonged constriction latency, slower maximum constriction velocity, and diminished constriction amplitude of the PLR (56). According to Loewenfeld and Lowenstein (58), the PNS predominantly influences the pupil constriction phase, while the SNS contribution is negligible. However, both the PNS and SNS contribute to the initial stages of the redilation phase. Hence, observing the constriction phase of the PLR theoretically provides an indicator of PNS activity that is not influenced by SNS activity (Figure 4).

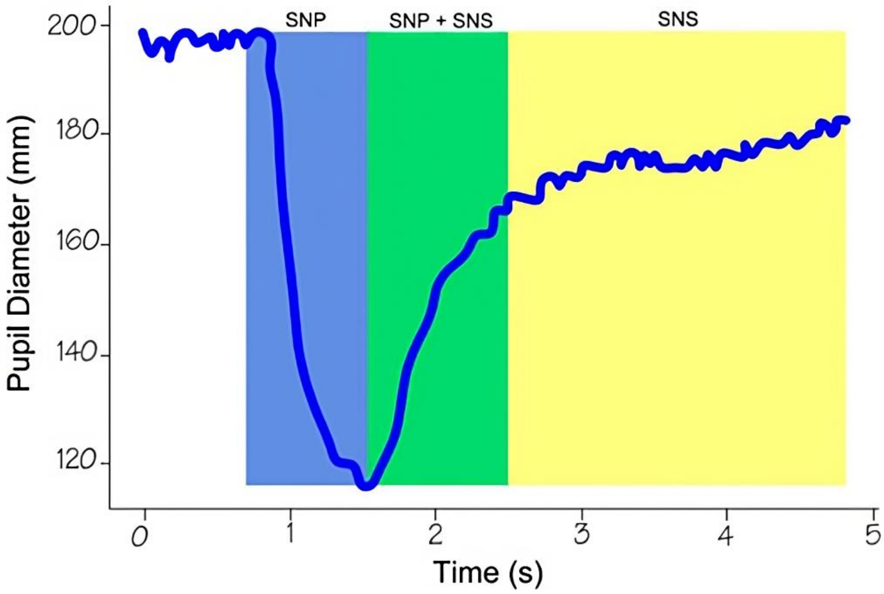

Figure 4. Schematic representation of the PLR, from Pinheiro & da Costa (55). Phase 1 (blue) is a fast constriction mainly controlled by PNS; Phase 2 (green) is a fast redilation under the control of both PNS and SNS; Phase 3 (yellow) is a slow redilation phase, predominantly controlled by SNS activity.

According to Halson (1), the future of AMS can be described as "a systems-based approach that integrates well-chosen diagnostic tests, with smart sensor technology and a real-time database and data management system". Considering this, and taking into account the existing literature on pupillometry, applying the PLR test using clinically validated HQIPs may offer a promising new avenue for sport scientists and practitioners to better capture and comprehend the stress-response dynamics of their athletes. Surprisingly, research regarding HQIPs in elite sports settings remain bounded by few areas of interest, such as concussion-related diagnostics and Quiet Eye analytics (2, 3, 42). While few researchers have already explored its potential as a diagnostic tool for ANS function in athletic populations (47, 49, 50), the validity and reproducibility of their methods and findings remains unclear. For instance, the study designs followed a cross-sectional approach, adopted non-standardized and non-validated testing procedures, used laboratory testing conditions, and involved only amateur and sub-elite athletes (47, 48, 49). In turn, researchers gain an opportunity to build upon these initial efforts and explore whether HQIPs could indeed serve as both a valuable and viable pathway for monitoring and managing player fatigue in elite sports settings.

To summarize, using the PLR test with HQIPs in the context of AMS shows great potential. It not only provides valid and reliable data for different fatigue dimensions in high-pressure environments but also offers a more convenient option. This approach is generally faster, less exhaustive, less intrusive, less expensive, and less influenced by subjective biases. Moreover, its sensitivity to both physical and cognitive fatigue makes it a comprehensive monitoring solution for elite basketball players. They face the combined effects of physical exertion and cognitive demands (5). Lastly, modern HQIPs are becoming increasingly portable and user-friendly (e.g., mobile applications) (73-77), which could further facilitate their integration into regular training and competition environments.

To explore and validate this potential, the present Ph.D. thesis outlines several research objectives. First, it aims to investigate the role and impact of air travel on player fatigue, health, well-being, and performance in the NBA, shedding light on the underlying mechanisms and potential avenues for intervention. Secondly, it seeks to systematically explore and examine the various factors that contribute to game-play performance at the NBA level, providing insights into the primary determinants of success at the highest level of the sport. Finally, the potential usefulness of a medically graded HQIP is examined within a real-world professional basketball team setting, questioning its feasibility, reliability, and ability to detect game-induced fatigue. Through these investigations, the present Ph.D. thesis intends to bridge the gap between theoretical potential and tangible benefits, ultimately contributing to the advancement of AMS in elite basketball, while enhancing our understanding of pupillometry's role in elite sports as a whole.

II - HYPOTHESES

II - HYPOTHESES

2.1. GENERAL HYPOTHESES

An overview of the current state of the literature reveals that the modern-day NBA environment is complex, ever-changing, and extremely demanding. Consequently, sport scientists and practitioners are continuously exploring more effective and efficient athlete monitoring tools that offer practically relevant, precise, and reliable insights regarding the daily stress-response dynamics of their athletes. However, further research is required to determine which particular aspects matter most when it comes to player health and performance in the NBA. In this respect, from a fatigue-management standpoint, and based on relevant data from previous investigations across high-pressure environments (e.g., astronauts, pilots, military, emergency care), it was hypothesized that the integration of HQIPs inside a professional basketball environment would result in a faster, more practical, and more comprehensive alternative to understanding the daily stress-response dynamics of each player. Consequently, it was hypothesized that the PLR test utilizing a medically graded HQIP would provide a new window of opportunity for AMS, revealing evidence for its feasibility, reliability, and ability to detect fatigue within a real-world professional basketball scenario.

2.2. SPECIFIC HYPOTHESES

The specific hypotheses outlined for each of the studies included in the present thesis are presented below:

Study 1:

- Frequent air travel and congested fixtures pose significant risks on NBA player health, well-being, and performance.
- Travel direction, duration, and time zone differential significantly contribute to the magnitude of travel-induced fatigue that occurs in NBA players.

- Recent adjustments to the NBA schedule are insufficient for reducing injuries and improving performance in NBA players.

Study 2:

- NBA game-play performance emerges from a complex set of interdependent factors, including individual, task, and environmental constraints.
- Traditional athlete monitoring tools employed in the NBA generally remains time-consuming, invasive, and impractical.
- Due to the density of the NBA schedule, game demands, frequent air travel, and congested fixtures remain the most critical concerns for athlete support staff personnel in the NBA.
- The eyes, and the pupils in particular, are generally neglected by NBA sport scientists and practitioners in the context of AMS.

Study 3:

- HQIPs serve as a feasible tool in the context of monitoring game-induced fatigue in professional basketball players.
- HQIPS serve as a reliable tool in the context of monitoring game-induced fatigue in professional basketball players.
- HQIPs can detect significant changes in game-induced fatigue in professional basketball players.
- HQIPs can extract biomarkers that are significantly related to multiple dimensions of game-induced fatigue, including physiological, muscular, cognitive, and perceptual.

III – OBJECTIVES

III - OBJECTIVES

3.1. GENERAL OBJECTIVES

Considering the hypotheses previously outlined, and within the general objectives of this thesis, the present compendium of articles aims to investigate the underlying aspects of player health, well-being, and performance in the NBA, in order to determine to what extent these key factors can be monitored and analyzed in a pragmatic, reliable, and useful manner during the in-season period. Moreover, it aims to narratively review the state of the literature with regards to travel demands imposed by the NBA schedule, as well as systematically review the state of the literature with regards to the main factors that constitute NBA game-play performance. Lastly, it aims to determine whether the use of HQIPs reveals any potential to be applicable, reliable, and useful in the context of monitoring NBA players, from a fatigue-management standpoint, during the competitive phase of the season.

3.2. SPECIFIC OBJECTIVES

The specific objectives outlined for each of the studies included in the present thesis are presented below:

Study 1:

- To analyze the NBA schedule and determine which factors pose the greatest risk to player health, well-being, and performance.
- To examine which are the most determining factors that contribute to travel-induced fatigue in NBA players.
- To examine the potential negative consequences associated with congested fixtures and frequent air travel demands in NBA players.
- To analyze which strategies and interventions may help minimize travel-induced fatigue in NBA players.

- To establish critical research gaps pertaining to travel and fatigue management in the NBA.

Study 2:

- To systematically review the current state of the literature about NBA game-play performance.
- To identify which factors play a significant and impactful role on NBA game-play performance.
- To identify possible limitations with regards to AMS tools, systems, and solutions traditionally employed by NBA support staff members.

Study 3:

- To establish normative benchmarks for pupillary behavior in professional basketball players during the competitive phase of the season.
- To examine whether PLR tests utilizing a medically graded HQIP could be embedded as part of an established AMS within a real-world professional basketball context, in-season, and in a practical and convenient manner.
- To examine whether the selected HQIP could extract reliable data within a real-world professional basketball context, in-season.
- To examine whether the data extracted by the selected HQIP could detect game-induced fatigue.
- To establish a baseline reference framework for pupillometry methodology in order to facilitate standardization of future research initiatives on this topic.

IV – GENERAL OVERVIEW OF THE STUDIES

IV – GENERAL OVERVIEW OF THE STUDIES

STUDY Nº 1:

THE NEGATIVE INFLUENCE OF AIR TRAVEL ON HEALTH AND PERFORMANCE IN THE NATIONAL BASKETBALL ASSOCIATION: A NARRATIVE REVIEW

Abstract

Air travel requirements are a concern for National Basketball Association (NBA) coaches, players, and owners, as sport-based research has demonstrated short-haul flights (≤6 h) increase injury risk and impede performance. However, examination of the impact of air travel on player health and performance specifically in the NBA is scarce. Therefore, we conducted a narrative review of literature examining the influence of air travel on health and performance in team sport athletes with suggestions for future research directions in the NBA. Prominent empirical findings and practical recommendations are highlighted pertaining to sleep, nutrition, recovery, and scheduling strategies to alleviate the negative effects of air travel on health and performance in NBA players.

STUDY Nº 2:

THE UNDERPINNING FACTORS OF NBA GAME-PLAY PERFORMANCE: A SYSTEMATIC REVIEW (2001–2020)

Abstract

Recognizing the high stakes associated with winning and losing in the National Basketball Association (NBA), a deep understanding of the underlying mechanisms of NBA game-play performance would provide substantial benefit to all stakeholders involved with preparing NBA players and teams for competitive success. To the best of the authors' knowledge, this systematic review presents the first attempt to systematically amalgamate and appraise the scientific literature published in the XXI Century, following a constraints-led approach (CLA). In particular, two underpinning factors of NBA game-play performance were investigated: (1) NBA player constraints (internal variables) and (2) NBA contextual constraints (external variables). Databases included PubMed (MEDLINE), Web of Science (WOS), ResearchGate, SPORTDiscus, SCOPUS, Google Scholar, and the World Association of Basketball Coaches' database (WABC). This review followed the Preferred Reporting Items for Systematic Review and Meta-Analyses (PRISMA) model and the Population, Intervention, Comparison and Outcomes (PICOS) guidelines. Ultimately, 43 articles met the inclusion criteria (n = 43). Promisingly, the vast majority of studies were published in recent years (>2016; n = 28; 65.1%). Topics related to 'contextual constraints' (n = 25; 58.1%) received more attention than topics related to 'player constraints' (n = 18; 41.9%). Even though the importance of longitudinal-interventional approaches to applied sports science is well-documented, descriptive-observational research emerged as the most popular method of choice (n = 27; 62.8%); interventional studies were absent; and near all researchers merely utilized secondary data sources (n = 37; 86.0%). Taking into account the total body of evidence (2001–2020), NBA practitioners may use this systematic review as a baseline reference to enrich their current knowledge about the nature, demands, and dynamics of the modern-day NBA ecosystem. Finally, adoption of an 'Applied Science Research Framework' is encouraged, fostering clearly outlined project incentives;

standardizing taxonomies; sequencing follow-up studies; embracing holistic and cross-disciplinary viewpoints; and integrating longitudinal-interventional projects to increase the reproducibility of their findings.

STUDY Nº 3:

PUPILLOMETRY AS A NEW WINDOW TO PLAYER FATIGUE? A GLIMPSE INSIDE THE EYES OF A EURO CUP WOMEN'S BASKETBALL TEAM

Abstract

Recognizing A rapidly emerging area of interest in high-pressure environments is that of pupillometry, where handheld quantitative infrared pupillometers (HQIPs) are able to track psycho-physiological fatigue in a fast, objective, valid, reliable, and non-invasive manner. However, the application of HQIPs in the context of athlete monitoring is yet to be determined. Therefore, the main aim of this pilot study was to examine the potential usefulness of a HQIP to monitor game-induced fatigue inside a professional female basketball setting by determining its (1) test-retest repeatability, (2) relationship with other biomarkers of game-induced fatigue, and (3) time-course from rested to fatigued states. A non-ophthalmologic practitioner performed a standardized Pupil Light Reflex (PLR) test using a medically graded HQIP among 9 professional female basketball players (2020–2021 Euro Cup) at baseline, 24-h pre-game (GD-1), 24-h post-game (GD+1) and 48-h post-game (GD+2). This was repeated over four subsequent games, equalling a total of 351 observations per eye. Two out of seven pupillometrics displayed good ICCs (0.95–0.99) (MinD and MaxD). Strong significant relationships were found between MaxD, MinD, and all registered biomarkers of game-induced fatigue ($r = 0.69$–0.82, $p < 0.05$), as well as between CV, MCV, and cognitive, lower-extremity muscle, and physiological fatigue markers ($r = 0.74$–0.76, $p < 0.05$). Three pupillometrics were able to detect a significant difference between rested and fatigued states. In particular, PC (right) ($F = 5.173$, $\eta^2 = 0.115$ $p = 0.028$) and MCV (right) ($F = 3.976$, $\eta^2 = 0.090$ $p = 0.049$) significantly decreased from baseline to GD+2, and LAT (left) ($F = 4.023$, $\eta^2 = 0.109$ $p = 0.009$) significantly increased from GD-1 to GD+2. HQIPs have opened a new window of opportunity for monitoring game-induced fatigue in professional female basketball players. However, future research initiatives across larger and heterogenous samples, and longer investigation periods, are required to expand upon these preliminary findings.

V – STUDY 1

V – STUDY 1:

THE NEGATIVE INFLUENCE OF AIR TRAVEL ON HEALTH AND PERFORMANCE IN THE NATIONAL BASKETBALL ASSOCIATION: A NARRATIVE REVIEW

5.1. INTRODUCTION

The National Basketball Association (NBA) is one of the most physically demanding professional sports leagues in the world (31). With a grueling 82-game regular season schedule, players are constantly on the move, travelling between games across the country (31). While travel is a necessary part of the job, it can also have negative effects on player performance and health. In particular, travel fatigue has been identified as a significant issue for NBA players, with potential impacts on sleep, recovery, and overall health (78).

Despite its importance, there has been relatively little research on travel fatigue in the NBA. Most research on fatigue in basketball has focused on physical fatigue, such as the effects of back-to-back games or playing on consecutive days (23). However, travel fatigue, which refers to the physical and psychological effects of long-distance travel, has received relatively little attention in the literature. This is surprising given the significant amount of time that NBA players spend travelling during the regular season (79).

Travel fatigue can result in a range of negative effects on players, including disrupted sleep patterns, decreased alertness, and impaired cognitive function (78, 80). These effects can have a direct impact on player performance, potentially leading to increased injuries, decreased shooting accuracy, and decreased overall productivity (81). Travel fatigue can also have indirect effects on player health, including increased risk of illness and decreased overall well-being (82).

Given the potential negative effects of travel fatigue, it is important to better understand its impact on NBA players and to identify strategies for mitigating its effects. This narrative review aims to explore the negative effects of travel fatigue in the NBA and to highlight potential strategies for mitigating its impact.

5.2. METHODS

A literature search was conducted using the following electronic databases: PubMed, MEDLINE, PsycINFO, and SPORTDiscus. The search terms used were "travel fatigue," "NBA," "basketball," "performance," and "health." Only studies published in English between 2000 and 2022 were included. In addition, references cited in the identified studies were also reviewed to identify additional relevant studies.

Studies were included in this review if they examined the effects of travel fatigue on NBA player performance and/or health. Studies that focused on other forms of fatigue (e.g., physical fatigue) or other sports were excluded. Quality assessment was not performed, as the purpose of this review is to provide a narrative overview of the existing literature on travel fatigue in the NBA.

Data was extracted and synthesized from the identified studies using a narrative approach. Key themes and findings were identified and summarized, and potential strategies for mitigating the negative effects of travel fatigue were discussed. In summary, this narrative review on the negative effects of travel fatigue in the NBA utilized a comprehensive search strategy and a narrative approach to synthesize and summarize the existing literature on this important topic.

5.3. RESULTS AND DISCUSSION

5.3.1. National Basketball Association: Schedule and Travel Requirements

The National Basketball Association (NBA) is the premier basketball league in the world (31, 78) and in recent years a greater emphasis has been placed on player safety (23, 79). In regard to player safety, there has been increased attention in the areas of training load (23, 80) as well as schedule and travel requirements (80). In an attempt to reduce the training load and schedule requirements of players, the NBA has modified the preseason schedule. Prior to 2017, NBA teams played eight preseason games across 3–4 weeks in preparation for the regular season (81, 82). Since the 2017–2018 season, the NBA season has consisted of 4-6 preseason games played across 3–4 weeks followed by an 82-game regular season played across 26 weeks (177 days). During the regular season, each team plays two to five games per week (~3.2 games per week) (31) with games lasting an average duration of 2 h and 15 min [2]. NBA teams rarely practice during the season and practices that occur are typically less than 1 h (31, 78). In response to teams resting players during back-to-back (two games within a 2-day span) games (83), the league extended the duration of the regular season by 7 days with the purpose of scheduling fewer back-to-back games (78). During the 2017–2018 season, NBA teams played an average of 14.4 ± 0.9 back-to-back games, which was the lowest on record compared to any previous season in the NBA (78). Furthermore, the 2017–2018 NBA season marked the first season in NBA history in which no team played four games in 5 nights (81). Despite adjustments to the NBA schedule, air travel demands remain high due to the geographical span of teams across four time zones (eastern, central, mountain, and western). In this regard, NBA players spend more time above 30,000 ft than athletes competing in all other team sports in the United States of America (USA) (82). Air travel requirements are a concern for NBA coaches, players, and owners, as research has demonstrated short-haul flights (≤6 h) increase injury risk (27, 30, 35, 78, 83, 84) and impede performance (27, 34, 36, 85, 86, 87, 88, 89). Competing in away games has been reported to significantly increase regular season injury risk in a sample of 1443 NBA players between 2012 and 2015 (27). Specifically, 54% of regular season injuries occurred in players playing games away from home, which was significantly greater than the expected injury rate for away games of 50% ($p < 0.05$) (27). Furthermore, the direction of air travel should be considered by NBA teams, as traveling westward exacerbates reductions in performance (34, 90). In a sample of 8495 NBA games between 1987 and 1995, west coast teams scored four more points per game ($p < 0.05$) when traveling to the east coast than east coast teams scored when traveling to the west coast (90). Furthermore, NBA teams traveling eastward had a winning percentage of 45.4% compared with 36.2% for teams traveling westward ($p < 0.001$) between 2010 and 2015 (34). The increased difficulty of traveling westward across the USA to compete has also been reported in the National Football League and the National Hockey League (34). Westward travel is likely more difficult since performance tends to peak in the late afternoon and players traveling from west to east tend to play games closer to their circadian peaks given most NBA games are played at night.

5.3.2. The Impact of Travel Fatigue on Performance

Frequent air travel can negatively affect hydration status, nutritional behaviors, sleep quality, and sleep quantity, thus extending the time for sufficient recovery between games and/or training in athletes (85). As a result, air travel should be considered as an additional stressor imposed on NBA players in conjunction with competition and training schedules (85), especially when less than 72 h of rest is experienced between games (90, 91). One of the main consequences associated with frequent air travel exposure is "travel fatigue". Travel fatigue refers to feelings of disorientation, light-headedness, gastrointestinal disruption, impatience, lack of energy, and general discomfort that follow traveling across time zones (85). The magnitude of travel fatigue depends on many factors such as regularity, duration, and conditions of travel (85). Specific causes of air-related travel fatigue include:

- Prolonged exposure to mild hypoxia (86, 92, 93)
- Difficulties in standing, walking, and moving around due to limited room inside the air cabin.
- Reduced air quality in the cabin, which may impair immune function (84)
- Dry cabin air and low hypobaric pressure potentially causing dehydration (94).
- Prolonged sitting in a cramped position reducing mobility and flexibility (83, 86)
- Disruption of routines (e.g., eating and sleeping) (95).
- Noise of plane and cabin (e.g., sleep disturbance) (86).
- Formalities of air travel may induce negative mood states (95).

A primary issue regarding air travel occurs as a result of significant reductions in oxygen saturation, which has been found to decrease significantly from 97% at ground level to 93% at cruising altitude ($p < 0.05$) (93). This finding is significant, as oxygen saturation levels of 93% could prompt physicians to administer supplemental oxygen in hospital patients (93) and thus would slow muscle recovery (96). One study examined the effects of air travel from the east coast to the west coast of the USA on physiological performance measures, sleep quality, and hormonal alterations (97). However, it is important to note the following: participants used in this investigation were not athletes, a simulated sporting event most closely related to demands experienced during soccer was administered, and there was no non-exercise (control) group. However, air travel induced jet lag symptoms, which resulted in decreased sleep quality and was paired with significantly increased melatonin levels on flight days (travel from east to west coast and travel from west to east coast) (97). The authors also examined markers of skeletal muscle damage, but since a non-exercise control was not included in the investigation meaningful interpretations of the data cannot be determined (97).

When flying across two or more time zones, symptoms of travel fatigue can remain up to 2–3 days after arrival (95). The physiological and perceptual stressors associated with flying across one or more time zones may alter sleep patterns in athletes (84). In particular, short-haul air travel has been reported to impair athletic performance due to the development of an inefficient internally-driven circadian rhythm (i.e., sleep deprivation or disorientation between the circadian system and the environment) (98). In this sense, NBA players may experience difficulty sleeping at night and excessive daytime sleepiness when traveling across multiple time zones. Subsequently, the greater the number of time zones travelled, the more difficult it is for an athlete to adapt to a new time zone. For example, a 2-h time zone shift may cause marginal disruption to the circadian rhythm, but a 3-h time zone shift (e.g., NBA players traveling coast to coast within the USA) can cause a significant desynchronization of circadian rhythm (95). Therefore, it is recommended that NBA players focus on physical activity, eating, and social contact during daylight in their new time zone in order to resynchronize their circadian rhythm, especially when traveling from coast to coast (35). The circadian rhythm plays a critical role in sports performance (89, 95, 99, 100). When an athlete's circadian rhythm is synchronized with the environment, the athlete should achieve optimal performance during late afternoons and early evenings (89). Considering air travel can cause an athlete's circadian rhythm to become unsynchronized with the environment, air travel may contribute to the home court advantage in the NBA (101, 102), as the body's core temperature (an endogenous measure of circadian rhythm) takes approximately 1 day for each time zone crossed to adapt completely to the new time zone (35, 103). Consequently, the number of time zones traveled plays a critical role in the magnitude of travel fatigue (35). The regularity, duration, and direction of air travel, combined with in-cabin conditions, likely predisposes

NBA players to travel fatigue (35). In turn, travel fatigue can have deleterious effects on player recovery and subsequent performance, particularly when scheduled soon after practices or games. Consequently, it is recommended that recovery and practices administered before and after air travel are modified to account for travel fatigue, especially considering the travel direction and flight duration experienced

5.3.3. Scheduling and Recovery Opportunities

Besides the direction and duration of air travel, the home court advantage is also influenced by the quantity of rest NBA teams attain prior to games (104). In particular, a consistent advantage was recorded when a team had more than 1 day of rest between games (the home team's score increased by 1.1 points per game and the away team's score increased by 1.6 points per game) in a sample of 8495 regular season NBA games between 1987–1995 (90). Moreover, average total scores (home and away teams) were highest when 3 days of rest were encountered between games with data collected from the 1987–1995 seasons (90). Consequently, the negative influence of air travel during an NBA season may be mitigated by incorporating supplemental days to recover from games.

An optimal recovery window of 72 h following games and practices is needed for an athlete or team to return to optimal levels of performance (91). Nevertheless, the NBA schedule dictates condensed game schedules that necessitate compressed training schedules, which may inhibit access to active rest days to fully recover from accumulated physical and psychological stress induced by NBA games and practices. Consequently, NBA teams are often obligated to intervene with various ergogenic practices in an attempt to speed up the recovery process, such as whole body cryotherapy, compression tights, cold water immersion, contrast water therapy, and soft tissue massage (105). While these commonly employed recovery practices, including compression tights (106), cold water immersion (107), and massage (108), have been investigated in various samples of basketball players, no data are available specifically in NBA players. Therefore, more research is needed to ascertain if these recovery practices benefit NBA players across the season.

Another factor to consider in reducing injury risk and optimizing performance in the NBA is the total amount of in-game minutes accrued by each player. While coaches have presumed withdrawing high-minute players from entire games may reduce injury risk and enhance performance, a tactic which is often seen nearing the conclusion of the regular season, data to support this approach is lacking. In fact, existing data revealed the average minutes played per game did not influence on-court performance or injury risk ($p < 0.001$) in 811 NBA players competing between 2000 and 2015 (27, 29). However, it should be noted these data are not reflective of performance and injury risk in players who were rested for entire games but rather are indicative of players completing reduced game minutes. Subsequently, future studies are needed to examine the consequences and confirm the efficacy of resting high-minute players for entire games in the NBA.

Scientific information about the specific demands of air travel on performance and health in professional team sports is scarce, with research existing in soccer (109) and rugby (110), which may not directly apply to the NBA. Therefore, research is needed to understand the impact of air travel on player health and game performance across the season in the NBA. Future research on the influence of air travel in NBA players should focus on the identification of causes and symptoms of travel fatigue as well as interventions to mitigate the effects of air travel on player health and performance.

5.5 CONCLUSIONS AND FUTURE RESEARCH

The NBA travel schedule induces misalignments in circadian rhythm that cannot be avoided. Air travel across three time zones has been reported to induce susceptibility to travel fatigue (88, 98, 111, 112, 113), increase injury risk (35, 98, 110), and reduce game performance (35, 34, 87, 98, 101). NBA schedule-makers and teams may succeed in mitigating the negative effects of air travel from coast to coast on sleep by implementing up-to-date, evidence-based strategies applied in other professional sports, such as blue light exposure in the morning and red light exposure in the evening, in order to resynchronize the circadian rhythms of players (114). Other strategies include the ingestion of a high-carbohydrate, low-protein meal in the evening, which may enhance serotonin production to promote drowsiness and sleep (89, 115), or the ingestion of a high-protein, low-carbohydrate meal in the morning, which may increase the uptake of tyrosine and its conversion to adrenaline, which elevates arousal and promotes alertness (85, 115). However, future studies are required to evaluate the efficacy of the abovementioned strategies in NBA players.

Despite recent schedule modifications and an increased awareness of the potential negative consequences of air travel on the health and performance of NBA players, there is still a need to implement effective strategies to address issues with sleep and travel fatigue to promote greater equity across western and eastern teams. Future research exploring various aspects of regularity, duration, directions, and conditions of air travel (35) in one or multiple NBA seasons can help identify origins of fatigue in players. Consequently, a holistic approach to future research is recommended, with some potential topics of interest encompassing descriptive and intervention-style studies.

First, it is important to understand the impact of air travel on NBA players at an individual level, given that NBA players often experience time zone transitions, which have been found to increase injury risk (27, 110) and hinder performance (85,89,90, 109, 111, 116). Considering frequent time zone transitions often disrupt the circadian rhythm in athletes (85, 86, 89, 95, 111, 112), future studies may focus on the measurement of salivary melatonin onset, adrenaline concentrations, and body temperature, as these are critical biomarkers of circadian rhythm (89, 117). Measurement of these biomarkers would provide insight into how each player individually adapts to air travel throughout the NBA season. Consequently, NBA performance support staff may then apply individualized approaches to training and game preparation to combat the negative impact of air travel.

Second, examination of various ergogenic aids will provide a better understanding of practices that may enhance physiological and perceptual responses to air travel in NBA players. For instance, nutrition (118) and hydration (118) are fundamental aspects underpinning circadian rhythm. Therefore, analyzing and comparing the hormonal responses of NBA players adopting different diets may provide NBA coaches and support staff with further insight into beneficial nutritional strategies for coping with air travel in the NBA.

Third, in order to mitigate the negative impact of air travel on mood state, it is recommended that each player's psychological and psycho-sociological reactions to air travel should be monitored during the season. For instance, comprehensive psychometric questionnaires such as the Acute Recovery and Stress Scale (119) and the REST-Q Sport (120) have been established as logical, practical, and versatile tools to measure self-perceived travel fatigue in professional team sports (119, 120). Considering the time constraints in the NBA, shorter customized versions of these questionnaires can be completed on a daily basis (121), which have been reported to be valid and reliable in elite Australian Rules Football (122). However, further research is necessary to provide normative standards, especially with a focus on individual interpretations, recommendations, and compliance in NBA players.

Finally, considering that skeletal muscle and connective tissues become shortened during flights and may stiffen, it is recommended for players to avoid sitting the entire trip, and instead, walk around the cabin every hour, unless they are asleep or advised not to do so by flight staff (115). With a tentative agreement between the NBA and Delta Airlines charters, walking inside the air cabin should be attainable, as most NBA teams (27 out of 30 teams) fly with private jets of Delta Airlines (including A319s and Boeing 757-200s) with almost 50 percent more cabin space than standard planes (123). This cabin space allows most NBA players, who possess an average stature of 6 feet and 7 inches, to have more freedom to stand erect during air travel (123). Additionally, simple stretching exercises can be applied while in the seat or in the cabin, which could help relax muscles while increasing blood flow and delivering oxygen and other nutrients to muscles (96, 115). As a result, stretching may reduce the negative effects of air travel on flexibility and skeletal muscle recovery. Consequently, future studies are encouraged to examine the efficacy of these in-flight travel strategies in NBA players.

VI – STUDY 2

VI – STUDY 2:

THE UNDERPINNING FACTORS OF NBA GAME-PLAY PERFORMANCE: A SYSTEMATIC REVIEW (2001–2020)

6.1. INTRODUCTION

The National Basketball Association (NBA) is widely recognized as the premier basketball competition in the World and one of the most popular sports leagues in and outside the United States (22). The typical NBA schedule requires teams to participate in 82 regular season games played across a 5.5-month competition period in which players are exposed to an average of 22.6 ± 10.6 minutes of playing time per game, 3.4 games per week, one game every 2.07 days, 13.3 back-to-back scenarios per season, alongside frequent air travel across four different time zones (e.g. NBA teams flew 250 miles a day for 25 straight weeks during the 2018–2019 season), as well as participation in individual and team practices and workouts amid all these endeavors (22, 33, 124). In addition, players typically go through one month of preseason activities (4–5 games) as well as potentially two months of post-season appearance (4–28 games) (22, 23, 27).

The monetary value of succeeding in this exceptional environment is substantial, with NBA teams generating a combined revenue of almost $US8.8 billion U.S. dollars (2018–2019) (125), and the 30 ranked teams during the 2019–2020 NBA season paid its 450 players $US3.66 billion in salaries alone (126). Hence, league executives, teams, coaches, players and support staff personnel are all interested in enhancing and sustaining the performance of teams and players during games to improve the likelihood of competitive success. Given the average margin of victory between NBA teams is considerably small (e.g. the 2018–2019 regular season's margin of victory equaled 11.8 points) (127), the competitive edge would not need to be large to make a difference between winning and losing a game. With significant international, national, and local pride associated with winning games, significant lower-limb injury rates (11.6 lower limb injuries per 1000 game appearances) (124), lack of definitive evidence in recommendations pertaining to NBA player training, recovery and injury risk mitigation during the regular season (124), and yet the monetary rewards available (191), an 'evidence-based framework' to precisely prepare NBA players and teams for the subsequent demands of game-play would benefit all club stakeholders involved in this process (128-131). Notably, according to Pol et al. (131), an evidence-based approach to coaching and training should not be defined as a framework that is 'intrinsically valid' nor 'intrinsically invalid', but instead, 'contextually more (in)appropriate or (un)functional' (131). Accordingly, within this concept, sports scientists and coaches operating in the NBA environment necessitate a deep understanding of the central properties of complexity during NBA games (i.e. the players and the teams), their interdependence, temporal nestedness, and circular causality acting upon all levels, timescales, and dimensions of game-play (131). Nevertheless, collecting, storing, organizing, analyzing, interpreting, disseminating, and ultimately taking action upon 'Big Data' remains a difficult task to conquer in the modern era of professional team sports (23). With the uncontrolled influx of advanced technologies, changes in the NBA's league rules, regulations and collective bargaining agreements, and often lingering conservative approaches toward data-driven decision-making processes in the modern era (22, 23), the aforementioned challenges faced upon NBA stakeholders still remains prominent today (22, 23, 33, 124).

In an attempt to surmount these challenges (132, 133), over the past two decades, projects related to 'game-play performance analysis' has rapidly grown, and continues to surface as a distinct sub-discipline and integral part of numerous applied sport science programs in elite sports (e.g. 'Performance Analysis UK'), as well as numerous peer-reviewed journals (e. g. International Journal of Performance Analysis in Sport; Journal of Quantitative Analysis in Sports), international conferences (e. g.' World Congress of Performance Analysis in Sport'), books (e.g. Routledge Handbook of Sport Performance Analysis), international scientific societies (e.g. International Society of Performance Analysis of Sport), and academic programs (e.g. M.Sc. in Sports Performance Analysis) (133). In turn, the pervasive investments in 'slow' research has already shown its value and viability across a wide range of professional basketball teams and team-sport organizations around the world (134-143). However, the traditional approach to rudimentary analysis of standalone 'game-play performance indicators' has provoked criticism, because it offered little information about the fundamental mechanisms and behaviors that underpin game-play performance (144). In response, the principles of 'ecological dynamics' and 'complex systems theory' have been revisited (131-133, 139, 144) and utilized to construct 'process-oriented analysis' of game-play performance, offering numerous benefits to both researchers and practitioners (144-146), including: generating new insights about the complex dynamics that serve as grassroots for the emergence game-play performance outcomes; gaining multi-level perspectives (inter-individual and intra-individual patterns); facilitating new opportunities for multi-disciplinary departments to collaborate and play a more prominent role in modulating the underpinning factors of game-play performance (144-146).

As a starting point to adopt such process-oriented approach to NBA game-play performance analysis, a well-defined taxonomical classification of factors that 'constrain' NBA game-play performance deems necessary (146-152). Although a number of different constraint models have been postulated by numerous researchers, the most widely cited model to date is grounded on the concepts of Newell (1989) (147) and later on Newell and Jordan (2007) (148). Advocated by numerous sports scientists and sport performance analysts, as well as other branches of sciences including mathematics, physics and biology (149, 151). In particular, Newell's Constraints-Led Approach (CLA) constitutes three central constraints that serve as the 'degrees of freedom' or 'boundaries' for the emergence of game-play performance, specifically: (1) player constraints (organismic characteristics), (2) contextual constraints (environmental characteristics), and (3) task constraints (game-play rules and regulations) (146-152). This triangular framework takes into account the continuous interactions that are predicated on the 'player-task-environment relationship', and the information yielded by this approach could be used to inform real-world practices by manipulating the constraints that impinge on the player-task-environment system (e.g. technical and tactical decision-making, injury risk mitigation protocols, training and recovery prescriptions, talent identification, etc.). Therefore, the authors conceded the CLA as a suitable framework and an appropriate scale of analysis for examination of complex ecological phenomena, such as NBA game-play performance.

Despite the NBA's demanding schedule, risk for injuries, great valuta of players, and major wager associated with winning games, to the best of the authors' knowledge, a comprehensive resource of scientific evidence about the underlying mechanisms and behaviors of NBA game-play performance remains unknown.

Therefore, the primary aim of this systematic review is to provide coaches, managers, medics, applied researchers, and support staff personnel with a complete compendium of peer-reviewed research spanning across the past two decades (2001–2020) specifically related to two constraints of NBA game-play performance (i.e. player and contextual constraints), and in turn, help promote the employment of evidence-based guidelines amidst the fast-pace NBA atmosphere. Secondly, the authors aim to provide this information in the most recent, reliable, accurate, and easy-to-understand language for practitioners in order to facilitate transfer of knowledge, and finally, offer short-term and long-term research agendas to promote the evolution of scientific knowledge about the modern-day NBA ecosystem.

6.2. MATERIALS AND METHODS

6.2.1. Search strategy and eligibility criteria

A systematic search of peer-reviewed research published between January 2001 and November 2020 was conducted on 2 December 2019; 4 April 2020; 10 October 2020; 14 November 2020 and 31 December 2020 utilizing PubMed (MEDLINE), Web of Science (WOS), ResearchGate, SPORTDiscus, SCOPUS, Google Scholar, and the World Association of Basketball Coaches' database (WABC). This review followed the Preferred Reporting Items for Systematic Review and Meta-Analyses (PRISMA) guidelines and the PICOS model (153) for the definition of the inclusion criteria: P (Population): 'Healthy AND injury-free NBA players', I (Intervention): 'competed in the NBA regular season or NBA playoff basketball competition', C (Comparators): 'same conditions with comparators', O (Outcome): 'described internal factors related to NBA game-play performance (i.e. structural and/or functional characteristics of NBA players); and/or external factors related to NBA game-play performance (i.e. game location, season period, game period, game status, difference of team quality, momentum effects, playing time, rest days, travel, and/or interactive effects)'; Study design (S): 'quantitative, qualitative, and/or mixed-method model with experimental, quasi-experimental, and/or non-experimental research design, utilizing primary and/or secondary data sources'. The search terms included a mix of medical subject headings (MeSH) and free-text words for key concepts related to 'NATIONAL

BASKETBALL ASSOCIATION', 'PROFESSIONAL BASKETBALL', 'NBA', 'ATHLETIC PERFORMANCE', 'GAME-PLAY PERFORMANCE', 'GAME PERFORMANCE' along with Boolean operators such as 'AND' or 'OR' including ('National Basketball Assocation'[MeSH Terms] OR 'National Basketball Association'[All Fields]) AND (('athletic performance'[MeSH Terms] OR 'athletic performance'[All Fields]) OR ('performance'[MeSH Terms] OR 'performance'[All Fields]) OR OR ('game-play performance'[MeSH Terms] OR 'game-play performance'[All Fields) OR ('game performance'[MeSH Terms] OR 'game performance'[All Fields)) AND (('professional basketball'[MeSH Terms] OR 'professional basketball'[All Fields]) OR ('NBA'[MeSH Terms] OR 'NBA'[All Fields])). Through this equation, relevant articles in this field were obtained applying the snowball strategy. All titles and abstracts from the search were cross-referenced to identify duplicates and any potential missing studies. The titles and abstracts were screened for a subsequent full-text review.

6.2.2. Study selection process

Two reviewers (TH, JC-G) independently screened citations and abstracts to detect articles that potentially met the inclusion criteria. Full-text versions of the selected articles were retrieved and independently screened by two reviewers (TH, JC-G) to determine whether they met inclusion criteria. Any disagreements that have occurred with regards to whether an article met the inclusion criteria were resolved through direct communication with the other authors (SB, PA) and a consensual decision was made for each final article through a joint decision-making process (i.e. computer-mediated Delphi process as a tool to scaffold idea generation and evaluation) (154). Titles and abstracts of publications were obtained in accordance with the search strategy and the two reviewers (TH, JC-G) determined the relevance of the publication for final inclusion. Based on the information within the full-text reports, the inclusion criteria was subsequently used to select the trials eligible for inclusion in the systematic review through discussions and consensus between all authors (TH, JC-G, SB, and PA). There were no filters applied to the NBA players' ethnicity, socio-economic or socio-cultural background, age, and/or training experience to increase the power of the analysis.

6.2.3. Quality assessment and risk of bias

In order to carefully consider the potential limitations of selected studies and obtain reliable conclusions, two authors independently assessed the methodological quality and risk of bias (TH, JC-G), whereas disagreements were resolved by the entire research group (TH, JC-G, SB, and PA). As demonstrated and consented by Faber et al. (155) and Sarmento et al. (139) in appraising the methodological quality of quantitative studies, the 'Critical Review Forms' conceptualized by Law et al. (156) was adopted to critically appraise the methodology of included studies. In particular, the articles were assessed based on the following items: purpose (item 1), relevance of background literature (item 2), appropriateness of study design (item 3), sample studied (items 4 and 5), use of informed consent procedure (item 6), outcome measures (item 7 and 8), intervention details (item 9, 10, and 11), significance of results (item 12), analysis (item 13), practical importance (item 14), description of drop-outs (item 15), and conclusions (item 16). All sixteen quality criteria were scored on a binary scale (0/1), wherein five of those criteria (items 6, 9, 10, 11, and and 15) encompassed the option: 'not applicable' (156). This 'if not applicable' option was included to account for non-experimental study designs, and studies in which explanation of informed consent and/or drop-outs was not required (139). Therefore, this tertiary option eliminated the negative effect of assuming '0' on a binary scale when that item was irrelevant to that particular study. Corresponding to previous studies (139, 156, 158), a final percentage score of methodological quality was calculated in order to compare studies with each other (Table 3). In this regard, the sum of the score of all items was divided by the number of relevant scored items for each research study. All articles were classified as: (1) low methodological quality – with a score ≤50%; (2) good methodological quality – between 51% and 75%, and; (3) excellent methodological quality – with a score>75% (139, 156, 158).

6.2.4. Outcome measures and data organization

Based upon Newell's CLA and preliminary scientific reports in team-sport game-play performance analysis (144-152), the included studies of this systematic review were presented according to two distinct, yet interdependent, constraints of NBA game-play performance. In particular: 1) player constraints and 2) contextual constraints. Subsequently, the topics and subtopics underlying these constraints were generated based upon Casals' preliminary report in 'NBA basketball game-play performance analysis' (158). Subsequently, two reviewers (TH, JC-G) independently organized and designated each article resulting from the analysis to their corresponding constraint, topic, and subtopic (Figure 1). Any disagreements were resolved through discussion with the other coauthors (SB, PA) until a consensus was established.

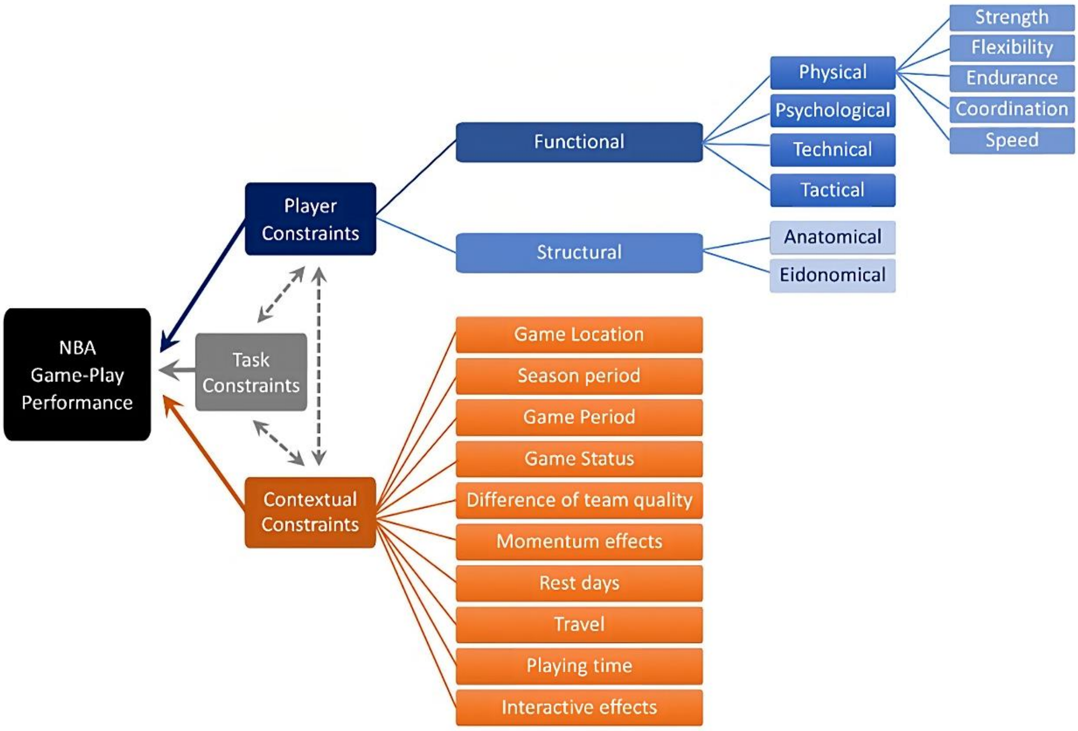

Figure 1. Systematic representation of the underpinning factors of NBA game-play performance.

6.2.5. Data extraction

Once the inclusion criteria was applied to each study, the following data were extracted and documented independently by two authors (TH and JC-G) for each article using a spreadsheet (Microsoft Inc, Seattle, WA, USA): main author, year of publication, subjects (sample size), constraint (including topic and subtopic), main variables included in the analysis (independent and dependent variables), type of data employed (secondary or primary data source), main research purpose (descriptive, exploratory, or explanatory), research model (quantitative, qualitative or mixed-method), research design (experimental, quasi-experimental, non-experimental), main findings, and research quality score based on Law's critical appraisal tool (156) (Tables 1 and 2).

6.3. RESULTS

The results of the interobserver reliability analysis, calculated by the Kappa index, was 0.93 (95% CI 0.93–0.98), indicating very good agreement between observers. The quality of indicators for the included papers was determined as following: (1) the mean methodological quality score for the 43 selected articles was 82.9%; (2) two articles achieved the maximum score of 100%; (3) three of the articles scored below 50%; (4) eight articles scored between 50% and 75% (good methodological quality); and (5), 32 articles achieved an overall rating of >75% (excellent methodological quality) (Table 3). Possible deficiencies identified in the 43 studies were mainly related to criterion 16 (reporting of drop-outs or missing values), and some studies lacked information in relation to criterion 7 (reliability of reported outcomes) due to either neglecting the computation of the required minimum sample size, involving sample sizes that did not meet the requirements to make the concluded inferences, or neglecting potential biases due to inter-observer or intra-observer reliability. The initial search process on NBA performance returned 192 articles (Figure 2). From the 103 records that were screened by the authors, a total of 60 studies were excluded due to being off-topic (e.g. salaries, racial differences, ethical issues, entertainment, branding and marketing, player health and injury issues, sports betting, etc.). A total of 43 studies (n = 43) were ultimately selected for final review based upon the authors' criteria to include only peer-reviewed articles from scientific journals between January 2001 and November 2020 simultaneously being most relevant to the main constraints, topics, and subtopics discussed in this systematic review (Figure 2). The main intention behind the included studies was to describe information (n = 27; 62.8%) rather than explore (n = 15; 34,9%) and/or explain (n = 1; 2.3%) research problems or hypotheses (Table 4). Furthermore, near all researchers employed secondary data sources (n = 37; 86.0%) compared to primary data sources (n = 6; 14.0%) and/or a mixture of both (n = 0; 0.0%). Interestingly, more than half of all researchers utilized an ecological study design (n = 24; 55.8%) encompassing large population-based datasets (e.g. numerous NBA teams across multiple seasons). The ecological study design was especially popular in studies examining contextual constraints (n = 20), while the case report was the preferred study design when examining player constraints (n = 8) (Table 4). Near all studies adhered a quantitative research model (n = 41; 95.3%), while only two studies were qualitative by nature (narrative review articles) (n = 2; 4.7%), and no mixed-method research models were identified. Promisingly, the vast majority of all studies were published in recent years, in particular within the last 4 years (n = 28; 65.1%) (>2016), the last 7 years (>2013) (n = 37; 86.0%), and near all studies were published within the last ten years (n = 41; 95.3%) (>2010). When evaluating the number of studies in each constraint, topic, and subtopic of interest, it appeared that the vast majority of researchers focused on external factors (i.e. contextual constraints) (n = 25; 58.1%) rather than internal factors (i.e. player constraints) (n = 18; 41.9%). Nevertheless, the most popular research topic was identified as ‘functional abilities’ of NBA players (n = 13; 30.2%), in which ‘physical qualities’ (n = 6) was the most prominent subtopic. The least popular topics were identified as ‘game status’, ‘tactical skills’, ‘momentum effects’, and ‘interactive effects’, in which each topic accounted for only one study (n = 1; 2.3%) (Table 4).

Table 1. Summary of scientific studies (2001-2020) included in this systematic review, specifically related to *player constraints* of NBA game-play performance.

Main Author	Year	Topic	Subjects	Main variables	Data type	Research purpose	Research model	Research design	Main findings	Quality Score
Bakkenbull [59]	2017	Structural (Eidonmical)	2015-2016 NBA regular season players.	Playing Efficiency (PER and PIE), physical characteristics, age, draft selection and player salaries.	Secondary	Descriptive	Quantitative	Non-exp Ecological	The relative wingspan is positively associated with performance whereas the vertical jumping influences it in a significantly negative way.	66,7
Cheema [66]	2020	Structural (anatomical)	From 2013 to 2018, all NBA players who attended the NBA Draft Combine's cardiac evaluation (307 players)	Using the P-wave as the reference point, speckle-tracking was utilized to measure left atrial booster, conduit, and reservoir strain over one cardiac cycle. Left atrial volume index (LAVI) of ≥34 mL/m² was considered enlarged.	Primary	Descriptive	Quantitative	Non-exp Cross-sectional	Mean LAVI was 34.5 mL/m² and LAVI was enlarged in 131 (48.2%) athletes. Comparing LA strain in those with enlarged vs normal sized atria, reservoir strain was significantly reduced, with no difference seen in booster strain (9.2% [SD 2.1%] vs 9.4% [SD 2.7%], *P* = .45).	91,7
Courel-Ibáñez [99]	2016	Functional (tactical)	808 inside passes (ball possession score differences below 10 points) from 25 games (NBA Playoffs, 2010)	Players' position, players' actions before and after receiving the ball, game condition and ball possession effectiveness	Secondary	Descriptive	Quantitative	Non-exp Case	The inside pass represents a large potential scoring option with a greater effective rate, even in tight competition situations. Particularly strong side actions (pick and roll, pass and cut) linked with weak side actions (out of ball screen, dive cut) to increase scoring options.	83,3
Cui [57]	2019	Functional (physical)	3,610 players participating in the 2000–2018 NBA draft combine test	height without shoes, weight, wingspan, standing reach, body fat percentage; no step vertical jump, no step vertical reach, max vertical jump, max vertical reach, bench press, lane agility and three-quarter court sprint.	Secondary	Exploratory	Quantitative	Non-exp Case-control	The drafted players outperformed the undrafted in height, wingspan, vertical jump height and reach, line agility and three-quarter sprint test ($p < 0.01$, ES = 0.26–0.87). Leg power predicts draft in guards, as did agility and speed for power forwards and centers.	91,7
Engel [65]	2016	Structural (anatomical)	526 NBA players competing during the 2013-2014 and 2014-2015 seasons	Left ventricular (LV) size, mass, wall thickness, and hypertrophy patterns and function; left atrial volume; and aortic root diameter. All dimensions were biometrically scaled	Primary	Descriptive	Quantitative	Non-exp Cross-sectional	LV hypertrophy was present in 144 athletes (27.4%). African American athletes had increased LV wall thickness and LV mass compared with LV wall thickness ($P < .001$) and LV mass ($P = .029$) in white athletes. The maximal aortic root diameter in the cohort was 42 mm. Aortic root diameters reached a plateau at the uppermost biometric variables.	91,7

Jones [85]	2019	Functional (psychological)	112 NBA players actively tweeting between 2009 and 2016.	Time-stamped social media activity and in-game performance (total points scored, shooting percentage, rebounds, turnovers, fouls).	Secondary	Exploratory	Quantitative	Non-exp Retrospective cohort	Acute sleep deprivation (Twitter usage between 11:00 PM and 7:00 AM) is associated with changes in next-day game performance in the NBA. In particular, players made shots at 1.7% less points following late-night tweeting.	66,7
Phatak [98]	2020	Functional (technical)	610,822 free throws from the NBA seasons between 2006 and 2016 (regular and playoffs)	FT success rates	Secondary	Descriptive	Quantitative	Non-exp Ecological	The success rate of the second FT was greater compared to the first FT. For triple FT's, the success rate increased with each successive FT. The results demonstrate differences between consecutive throwing percentages.	91,7
Ranisavljev [77]	2020	Functional (physical)	58 NBA players (rookies) who matched the inclusion criterion of average playing time and number games in the period 2012-2015	Lane agility, shuttle run, ¾ court speed, VJ from running, 185 lbs bench press, and key basketball performance variables.	Secondary	Exploratory	Quantitative	Non-exp Case	Pre-Draft Combine testing procedures show the highest correlation between upper body strength and number of rebs (r = .403, p = .002) and blocks (r = .333, p =.011). Regression model of Combine performance explained 24.7% of basketball performance with three physical performance tests.	91,7
Rauch [78]	2020	Functional (physical)	178 NBA players that were active on an NBA roster	Standing height, playing position, body weight, CMJ's jump height, net relative impulse, relative un-weighting force, sum (left and right) braking force, relative sum (left and right) concentric force, total movement time, maximum joint flexion average, delta joint flexion, joint total range of motion, maximal joint flexion velocity, joint flexion acceleration, joint extension, joint extension velocity, joint extension acceleration, and time to maximum joint flexions and extensions.	Primary	Descriptive	Quantitative	Non-exp Case	Lower limb joint angular displacement (i.e., delta flexion) explained the highest portion of point variability (89.3%), and three clusters were recommended (Ball Hall Index). Delta flexion was significantly different between clusters and players were characterized as "stiff flexors", "hyper flexors", or "hip flexors". There were no significant differences in jump height between clusters (p > 0.05).	91,7
Sampaio [96]	2015	Functional (technical)	548 NBA players during the 2013–2014 regular season.	Playing positions, pull-up shots, catch and shoot, close shots, drives, passing-variables, touches-variables, speed and distance, rebounds, free-throw percentage.	Secondary	Exploratory	Quantitative	Non-exp Ecological	All-star players performed consistently better than non-all-star players in elbow touches, offensive rebounds, close touches, close points and pull-up points (within 12 feet of the basket).	91,7

Sedeaud [58]	2014	Structural (eidonomical)	50,736 NBA players from 1987 to 2011.	Player mass, height, body mass index (BMI), age, field goals in relation to players height.	Secondary	Descriptive	Quantitative	Non-exp Ecological	In the NBA, a height-attractor at 201.3 ± 6.3 cm for the best scorers is invariant, regardless of the level of play. Discrepancies between some mass and height developments question the (disproportionate) large mass increase (relative to the height increase) during the 1980s and 1990s.	83,3
Teramoto [61]	2018	Structural (eidonomical) and functional (physical)	2010-2015 NBA combine data and subsequent NBA game performances (1-3 years following the combine)	Game-related statistics and NBA combine test results	Secondary	Exploratory	Quantitative	Non-exp Case	H without shoes, standing reach, W, WS, and HL, and subscale of L-S, had positive, medium-to-large-sized correlations (with Defensive Box Plus/Minus. Combine subscale of length-size was a predictor most significantly associated ($p \leq 0.05$) with Win Shares, BPM, and VORP, followed by upper-body strength.	33,3
Xu [83]	2015	Functional (psychological)	NBA players (in the 2012-13 season)	91,659 tweets, game date, game type, home/away, opponent and win/loss (score), age, games started, minutes played, FG, 3PFG, FT's, +/-.	Secondary	Descriptive	Quantitative	Non-exp Case	Sentiment analysis on NBA players' tweets was directly related to GPP after controlling for other factors affecting performance.	83,3

Table 2. Summary of scientific studies (2001-2020) included in this systematic review, specifically related to *contextual constraints* of NBA game-play performance.

Main Author	Year	Research Topic	Subjects	Variables	Data type	Research purpose	Research model	Research design	Main findings	Quality score
Arkes [131]	2011	Player momentum	3452 NBA games from 2007 season through the 2009 season	Home vs. away team, game outcome, rest days, team records and how they did 3 and 5 games prior to the game.	Secondary	Exploratory	Quantitative	Non-exp Ecological	Marginal effects indicate that an extra win in the past 5 games, on average, increases the probability of winning by between 2.2 and 2.8 percentage points using Model A (full season winning percentages) and between 3.3 and 4.0 percentage points using Model B (half season winning percentages).	75,0
Belk [102]	2017	Rest days	811 NBA players (2005-2015) who made the playoffs while playing a minimum of 20 minutes per game.	Playing position, age, regular season minutes per game, player efficiency ratings, shooting percentage, points per game, assists per game, productivity and inefficiency on the court, steals, blocks.	Secondary	Exploratory	Quantitative	Non-exp Retrospective cohort	There were no significant differences between players who missed 5 to 9 games due to rest versus players who missed less than 5 games due to rest at any position in terms of points per game, assists per game, player efficiency rating, true shooting percentage, blocks, steals, or number of playoff games missed because of injury.	75,0
Cao [118]	2011	Game period	National Basketball Association (NBA) free throw data from the 2002-2003 through 2009-2010 seasons	Scoring statistics, the time in the game at which the various shots were taken, and the score difference at the time of the shots.	Secondary	Descriptive	Quantitative	Non-exp Ecological	NBA players shoot on average 5–10 percentage points worse than normal in the final seconds of very close games. Choking is more likely for players who are worse overall FT shooters, and on the second shot of a pair after the first shot is missed.	83,3
Casals [40]	2013	Interactive effects	27 NBA players competing during the 2007 regular season	win score, division, conference and team, season period, home advantage, difference of team quality, rest days, game started, player momentum, player wage relative to team salary, teams fighting for playoffs, player position, age, contract condition, minutes played, usage percentage.	Secondary	Descriptive	Quantitative	Non-exp Retrospective cohort	Minutes played, the usage percentage and the difference of quality between teams were the main factors for variations in points made and win score. The interaction between player position and age was important in win score.	100

Christmann [120]	2018	Game period	Offense play types in final 120 s of 115 close games (5 points score difference) in the NBA (all 2015 regular season post-Allstar games)	The video-captured frequencies and outcomes of six defined play types: 1 on 1 without isolation; 1 on 1 with isolation; pick-and-roll; complex team play; inbound play; and transition play.	Secondary	Descriptive	Quantitative	Non-exp Ecological	During endgame play in the NBA, the pick-and-roll was employed the most and inbound play the least frequently. The 1 on 1 with or without isolation were the least effective play types, averaging 0.9–1.0 pts/possession. In contrast, transition, inbound and complex team plays were the most effective (means 1.3–1.5 pts/possession).. Overall, plays led to 0.8 pts/possession when being in the lead vs. 1.4 pts/ possession when being down.	91,7
Dehesa [128]	2019	Difference of team quality	1,311 NBA games (472 players analyzed) during the 2014-2015 season	+/- on-court and off-court, difference between +/- on-court and off-court, maximum negative points difference, maximum positive points difference, PT, team wins, pace, offensive and defensive EFF, FG%, ORB%, TO%, FT's/FG's	Secondary	Descriptive	Quantitative	Non-exp Ecological	NBA performance could be divided into five clusters during the regular season and four clusters during the playoffs. These clusters were mainly characterized by the game quarter, and the negative difference in plus/minus between on-court and off-court play during the season, and the positive difference in plus/minus between on-court and off-court play during the playoffs, as well as second and third game-quarters.	91,7
Entine [103]	2008	Rest days	NBA data for the 2004-2005 and 2005-2006 seasons.	Average margin of victory experienced by home teams over visitors, strengths of each team year, home court advantage for the host team, amount of rest coming into the game.	Secondary	Descriptive	Quantitative	Non-exp Ecological	Lack of rest for the road team and length of the road trip, while not a dominant factor, are important contributors to the home court advantage in the NBA. However, the bulk of the advantage for home team arises from other, non-related factors.	33,3
Esteves [101]	2020	Rest days	Data from 82 games from all teams participating in NBA 2016-2017 regular season	Playing back-to-back games, playing on one day's rest, playing on two day's rest, playing on three or more day's rest) and performance of NBA basketball teams	Secondary	Exploratory	Quantitative	Non-exp Ecological	Fixture congestion cycles has a significant impact on the game outcome and team performance in the NBA. In particular, the likelihood of winning a game increased significantly from playing back-to-back games to having one day rest in between.	75,0
Flynn-Evans [109]	2020	Travel	499 postseason games played during the 2013–14 to 2018–2019	Direction of travel and time zones traveled on game outcomes, Elo rating differences, win probability, and team scoring.	Secondary	Exploratory	Quantitative	Non-exp Ecological	Direction and magnitude of travel were related to win probability, team scoring, and game outcomes, whereby teams travelling eastward and within the same time zone gained an advantage over those travelling westward.	91,7

García-Manso [119]	2015	Game period	5 NBA regular seasons	Difference between the last minute and the rest of the game from the collected scores (1, 2 and 3 points), substitutions and timeouts	Secondary	Descriptive	Quantitative	Non-exp Ecological	NBA games during the final moments present typically shorter possessions (especially by the disadvantage team), played with fewer number of passes and participating players, higher number of fouls, higher game stops and number of changes.	91,7
Gomez [117]	2016	Game location	48 NBA close games (below 10 points difference) during the 2013-2014 season played by 27 teams.	Situational and technical-tactical variables: starting quarter score, game location, quality of opposition, game situation, defense type, outcome, shot type , technical execution, defense on the shooter, play events, mean played clock-time.	Secondary	Exploratory	Quantitative	Non-exp Ecological	The main differences between HT's and AT's are starting quarter score, FT's scored, 3 point FG from central positions. During balanced games: defensive fouls, game location, quality of opposition, ball possession success, 2FGIO, 3PFGCR, and defensive rebounds during HT's positive scoring trends.	91,7
Gonzalez [81]	2013	Playing time	7 NBA players from the Orlando Magic (53-30 record, 1st round of playoffs)	Body mass, BF%, vertical jump, quickness, reaction time, squat power.	Primary	Exploratory	Quantitative	Non-exp Prospective cohort	NBA players can enhance lower-body power, repetitive jump ability and reaction time during a competitive season, which can be stimulated by playing time (less subjective overall fatigue in starters vs. non-starters).	100
Guerra [123]	2013	Game status	6150 NBA games between 2005 and 2010	Two and three point shots, free throws, rebounds, steals, turnovers, fouls, substitutions, time between each point.	Secondary	Descriptive	Quantitative	Non-exp Ecological	There is no uniform behavior in scoring points in the NBA. However, different behaviors exist depending on the time of scoring. Future research may look at the complexity of the game and analyze whether memory generates different scoring behaviors inside the NBA.	83,3
Harris [115]	2019	Game location	32 seasons (1983–84 to 2017–18)	Home and home opponent 2pt, 3pt, and FT; away and away opponent 2pt, 3pt and FT	Secondary	Descriptive	Quantitative	Non-exp Ecological	The style of play is a key factor in the home advantage. Teams that make more two point and free-throw shots see larger advantages at home.	91,7
Huyghe [1]	2018	Travel	Studies related to travelling demands in the NBA.	Recommendations pertaining to sleep, nutrition, recovery and scheduling strategies to mitigate the risk involved with frequent air travel in the NBA	Secondary	Descriptive	Qualitative	Non-exp Review	Future research will provide a better understanding of practices that may enhance physiological and perceptual responses to air travel in NBA players.	91,7

Jones [85]	2007	Game location	17 unmatched NBA games in the 2002-2003 and 2003-2004 regular season	Home court advantage factoring in for team quality, average points scored by quarter and overtime	Secondary	Descriptive	Quantitative	Non-exp Ecological	Home advantage in the NBA is strongly front-loaded. Home teams accumulated two thirds of the home advantage it had at the end of the game in the first quarter. It accumulated less of an advantage in the second and third quarters, and still less in the fourth quarter. Further, the home team does not on average lengthen its lead in quarters which it enters ahead, but gains strongly in any quarter which it enters behind.	75,0
Mateus [97]	2017	Playing time	NBA Players competing in 2013-2014 season (n=712).	Player position, player minutes , coefficient of variability from game to game.	Secondary	Exploratory	Quantitative	Non-exp Retrospectivecohort	Less PT decreases the probability of maintaining stable performance across games and long PT in away and losing games may vary due to the constraints imposed by opponent teams. FT's seem to be the variables that best discriminate between winning and losing teams.	84,6
Mikolajec [95]	2013	Difference of team quality	2003-2011 NBA seasons (30 teams)	official box scores of NBA and included 52 variables that characterized offensive and defensive effectiveness of 30 teams	Secondary	Descriptive	Quantitative	Non-exp Ecological	The main factors which influence sports results in the NBA indicated in the present study are much more connected with offense than defense.	91,7
Nutting [108]	2017	Travel	NBA games from 1991 until 2013	Winning percentage, time zone, travel direction, game time, game frequency, distance traveled, length of home stands, and length of road trips.	Secondary	Exploratory	Quantitative	Non-exp Ecological	Visiting teams traveling in westwards direction are 7.7 percent less likely to win for each time zone further away from home. The consequences of travel direction are more prominent in day games (before or at 4:00 pm) rather than night games (after or at 7:00 pm).	25,0
Ribeiro [113]	2016	Game location	16,133 games covering 13 NBA seasons (from the 2001–02 to the 2013–14).	Game place, team names, match date, score evolution $S(t)$ of each team as a function of the game time t.	Secondary	Descriptive	Quantitative	Non-exp Ecological	Home advantage affects the microscopic dynamics of the game. However, average differences have slightly decreased over time, suggesting a weakening of the phenomenon.	83,3

Teramoto [94]	2010	Season period	1999–2000 and 2008–2009 seasons	Overall efficiency (offensive and defensive ratings), and effective field goal percentage, turnover percentage, rebound percentage, and free throw rate	Secondary	Descriptive	Quantitative Lastly,	Non-exp Ecological	The importance of defense in winning games may be greater in the playoffs than in the regular season. Fewer TO's could be another key to winning games, especially in the regular season. Lastly, rebounding may play a significant role in deciding the outcome of the Conference Finals where two teams most likely have similar shooting efficiency and TO rates.	91,7
Urban [100]	2018	Rest days	NBA Finals data between 1984 and 2018	Margin of victory for each game in the NBA finals, home court advantage, game to game momentum effects, previous NBA finals experience, and relative team quality.	Secondary	Exploratory	Quantitative	Non-exp Ecological	Additional time between NBA playoff rounds provides a significant advantage, predominantly on the second game of the subsequent round (moderately significant with doubling the odds of winning game two when given supplemental rest between series)	91,7
Zhang [129]	2018	Difference of team quality	354 players across 699 regular season balanced games (10 points or less) during the 2015-2016 regular season.	Team ranking, game-related statistics, playing experience, height and weight	Secondary	Descriptive	Quantitative	Non-exp Ecological	Top H and W combined with low experience was associated with 2PFG's made and missed, offensive and defensive rebs, blocks, and fouls; whereas low H and W combined with low PE is associated with the fewest passes and touches. Weaker teams typically demonstrate low H and W combined with low PE, whereas stronger teams are characterized by low H and W with medium PE, and Finals' appearance was associated with medium H and W combined with medium PE.	91,7
Zhang [130]	2019	Difference of team quality	355 players playing in 692 balanced NBA games (final score is equal or less than 10 points difference) of the 2016-2017 season.	Quality of the team and opposition, match outcome, match location, points made in the paint, two point field goals, free throws made, turnovers, assists, touches, passes, offensive rebounds, defensive rebounds, steals, blocks, personal fouls, field goals defended at rim made, deflections, distance run, average speed, playing position,	Secondary	Descriptive	Quantitative	Non-exp Ecological	Stronger NBA teams show better performance qualities in defensive rebs, blocked shots, and assists while defensive rebs and TO's determined the outcome of the game for weaker teams. In stronger vs stronger team matchups, all players from winning teams ran slower in home games than their peers in losing teams, while an opposite trend was found for away games. In stronger versus weaker team match-ups, all players from winning teams in home games covered more distance and ran faster than their peers from losing teams. In weaker versus weaker team match-ups defensive effectiveness determined the outcome of the game.	91,7
Zhang [125]	2019	Season period	30 teams with each participating in 82 games during the NBA regular season (1230 games between 25 October 2016 and 12 April 2017).	Two-point field goals made, wo-point field goals missed, three-point field goals made, three-point field goals missed, free throws made, free throws missed, offensive rebounds, defensive rebounds, assists, turnovers, steals, blocked shots, personal fouls	Secondary	Descriptive	Quantitative	Non-exp Ecological	NBA team profiles generally presented similarity, while the beginning and ending of the season showed relative dissimilarity. The dominant teams presented similar game styles. In addition, the game-play of the teams evolved into effective interactions in terms of offense and defense as the competition progressed while presenting an increased trend in the number of 3PFG's made.	91,7

Table 3. Critical appraisal (risk of bias) of scientific studies included in this systematic review, related to player constraints and contextual constraints as underpinning factors of NBA game-play performance.

FIRST AUTHOR	PURPOSE	LITERATURE	DESIGN	SAMPLE			OUTCOMES		INTERVENTION			RESULTS				CONCLUSION	TOTAL	
	Purpose	*Relevance background*	*Study design*	*Sample details*	*Sample justified*	*Informed consent*	*Outcomes reliable*	*Outcomes valid*	*Intervention details*	*Contamination avoided*	*Cointervention avoided*	*Statistical significance*	*Analysis methods*	*Clinical importance*	*Drop-outs or missing data*	*Conclusions & Implications*	*Score*	*%*
PLAYER CONSTRAINTS																		
BAKKENBULL	1	1	1	0	0	N/A	0	1	N/A	N/A	N/A	1	1	1	0	1	8/12	66,7
CHEEMA	1	1	1	1	1	N/A	1	1	N/A	N/A	N/A	1	1	1	0	1	11/12	91,7
CHENYAN	1	1	1	1	1	N/A	0	1	N/A	N/A	N/A	1	1	1	0	1	10/12	83,3
COUREL-IBÁÑEZ	1	1	1	1	1	N/A	0	1	N/A	N/A	N/A	1	1	1	0	1	10/12	83,3
CUI	1	1	1	1	1	N/A	1	1	N/A	N/A	N/A	1	1	1	0	1	11/12	91,7
ENGEL	1	1	1	1	1	N/A	1	1	N/A	N/A	N/A	1	1	1	0	1	11/12	91,7
JONES	1	1	0	1	1	N/A	0	0	N/A	N/A	N/A	1	1	1	0	1	8/12	66,7
KOSTER	1	1	1	1	1	N/A	0	1	N/A	N/A	N/A	1	1	1	0	1	10/12	83,3
KRAUS	1	1	1	1	0	N/A	0	1	N/A	N/A	N/A	1	1	1	0	1	9/12	75,0
LABY	1	1	1	1	1	1	0	1	N/A	N/A	N/A	1	1	1	1	1	12/13	92,3
MANGINE	1	1	1	1	0	N/A	0	1	N/A	N/A	N/A	1	1	1	0	1	9/12	75,0
MCLEAN	1	1	1	1	1	N/A	1	1	N/A	N/A	N/A	1	1	1	0	1	11/12	91,7
PHATAK	1	1	1	1	1	N/A	1	1	N/A	N/A	N/A	1	1	1	0	1	11/12	91,7
RANISAVLJEV	1	1	1	1	1	N/A	1	1	N/A	N/A	N/A	1	1	1	0	1	11/12	91,7
RAUCH	1	1	1	1	1	N/A	1	1	N/A	N/A	N/A	1	1	1	0	1	11/12	91,7
SAMPAIO	1	1	1	1	1	N/A	1	1	N/A	N/A	N/A	1	1	1	0	1	11/12	91,7
SEDEAUD	1	1	1	1	0	N/A	1	1	N/A	N/A	N/A	1	1	1	0	1	10/12	83,3
TERAMOTO	1	1	0	1	1	N/A	0	0	N/A	N/A	N/A	0	0	0	0	0	4/12	33,3

	CONTEXTUAL CONSTRAINTS																	
ARKES	1	1	1	1	1	N/A	0	0	N/A	N/A	N/A	1	1	1	0	1	9/12	75,0
BELK	1	1	0	1	1	N/A	1	0	N/A	N/A	N/A	1	1	1	0	1	9/12	75,0
CAO	1	1	1	1	1	N/A	1	1	N/A	N/A	N/A	1	1	1	0	0	10/12	83,3
CASALS	1	1	1	1	1	N/A	1	1	N/A	N/A	N/A	1	1	1	1	1	12/12	100
CHRISTMANN	1	1	1	1	1	N/A	1	1	N/A	N/A	N/A	1	1	1	0	1	11/12	91,7
DEHESA	1	1	1	1	1	N/A	1	1	N/A	N/A	N/A	1	1	1	0	1	11/12	91,7
ENTINE	1	0	0	0	0	N/A	0	0	N/A	N/A	N/A	1	1	1	0	0	4/12	33,3
ESTEVES	1	1	1	1	1	N/A	0	1	N/A	N/A	N/A	1	1	1	0	0	9/12	75,0
GARCÍA-MANSO	1	1	1	1	1	N/A	1	1	N/A	N/A	N/A	1	1	1	0	1	11/12	91,7
GOMEZ	1	1	1	1	1	N/A	1	1	N/A	N/A	N/A	1	1	1	0	1	11/12	91,7
GONZALEZ	1	1	1	1	1	1	1	1	N/A	N/A	N/A	1	1	1	1	1	13/13	100
GUERRA	1	0	1	1	1	N/A	1	1	N/A	N/A	N/A	1	1	1	0	1	10/12	83,3
HARRIS	1	1	1	1	1	N/A	1	1	N/A	N/A	N/A	1	1	1	0	1	11/12	91,7
HUYGHE	1	1	1	1	1	N/A	1	1	N/A	N/A	N/A	1	1	1	0	1	11/12	91,7
JONES	1	1	1	1	1	N/A	0	0	N/A	N/A	N/A	1	1	1	0	1	9/12	75,0
MATEUS	1	1	1	1	1	0	1	1	N/A	N/A	N/A	1	1	1	1	0	11/13	84,6
MIKOLAJEC	1	1	1	1	1	N/A	1	1	N/A	N/A	N/A	1	1	1	0	1	11/12	91,7
NUTTING	1	0	0	1	1	N/A	0	0	N/A	N/A	N/A	0	0	0	0	0	3/12	25,0
FLYNN-EVANS	1	1	1	1	1	N/A	1	1	N/A	N/A	N/A	1	1	1	0	1	11/12	91,7
RIBEIRO	1	1	1	1	1	N/A	1	0	N/A	N/A	N/A	1	1	1	0	1	10/12	83,3
TERAMOTO	1	1	1	1	1	N/A	1	1	N/A	N/A	N/A	1	1	1	0	1	11/12	91,7
URBAN	1	1	1	1	1	N/A	1	1	N/A	N/A	N/A	1	1	1	0	1	11/12	91,7
ZHANG	1	1	1	1	1	N/A	1	1	N/A	N/A	N/A	1	1	1	0	1	11/12	91,7
ZHANG	1	1	1	1	1	N/A	1	1	N/A	N/A	N/A	1	1	1	0	1	11/12	91,7
ZHANG	1	1	1	1	1	N/A	1	1	N/A	N/A	N/A	1	1	1	0	1	11/12	91,7

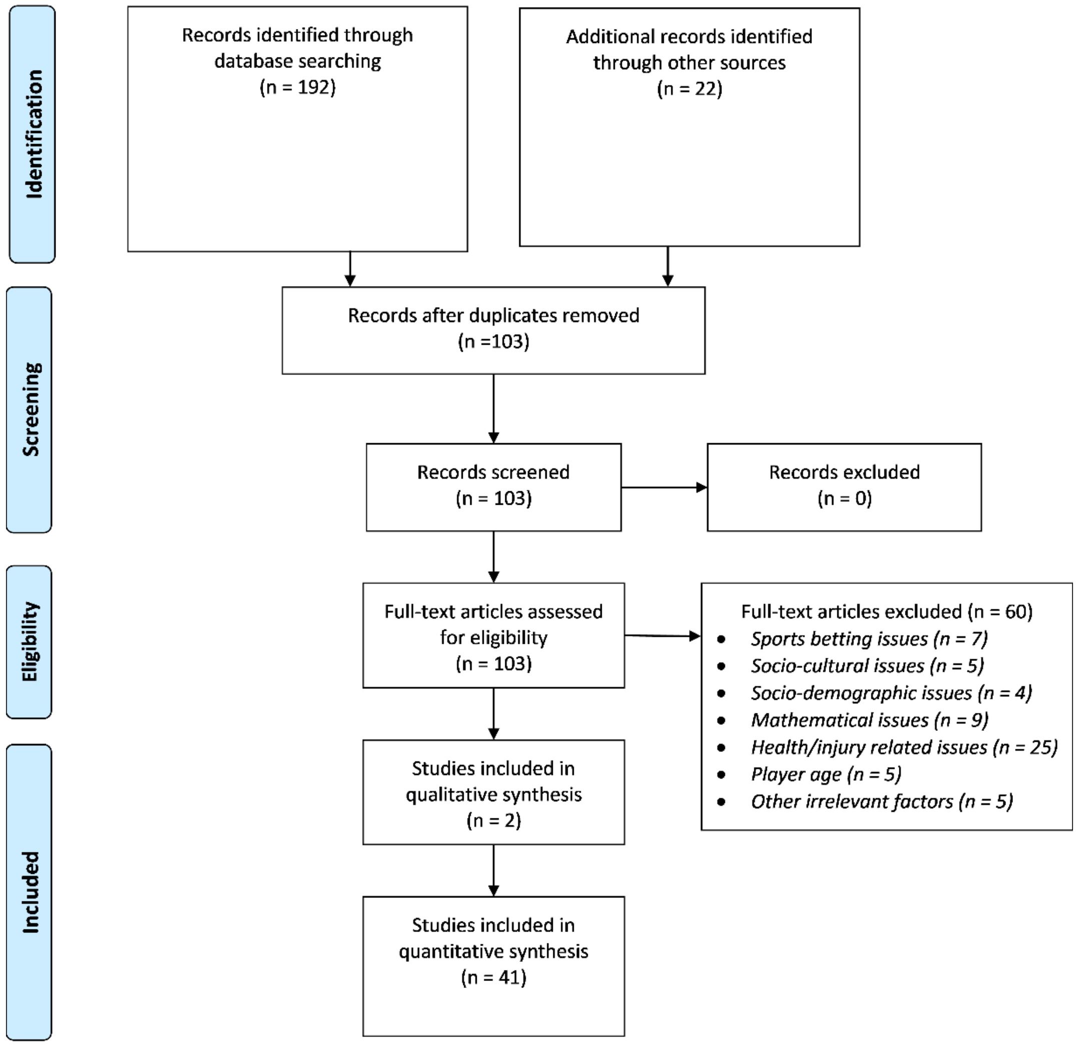

Figure 2. Flow diagram of the systematic review process.

Table 4. Overview of research trends and methodologies applied in included studies of this systematic review.

	Player constraints		Contextual constraints		Total	
	N	**%**	**N**	**%**	**N**	**%**
Research purpose						
Exploratory	6	33.3	9	36.0	15	34.9
Explanatory	1	5.6	0	0.0	1	2.3
Descriptive	11	61.1	16	64.0	27	62.8
Data type						
Secondary	13	72.2	24	96.0	37	86.0
Primary	5	27.8	1	4.0	6	14.0
Combination	0	0.0	0	0.0	0	0.0
Research design						
Experimental	0	0.0	0	0.0	0	0.0
Quasi-experimental	0	0.0	0	0.0	0	0.0
Non-experimental	18	100	25	100	43	100
Prospective Cohort	0	0.0	1	4.0	1	2.3
Retrospective Cohort	1	0.0	3	12.0	4	9.3
Case report	8	44.4	0	0.0	8	18.6
Review	1	5.6	1	4.0	2	4.6
Case-control	1	5.6	0	0.0	1	2.3
Case series	0	5.6	0	0.0	0	0.0
Ecological	4	22.1	20	80.0	24	55.8
Cross-sectional	2	11.1	0	0.0	2	4.7
Ethological	1	5.6	0	0.0	1	2.3
Research model						
Quantitative	17	94.4	24	96.0	41	95.3
Qualitative	1	5.6	1	4.0	2	4.7
Mixed-method	0	0.0	0	0.0	0	0.0
Publication year						
>2016	13	72.2	15	60.0	28	65.1
>2013	17	94.4	20	80.0	37	86.0
>2010	18	100	23	92.0	41	95.3

6.4. DISCUSSION

This manuscript used systematic review methodology (139, 153) to investigate the scientific literature (2001–2020) about two underpinning factors of NBA game-play performance (i.e. player constraints and contextual constraints). Promisingly, the body and scope of research published about this matter has significantly grown in recent years (65.1% of studies published >2016), and at first glance, the number of articles selected in this systematic review (n = 43) appears to prevail as a comprehensive resource for evidence-based extrapolations. In the following sections, we discuss the most frequently employed NBA Game-Play Performance Indicators first, followed by our main findings and insights about NBA player constraints and NBA contextual constraints, and finally, we acknowledge the main limitations and present practical suggestions for future research.

6.4.1. NBA Game-Play Performance Indicators

Ultimately, all NBA team stakeholders desire to win as many games as possible. However, utilizing the outcome of a game as the only indicator of 'game-play performance' entails two important limitations. First, this approach disregards underlying behaviors (at the intra-player, inter-player, and interteam level) that may cooperatively influence the final outcome of a game (144, 145, 149-152). Secondly, key stakeholders often prioritize long-term mission, vision, strategy, culture-building, human resources, and organizational efficiency rather than winning one single game (160, 161). Surprisingly, to the best of the authors' knowledge, the majority of researchers solely utilized outcome-based metrics of game-play performance, via open-source box-score statistics, and subsequently analyzed to which extent these box-score statistics retain power in describing, explaining or predicting future game-play performance (e.g. linear and logistic regression techniques) (Tables 3 and 5).

Table 5. Scientific evidence, practical applications, and future research lines specifically related to the computation, analysis, and interpretations of NBA game-play performance indicators.

NBA GAME-PLAY PERFORMANCE INDICATORS		
Scientific evidence	**Practical Applications**	**Future Research**
Frequently generated algorithms • GmSc[a] • WinSc[b] • Win % CG • UR[c] • TP[d] • PER • BPM • Adjusted BPM • Points Differential • Points Made • GGV • TR[f] • PIE • Win-S • HCA • FDP **Frequently employed statistical-analytical techniques** • Linear and Logistic Regression • GMLM • Functional data analysis • K-means clustering • PCA and PCR • NMMS • MBI	• Coaches, scouting personnel, and performance analysts may use previously established NBA GPP indicators to analyse and monitor NBA GPP within and across games in their respective team. • Underlying methods and variables employed to compute NBA GPP indicators should be well-understood prior to implementation.	• Which holistic measures of NBA GPP may provide a more complete picture of NBA GPP than previously established? o *Examples: Player Impact Plus Minus, CARMELO, Elo Ratings, Expected Possession Value, Wins Above Replacement, Performance Index Rating, Net Rating, Pythagorean Win Percentage, Value over Replacement Player, Win Shares, Tendex, Exposed position value, Factors determining production* • Are any alternative methods of statistical-analytical techniques superior to previously established methods to predict and/or explain NBA GPP? o *Examples: Random Forest, Adaboost, Multilayer Perceptron, Radial Basis Function Networks, Association Rule based models, Neural Networks, Decision Trees, Bayesian Networks, Support Vector Machines, Markov Modelling, Functional data analysis, Archetype Analysis and Archetypoid Analysis* • How can NBA GPP be better visualized through a multi-factorial and trans-disciplinary viewpoint, reflecting the player (organism), team (aggregation of organisms), and competition (ecosystem) behaviours?

Algorithms: [a]GmSc = *1.43934 - (.43008 x Lane agility) + (.04234 x VJ from running) - (.06169 x Bench press)*; [b]WinSc= *Points + Rebs + Steals + 0.5 Assists + 0.5 Blocks – TO's – FGA's – 0.5 Fouls – 0.5 FTA's*;[41] [c]UR= *[FGA+ (FTA×0.44) + (AST ×0.33) +TOV]×40×LP (Minutes × TP)*; [d]TP= *[FGA−ORB+TOV + (FTA×0.44)]×48 (Team Minutes × 2)*; [f]TR = 22,868 + 59,08 Win % + 0,18 Avg Fouls + 21,33 Offensive EFF + 2,46 Win% CG + 3rd Qrt PPG + 0,28 Avg Steals.
Abbreviations: *GGV = Game-to-game variability; Win-S = Win Shares; BPM = Box Plus/Minus; GPP = Game-play Performance; FT = Free Throw; FTA = Free Throw Attempt; HCA = Home Court Advantage; TR = Team Ranking; Win % CG = Win percentage in close games; GmSc = Game Score; WinSc = Win Score; UR = Usage Rate; TP = Team Pace; PER = Player Efficiency Rating; PIE = Player Impact Estimate; LP = League Pace; PCA = Principal Component Analysis; GMLM = General Mixed Linear Models; NMMS = Non-metric multidimensional scaling techniques; PCR = Principal Component Regression; FDP = Factors Determining Production; MBI = Magnitude-based inferences*

Recognizing the rapid advancements in basketball analytics (data-mining and machine learning techniques) (162), numerous sophisticated approaches and algorithms have been applied to personalize the computation of NBA game-play performance indicators to team and players preferences (Table 5) (162). Unfortunately, as a side effect, the lack of agreement and growing variety of statistical possibilities have evoked discrepancies among researchers, which in turn complicates our ability to compare and express definitive inferences between the included studies because an inherently different dependent variable was determined in an inherently different ecosystem each time. Generally, researchers favored 'offense-specific' box-score statistics and focused on the team-level of performance, neglecting 'quality of opposition' as a potential confounding variable. Therefore, the 'Factors Determining Production' metric (FDP) (163) may serve as a simple and valuable alternative, because this metric integrates non-scoring box-score statistics across more than one game, incorporates quality of opposition, allows player-level performance analysis, takes into account the final result of each game, relies on a validated statistical procedure, overcomes 'Win Score' from a theoretical viewpoint, and finally, it offers a simple linear weight formula which altogether yields a more holistic and realistic representation of how well an NBA player performs (163). By understanding the team's strength and weaknesses, as well as the key underpinning fixed and random factors associated with NBA game-play performance, sports scientists and data scientists can generate valuable exploratory, explanatory, and predictive metrics to help practitioners in data-supported decision-making (158, 162, 163). However, we encourage future researchers to adopt a structured 'applied science research framework' that sequences research incentives in a scientifically rigorous fashion (e.g. piloting toward randomized control trials), which in turn would foster better reproducibility of their research methods, designs, and results (164). Finally, future researchers may consider aggregating traditionally used boxscore statistics (technical-tactical parameters) with other components of game-play performance behavior, such as physical (165, 166), psychological (167) or injury-related determinants [49], because for coaches, managers, medics, and support staff personnel, it is a unique opportunity to improve decision-making specifically concerned with risk mitigation (e.g. mental health issues, nagging pain, energy deficiency) that could ultimately cost in team and player game-play performance.

6.4.2. NBA Player Constraints

The majority of studies related to NBA player constraints focused on functional abilities (n = 13), in which 'physical qualities' emerged as the primary topic of interest (n = 6) (Table 4). However, the proposed research questions were polarized and non-sequential (e.g. quiet-eye training, individual scoring ability, visual tracking speed, combine testing, vertical jumping mechanics, social media influences, etc.). Taking into account the large divergence of topics reported, we organized the most relevant player constraints according to (1) structural characteristics (eidonomical, anatomical) and (2) functional abilities (physical, psychological, technical-tactical) in the following sections respectively. Notably, scientific information related to the biography of NBA players (e.g. age, socio-demographic background, training history, injury history) was excluded from the scope of this systematic review.

6.4.2.1. Structural aspects – Eidonomical characteristics

Not every eidonomical factor (i.e. factors related to the external appearance of an organism) plays a substantial role in NBA game-play performance, however two discriminative, commonly discussed, and readily available eidonomical variables in NBA players are: 'height' and 'mass' (169-172). Similar to secular trends in other sports, NBA players are becoming taller and more massive over time with the rates of growth exceeding those predicted by secular trends (Table 6) (169, 172). For instance, an arm length-to-height ratio of 1.01-to-1 is considered as 'normal' in human beings (173), however NBA players generally represent an arm-to-height ratio of 1.06-to-1 (170, 172) which meets the diagnostic criteria for Marfan syndrome, a disorder of the body's connective tissues that often results in elongated limbs (173). Hence, this clearly demonstrates the extreme morphology that typifies playing at the NBA level. Although these measures can be easily obtained from a variety of sources and have been recorded as far back as records allowed (169), to date, only four studies (n = 4) that presented eidonomical characteristics of NBA players could be identified (28, 170-172). In particular, Sedeaud et al. (171) indicated that the 'optimum' wingspan and height in NBA's top scorers (3453 players; 1950–2011) was situated at 201.3 ± 6.3 cm (defined as the 'height-attractor') (171). Indeed, having a relative longer wingspan and height may increase an NBA player's ability to perform, particularly in blocking shots and taking rebounds, because his arms are longer than his direct opponents (172), and likewise, having a relative long wingspan likely makes it more difficult for the opponents to block his shot when he acquires possession of the ball (172, 174-176). Consistently, height without shoes, standing reach, weight, wingspan, and hand length, and subscale of length-size measured at the 2010– 2015 NBA combines, all had a positive medium-to-large-sized relationship ($r = 0.313–0.545$) with Defensive Box Plus/Minus in the subsequent 1–3 years of NBA competition, and length-size was identified as the main predictor of Win Shares, Box Plus/ Minus, and Value Over Replacement Player ($p \leq 0.05$) (28). However, given the difficulty in modulating a player's height, future studies may focus on eidonomical characteristics that are more tangible and modifiable in relation to NBA game play performance. For instance, whole-body and limb skinfolds, circumferences, and postural deviations have yet to be presented, and may provide unique opportunities for future research to expand upon the current body of evidence. Finally, potential higher-order interactive effects between 'coaching philosophy' (e.g. playing 'small ball', player usage, team style of play), eidonomical characteristics, and game-play performance indicators, may help us better understand how coaches can specifically compensate (smaller roster) or capitalize (taller roster) through opponent-specific in-game coaching tactics as well as technical-tactical training stratagems.

6.4.2.2. Structural aspects – Anatomical characteristics

Concerning the study of anatomical factors of NBA (i.e. factors related to the internal appearance of an organism), only two studies ($n = 2$) could be identified (177, 178) in which both studies focused on the normative values of cardiac morphology through the application of transthoracic echocardiograms. In particular, the authors consented that NBA players tend to have a significant enlargement of the left atrium and left ventricle (177, 178). Although this information enables medics and paramedics to better understand what the 'normal' and 'abnormal' heart morphology entails in NBA players, the cross-sectional design of the study prevents the possibility to draw inferences upon 'heart function' (e.g. adaptability to specific imposed stressors). Hence, repeated measurements at specific timepoint intervals (e.g. pre-post training, pre-post flights) would allow practitioners to better understand how the heart of NBA players adapt and respond to specifically imposed stressors, and subsequently, create individualized training and recovery stimuli targeting optimal athletic cardiac remodeling trends in each NBA player respectively (179, 180). For instance, Stanley et al. (179) reported that the time required for complete cardiac autonomic nervous system (ANS) recovery after a single bout of aerobic training equals 24 h following low-intensity exercise, 24–48 h following threshold-intensity exercise and at least 48 h following high-intensity exercise (179). However, ANS recovery occurs more rapidly in individuals with greater aerobic fitness, thus the importance of maintaining an adequate level of aerobic fitness in NBA players is an important discussion point, especially during potentially detrimental periods of inactivity (e.g. offseason, transition period, injury) (181, 182). Therefore, future applied sport scientists may consider examining the cardiac responses in NBA players following exercise (e.g. games, practices, workouts), travel (international and domestic flights), or following COVID-19 contraction, in order to better prepare players for the cardiorespiratory demands of the NBA ecosystem. At this point, NBA coaches and support staff may refer to the general scientific insights and proposed guidelines about cardiac parasympathetic recovery kinetics in elite athletes by Stanley et al. (179), Kovacs et al. (180) and Baggish et al. (182), while maintaining a critical viewpoint given this preliminary body of evidence has yet to be confirmed or disputed in NBA players most specifically. Finally, recognizing that cardiac musculature has been the only topic of interest thus far, atomic, cellular, and tissue-level analyses of other organs are needed in order to gain more context and insights into how training and recovery prescriptions can be individualized in NBA players to evoke optimal adaptations at the micro-level. For instance, the growing technological advancements in noninvasive neuroimaging devices (183) facilitate brain-focused research as they become more readily available in applied sciences, enabling real-time and/ or quasi real-time feedback during practices or games (183, 184). Similarly, advancements in monitoring exercise-induced adaptations at the local innate muscles, tendons, cartilage, and/or bones (e.g. tensiomyography, sonography, thermography, elastography, dynamometry, digital palpation) (185-187) may continue help researchers to collect and examine primary datasets on a wide spectrum of anatomical variables in NBA players, in a frequent and consistent manner (e.g. Achilles and Patellar tendon viscosity), hence promoting the ability to establish normative scales of 'functional status' (adaptability), rather than only 'structural status' in NBA players.

6.4.2.3. Functional aspects – Physical qualities

From a general perspective, physical qualities can be classified into five components of 'physical condition' (i.e. bio-motor abilities: speed, strength, endurance, flexibility, and coordination) (181). In the NBA, these components of physical condition are typically measured during the NBA combine (28, 170, 188). Consequently, three studies examined the physical condition of NBA players during the pre-draft combine and examined its predictive value on future on-court performance (n = 2) and/or odds of getting drafted (n = 1) (28, 170, 188). In particular, the regression model by Ranisvavlev et al. (188) demonstrated that three physical tests (i.e. lane agility, vertical jump, and bench press) explained 24.7% of future game-play performance in NBA prospects who competed at least 30 games and averaged at least 16 minutes of playing time per game in the first year of entering the NBA (188). These findings partially align with the results from principal-component regression analysis by Teramoto et al. (28) (2010– 2015 NBA combine), in which upper-body strength was determined to be the second most influential component of future NBA game-play performance, followed by their power-quickness ability (28). Finally, Cui et al. (170) examined near two decades of combine data (2000–2018) and concluded vertical jump height and reach, lane agility, and three-quarter sprint as the most determining parameters for increasing an NBA player's odds of being selected in the annual NBA draft (170). Given upper-body strength (185-lbs bench press test) seems to play a significant role in future game-play performance, but not in getting drafted, managers may reconsider their approach and take this parameter into account. However, it is important to note that the combine testing data employed by these researchers are a static reflection of the players' physical characteristics (one-time measurement), thus 'physical progress' was not considered when computing the predictive value on any dependent variable. In turn, these findings cannot be regarded as a true reflection of an NBA player's 'physical work capacity' or 'physical adaptability' to the NBA ecosystem. Hence, regular physical testing in NBA players is required in order to gain insights into how physical strengths can be maximized, and conversely, how physical shortcomings can be compensated, in an evidence-based manner. In this sense, extended partnerships with internal and external academic and commercial entities may support and enforce this process. Promisingly, four studies have already demonstrated the viability and value of adopting such collaborative efforts in repeated physical testing in NBA players, and have disseminated useful findings based on primary data that can immediately help improve the practices and decision-making of NBA strength and conditioning (SC) coaches (189-192). In particular, Rauch and colleagues (189) conducted a biomechanical assessment (utilizing force plates and 3D motion capture suits) in 178 NBA players, which resulted in a detailed report of movement mechanics applied during the 'descent phase' of three maximal-effort countermovement jumps (CMJ) (189). Given the relative large sample size and robust methodology applied in their investigation, this study offers an insightful and useful framework to help profiling NBA players according to their recurrent movement patterns and jumping styles, and in turn, allowing to construct player-centered plyometric and coordination exercises that help them better produce ground-based forces in an efficient and ergonomic manner (189). Besides jumping mechanics, two researchers focused on visuomotor skills in NBA players (190, 191). In particular, Laby (190) demonstrated that NBA players who tend to have more frequent and longer visual fixations on the rim ('quiet eye') are more likely to have a higher Three-Point Field Goal Percentage (FG3%) (190), which aligns with previous findings in basketball shooting (190). Notably, this initial report included a relative small sample size and utilized a controlled testing environment (30 practice free-throw attempts wearing eye-tracking glasses in an uncontested situation), thus future studies may consider larger sample sizes, incorporating contested and semi-contested shot situations. Ultimately, randomized controlled trials may be considered to evaluate the effects of quiet-eye training regimen to improve shooting skills in NBA players. Aside of the quiet eye in NBA players, Mangine et al. (191) demonstrated that 'visual tracking speed' is positively related with assists, steals, and assist-to-turnover ratio in NBA players (191). Unfortunately, in this study, visual tracking speed was measured only once in also a relative small sample size (n = 12), thus future studies are required on this matter to draw more conclusive inferences across players and teams. Finally, to the best of the authors' knowledge, Gonzalez et al. (192) were the only staff members of an NBA team that followed a cohort of NBA players during the course of a season and subsequently published their findings on the 'physical progress' of their players (i.e. the 2012–2013 Orlando Magic team) (192). This baseline report indicated that playing time (average of 27.8 ± 6.9 minutes per game compared to 11.3 ± 7.0 minutes per game) likely promotes the sustainability of vertical jump power (5 consecutive countermovement jumps), reaction time (20-seconds reaction time), and alertness in NBA players (192). Nevertheless, this single study, involved a relative small sample size (7 players, tested twice), and previous playing experience and age were not accounted as potential co-factors in their analysis. In turn, this limits our ability to draw conclusive inferences across players and teams, as well as determine which particular factors (e.g. playing experience, coaching philosophy, player usage, etc.) and mechanisms (e.g. training and recovery regimen) were most relevant to maintaining the physical ability of their players throughout the season. Therefore, follow-up studies encompassing a broader context, larger sample size, and more frequent testing administrations is required.

6.4.2.4. Functional aspects – Psychological qualities

Psychological aspects Based upon all studies related to psychological factors of NBA players included in this systematic review (n = 4), it appears that all researchers focused on 'psycho-social' factors. In particular, 'touching behavior among teammates' (n = 1) (193) and 'social media usage' (n = 3) (194-196). Specifically, Kraus et al. (193) were able to propose 12 distinct behaviors of 'teammate touching' (e.g. fist bumps) that provided predictive value for future NBA game-play performance, even after accounting for player status, preseason expectations, and early season performance (2008–2009) (193). However, other contextual factors (e.g. cumulative fatigue, age, playing experience, personality type) and potential variations among different events (e.g. team practices vs games) were not considered as potential confounding variables. Recognizing the COVID-19 pandemic has enforced social distancing regulations (i.e. restricting or reducing tactile communication for player health and societal safety purposes) (197) resulting into well-documented mental health issues across the elite sport and public landscape (33, 197-201), future research aimed at investigating tactile communication and psychological function of players in the NBA's postCOVID-19 era is an important research line to consider. Besides touching behavior, the remaining researchers focused on social media behavior in NBA players and its relation to game-play performance (n = 3) and were all published within the last five year (194-196). Considering a total of 330 million active Twitter users (San Francisco, CA, United States) were reported in 2019 (202), while 79% of NBA players had a Twitter account between 2012 and 2015 (194, 195), the social media space has clearly grown into an inseparable part of the modern NBA player's lifestyle. In response, sentiment analyses (i.e. text and emoticon tagging and labeling of Tweets according to individual mood state) has become a research strategy to evaluate psychological status in NBA player (194, 195). For instance, Xu et al. (195) defined NBA players' pre-game 'mood states' (scale from −5 to +5) of 353 NBA players (2012–2013 season), and in turn, investigated how these mood states impacted future NBA game-play performance (195). Hence, this data-mining technique has the possibility to be continuously implemented by NBA organizations to support their game-day player assessments, administrative and operational decision-making, and proactively educate players on the potential negative effects of social media mis-usage or over-usage (196). Interestingly, social media behavior may not only relate to NBA players' mood states, but also their own team's chemistry and performance (196). For instance, online teammate Twitter unfollowing behavior of high-status players (e.g. NBA all-stars) has demonstrated to be significantly associated with underperformance of their respective team (196), which aligns with research on status inconsistency, suggesting that individuals deemphasize their group affiliation when it jeopardizes their individual status (196). Interestingly, this finding also aligns with recent anecdotal reports, such as the 2019–2020 NBA's Most Valuable Player who unfollowed all of his teammates on Instagram (Menlo Park, CA, United States) after his team was eliminated during the 2019–2020 playoffs. Nevertheless, future research is needed to make it possible for cause-effect inferences as well as enable deeper insights into how these specific psycho-social behaviors on social media channels can be properly addressed to improve the overall team chemistry and performance in their team respectively. Besides 'Tweeting content' and 'following of teammates', the 'timing' of social media behavior has been examined by one research group, indicating that Tweeting between 11:00 PM and 7:00 AM is negatively associated with next-day game-play performance in 122 NBA players (2009–2016) as represented by fewer points scored, fewer rebounds, and less time played (196). Although this study did not directly address the question of whether late-night and mid-night social media usage affects sleep quality or sleep quantity, a recent meta-analysis demonstrates that time spent watching mobile devices at night is associated with inadequate sleep duration, poor sleep quality, and excessive daytime sleepiness among youth (203), thus future studies have an opportunity to examine to what extent late-night tweeting behavior in NBA players impact sleep quality and/or quantity. In turn, this may help NBA coaches and support staff personnel to make proactive player-centered efforts to mitigate the associated risk that may come with uncontrolled, mis-used, or over-used social media activities. Additionally, validated comprehensive psychological assessment tools recently developed by the International Olympic Committee (Figure 3) (204) may serve as a starting point to identifying and stratifying (modifiable and non-modifiable) psycho-sociological risk factors in NBA players.

6.4.2.5. Functional aspects: Technical and tactical skills

NBA coaches routinely teach technical and tactical skills to enhance player and team success. Hence, analyzing tactical and technical skills according to various levels of play (e.g. all-stars vs non all-stars, professional vs amateur, etc.) can help determine which skills are most important for success at the NBA level. Given NBA team salaries are associated with offensive quality and not defensive quality, and offensive quality is correlated with team winning percentage (205, 206), it is non-surprising that all studies included in this systematic review concentrated on offensive technical-tactical factors of NBA game-play performance (n = 3). In particular, Sampaio and colleagues reported that all-star players performed better in points within 12 ft (366 cm) away from the basket compared to non-all-star players (31). However, it is important to acknowledge that all-star players typically play more minutes accumulated over the season compared to non-all-star players, thus limiting our ability to determine whether the differences were attributed to playing time or inherent motor ability (207). With specific attention to free-throw (FT) shooting, Phatak et al. (208) demonstrated that NBA players may benefit from the 'calibration effect' (i.e. the success rate of the second FT attempt is typically greater compared to the first FT, and for triple FT's, the success rate increased with each successive FT) (208). Given the dataset used within this study included more than 610,000 FT's from over ten NBA seasons (208), the 'calibration effect' during FT shooting is a well-documented phenomenon in the NBA. However, the behavior between two subsequent FT's was not described, nor examined. Therefore, future studies may investigate behavioral indicators (e.g. ball tracking systems, change of position, body language or interaction with other players) in order to gain a better understanding of how and why this calibration effect takes place, as well as how it can be entrained to promote successful acquisition of this skill. From an offense tactical skill standpoint, only one study could be identified. In particular, Courel-Ibanez et al. (209) described the inside-outside configurations according to playing position in NBA Playoff contenders, and highlighted the value of employing concurrent strong side (pick and roll, pass and cut) actions with weak side (out of ball screen, dive cut) actions to increase scoring options when using the inside pass (209). Consequently, these preliminary findings may support coaches in designing player development plans that align with the offensive collective dynamics that can be expected during NBA playoff games. Nevertheless, given only 8 teams in a total of 25 NBA Playoff games (2011) were examined in this initial sample, the final outcomes may not automatically replicate to other team settings and coaching philosophies. Hence, future studies examining larger sample sizes, while factoring in the defensive team tactics that are specifically constructed to disrupt the offensive team tactics, would likely provide more context and insights in the future.

PLAYER CONSTRAINTS OF NBA GAME-PLAY PERFORMANCE			
	Scientific Evidence	**Practical Applications**	**Future Research**
STRUCTURAL – **Eidonomical**	• ↗ 14.2 kg of Avg M from 1950 to 2011. [58] • Avg A-to-H ratio of 1.06-to-1.59 • Median H of 204 cm, Avg H of 198.62 cm, Avg WS of 209.57 cm, Avg SR of 263.24 cm, Avg HL of 22.31 cm, Avg HS of 23.93 cm. [59] • Avg H of top scorers = 201.3 ± 6.3 cm (1950-2011). [59] • HWS, SR, MM, WS, HL, and L-S at 2010-2015 NBA combines is associated with GPP in <3 subsequent years. [60] • L-S predicts BPM and VORP. [58]	• Managers may use historical data regarding secular in NBA players' Eidonomical characteristics as a benchmark for talent identification purposes. • Combining anthropometric and biomechanical testing protocols can help coaches evaluate, profile, and compare players to optimize the safety and efficiency of inherited movement mechanics.	• What are the characteristics of whole-body and limb skinfolds, circumferences, length ratios, and postural deviations in NBA players? • Does coaching philosophy (e.g., playing "small ball") compensate for a lack of high-eidonomical profile players?
STRUCTURAL – **Anatomical**	• LA and LV hypertrophy can be expected. [65,66] • Heart ventricles augmented normally with exercise. [65,66]	• Cardiorespiratory profiling is an important task for NBA support staff given the importance of aerobic condition, especially during and following the COVID-19 pandemic. [90] • At present, scientific reports on EI cardiac parasympathetic recovery kinetics in elite athletes [67,68] may help NBA coaches design appropriate training stimuli according to players' cardiac adaptability to EI demands.	• What is the cardiac remodelling process in NBA players following training, games, and/or air travel? • How do NBA players (mal)adapt to the demands of NBA games at the atomic, cellular, and tissue level? *E.g., local innate muscles, tendons, cartilage, and bones* • How does the cerebellum of NBA players respond to visual, auditory, and somatosensory (tactile) stimulation?
FUNCTIONAL – **Physical**	• Bench press and PQA ↗ → rebs and blocks ↗. [61,77] • Lane agility, VJR, and bench press explained 24.7% of variance in NBA GPP. [77] • ↗ VJHR, ↗ lane agility, and ↗ ¾ sprint → ↗ odds of being drafted (2000-2018). [57] • ↗ "quiet eye" = ↙ USG%, ↙ ORB% and ↗ FG3%. [79] • ↗ VTS → ↗ assists , ↗ steals and ↗ A-to-T ratio. [80] • Overall PT ↗ → likely ↗ ability to stustain of VJP. [81]	• The protocol of Rauch et al. provides a viable and valuable blueprint to standardize and implement movement profiling in NBA players. • Individualized training and recovery prescriptions for players receiving less overall PT is warranted to avoid potential detriments in LBSP, RT, VJP, alertness, and subjective feeling of fatigue accumulating during the regular season.	• What is the difference in VTS between rookies and veterans? • How do baseline markers of 'fitness' fluctuate during the season and how does season period, playing experience, position, and playing time interact with these variances? • How does the "quiet eye" differ between contested, semi-contested, and non-contested shot situations, and how does this impact scoring?
FUNCTIONAL – **Psychological**	• Tactical communication in the beginning of the season ↗ → ↗ NBA GPP later in the season (2008-2009 season). [82] • 79% of players used Twitter (2012 till 2015). [83,84] • Twitter "teammate following behavior" of NBA star players impacts their team GPP.85 • Tweeting between 11:00 PM and 7:00 AM = ↙ next-day GPP, in particular ↙ points, ↙ rebounds, ↙ PT. [85]	• Practice scenarios that stimulate tactile communication and behavior is encouraged, especially in the first phase of the season. • SMHAT-1 and SMHRT-1 may help design individual mental preparedness profiles. [93] • Regular implementation of player-centred educational programs to help support a performance-friendly, sustainable, and healthy approach to using social media is warranted.	• What is the impact of the "NBA Bubble" on the psycho-social behaviour of NBA players, factoriong in their age, playing experience, and personality type? • What is the impact of social media based mood state scores on future team and player NBA GPP? • What is the most common personality types in successful or high-achieving NBA players?

Figure 3. Scientific evidence, practical applications, and future research lines specifically related to player constraints of NBA game-play performance.

6.4.3. NBA Contextual Constraints

Taking into account the individual strengths and limitations of each included study, this section provides a discussion on the following topics respectively: rest days, travel, game location, game period, game status, season period, difference of team quality, momentum effects, playing time, and finally, interactive effects. Notably, socio-cultural and socio-demographic constraints, including family support, demographic backgrounds, peer pressure, as well as public norms and expectations, were not included in the scope of this systematic review.

6.4.3.1. Rest days

All researchers (n = 4) consented that the number of rest days leading up to a game is positively correlated with an NBA team's ability to win that game (29, 104, 210, 211). In particular, when additional rest days were offered between playoff series, a two-fold increase in the odds of winning the second game in the next NBA playoff series (1984–2018 Finals) has been reported (210). Similarly, during the regular season, Esteves et al. (211) revealed that having at least one day of rest between games increased the likelihood of winning the next regular season game by 37.6% (211). Interestingly, when coaches voluntarily decided to rest players, a potential 'rust' phenomenon may emerge (i.e. trade-off effect on individual fitness and/or performance level) once more rest days are offered than what their players actually need in order to recover from previous stressors (29). In particular, coaches who rested players for preventive reasons lasting five-to-nine games during the regular season (811 players; 2005–2015) did not display any benefits (i.e. points per game, assists per game, player efficiency rating, true shooting percentage, blocks, steals, or number of playoff games missed because of injury) over coaches who rested players for less than five games (29). Hence, a quarter-by-quarter minute-restriction plan during games to avoid full 'under-loading' or 'detraining status' may likely present a better alternative than eliminating game-play opportunities entirely. Although evidence supports the positive relationship between rest days and subsequent game-play performance, future research is needed to disseminate more conclusive findings on this subject matter, especially regarding which in-game and between-game resting strategies likely evoke the greatest benefit on subsequent game-play performance in teams and players individually.

6.4.3.2. Travel

In the NBA, air travel demands remain high due to the obligatory geographical span (four different time zones) and time spent above 30,000 ft (22). Consequently, air travel requirements have been a concern for NBA coaches, players, and owners, given research in team sports have demonstrated short-haul flights (e.g. domestic ≤6 h flights) increase injury risk and impede performance (22, 27, 85, 87, 89). Surprisingly, only three studies (n = 3) specifically focused on the role of air travel on NBA game-play performance (22, 212, 213). In particular, researchers generally consented that traveling in westward direction is likely more demanding than traveling in eastward direction, as demonstrated by points scored and winning percentage at the NBA team level (22), which also aligns with previous reports in the National Football League and the National Hockey League (22). Westward travel is likely more difficult since alertness and focus tends to peak in the late afternoon and players traveling from west to east tend to play games closer to their circadian peaks given most NBA games are played at night (22). Subsequently, NBA teams should carefully and proactively map out their travel schedule when flying westward at any point of the season or playoffs and recognize that NBA players are typically handling night games better than day games (22, 213). Noteworthy, the abovementioned findings were derived from observational-descriptive research studies, thus clearly defined protocols that would help mitigate potential negative consequences associated with air travel demands in NBA players remains unknown. Subsequently, the lack of longitudinal-interventional research on this topic forces NBA practitioners to employ cross-contextual inferences based on other elite sport populations that may not automatically apply to the NBA. Therefore, pre and post flight data collection involving physiological, psychological, and environmental parameters, through clinically validated self-reported questionnaires (214, 215) and user-friendly mobile applications (216) would allow coaches and support staff to create individual player profiles according to their 'travel-adaptability' against various stressors (e.g. temperature, travel distance, travel duration, travel direction, altitude, humidity, and ultraviolet radiation) that are typical for the NBA ecosystem (22, 214-216). In this sense, the 2020 NBA playoffs, which began on 17 August 2020, offers an exceptional opportunity for comparative research purposes, because this new competition format eliminated short and long haul travel entirely due to the COVID-19 pandemic (201, 213).

6.4.3.3. Game location

In alignment with previous studies in professional basketball, the home court advantage in the NBA is a well-documented phenomenon (n = 4), verified in over 7000 games spanning across 14 seasons (2004–2018) altogether (104, 217-221). However, to what extent lack of rest, travel duration and direction, time zone differential, stadium attendance, altitude, and team market size influenced these home court advantages remains ambiguous territory (103, 104, 217-219). Thus, future studies have an opportunity to unravel these potential co-factors in order to help coaches better understand how the home court advantage can be modulated in their favor. Interestingly, one particular study examined the home court advantage from a 'microscopic dynamics' perspective (221). In particular Gomez et al. [109] evaluated the impact of game location (alongside quality of opponent and starting quarter score) on final point differential in 48 NBA close games (below 10 points of difference) during the 2013–2014 season (221). More specifically, the authors distinguished these games according to three different game types: (1) equal scoring trend between teams; equal outcome at the end of the 3rd and 4th quarter (n = 29) (type 1), (2) home team positive trend: home team winning by less than 10 points or even outcome at the end of the 3rd quarter and winning at the end of the 4th quarter (n = 10) (type 2), and (3) away team positive trend: away team winning by less than 10 points or even outcome at the end of the 3rd quarter and winning at the end of the 4th quarter (n = 9) (type 3). Through the assurance of good intra-observer reliability (values greater than .86) and inter-observer reliability (values greater than .81) by the authors (graduated in Sports Sciences and certified as basketball coaches with a minimum of ten years of experience), they revealed that game location had the greatest impact on NBA game-play performance during type 2 ($p = 0.007$) and type 3 ($p = 0.001$) games (221). Hence, these findings can help support NBA coaches to better understand which type of games are most susceptible to impact their team's game-play performance due to changing locations, and conversely, which variables of game-play performance should be prioritized in this particular case (Table 7). Finally, even though the home court advantage has been examined at the macro level predominantly (team analyses), future studies may consider investigations at the micro level (player analyses) given this would allow NBA coaches and support staff personnel to generate player-centered incentives, especially for players who are most susceptible to rapidly changing game locations during the season.

6.4.3.4. Game period

In general, game period can be defined as: the beginning (first quarter), middle (second and third quarter), and end (4th quarter and last 5 minutes) of an NBA game (144). Among these periods, the final moment has been the most popular timeframe of investigation (222-224). For instance, shorter possessions (224), fewer number of passes and participating players (223), higher number of fouls (223), and higher game stops and number of changes (223) can be expected during the final moments of an NBA game. More specifically, one-on-one isolation plays tend to generate the least team possessions, while inbound and complex team plays tends to generate the most team possessions (224), thus advocating collective-driven tactics as a profitable strategy during 'money time' (223, 224). Nevertheless, future studies are needed to examine how these findings are influenced by cofactors, such as: player status (e.g. all-star vs non all-star players), playing time, player usage, game location, fan attendance, and whether or not previous trends during the regular season may or may not transcend to post-season games. Finally, preliminary evidence in youth basketball players have indicated that playing after prolonged periods of sitting (up to 20 minutes) decreased their subsequent jumping height during simulated basketball games (225), thus the first moments following 'tip-off' as well as the 'halftime break' may add broader insights into how game periods influence game-play performance in NBA players and teams (226).

6.4.3.5. Game status

Game status Game status can be defined as: the time a specific behavior is recorded in which an NBA team or player is losing, winning, or drawing (144). Hence, game status can be viewed as a measure of 'interim performance', thus potentially impacting the effort made by a player (144, 158). For instance, during a specific moment of a positive point differential, teams may change their tactics, or players may adopt a ball retention strategy, slowing down the game, resulting in lower running speeds (144). Surprisingly, Guerra et al. (227) were the only researchers (n = 1) to explore this underpinning factor of game-play performance in the NBA setting. In particular, they were able to identify in-game 'tipping points' (i.e. the non-equilibrium state when the slightest change causes a significant difference in the game score) (Figure 4) (227). Although these tipping points may help coaches understand what particular moments of the game are most critical in the performance of their team, the underlying tactics (e.g. time-outs) employed to counteract (nearby) tipping points is yet to be explored. Hence, it is important to recognize that tipping points may result from numerous underlying physiological and psychological processes (228), shaped by individual (e.g. personality type) and situational forces (e.g. referee disagreements) (228), which are yet to be discovered in the NBA. Hence, with only one study to date on this matter, follow-up studies are required to formulate more clear and conclusive inferences.

6.4.3.6. Season period

Previous evidence suggests that key moments arise during the NBA season in which game-play performance significantly changes at the individual and/or team level (144, 158). In this sense, the comparison between regular season games and playoff games have been the most popular type of investigation (n = 2) (144, 205, 225). Unfortunately, all researchers solely focused on outcome-based metrics (box-score statistics), thus neglecting potential underlying mechanisms for how seasonal variations influenced variations in NBA game-play performance (205, 229), hence potential biases in outcomes may exist, and thus conclusive inferences remain limited at this moment. Finally, considering that the timeframe of the regular season and playoffs are inherently imbalanced (e.g. 5.5 months versus 2 months), researchers may instead consider adopting a split-series comparison of four different periods (i.e. 21, 20, 20, and 21 games) across the season (230). Consequently, this approach would help us better understand the impact of season period on NBA game-play performance across consistent time intervals throughout the year, hence providing a better reference point for annual planning and periodization strategies respectively.

6.4.3.7. Difference of team quality

Some teams are inherently better than others, and has been frequently defined by the team's 'winning percentage' or 'team ranking at the end of the season' [39]. Four studies (n = 4) aimed to better understand the quantification of an NBA team's inherent quality compared to other teams (206, 231-233). Interestingly, researchers were mainly concerned with the following parameters: playing experience, height, weight, and traditional box-score statistics, disregarding potential internal factors (e.g. physiological and psychological parameters). Nevertheless, irrespective of the internal factors, regression techniques enabled researchers to explain 86% of variances in team quality by only six key variables derived from box-score statistics (Figure 4) (206). Conversely, Zhang et al. (233) determined the 'difference of NBA team quality' based on other box-score statistics, and mapped out the most important variables according to various possible confrontation types (i.e. strong vs weak, strong vs strong, weak vs weak teams) (233). Although these preliminary findings can help support coaches to highlight specific technical-tactical variables that best explain the 'difference of quality of their team', the ability to determine how these outcomes have accumulated and emerged over time remains limited, thus restricting our ability to modulate these outcomes accordingly (Figure 4). Therefore, it is recommended that future researchers take into account behavioral parameters (e.g. coaching philosophy, personality type), combine qualitative and quantitative datasets, and regularly repeat their analyses throughout the season, in order to gain a picture of when and how 'difference of team quality' can be built and/or maintained.

6.4.3.8. Momentum effects

The belief of a 'momentum effect' in professional team sports is evident and can be defined as: a team gaining a higher chance of winning in a game because they had been playing well in the few games leading up to that game (234). However, to the best of the authors' knowledge, only one study focused on the investigation of the momentum effect in the NBA in particular (234), indicating that winning in the past 5 games significantly increases the odds of winning the subsequent game, even after controlling for difference of team quality (234). Although these early findings tend to align with the literature on momentum effects in elite sports, future studies are warranted to control for other potential confounding variables (e.g. abrupt changes in team's composition due to injury or trades, game location, season period, leadership and personality traits, coaches' tactical strategies, etc.). Finally, as highlighted by Crust et al. (235), future researchers may consider focusing on the players' personal experiences and employing qualitative data collection methods (235) in order to help NBA coaches and support staff personnel develop a clearer conceptualization of momentum effects from a cognitive and behavioral-change viewpoint, as well as, paint a more a holistic picture about the impact of momentum effects on subsequent NBA game-play performance at the individual level (235).

6.4.3.9. Playing time

To the best of the authors knowledge, only two studies (n = 2) were concerned with examining NBA players' playing time and their subsequent ability to perform during games (192, 207). In particular, Mateus et al. (207) utilized a statistical clustering technique to categorize players according to 'short playing minutes' (11.5 ± 5.3 minutes), 'medium playing minutes' (25.2 ± 3.5 minutes), and 'long playing minutes' (36.8 ± 3.9 minutes), demonstrating that NBA players who played more overall minutes during the 2012–2013 season are less likely to present game-to-game variances in performance (i.e. boxscore statistics), mainly in offensive statistics (207). On the other hand, Gonzalez et al. (192) compared starters (27.8 ± 6.9 minutes per game) with nonstarters (11.3 ± 7.0 minutes per game), and used a much smaller sample size (7 players, 2 moments of observation) than Mateus et al. (474 players, 712 games played, 14,150 performance records). Nevertheless, to the best of the authors' knowledge, to date, Gonzalez et al. (192) were the first and only researchers to quantify the impact of NBA players' playing time on 'physical performance' rather than the traditionally used box-score statistics to evaluate game-play performance (192). In particular, their findings implied that NBA players who gained more overall playing time during the season are better equipped to maintain and/or enhance their vertical jump power, reaction time, energy, focus, and control perceptual fatigue throughout the regular season (192). At first glance, these findings tend to align with trends reported in similar investigations completed in European basketball (236). Nevertheless, it is important to acknowledge that the underlying mechanisms of how and why less playing time plays a role in an NBA player's ability to maintain their fitness levels over the course of the season is yet to be explored. Interestingly, seasonal mood fluctuations (perceptual fatigue and tension related) has been displayed in other professional basketball competitions (237), hence advocating for including psychological measures when evaluating the impact of playing time on gameplay performance in NBA players. Recognizing that inter-personal relationships between players, coaches, and support staff members play an integral part and important catalyst in driving motivation and mental well-being in professional basketball players (237), future studies may also consider investigating when, how, and why training, recovery, and mindfulness strategies specifically aimed at compensating a dearth of playing time can accommodate NBA players to stay physically and mentally ready for game-play demands throughout the season.

6.4.3.10. Interactive effects

With the exception of Casals et al. (158), to the best of the authors' knowledge, possible higher-order interactive effects (e.g. the role of momentum effects on playing time and playing time on home court advantage) has been frequently neglected. As previously reported, scientific research practices in elite sports are generally dominated by quantitative types of research (63.3%), while qualitative (36.2%), and mixed-method type of research (0.5%) are scarce (221 articles reviewed) (238), thus aligning with the outcomes reported in this systematic review. Given the scarcity of published mixed-model and mixed-method research in the sciences related to NBA game-play performance analysis, adopting a pragmatic, pluralistic, sequential, and multiphase research philosophy in future investigations is recommended (239, 240) while simultaneously respecting the design, analytical, and statistical procedures that are required to implement a robust mixed-method and mixed-model research project (239-242).

CONTEXTUAL CONSTRAINTS OF NBA GAME-PLAY PERFORMANCE	Scientific Evidence	Practical Applications	Future Research
Rest Days	• Rest days between playoff series → ↗ chance of winning Game 2 in subsequent series. [100] • For each day of rest between games → winning odds ↗ by 37.6%. [101] • NBA GPP when resting players 5-9 days ≈ resting players <5 days. [102]	• To avoid potential "rust" effects, coaches may consider quarter-by-quarter minute-restriction plans to promote recovery in key players, rather than completely eliminating them from games.	• How does active recovery days differ from passive recovery days with regards to subsequent NBA GPP? • How does gradual reduction, exponential reduction, and steady reduction of PT influence future NBA GPP?
Travel	• Following westward travel → ↙ chance of winning, especially in evening games. [1,108,109]	• Adjust to the timing, duration, and intensity of activities before, during, and following short and long haul flights, in order to support optimal hormonal regulation and secretion before, at, and following game tip-off time.	• How does the complete elimination of air travel during the "NBA Bubble" relate to retrospective and prospective measures of NBA GPP? • How does air travel impact sleep, mental health, energy, focus, alertness, and training attractiveness in NBA players in the short term (acute) and long term (chronic)?

Game Location	• The HCA is a well-documented phenomenon in the NBA.41,104,115–[117]
	• Particularly in <u>type 2</u> game scenarios:
	  ○ HT's = ↗ BPS and ↗ 2PFGIO. [117]
	  ○ AT's = ↗ 3PFGCR and ↗ defensive rebs. [117]
	• Particularly in <u>type 3</u> game scenarios:
	  ○ HT's = ↗ BPS, penetrations and 2 or >2 on the shooter. [117]
	  ○ AT's = ↗ missed FT's. [117]
		• Testing and profiling players according to their level of "travel-adaptability" may help detect players who are most susceptible to changing environments.
		• The technical-tactical factors established as distinctive between HT's and AT's can be mapped out against game type, and subsequently prioritized in training when aiming to improve T-POS effectiveness. [117]
			• What are the differences in "microscopic" dynamics between AT's and HT's?
			• What individual factors magnify or alleviate the HCA in NBA players respectively?
			• How does lack of rest, long road trips, stadium attendance, altitude, and team market size influence team-level and player-level HCA?

Game Period	• Final seconds of CG → ↙ 5-10% points, [118] and ↙ possessions (especially by the disadvantage team), ↙ passes, ↙ fouls, ↗ game stops and ↗ number of changes. [120] • Final seconds of CG → 1v1 play = ↙ T-POS, while transition, inbound and complex team plays = ↗ T-POS. [119]	• Coaches may benefit from creating "late-game" practice scenarios in which transition, inbound, and complex team plays are enforced. • Coaches may benefit from late-game practice scenarios in which shooting accuracy in pressured situations are challenged.	• What are the differences in microscopic dynamics between the AT and HT during the 1st quarter? • What is the impact of team playing style in the 1st quarter on subsequent team playing style in the 4th quarter, as well as the outcome, and overall GPP of the game?

Game Status	• Most critical moments during NBA games: [123]
	  ○ *≤10 points*
	  ○ *10-28 points*
	  ○ *≥28 points*
		• Coaches may strategically construct their tactics (e.g., time-outs) based upon previously established game tipping points.	• What are the effects of technical fouls, ejections, TO's, slam dunks, buzzer beaters, and/or alley-oops on the microscopic dynamics of NBA games?

Season Period	• 3PT FGM ↗ as the season evolves. [125] • Importance of defense → ↗ during playoffs. [126] • ↙ TO's → ↗ winning during the regular season. [126] • ↗ Rebs → ↗ winning during Conference Finals when facing teams with similar shooting efficiency and TO rates. [126]	• Coaches may benefit from focusing on defensive tactics during the playoffs, limit TO's during the season, and focus on rebounding skills during the Conference Finals, especially when the opponent has similar shooting efficiency and TO rates.	• What are the most important factors of NBA winning games during the first 21 games, second 20, third 20, and final 21 games of the season, taking into account technical, tactical, mental, and physical parameters?

Figure 4. Scientific evidence, practical applications, and future research lines specifically related to the contextual constraints of NBA game-play performance.

6.4.4. Limitations

First, although the research articles included in this systematic review (n = 43) represented a substantial source of information, we recommend the readers to take caution in externalizing these findings given the research questions and hypotheses were largely heterogeneous (i.e. all studies aimed at answering a distinctive question rather than sequentially following up on preliminary evidence). Hence, the totality of information tends to lack consistency in research interests, terminology, and methodology, which in turn, may jeopardize the reproducibility of its findings to the real-world milieu. Second, the vast majority of studies followed an ecological study design, examining multiple NBA teams at once and altogether, however none of these articles were encompassed recent competitions (>2017), thus inferences on player and team specific inner variables with similar conditions for the outer variables in the modern NBA competition cannot be automatically assumed. Third, the procedures in which 'indicators' of game-play performance were determined by the authors were non-uniform (e.g. margin of victory in one single game vs. team ranking at the end of the regular season), thus clarity and uniformity in determining what 'NBA game-play performance' represents from a holistic and multi-disciplinary viewpoint, is an important challenge facing upon future sport scientists and performance analysts. In general, the selected indicators of NBA game-play performance were outcome-driven, thus lacking the ability to draw inferences on how teams and/or players may change their behaviors during the course of a game to ultimately arrive at successful game-play outcomes. Therefore, future studies concerned with a behavioral-driven approach to examining NBA game-play performance in-game and end-game statistics is warranted. As an illustration, by factoring in player-specific covariates (position, usage rate, and average minutes played per game), Page et al. (243) were able to apply a hierarchical Gaussian regression process to compute critical NBA game-play performance indicators that were more comprehensive in nature than previously proposed (243). Fourth, the vast majority of findings were descriptive-observational designs (n = 27; 62.8%), hence lacking the ability to draw hypotheses generating (exploratory), causal-comparative (explanatory), predictive, and/or prescriptive inferences. Consequently, the absence of interventional research inhibited the ability to draw causal-comparative conclusions between independent and dependent variables due to the lack of manipulation, control, and randomization of subjects, and may complicate future research due to potential intra and inter-observer biases in observations, recording, and interpreting previously reported information. Fifth, near all studies neglected reporting of subject drop-outs and/or missing values, which tends to be a common problem across social sciences research (244). Therefore, the authors recommend to consider and address missing values at each stage of the research process (design, data collection, analysis, and reporting) to prevent missing data, define the estimand, and specify primary and sensitivity analyses (245). Sixth, because linear models (e.g. linear and logistic regression) are relatively simple to execute, it is not surprising that the majority of researchers have favored this particular method of statistical analysis to try answering various proposed research questions. Unfortunately, this type of analysis may overlook random effects by treating each variable as a 'fixed effect', thus undervaluing the importance of variability in NBA basketball and the inherent complexity of team-sport research in general [39]. Therefore, if and when variances of errors in the datasets are normally distributed, mixed model research (e.g. Generalized Linear Mixed Model) may serve as an adequate and parsimonious alternative to investigating relationships among key underpinning factors inside complex systems such as NBA games (139, 144-146, 158). Seventh, near all researchers analyzed secondary data sources. Unfortunately, this type of data limits the researchers' ability to gain control over potential risks of biases during the data collection process (observers' interobserver and intra-observer reliability), as well as establish targeted research questions to elicit the data that will help them with their specific purpose of the study, gain ownership of on-demand data, and generate real-time and/or quasi-real-time feedback to help players and coaches better adapt the contemporary demands within the course of NBA games (246). Therefore, we encourage future researchers and practitioners to collaborate with both internal and external parties (e.g. academic institutes, player agencies, data science consultants, sports technology companies, data protection officers, league executives, national and international Olympic committees, etc.) to facilitate the storage, modeling, aggregation, and replication of various data sources. Considering the main limitations described above, the authors encourage future researchers to embrace a stepwise framework, such as the Applied Research Model for Sport Sciences (ARMSS) conceptualized by Bishop et al. (164) because it sequentially integrates descriptive, exploratory, and explanatory study designs, and links them altogether in a progressive manner (8-step process) (164). In turn, this approach would foster the reproducibility and transferability of scientific findings to the real-word NBA settings (i.e., dynamic correspondence). Recognizing the complexity of NBA games and lack of consistency in research over the past two decades, we also encourage the full integration of NBA coaching staffs and key decision-makers to support new research thrusts, facilitate inter-staff and cross-disciplinary discussions, to create worthwhile research lines that would help build theoretical and practical grounds for future sport scientists (164, 247, 248). Consequently, this joint approach to more applied research would foster new insights that may not only be 'statistically significant', but perhaps more importantly, 'clinically useful' to act upon new insights (164, 247, 248). In summary, adhering to our inclusion criteria, a total of 43 articles could be identified. Piloting of the search strategy and subjunction of outcomes generated by electronic databases with hand searching the reference lists of each article, permitted our confidence in ensuring that all relevant studies were included in this systematic review, and that suppositions arising from this systematic review can be based on the synthesis of all available evidence up to this date. With respect to the overall strengths and limitations of included studies, as well as procedures applied in systematically reviewing them, our main findings, practical applications and new future research line proposals are presented in the following sections. Specifically, the first section presents a discussion of research trends regarding the popular computations and analyses of 'NBA game-play performance indicators', followed by their underpinning factors ('NBA player constraints' and 'NBA contextual constraints') (Tables 5; Figure 3 and 4). Noteworthy, prior to applying the information generated from our discussion as an immediate source of knowledge, it is important that readers take into account the unique and everchanging dynamics and demands of the NBA ecosystem (e.g. post-COVID-19 era); various individual differences that may exist across players, teams, and generations; and the administrative and operational resources that may or may not be available within their respective team setting.

6.5. CONCLUSIONS AND PRACTICAL APPLICATIONS

To the best of the authors' knowledge, this systematic review presents the first attempt to disseminate a comprehensive portfolio of scientific information about the underpinning factors of NBA game-play performance. Taking into account the total body of evidence (2001–2020), and respecting the strengths and limitations of included studies, NBA coaches and support staff members may use this systematic review as a baseline reference point to explore and enrich their current knowledge about the NBA ecosystem. Acknowledging the vast majority of included studies were disseminated in recent years, the future of applied science in the NBA deems promising. However, given the polarization of research topics and popularity in descriptive-observational oriented research designs up to this date, future researchers may consider the employment of an applied science research framework that fosters (1) clearly outlined incentives (time frame, objectives, organizational and operational demands, strengths, limitations, and outcomes); (2) standardization of taxonomies; (3) sequential follow-up of research projects; (4) holistic, pragmatic, and trans-disciplinary viewpoints; and (5) implement longitudinal-interventional, mixed-method, and mixed-model research designs to increase the overall ecological validity and reproducibility of their findings.

VII – STUDY 3

VII – STUDY 3:

PUPILLOMETRY AS A NEW WINDOW TO PLAYER FATIGUE? A GLIMPSE INSIDE THE EYES OF EURO CUP WOMEN'S BASKETBALL TEAM

7.1. INTRODUCTION

In high-performance sports, excessive levels of fatigue can inhibit the desired adaption to training, increase injury risk, and potentially hinder athletic performance (3). Therefore, continuously exploring new ways to quantify player readiness is considered a priority within elite sporting organizations (3, 249). In light of this pursuit, numerous fatigue monitoring tools have emerged (3, 249). However, from a practical perspective, traditional fatigue monitoring tools often remain exhaustive (e.g., maximal-effort physical testing) (249, 250), subjective (e.g., self-reported questionnaires) (38, 249), invasive (e.g., blood sampling) (249, 251), expensive (e.g., electroencephalogram) (249, 252), or relatively slow to conduct (e.g., 5-min recordings of heart rate indices in standing and lying postures) (253). Hence, there's an ongoing need for innovative solutions that enable real-time, multi-modal, non-invasive, cost-effective, valid, and reliable insights into player fatigue, and in turn, improve the day-to-day decision-making processes of coaches and support staff personnel (3, 249).

Some of the most promising innovations to date in this space have emerged from collaborative initiatives between engineers, developers, scientists, and practitioners who operate in high-pressure environments (i.e., transatlantic flights, space shuttle missions, military combat, medical surgery, long-haul truck driving, etc.) as a lack of operational readiness in these positions could lead to lethal consequences (42, 43, 44). Consequently, pupillometry has gained a rapid surge in interest by the research community across high-stake industries (43, 44). Pupillometry can be defined as the study of the central opening of the iris through which light passes before reaching the lens and being focused onto the retina (45). Because the pupils are directly innervated by the second cranial nerve (CN II) and third cranial nerve (CN III) (45), measuring pupil reflexes provides an objective representation of the autonomic nervous system (ANS) (47-50) as well as cognitive, emotional, physical, and physiological status in real time (51, 52). Since the first discovery of pupillometry as a human fatigue detection tool in 1936 (57), the field has rapidly advanced in recent years due to the emergence of Handheld Quantitative Infrared Pupillometers (HQIPs) (57, 58, 60, 62). In particular, HQIPs are now able to repeatedly measure the pupil diameter (1 measurement every 30ms) with a minimum detectable change of <0.03mm (i.e., practical error of 0.88% in relation to the average pupil diameter) (62, 63). Consequently, a vast range of Intensive Care Units (ICUs) settings (64) and high-stake occupations are progressively integrating HQIPs as a first-point-of-care instrument (66, 67, 68).

Surprisingly, the use of modern HQIPs in professional sports remains bounded by a few use cases (e.g., concussion-related diagnostics (254, 255, 256) and "quiet eye" analytics (257)). While some researchers have introduced HQIPs as a method to evaluate ANS function in athletes (47, 49, 50), the validity and reproducibility of their methods and findings remains unclear. For instance, the investigations typically followed a cross-sectional study design, adopted non-standardized and non-validated pupil testing procedures, executed in laboratory conditions, and involved only amateur and sub-elite athletes. Besides the application of HQIPs to monitor ANS function, researchers have also demonstrated its effectiveness to monitor cognitive effort (i.e., pupil dilation can be viewed as an indirect index of effort in cognitive control tasks across the domains of updating, switching and inhibition) (53). This could imply an important discovery as player performance and fatigue originates from the complex state of both physiological and psychological processes (20). Hence, HQIPs may potentially reveal itself as a multi-model at monitoring instrument.

Acknowledging the inherent potential of HQIPs, and appreciating the efforts made by previous researchers on this research line, this pilot study aims to explore the potential usefulness of a medically graded HQIP to monitor game-induced fatigue in nine professional female basketball players by determining 1) the test-retest repeatability, 2) the relationship between pupillometrics and other biomarkers of game-induced fatigue, and 3) the time-course of pupillometrics from baseline and 24h before games up to 24h and 48h following games. In turn, the reported baseline findings and methodological framework may serve as a valuable reference for future research initiatives on this topic.

7.2. METHODS

7.2.1. Experimental approach to the problem (study design)

This pilot study followed a prospective observational study design and was conducted in non-experimental conditions, so the coaching staff, support staff personnel, and participants did not receive any input from the research team. Training data, competitive schedule and fixture outcomes were supplied by the coaching staff of the team. Two weeks prior to the investigation period, a baseline pupil test was performed after two consecutive off days (i.e., no scheduled or organized practices or workouts during these days) to optimize physical and psychological recovery. Subsequently, the participants played four home games over a 5-week investigation period (1 week apart, all games commenced between 8:00 - 8:30 PM). For each game, a pupil testing sequence was executed at the following timepoints: 24-h pre-game (GD-1), 24-h post-game (GD+1), and 48-h post-game (GD+2). All pupil tests were completed and performed inside a standard clinical testing room during regular pre-practice physiotherapy session hours (6:00 PM – 7:30 PM) to emulate a standardized clinical testing time and environment.

7.2.2. Participants

Nine female Belgian professional basketball players (n=9) competed in the 2020-2021 Euro Cup Women's Basketball Tournament and voluntarily participated in this study. All participants were aged 18 years or older (range: 18-33 years; mean age: 21.20 ± 4.92 years), with a mean height of 181 ± 5.36 (cm) and body mass of 80.61 ± 10.73 (kg). Based on positional groupings: 45 % were grouped as Posts, 33% as Guards, and 22% as Wings. Based on the role: 55% were starters and 45 % non-starters.

Players were not eligible to participate when they encountered at least one of the following criteria: <18 years of age; unable to participate in individual and/or team practices due to injury or illness at any point of the investigation period;

unable to sit for testing; history in genetic syndromes, neurologic pathologies (including intracranial masses) or intraocular pathologies that would affect pupillary function (e.g. uveitis, cataracts, diabetes, glaucoma, optic nerve dysfunction); ingestion of alcoholic and/or caffeinated foods, drinks, or substances within <12h of any pupil examinations; use of ergogenic aids and/or medical support that may have altered the neurophysiological state of the athlete at any point of the investigation period. Prior to the investigation, this study was approved by the Institutional Review Board of UCAM University, Murcia, Spain (code: CE122002) and conformed to the requirements of the European Union General Data Protection Regulation and United States Health Insurance Portability and Privacy Act with adherence to the tenets of the Declaration of Helsinki with Fortaleza actualization 2013 (259). All test procedures strictly adhered to the World Health Organization (WHO), European Commission, and local government safety guidelines regarding scientific research during the COVID-19 pandemic.

7.2.3. Testing procedure

To verify whether any pupillometrics could detect a significant change in game-induced fatigue and recovery, participants were instructed to go through a comprehensive fatigue test battery at each allocated timepoint (i.e., baseline, GD-1, GD+1, GD+2). The fatigue test battery consisted of the pupil test in combination with four other fatigue tests: cognitive fatigue test (i.e., visuomotor reaction time) (260, 261), lower-extremity muscle fatigue test (standing postural sway) (262, 263), perceptual fatigue test (self-perceived exertion) (263), and ANS fatigue test (heart rate variability indices) (265-269). More specifically, upon arrival to the clinical testing room, the player was instructed to wear the Polar H10 heart rate chest strap (Polar Electro Oy, Kempele, Finland) and complete a 5-min heart rate variability (HRV) test in rested condition and seated posture using the EliteHRV software (Asheville, NC, United States) (269) on an iPhone SE (Apple Inc., Los Altos, California, United States). The Polar H10 was selected based on its underlying support as a medically graded heart rate sensor (265, 266) and the EliteHRV was selected based on its ability to record, store, and export HRV data in a secure and user-friendly manner (269). Particularly, the natural log of the root-mean-square difference of successive normal RR intervals (lnRMSSD) was used for HRV analyses given its well-documented support for monitoring physiological fatigue in young female basketball players (266) as well as numerous other sport athletes (268). Following the HRV test, the player completed two subsequent Sway tests using the Sway Medical, Inc. software (Tulsa, Oklahoma, United States) (260-263) via touch screen display as well as tri-axial accelerometry (i.e., motion detection) on an iPad (6th generation) by Apple Inc. (Los Altos, California, United States). The Sway test protocols have been established as an objective and reliable method for assessing reaction time, impulse control, timed visual processing, and working memory (260-263). Particularly, the first Sway test examined the cognitive fatigue status through the Simple Reaction Time (SRT) test (ms) (260). During this test, the player held the iPad horizontally (landscape mode) and moved it as fast possible in any direction when the screen display changed from a white to orange color. Each SRT test started after a variable delay of 2–4s in order to prevent the player from anticipating the stimulus ahead of time. Each player completed five trials. The fastest and the slowest SRT scores were excluded in order to remove outliers and reflect only the typical response times of the player (259). Subsequently, the scores of the three remaining trials were averaged to calculate the individual score for each player. Following the SRT test, the player performed the Sway Balance test, which quantified postural sway during the performance of a series of tasks to reflect lower-extremity muscle fatigue (270). Specifically, the Sway Balance test consisted of five stance conditions (10-s in duration per stance) on a firm surface and with the eyes closed. The postural sway was quantified through the iPad's triaxial accelerometer, and the units that corresponded with the accelerations were used to calculate the final proprietary Sway Balance score (263).

Subsequently, the test administrator manually performed the standard Pupil Light Reflex (PLR) test (47, 254) in each player's eye respectively, using the NeurOptics NPi-200 pupillometer (NeurOptics, Laguna Hills, CA, U.S.A.), a medically graded HQIP (Class I medical device as listed under 21CFR 886.1700) (45, 55). More specifically, this HQIP integrated a calibrated full-field white light stimulus with peak wavelengths comprised of red, green, and blue at a fixed intensity (1000 Lux) and fixed flash duration (0.8s) to simulate a standard pupil light reflex (PLR) (45, 55). Subsequently, this HQIP digitally registered the pupil light response as a video (sampling rate of 30 Hz) for a duration of 3.5 s, followed by a display of numeric results on a screen for each eye respectively (45, 55). The device highlighted an outline of the pupil and graphed its displacement over time with an accuracy of 0.03 mm (i.e., practical error of 0.88% in relation to the average pupil diameter) (45, 55). Scotopic lighting conditions (434-440 lumen/m2) were verified prior to each pupil exam by measurement of luminance of less than 2 Lumens with a luminometer (Dr. Meter LX1330B Digital Illuminance/Light Meter, Hisgadget, Union City, CA, U.S.A.) at the level of the players' eyes. Furthermore, normal forehead temperature was measured and controlled (35.4 °C to 37.4 °C) prior to each test via a forehead thermometer (iProven DMT-489, Beaverton, Oregon, U.S.A.). Each pupil test was conducted sitting stationary looking straight ahead. Each player was prompted to maintain a forward head posture and binocular viewing conditions in a seated position throughout the test. The non-test eye was fixated on a neutral wall at 3-m distance to the chair's front leg. The right eye was tested first, immediately followed by the left eye. This sequence was completed three consecutive times using 60-s intervals to allow sufficient recovery of the pupil before the next light stimulus (45, 55, 271). A retest was taken whenever the HQIP was held incorrectly, or blinking was detected by the HQIP. All pupil tests were relatively quick to conduct and did not exceed ~4 min in duration per player, and ~60 min in total duration for the entire team. Notably, ease of use was reported by the test administrator (i.e., performance coach without previous clinical experience in using HQIPs). In particular, a total of 351 pupillary measurements were recorded in each eye, without any interference with the daily predetermined schedule of the team.

The selected HQIP extracted seven pupillometrics, which represented parameters of both the Sympathetic Nervous System (SNS) function and Parasympathetic Nervous System (PNS) function (45). Furthermore, the HQIP used an algorithm to calculate the overall reactivity of the pupil (proprietary score), called the Neurological Pupil Index (NPi) (45). However, the authors excluded the NPi pupillometric from the final analyses as the company did not publicly provide any details on the computation of the NPi. Descriptions and calculations for the seven remaining pupillometrics are presented in Table 1.

Table 1. Descriptions of All Pupillometrics.

Pupillometrics		Units	Description
MaxD	Maximum Diameter	Mm	Maximum pupil size before constriction.
MinD	Minimum Diameter	Mm	Pupil diameter at peak constriction.
PC	Percentage of Change	%	The change in pupil size over time, computed as: $PC = \left(\frac{MaxD - MinD}{MaxD}\right) * 100$
LAT	Latency	mm/s	Time of onset of constriction following initiation of the light stimulus.
CV	Constriction Velocity	mm/s	Average of how fast the pupil is constricting after exposure to light.
MCV	Maximum Constriction Velocity	mm/s	Represents the maximum velocity of pupil constriction.
DV	Dilation Velocity	mm/s	The average pupillary velocity when, after having reached the peak constriction, the pupil tends to recover and dilate back to the initial resting size.

Finally, within <1h following any practice or game, the players completed an online survey to record their RPE score based on Borg's rate of perceived recovery status scale of 100 points (263), in which 0 means 'very poorly recovered/extremely tired,' 20 represents 'poorly recovered/very tired,' 40 means 'minimally recovered/ tired,' 50 denotes 'slightly recovered/somewhat tired,' 60 signifies 'moderately recovered,' 80 represents 'well recovered,' and 100 represents 'very well recovered/highly energetic' (264).

7.2.4. Statistical Methods

Prior to the statistical analyses, normal distribution of the dataset was confirmed (Shapiro-Wilkinson test; n > 50). Participant demographic information, including: age, height, body mass, playing position and role were calculated using descriptive statistics. The pupillometrics were compared between the left and the right eye through a paired t-test. The intraclass correlation coefficients (ICCs) were computed to examine test-retest reliability for each pupillometric using the thresholds outlined by Martins et al. (272) for the assessment of technological equipment in research and clinical practice: very poor: ICC <0.70, poor: ICC = 0.70-0.90, moderate: ICC = 0.90-0.95, good: ICC = 0.95-0.99, and very good: ICC >0.99 (272). The Pearson's Product Moment Correlation (r) examined the linear relationship between each pupillometric and various other measures of game-induced fatigue and recovery, including: perceptual fatigue (i.e., average daily Borg Rating of Perceived Exertion scores) (264), lower-extremity muscle fatigue (i.e., Sway Balance Error Scoring System test scores)(270); cognitive fatigue (i.e., Sway reaction time score)[34], and ANS fatigue (i.e., lnRMSSD)(268). The Pearson's correlation coefficients were interpreted using the reference standards by Hopkins et al. (2009): trivial: $r < 0.1$; small: $0.1 < r < 0.3$; moderate: $0.3 < r < 0.5$; large: $0.5 < r < 0.7$; very large: $0.7 < r < 0.9$; nearly perfect: $r > 0.9$; perfect: $r = 1$ [49,50]. To explore whether any pupillometrics differed between rested conditions (baseline and GD-1) and fatigued conditions (GD+1 and GD+2) at the group level, the Levene test was applied as a derivation of the classical one-way analysis of the variance (ANOVA) to compute the F-statistics, Effects sizes (expressed as "η2" or Eta Squared), Coefficient of Variation (CV), absolute and relative differences, Confidence Intervals at 95% (CI95), and p-values. The post-hoc Tukey test was examined for pairwise comparisons. The η2 was interpreted with the following thresholds: small effect: η2 = 0.01; medium effect: η2 = 0.06; large effect: η2 = 0.14 (274, 275). Additionally, the magnitude of these differences were visually presented by a 'percentage difference' in which postgame data (value x_2) was subtracted by either baseline data or pregame data (value x_1) represents, and divided by the baseline or pregame data (value x_1). The significance of all inferential statistics was set for $p < 0.05$. All analyses were performed at 95%-Confidence Interval. All statistical tests were performed using IBM SPSS Version 28.0.0.0.

7.3. RESULTS

7.3.1. Descriptive Statistics

A paired sample t-test revealed statistically significant difference between left and right eye pupillometrics at the group level (mean difference = -0.034; p-value < 0.001). Therefore, all statistical tests and analyses were performed and analyzed for each eye separately. The normative data (means and standard deviations) of all pupillometrics (at the group level) of both eyes are displayed in Table 2.

7.3.2. Test-Retest Reliability

Table 3 displays the ICC's of all pupillometrics, which range from very poor to good (0.286 to 0.963). Particularly, LAT, DV, and MCV showed very poor ICCs (<0.70), whereas CV and PC showed poor ICCs (0.70-0.90). However, MinD (left eye), and MaxD (both eyes) showed good ICCs (0.95-0.99). Minimal measurement bias was detected for all pupillometrics with the maximum bias for the left eye being +2.9% (MaxD) and right eye being +1.98% (MaxD). The average bias across all pupillometrics was 0.001 ± 0.450. When comparing baseline (BL) to post-game (GD+1 and GD+2) timepoints, the smallest read difference (SRD) was widest for MaxD (R = 0.340; L = 0.318) and MCV (R = 0.304; L = 0.263), and least for LAT (R = 0.005; L = 0.005) and DV (R = 0.074; L = 0.085). When comparing pre-game (GD-1) to post-game (GD+1 and GD+2) timepoints, the SRD was widest for MaxD (R = 0.285; L = 0.266) and MCV (R = 0.249; L = 0.199) and least for LAT (R = 0.007; L = 0.007) and DV (R = 0.066; L = 0.068).

Table 2a. Descriptive statistics of all pupillometrics (right eye).

		N	Mean	Std. Dev.	Std. Error	95% CI Lower Bound	95% CI Upper Bound	Min	Max
MaxD (right)	GD-1	35	6.3223	1.02479	.17322	5.9703	6.6743	4.01	8.11
	GD+1	35	6.3500	1.01662	.17184	6.0008	6.6992	3.97	7.91
	GD+2	34	6.3224	1.06745	.18307	5.9499	6.6948	4.16	8.22
	Baseline	8	6.4775	1.06054	.37496	5.5909	7.3641	4.63	7.97
	Total	112	6.3421	1.02446	.09680	6.1502	6.5339	3.97	8.22
MinD (right)	GD-1	35	3.9794	.76203	.12881	3.7177	4.2412	2.58	5.85
	GD+1	35	3.9837	.69930	.11820	3.7435	4.2239	2.58	5.23
	GD+2	34	4.0256	.73358	.12581	3.7696	4.2815	2.62	5.65
	Baseline	8	3.8788	.76868	.27177	3.2361	4.5214	2.74	5.38
	Total	112	3.9876	.72542	.06855	3.8518	4.1234	2.58	5.85
PC (right)	GD-1	35	.3720	.03437	.00581	.3602	.3838	.28	.44
	GD+1	35	.3769	.03151	.00533	.3660	.3877	.32	.44
	GD+2	34	.3703	.03389	.00581	.3585	.3821	.27	.42
	Baseline	8	.4013	.03796	.01342	.3695	.4330	.32	.43
	Total	112	.3751	.03404	.00322	.3687	.3815	.27	.44
CV (right)	GD-1	35	3.2737	.46457	.07853	3.1141	3.4333	2.38	4.37
	GD+1	35	3.3029	.42080	.07113	3.1583	3.4474	2.37	4.23
	GD+2	34	3.2750	.45240	.07759	3.1171	3.4329	2.42	4.13
	Baseline	8	3.4250	.46605	.16477	3.0354	3.8146	2.65	4.08
	Total	112	3.2940	.44317	.04188	3.2110	3.3770	2.37	4.37
MCV (right)	GD-1	35	5.3266	.77629	.13122	5.0599	5.5932	3.49	6.52
	GD+1	35	5.1871	1.10929	.18750	4.8061	5.5682	.63	7.04
	GD+2	34	5.2035	.66672	.11434	4.9709	5.4362	4.02	6.37
	Baseline	8	5.7250	.66002	.23335	5.1732	6.2768	4.85	6.61
	Total	112	5.2741	.86056	.08132	5.1130	5.4352	.63	7.04
LAT (right)	GD-1	35	.2131	.02898	.00490	.2032	.2231	.17	.30
	GD+1	35	.2223	.02787	.00471	.2127	.2319	.17	.27
	GD+2	34	.2147	.02135	.00366	.2073	.2222	.17	.27
	Baseline	8	.2150	.01604	.00567	.2016	.2284	.20	.23
	Total	112	.2166	.02573	.00243	.2118	.2214	.17	.30
DV (right)	GD-1	31	1.4132	.25639	.04605	1.3192	1.5073	1.02	2.28
	GD+1	34	1.3756	.20289	.03480	1.3048	1.4464	.90	1.82
	GD+2	32	1.3850	.24336	.04302	1.2973	1.4727	.97	2.14
	Baseline	7	1.4343	.24845	.09391	1.2045	1.6641	1.18	1.84
	Total	104	1.3937	.23263	.02281	1.3484	1.4389	.90	2.28

Table 2b. Descriptive statistics of all pupillometrics (left eye).

		N	Mean	Std. Dev.	Std. Error	95% CI Lower Bound	95% CI Upper Bound	Min	Max
MaxD (left)	GD-1	35	6.0817	.99069	.16746	5.7414	6.4220	3.49	7.68
	GD+1	35	6.0891	.95812	.16195	5.7600	6.4183	3.65	7.56
	GD+2	34	6.1238	.97442	.16711	5.7838	6.4638	3.94	7.85
	Baseline	8	6.2650	1.03907	.36737	5.3963	7.1337	4.39	7.73
	Total	112	6.1099	.96662	.09134	5.9289	6.2909	3.49	7.85
MinD (left)	GD-1	35	3.7314	.64574	.10915	3.5096	3.9532	2.34	5.21
	GD+1	35	3.6911	.60097	.10158	3.4847	3.8976	2.45	4.92
	GD+2	34	3.7662	.63090	.10820	3.5460	3.9863	2.48	5.20
	Baseline	8	3.7687	.66827	.23627	3.2101	4.3274	2.77	4.95
	Total	112	3.7321	.62115	.05869	3.6157	3.8484	2.34	5.21
PC (left)	GD-1	35	.3851	.03568	.00603	.3729	.3974	.30	.44
	GD+1	35	.3929	.03259	.00551	.3817	.4041	.32	.47
	GD+2	34	.3847	.02339	.00401	.3765	.3929	.34	.44
	Baseline	8	.3975	.02964	.01048	.3727	.4223	.36	.44
	Total	112	.3883	.03087	.00292	.3825	.3941	.30	.47
CV (left)	GD-1	35	3.3491	.56844	.09608	3.1539	3.5444	1.60	4.21
	GD+1	35	3.2971	.45486	.07689	3.1409	3.4534	2.18	4.16
	GD+2	34	3.3165	.46990	.08059	3.1525	3.4804	2.17	4.32
	Baseline	8	3.4075	.56835	.20094	2.9323	3.8827	2.23	3.96
	Total	112	3.3271	.49930	.04718	3.2337	3.4206	1.60	4.32
MCV (left)	GD-1	35	5.4780	.81903	.13844	5.1967	5.7593	3.20	6.67
	GD+1	35	5.3737	.77775	.13146	5.1065	5.6409	3.45	6.77
	GD+2	34	5.3509	.73337	.12577	5.0950	5.6068	3.64	6.91
	Baseline	8	5.6800	1.02745	.36326	4.8210	6.5390	3.94	7.18
	Total	112	5.4213	.79076	.07472	5.2732	5.5693	3.20	7.18
LAT (left)	GD-1	35	.2320	.02753	.00465	.2225	.2415	.20	.27
	GD+1	35	.2186	.02992	.00506	.2083	.2288	.17	.27
	GD+2	34	.2118	.02167	.00372	.2042	.2193	.17	.27
	Baseline	8	.2063	.03420	.01209	.1777	.2348	.13	.23
	Total	112	.2198	.02828	.00267	.2145	.2251	.13	.27
DV (left)	GD-1	34	1.3765	.24277	.04164	1.2918	1.4612	.96	1.84
	GD+1	33	1.3009	.21842	.03802	1.2235	1.3784	.87	1.79
	GD+2	33	1.3936	.24903	.04335	1.3053	1.4819	.94	2.09
	Baseline	7	1.5057	.43412	.16408	1.1042	1.9072	.82	2.04
	Total	107	1.3669	.25499	.02465	1.3180	1.4158	.82	2.09

Table 3. ICC scores for all 7 pupillometrics

Pupillometrics	ICCs (CI_{95})	
	Right	Left
MaxD (mm)	0.955 (0.937-0.968)**	0.963 (0.949-0.974)**
MinD (mm)	0.945 (0.920-0.962)**	0.955 (0.935-0.970)**
PC (%)	0.756 (0.680-0.819)**	0.749 (0.674-0.813)**
CV (mm/sec)	0.755 (0.679-0.818)**	0.827 (0.770-0.873)**
MCV (mm/sec)	0.626 (0.528-0.714)**	0.667 (0.575-0.748)**
LAT (sec)	0.452 (0.335-0.566)**	0.287 (0.165-0.413)**
DV (mm/sec)	0.501 (0.379-0.616)**	0.656 (0.558-0.742)**

** p<0.001

7.3.3. Relationships with other biomarkers of game-induced fatigue

With regards to perceptual fatigue, the findings demonstrated a very large positive significant correlation between average RPE and MinD ($r = 0.78$, $p < 0.05$) and MaxD ($r = 0.77$, $p < 0.05$). With regards to lower-extremity muscle fatigue, Sway Balance (left and right) showed a very large positive significant association with MaxD, MinD, CV, and MCV ($r = 0.75$-0.78, $p < 0.05$). With regards to cognitive fatigue, a large significant positive relationship was identified between Sway SRT scores and MinD ($r = 0.69$, $p > 0.05$) and a very large significant positive relationship between Sway SRT scores and MaxD ($r = 0.70$, $p > 0.05$). Finally, with regards to physiological fatigue, a very large positive significant relationship was detected between lnRMSSD scores and MinD ($r = 0.77$, $p < 0.05$), CV ($r = 0.74$, $p < 0.05$), and MCV ($r = 0.74$, $p < 0.05$) whereas a very large inverse significant relationship was found between MaxD and lnRMSSD ($r = -0.82$, $p < 0.05$) (Table 4). All significant correlations have been highlighted in bold in table 4. Overall, the combination of MaxD, MinD, CV and MCV demonstrated to be the most representative of overall game-induced fatigue.

Table 4. Pearson's correlation coefficients between the 7 pupillometrics and other biomarkers of game-induced fatigue and recovery.

Pupillometrics	Sway SRT	lnRMSSD	Sway Balance (Right)	Sway Balance (Left)	Average RPE
MaxD	**0.70***	**-0.82***	**0.77***	**0.79***	**0.77***
MinD	**0.69***	**0.77***	**0.78***	**0.78***	**0.78***
PC	-0.17	0.22	-0.28	-0.20	0.28
CV	-0.62	**0.74***	**-0.75***	**-0.75***	0.45
MCV	-0.62	**0.74***	**-0.75***	**-0.76***	0.44
Lat	0.14	-0.22	-0.10	-0.10	0.10
DV	-0.20	0.22	-0.10	0.00	0.24

* Coefficients presented in bold are significant ($p < 0.05$)

7.3.4. Time course of pupillometrics following games (at the group level)

Initially, the ANOVA analysis revealed that there was no statistically significant difference in pupillometrics between rested states (baseline and GD-1) and fatigued states (GD+1, GD+2) ($p < 0.05$), except for LAT (left) in which a medium-to-large difference was detected (F=4.023, $\eta2$ =0.109 p = 0.009). In particular, a post-hoc Tukey HSD test revealed that LAT (left) on GD-1 (0.232 ± 0.027 mm/s) was significantly higher than on GD+2 (0.212 ± 0.216 mm/s) (mean difference = 0.202, std. error = 0.006, p = 0.013, $\eta2$ = 0.101), thus the time from onset of the light stimulus to pupil constriction in the left eye typically took longer on GD-1 than on GD+2. Although LAT (left) was the only pupillometric that could detect a statistically significant change between rested conditions and fatigued conditions ($p < 0.05$), small-to-moderate effect sizes were detected for PC (right) ($\eta2$ = 0.052, p = 0.121), MCV (right) ($\eta2$ = 0.026, p = 0.410), LAT (right) ($\eta2$ = 0.023, p = 0.470), PC (left) ($\eta2$ = 0.021, p = 0.518), and MCV (left) ($\eta2$ = 0.013, p = 0.587). All other pupillometrics showed very small ($\eta2 < 0.01$) and non-significant effects ($p > 0.05$) across all timepoints. With regards to the magnitude of change between timepoints (% difference using Equation 1), the largest differences were found between baseline and GD+2, in which MCV (both eyes) represented the largest relative difference (left = -7.77%; right = -5.64%) (Table 5a and 5b; Figure 1).

Table 5a. ANOVA results of the pupillometric changes between baseline (BL) and post-game timepoints (GD+1 and GD+2)

ANOVA results	BL to GD+1					BL to GD+2				
	Mean Difference	Std. Error	F	η^2	p	Mean Difference	Std. Error	F	η^2	p
MaxD (mm) (R)	.127	.406	.101	.002	.752	.155	.407	.137	.003	.713
MinD (mm) (R)	-.104	.287	.142	.003	.709	-.146	.288	.255	.006	.616
PC (%) (R)	.024	.013	3.623	.081	.064	**.030**	**.013**	**5.173**	**.115**	**.028**
CV (mm/s) (R)	.122	.175	.528	.013	.472	.150	.175	.704	.017	.406
MCV (mm/s) (R)	.537	.337	1.884	.040	.197	**.521**	**.338**	**3.976**	**.090**	**.049**
LAT (s) (R)	-.007	.010	0.502	.012	.483	.000	.010	.001	.000	.971
DV (mm/s) (R)	.058	.097	.451	.011	.506	.049	.981	.234	.006	.631
MaxD (mm) (L)	.175	.383	.213	.005	.647	.141	.384	.133	.003	.718
MinD (mm) (L)	.077	.246	.104	.003	.748	.002	.247	.000	.000	.992
PC (%) (L)	.004	.012	.136	.003	.714	.012	.012	1.752	.042	.193
CV (mm/s) (L)	.110	.197	.350	.008	.557	.091	.198	.225	.006	.638
MCV (mm/s) (L)	.306	.312	.896	.021	.349	.329	.312	1.116	.027	.297
LAT (s) (L)	-.012	.010	1.050	.025	.312	-.005	.010	.333	.008	.567
DV (mm/s) (L)	.204	.168	3.464	.084	.070	.112	.169	.885	.023	.353

* Coefficients presented in bold are significant ($p < 0.05$)

Table 5b. ANOVA results of the pupillometric changes between pre-game (GD-1) and post-game timepoints (GD+1 and GD+2)

ANOVA results	GD-1 to GD+1					GD-1 to GD+2				
	Mean Difference	Std. Error	F	η^2	p	Mean Difference	Std. Error	F	η^2	p
MaxD (mm) (R)	-.028	-.248	.013	.000	.910	-.000	.249	.000	.000	1.000
MinD (mm) (R)	-.004	.175	.001	.000	.981	-.046	.176	.066	.001	0.799
PC (%) (R)	-.004	.008	.380	.006	.540	.001	.008	.430	.001	0.836
CV (mm/s) (R)	-.029	.106	.076	.001	.784	-.001	.107	.000	.000	0.991
MCV (mm/s) (R)	.139	.205	.371	.005	.544	.123	.207	.498	.007	0.483
LAT (s) (R)	-.009	.006	1.810	.026	.183	-.001	.010	.065	.001	0.800
DV (mm/s) (R)	.037	.058	.435	.007	.512	.028	.059	.201	.003	0.656
MaxD (mm) (L)	-.007	.233	.001	.000	.975	-.042	.235	.032	.000	0.859
MinD (mm) (L)	.040	.150	.073	.001	.788	-.034	.151	.051	.001	0.822
PC (%) (L)	-.007	.007	.892	.013	.348	.000	.007	.004	.000	0.952
CV (mm/s) (L)	.052	.120	.179	.003	.674	.032	.121	.068	.001	0.796
MCV (mm/s) (L)	.104	.190	.298	.004	.587	.104	.190	.460	.007	0.500
LAT (s) (L)	.013	.006	3.819	.053	.055	**.020**	**.006**	**11.469**	**.146**	**0.001**
DV (mm/s) (L)	.075	.061	1.790	.027	.186	-.017	.061	.82	.001	0.776

* Coefficients presented in bold are significant (p < 0.05)

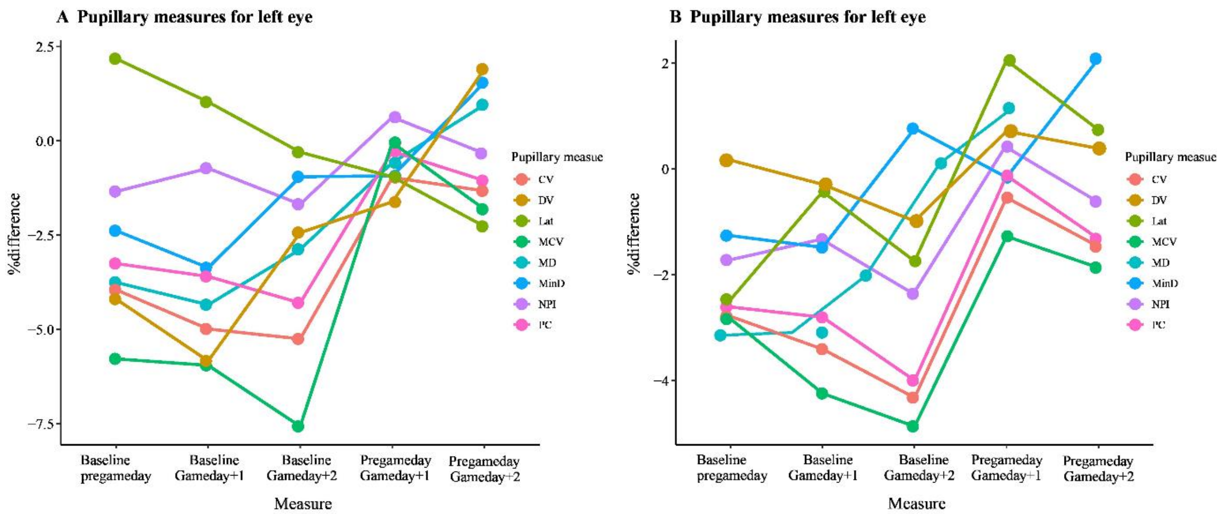

Figure 1. The percentage difference of pupillometrics between test moments.

7.4. DISCUSSION

The main purpose of this pilot study was to explore the potential usefulness of HQIPs in the context of monitoring game-induced fatigue in professional female basketball players. The reported findings may not only serve as a benchmark for future comparisons and hypothesis testing in athletic populations that includes PLR data from automated pupillometry, but also provide point estimates and variance for PLR measures, as well as inferential statistics to describe the effect of game-induced fatigue on pupillary behaviour, when used in naturalistic elite sports environment. Overall, the main findings of this pilot study suggest that (1) two out of seven pupillometrics represented good repeatability scores (MinD and MaxD) (ICC = 0.95-0.99), (2) Statistical significant relationships were found between MaxD, MinD, and all other biomarkers of game-induced fatigue ($r = 0.69$-0.82, $p < 0.05$), as well as between CV, MCV, and biomarkers of cognitive, lower-extremity muscle, and physiological game-induced fatigue ($r = 0.74$-0.76, $p < 0.05$), and (3) Statistically significant differences were found between rested and fatigued states for three pupillometrics: PC (right) and MCV (right), and LAT (left) ($p<0.05$).

7.4.1. Feasibility and test-retest repeatability

In response to the first research question, good ICCs were reported for two out of seven pupillometrics, in particular: MinD (left) and MaxD (left and right) (0.95-0.99). Conversely, poor ICCs were reported for CV and PC (0.70-0.90) and very poor ICCs were reported for LAT, DV, and MCV (<0.70). Nevertheless, the smallest read difference was extremely narrow for LAT in both eyes (0.005-0.007) as well as DV in both eyes (0.066-0.085). Therefore, the quantification of the maximum and minimum pupil diameter seem to be least prone to errors or noise due to external factors when examining professional female basketball players. However, this remains to be questioned as to the best of the authors knowledge, Swanson et al. (276) were the only researchers that provided open access to ICC results from PLR tests using the Neuroptics NPi-200 in an athletic population (i.e., 186 collegiate athletes across eight sports) (276). Unfortunately, the only pupillometric reported in their investigation was the Neurological Pupil Index (NPi) (i.e., a proprietary score generated by the manufacturer). Furthermore, the PLR tests were completed at different time intervals, executed by multiple trained test administrators, and focused on a different use case (i.e., the detection of traumatic brain injury instead of fatigue monitoring). In turn, meta analyses and comparative inferences remain challenging. From a general viewpoint, the ICCs reported in this pilot study tend to follow the trend of various HQIPs applied in different use cases. For instance, Zheng et al. (277) also reported that LAT was the least reliable of all pupillometrics (i.e., very poor ICC of 0.65) using the RAPDx pupillometer (Konan Medical, Irvine, California, USA) and Chopra et al. (278) reported moderate to good ICCs for MinD and MaxD (ICC > 0.90) using the same RAPDx pupillometer.

Taking into account the abovementioned limitations, combined with the overall lack of consistency and transparency in pupillometric research over the past 50 years (as recently highlighted by an international panel of pupillometry experts across disciplines) (271), future researchers may use this pilot study as a baseline framework and prioritize transparency and standardization when executing their initiatives on this research topic.

7.4.2. The relationship between pupillometrics and other biomarkers of game-induced fatigue

In response to the second research question, four pupillometrics were identified as the strongest indicators of game-induced fatigue in professional female basketball players. In particular, MaxD and MinD represented the strongest indicators for all other biomarkers of game-induced fatigue ($r = 0.69$-0.82, $p < 0.05$), whereas CV and MCV were identified as the strongest indicators for cognitive, lower-extremity muscle, and physiological biomarkers of game-induced fatigue ($r = 0.74$-0.76, $p < 0.05$). Hence, keeping track of these four pupillometrics on a daily basis may present a multi-modal solution to better understanding the psycho-physiological processes that underpin game-play fatigue in elite sports settings. However, the lack of existing literature on pupillometry in relation to sports-specific fatigue creates barriers for deeper comparative analyses. From a general perspective, the reported findings in this pilot study tend to align with previous investigations that examined the role of pupillometry in acute human fatigue. For instance, previous researchers have revealed strong relationships between multiple pupillometrics and biomarkers of HRV indices (e.g., lnRMSSD) (47-50), as well as lower-extremity muscle fatigue (e.g. Postural Sway) (279, 280), subjective ratings of effort and tiredness from prolonged listening and attentional efforts (281), subjective ratings of perceived exertion from muscular contraction during a power grip task (282). Neverthelesss, there was a clear lack of consistency in terms of the selected testing timeframes (i.e., measuring before, during, or after given tasks or events), testing conditions (i.e., naturalistics vs. laboratory settings), selected HQIPs (i.e., self-engineered vs. commercial instruments), extracted pupillometrics (i.e., standard vs. proprietary scores and algorithms), and none of the investigations involved professional basketball competition. Acknowledging these limitations, and given that pupil responses vary based on the sport and context in which players participate in (47, 49) more detailed comparative analyses remain inappropriate at this point of time. Hence, a vigilant, transparent, and consistent research strategy is required to expand upon our existing knowledge regarding this use case.

7.4.3. The time-course of pupillometrics from rested to fatigued states

In response to the third research question, three pupillometrics were capable of detecting a significant change from rested states (baseline and GD-1) to fatigued states (GD+1 and GD+2). In particular, PC (right) ($F=5.173$, $\eta2 = 0.115$ $p = 0.028$) and MCV (right) ($F=3.976$, $\eta2 = 0.090$ $p = 0.049$) significantly decreased from baseline to GD+2, while LAT (left) ($F=4.023$, $\eta2 = 0.109$ $p = 0.009$) significantly increased from GD-1 to GD+2. Hence, at timepoints where residual fatigue was expected to remain present (48h following games), the pupils constricted slower (MCV), with a smaller magnitude (PC), while it took longer to begin its constriction phase (LAT). This further supports the underlying physiological concept of pupillary behavior as LAT can be regarded as an index of sympatho-vagal balance (i.e., higher values indicate sympathetic dominance) (49), whereas PC and MCV can be regarded as an index of parasympathetic activity (i.e. higher values indicate parasympathetic dominance) (49). Hence, this confirms, at least in part, that the players' ANS were not fully reverted to normal levels 48-h following games. Interestingly, this trend of LAT, PC, and MCV is inconsistent with earlier findings by Kaltsatou et al. (49) who examined the immediate effects of physical exertion (maximal ergometer stress test) on pupillary behavior in power -and endurance-trained athletes. Specifically, in their investigation, LAT decreased, while MCV and PC increased from peak exertion to 5-min following the test (when heart rate return to baseline levels). Consequently, similar to how sports scientists typically evaluate traditional game-induced fatigue markers (e.g. Heart Rate Variability indices) (59, 273, 283, 284), the before-after, day-to-day, and week-to-week fluctuations in pupillometics should be analyzed distinctively and individually, and contextualized against other external factors.

It is also important to acknowledge that the reported findings in this pilot study does not inform about the underlying factors that may have contributed to its overall acute fatigue state, nor does it imply the practical relevance of it. For instance, in a recent systematic review on post-game recovery kinetics in team ball sport athletes, Doeven et al. (285) highlighted the many covariables that play an influential role on the recovery dynamics of each player (e.g., menstrual cycle, physical fitness, role within the team, playing time, exertion, playing level, playing style, age, gender, genetic make-up, game location, preceding travel duration, opponent quality, imposed workload, lifestyle habits, sleep quantity and quality) (285). Hence, future researchers are encouraged to integrate these cofactors in future investigations in order to pinpoint the underlying mechanisms for pupillary change following games. Additionally, to determine the practical relevance of these changes, future researchers may include predetermined anchor points that are practically relevant to their organization (e.g., specific injury occurrence per minute of activity exposure, on-court game-play performance metrics, pre-game alertness levels) (3, 273, 283). This anchoring approach, often referred to as the Minium Clinical Important Difference (MCID), would allow practitioners to track pupillometrics per player over time and transform them into a prediction or prescription tool informing the onset to critical states via real-time alerting or traffic-light based visualization systems (273, 283, 284, 285). For instance, Umesh et al. (286) were able to predict a self-reported Visual Analogue Scale state of sleepiness score of ≥ 6 (the target variable) by using a MCV threshold value (age adjusted) of 2.8, with a sensitivity of 83% and specificity of 84%. Similarly, future researchers could determine the MCID's for MaxD, MinD, CV, and MCV against their self-determined threshold values.

Finally, emerging technologies may enable faster interventions in the future. For instance, Stoeve et al. (287) created a VR-based stress test during a football goalkeeping scenario, and achieved a performance of 87.3% accuracy through the Random Forest classifier, claiming a comparable outcome to state-of-the-art approaches fusing eye tracking data and additional biosignals. Given the strong resurgence and further democratization of VR, Mixed Reality (MR) and augmented reality (AR) based eye-tracking applications in recent years (288-291), new opportunities may arise to accelerate pupillometric research in the context of real-time athlete monitoring.

In summary, the findings of this pilot study promotes HQIPs as a potential instrument for monitoring game-induced fatigue in female professional basketball players. From an ergonomic standpoint, the PLR testing routine took little time and effort on the practitioner's side, and good test-retest repeatability scores were reported for two pupillometrics (MaxD and MinD). Additionally, strong relationships were found for four pupillometrics (MaxD, MinD, CV, and MCV) and all other biomarkers of game-induced fatigue, and three pupillometrics were able to distinguish rested states from fatigued states (LAT, PC, and MCV). Although these preliminary findings tend to support the potential adoption of pupillometry as an athlete monitoring tool in elite sports settings, researchers should remain cautious when drawing conclusive inferences as the dataset was extracted from a relatively small and homogenous sample, tracked over a relatively short timeframe (4 games across 5 weeks). Therefore, future researchers should aim to cover a larger and more heterogenous sample across various time intervals to allow for more precise estimations of "normal pupillary behaviour" in elite athletes. The recent technological advancements in HQIPs that are compact and versatile (e.g., smartphone-based and VR-based pupillometers) (286-293) may further accelerate and facilitate investigations on this topic.

7.4. CONCLUSIONS AND PRACTICAL APPLICATIONS

HQIPs have opened a new window of opportunities for sports practitioners given its ease of use and ability to extract objective insights on player fatigue in a quick, reliable, valid, and non-invasive character. Overall, the pupillometrics MinD, MaxD, CV, and MCV were identified as the most promising indicators of game-induced fatigue in female professional basketball players. However, it's important to acknowledge that this research line is still in its infancy, and the findings stem from a small homogenous sample, thus the statistical inferences remain indicative rather than confirmative or directive. However, future researchers are encouraged to leverage this pilot study as a baseline framework for future investigations, and ensure standardization is prioritized throughout the process in order to maximize the reproducibility of findings across a variety of sports, timeframes, contexts, and use cases.

VIII – SUMMARY AND DISCUSSION OF RESULTS

VIII – SUMMARY AND DISCUSSION OF RESULTS

The main objective of the present compendium of studies was to gain a deeper understanding of the factors and mechanisms that underpin NBA game-play performance and explore whether pupillometry may provide a promising new alternative to monitoring player fatigue in this particular ecosystem. Results indicated that (I) frequent air travel and congested fixtures play a substantial negative role on the health, wellbeing, and performance of NBA players; (II) NBA game-play performance emerges from a wide variety and complex interaction of internal factors (i.e., eidonomical, anatomical, physical, psychological, technical-tactical factors) and external factors (i.e., rest days, travel, game location, game period, game status, season period, difference of team quality, momentum effects, playing time, and interactive effects) and (III) the use of HQIPs emerged as a promising new window of opportunity for sports scientists and practitioners to monitor game-induced fatigue in a feasible, holistic, fast, reliable, valid, objective, non-invasive, and non-exhaustive manner.

Frequent air travel and congested fixtures have long been recognized as potential stressors in the demanding NBA schedule. Study 1 aimed to synthesize existing literature and shed light on the detrimental effects of these factors on the health, well-being, and performance of NBA players. By analyzing a wide range of studies, including physiological, psychological, and performance-related aspects, a comprehensive understanding of the challenges posed by air travel and congested fixtures on NBA player health and performance was obtained. As expected, frequent short-haul flights (≤6 h) demonstrated a well-known issue in NBA players as it increased injury risk and impede performance. In particular, frequent air travel can negatively energy levels, oxygen saturation level, mood state, skeletal muscle and connective tissue health, hydration status, nutritional behaviors, sleep quality, and sleep quantity, thus extending the time for sufficient recovery between games and/or training (85). In comparison with other major sports leagues, these potential risks are particularly prevalent in the NBA environment because NBA players typically spend more time above 30,000 ft than athletes competing in any other team sport in the United States of America (USA) (253). Additionally, the number of time zones traveled play a critical role in the magnitude of travel fatigue (48) as flying across two or more time zones may induce travel fatigue symptoms up to 2–3 days after arrival (35), causing a significant desynchronization of the players' circadian rhythm (35). In this sense, Study 1 concluded that the inevitable desynchronization of NBA players' circadian rhythm may, at least in part, contribute to the home court advantage in the NBA (101, 102) as well as heightened NBA injury risk during away games (i.e., 54% of regular season injuries occurred in players playing games away from home in a sample of 1443 NBA players between 2012 and 2015) (27).

Acknowledging the widespread risks and concerns associated with travel fatigue on player recovery and subsequent performance, several practical recommendations were proposed for coaches in Study 1, including adjustments to pre -and postflight recovery and practice timing and duration; the use of ergogenic aids to speed up the recovery process (e.g., whole body cryotherapy, compression tights, cold water immersion, contrast water therapy, and soft tissue massage); and the use of sleep optimization strategies (e.g., blue light exposure in the morning and red light exposure in the evening, ingestion of a high-carbohydrate, low-protein meal in the evening, or the ingestion of a high-protein, low-carbohydrate meal in the morning). However, it is important to acknowledge that scientific information about the specific demands of frequent air travel on performance and health in professional team sports is still scarce, with research existing in soccer (109) and rugby (110) that may not directly apply to the NBA. Additionally, it is crucial to recognize that correlation does not necessarily imply causation, and multiple confounding factors could contribute to the observed injury and performance patterns in the NBA. For instance, the influence of travel-related factors, such as jet lag, fatigue, and disrupted sleep patterns, may vary among each individual. Moreover, the absence of controlled experimental designs and reliance on observational studies further complicate drawing definitive conclusions and providing evidence-based recommendations that are ecologically valid and aligned with the modern-day NBA ecosystem. Therefore, as part of the present compendium, it was intended to bring further understanding and develop a more holistic perspective regarding the unpredictable, multifaceted, and interconnected nature of factors that influence NBA game-play performance.

Particularly, in Study 2, the main objective was to systematically review the literature within the last two decennia about the underpinning factors of NBA game-play performance. In this context, the CLA was determined as an appropriate framework for the comprehensive synthesis of the existing research, analyzing various factors that contribute to both individual and team performance in the NBA. By adopting this framework, Study 2 deliberately embraced "complex systems thinking" to acquire a more nuanced understanding of the factors influencing NBA game play performance, capturing the interdependencies and interactions between different constraints and their collective influence on performance outcomes.

Through a rigorous search and screening process, a total of 42 articles (published between 2001 and 2020) were identified, highlighting the growing interest in understanding the determinants of NBA game play performance over the past two decades. For each particular variable that was identified as an underpinning factor of NBA game-play performance, practical recommendations and future research suggestions were provided in Study 2. Surprisingly, despite the demanding schedule and high value of athletes in the NBA and despite provisions in the NBA collective-bargaining agreement allow for research designed to improve player health and broaden medical knowledge, Study 2 confirmed the reports by Mclean et al. (23) in which no public data was available on practice and game load demands throughout an NBA season. Additionally, the total body of evidence accumulated in Study 2 demonstrated widespread heterogeneity and inconsistency in study designs, statistical methods, and research topics. As highlighted by McLean et al. (23), this current lack of information likely results from multiple factors including limited understanding of (basketball-related) emerging technologies, impact of specific league rules, and steps taken to protect players in the age of Big Data. Additionally, previous studies across professional team sports demonstrated that existing athlete monitoring tools often suffer from limitations such as being time-intensive, subjective, and lacking comprehensiveness in capturing multiple underlying factors of fatigue, recovery, and overall player well-being.

In response of this critical research gap, Russell et al. (37) published the first scientific report on seasonal training data in NBA players. In particular, they collected the internal and external training and game load data of 14 NBA players during the 2017-2018 season and concluded that the total weekly duration was significantly different between years of NBA playing experience, whereas no significant differences were found in integrated load or duration between positions. While this study advanced current understanding of the physical demands experienced throughout an entire NBA season, challenges remained in establishing definitive benchmarks for the demands of NBA competition due to a small sample size and reported missing data. Notably, the authors highlighted that current athlete monitoring technologies and systems in the NBA are likely too cumbersome to apply during all on-court activity throughout the season (23). Furthermore, they reported that a "one system approach" to athlete monitoring would be far more desirable than the traditional approach of integrating multiple systems that measure load differently (1, 23). Finally, given the lack of gold-standard validity and many logistical and data processing issues experienced, current athlete monitoring systems and tools were considered insufficient to quantify workload in NBA players in a consistent, year-round manner. In light of these findings, and realizing the importance of quantifying the individual demands of NBA players, it was concluded that discovering new, innovative, and comprehensive athlete monitoring solutions that can benefit all parties involved (i.e., NBA players, staff, agents, league entities, clubs, commercial partners, and outside research institutions) is an important issue. Consequently, keeping in mind this critical research gap, alongside the key findings and factors of NBA game-play performance identified in Study 2, the objective of Study 3 was to conduct an exploratory pilot study, which sought to evaluate whether HQIPs could serve as a promising new alternative to traditional athlete monitoring approaches in the professional basketball ecosystem.

Based on the data of Study 3 and those from previous investigations on the use of HQIPs in the context of human fatigue detection, there seems to be compelling evidence supporting the use of HQIPs as a viable and valuable option to quantify, analyze, and ultimately mitigate the risk of excessive fatigue levels in NBA players. Particularly, three key discoveries are worth considering here.

Firstly, Study 3 demonstrated that it was practically feasible for a non-medical practitioner to implement a pupil measurement routine utilizing a medically graded HQIP with acceptable reliability scores for two pupillometrics (MinD and MaxD) and with minimal measurement bias for all pupillometrics (i.e., average bias across all pupillometrics (0.001±0.450). Notably, the execution of the pupil measurement routine was subjectively perceived by the test administrator as relatively simple and pragmatic, with a total daily pupil recording time that did not exceed ~4 min in duration per player, and ~60 min in total duration, without any interference with the daily predetermined schedule of the team. This is very relevant for sport scientists and practitioners employed in the NBA as it supports the viability of using the HQIPs in similar environments, during time-intensive scenarios that may occur during the course of an NBA season (e.g., back-to-backs). Consequently, the method described in Study 3 may serve as a useful baseline reference framework for further experimentation and exploration at the NBA level.

Secondly, Study 3 revealed that four pupillometrics were related to other forms of fatigue expression in professional female basketball players. In particular, MaxD and MinD was associated with all other selected biomarkers of game-induced fatigue ($r = 0.69–0.82$, $p < 0.05$), while CV and MCV were the strongest indicators of cognitive, lower-extremity muscle, and physiological biomarkers of game-induced fatigue ($r = 0.74–0.76$, $p < 0.05$). Therefore, the combination of MaxD, MinD, CV, and MCV may open up new avenues for basketball sports scientists to quickly capture the players' objective response to game loads, in a holistic manner.

Third and finally, three pupillometrics demonstrated the ability to detect a significant change from rested states (baseline and GD-1) to fatigued states (GD+1 and GD+2). More specifically, at timepoints where residual fatigue was expected to remain present (48 h following games), the pupils constricted slower (MCV), with a smaller magnitude (PC), while it took longer to begin its constriction phase (LAT). As expected, these findings confirm the underlying neurobiological concept of pupillary behavior as previous studies regarded LAT as an index of sympathovagal balance (i.e., higher values indicate sympathetic dominance) (49), whereas PC and MCV as an index of parasympathetic activity (i.e. higher values indicate parasympathetic dominance) (49). However, recognizing the heterogeneity in recovery time-course kinetics between athletes, sports, imposed stressors, chosen interventions, and type of fatigue, it remains inappropriate to make conclusive statements regarding the sensitivity of pupillometrics in relation to game load. Therefore, it is recommended that basketball sports scientists and practitioners approach HQIPs as a potential complementary part of an overarching AMS (e.g., first point of care signal), rather than a complete substitute. It is also worth noting here that Study 3 does not inform about the underlying factors and dynamics of fatigue accumulation. As highlighted by Doeven et al. (285), there are many covariables that play an influential role on the recovery dynamics of each player (e.g., menstrual cycle, physical fitness, role within the team, playing time, exertion, playing level, playing style, age, gender, genetic make-up, game location, preceding travel duration, opponent quality, imposed workload, lifestyle habits, sleep quantity and quality) (285). Hence, future researchers are encouraged to integrate these cofactors in future investigations in order to pinpoint the underlying mechanisms for pupillary change following games. Furthermore, to make pupillary data more practically relevant, future researchers may include predetermined anchor points that are prioritized by their organization (e.g., specific injury occurrence per minute of activity exposure, on-court game-play performance metrics, pre-game alertness levels) (3, 273, 283). This anchoring approach, often referred to as the Minium Clinical Important Difference (MCID), would allow practitioners to track pupillometrics per player over time and transform them into a prediction or prescription tool informing the onset to critical states via real-time alerting or traffic-light based visualization systems (273, 283-282).

In summary, from a practical and applied perspective based on the results of the present compendium of studies, basketball S&C coaches and sport scientists should be aware that NBA game-play performance emerges from a complex and dynamic system of interdependent factors in which athlete monitoring is widely viewed as an important modulator for optimizing player health, well-being, and performance. In this sense, pupillometry opens up a new avenue for research and potential interventions to evaluate athletes in a fast, objective, valid, reliable, non-invasive, cost-effective, and comprehensive manner amidst highly demanding schedules. Although the initial results are promising, further research and validation are needed to confirm or dispute the usefulness of pupillometry inside the real-world NBA environment. Finally, given the scarcity of literature on this topic as well as the overall lack of consistency and transparency in pupillometric research reported over the past 50 years (as recently highlighted by an international panel of pupillometry experts across disciplines) (271), basketball S&C coaches and sport scientists are encouraged to harness this present compendium of studies as a baseline reference framework for future exploration, while prioritizing transparency and standardization when executing their future research projects.

IX – CONCLUSIONS

IX. CONCLUSIONS

7.4. GENERAL CONCLUSIONS

The results of the present compendium of articles allowed concluding that HQIPs open a new pathway of opportunities for basketball sport scientists and practitioners to monitor game-induced fatigue, during the in-season period. Particularly, it was revealed that the pupillometrics MinD, MaxD, MCV, and CV may provide the most potential in this particular context. Additionally, through the narrative and systematic review, it was concluded that evidence-based practice in the NBA remains challenging due to the scarcity and heterogeneity of available literature and published data regarding its players and ecosystem. Hence, the compilation of research, and established pupillometry methodology, may serve as a normative database and baseline reference framework for future applied science initiatives within the NBA ecosystem.

7.4. SPECIFIC CONCLUSIONS

The specific conclusions of the studies comprising the present thesis are displayed below. Importantly, the following conclusions are only applicable to athletes with similar characteristics to those presented in each investigation.

Study 1:

- Travel fatigue is a major concern in the NBA due to the geographical span of teams across four time zones as NBA players spend more time above 30,000 ft than athletes competing in all other team sports in the United States of America (USA).
- Despite recent schedule modifications and an increased awareness of the potential negative consequences of air travel on player health and performance in the NBA, the effectiveness of currently employed strategies to manage these risks remain ambiguous. In turn, this forces NBA practitioners to employ cross-

contextual inferences based on other elite sport populations and environments that may not automatically apply to the NBA.

Study 2:

- The systematic review of the scientific literature (2001-2020) performed on the underlying factors of NBA game-play performance yielded that contextual constraints received substantially more attention than topics related to player constraints (58.1% vs. 41.9%).
- Descriptive-observational research emerged as the most popular method of investigation; interventional studies were absent; and near all researchers merely utilized secondary data sources (86.0%).
- In light of the many different interdependent factors that influence NBA game-play performance, and acknowledging the fast-paced nature of the NBA ecosystem, the lack of fast, valid, reliable, non-invasive, objective, and comprehensive AMS tools was viewed as an urgent and important research gap in order to help NBA players stay healthy and game-ready.

Study 3:

- HQIPs demonstrated to be a feasible, fast, objective, reliable, valid, non-invasive, and comprehensive solution to quantify game-induced fatigue in female professional basketball players over a 5-week in-season period.
- The most promising pupillometrics were identified as MinD, MaxD, CV, and MCV.
- Two out of seven pupillometrics (MinD and MaxD) displayed good test-retest reliability scores, which aligned with previous investigations on pupillometry across different use cases, HQIPs, and populations.
- Strong significant relationships were found between MaxD, MinD, and all registered biomarkers of game-induced fatigue.
- Strong significant relationships were found between CV, MCV, and biomarkers of cognitive, lower-extremity muscle, and physiological fatigue.
- From a recovery time course perspective, a significant difference could be detected between rested and fatigued states for PC (right) and MCV (right) from baseline to GD+2, and for LAT (left) from GD-1 to GD+1.

X – LIMITATIONS

VIII –LIMITATIONS

Some limitations of the studies composing the present thesis must be addressed:

- In Study 1, a broad perspective and understanding was acquired on the schedule and travel demands within the NBA, which does not allow for direct comparisons between studies (e.g., meta analyses).

- The small number of papers included in Study 2, due to the few existing publications that attempt to examine the underlying factors of NBA game-play performance, may have imposed biases on the conclusions obtained. Consequently, caution is necessary when generalizing the results found herein.

- The high heterogeneity in research topics of the studies included in Study 2 made comparison between studies difficult, which in turn impacted the generalizability of the outcomes reported.

- The vast majority of studies included in Study 2 followed an ecological study design, examining multiple NBA teams at once and altogether, however none of these articles were encompassed recent competitions (>2017), thus inferences on player and team specific inner variables with similar conditions for the outer variables in the modern NBA competition cannot be automatically assumed.

- In study 2, the selected indicators of NBA game-play performance were outcome-driven, thus lacking the ability to draw inferences on how teams and/or players may change their behaviors during the course of a game to ultimately arrive at successful game-play outcomes.

- The small, homogenous, single-sex, and relatively short-term sample size in Study 3 may have prevented the identification of significant and meaningful pupillary changes at the group level. In turn, it does not allow for conclusive inferences regarding other populations, timeframes, and ecological contexts.

- The absence of any task-specific workload measures in Study 3 (e.g., accelerometry data), made it impossible to establish the actual underlying factors and reasons that contributed to the pupillary fatigue measures obtained. Hence, making conclusive inferences regarding the dose-response relationship between EL and IL was not possible.

XI - PRACTICAL APPLICATONS

XI –PRACTICAL APPLICATIONS

From an applied and practical perspective, according to the results from the studies in the present thesis, basketball SC coaches and sport scientists should consider that:

- Based on the total body of evidence about the NBA, sport scientists and practitioners in the NBA are encouraged to embrace a stepwise framework, such as the Applied Research Model for Sport Sciences (ARMSS) conceptualized by Bishop et al. (164) because it sequentially integrates descriptive, exploratory, and explanatory study designs, and links them altogether in a progressive manner (8-step process). In turn, this approach would foster higher reproducibility and transferability of scientific findings pertaining to the real-word NBA ecosystem (i.e., dynamic correspondence).

- The selected HQIP and PLR test routine has demonstrated, at least in part, to serve as a promising contribution to AMS in high-performance team-sport environments (Euro Cup basketball in this case). In particular, a non-medical practitioner was able to apply the pupillometry methodology across 5 weeks, without any disruption of the predetermined schedule, and with reliable outcomes for two pupillometrics (MaxD and MinD).

- From an AMS standpoint, four pupillometrics (MaxD, MinD, MCV, and CV) reflected a strong relationship with other biomarkers of game-induced fatigue, and three pupillometrics were able to distinguish rested states from fatigued states (LAT, PC, and MCV). Thus, these particular pupillometrics may be further explored as potential key determining indicators of overall game-induced fatigue.

- NBA sport scientists and practitioners gain an opportunity to explore even faster and more accessible HQIPs through the advancements of mobile applications, camera systems, computer vision, VR, AR, and AI technology.

XII – FUTURE RESEARCH LINES

XII – FUTURE RESEARCH LINES

After the completion of the present thesis, future research lines arise from the results obtained. In this regard, potential future investigations that could bring further understanding on the topics studied herein are presented below:

- To examine NBA game-play performance statistics from a behavioral perspective. As an illustration, Page et al. (243) factored in player-specific covariates (position, usage rate, and average minutes played per game), and applied a hierarchical Gaussian regression process to compute critical NBA game-play performance indicators that were more comprehensive in nature than previously proposed.

- To examine the clinical validity and test-retest reliability of more advanced and/or more portable HQIPs, such as mobile applications.

- To examine the underlying factors and mechanisms of pupillary fatigue dynamics in the context of other critical stressors (e.g., travel, media obligations).

- To investigate the impact of training and/or recovery interventions (e.g., breathwork, meditation, cold water immersion, etc.) on pupillary fatigue behavior.

- To examine the feasibility, test-retest reliability, and sensitivity of the selected HQIP in broader contexts, including different sports, sexes, timeframes, levels, competitions, and use cases.

- To examine HQIPs as a potential tool for analyzing the individual adaptations to neurocognitive training (e.g., mental priming techniques, eye muscle training).

- To determine the dose-response relationship between various well-established EL measures (e.g., high speed decelerations) and pupillary fatigue measures (e.g., MinD, MaxD, MCV, CV).

XIII - MENCIÓN INTERNACIONAL

XIII. – MENCIÓN INTERNACIONAL

Con el objetivo de cumplir con los criterios especificados en el Real Decreto 99/2011 para la obtención de la Mención Internacional en el Título de Doctor, se presentan las conclusiones del presente compendio de estudios en un idio distinto al utilizado en la restante tesis.

7.4. CONCLUSIONES GENERALES

Los resultados del presente compendio de artículos permitieron concluir que los HQIP abren un nuevo camino de oportunidades para que los científicos y practicantes del baloncesto monitoreen la fatiga inducida por el juego durante el período de temporada. En particular, se reveló que la pupilometría MinD, MaxD, MCV y CV pueden proporcionar el mayor potencial en este contexto particular. Además, a través de la revisión narrativa y sistemática, se concluyó que la práctica basada en evidencia en la NBA sigue siendo un desafío debido a la escasez y heterogeneidad de la literatura disponible y los datos publicados sobre sus jugadores y ecosistema. Por lo tanto, la compilación de la investigación y la metodología de pupilometría establecida pueden servir como una base de datos normativa y un marco de referencia de referencia para futuras iniciativas de ciencia aplicada dentro del ecosistema de la NBA.

7.4. CONCLUSIONES ESPECÍFICAS

Las conclusiones específicas de los estudios que componen la presente tesis se muestran a continuación. Es importante destacar que las siguientes conclusiones solo son aplicables a atletas con características similares a las presentadas en cada investigación.

Estudio 1:

- La fatiga del viaje es una preocupación importante en la NBA debido a la extensión geográfica de los equipos en cuatro zonas horarias, ya que los jugadores de la NBA pasan más tiempo por encima de los 30 000 pies que los atletas que compiten en todos los demás deportes de equipo en los Estados Unidos de América (EE. UU.).
- A pesar de las modificaciones recientes en el horario y una mayor conciencia de las posibles consecuencias negativas de los viajes aéreos en la salud y el rendimiento de los jugadores en la NBA, la efectividad de las estrategias empleadas actualmente para gestionar estos riesgos sigue siendo ambigua. A su vez, esto obliga a los practicantes de la NBA a emplear inferencias contextuales cruzadas basadas en otras poblaciones y entornos deportivos de élite que pueden no aplicarse automáticamente a la NBA.

Estudio 2:

- La revisión sistemática de la literatura científica (2001-2020) realizada sobre los factores subyacentes del rendimiento del juego de la NBA arrojó que las restricciones contextuales recibieron mucha más atención que los temas relacionados con las restricciones de los jugadores (58,1 % frente a 41,9 %).
- La investigación descriptiva-observacional surgió como el método de investigación más popular; los estudios de intervención estaban ausentes; y casi todos los investigadores simplemente utilizaron fuentes de datos secundarias (86,0%).
- A la luz de los diferentes factores interdependientes que influyen en el rendimiento del juego de la NBA, y reconociendo la naturaleza acelerada del ecosistema de la NBA, se observó la falta de herramientas AMS rápidas, válidas, confiables, no invasivas, objetivas y completas. como una brecha de investigación urgente e importante para ayudar a los jugadores de la NBA a mantenerse saludables y listos para el juego.

Estudio 3:

- Los HQIP demostraron ser una solución factible, rápida, objetiva, confiable, válida, no invasiva y completa para cuantificar la fatiga inducida por el juego en jugadoras profesionales de baloncesto durante un período de temporada de 5 semanas.
- Las pupilometrías más prometedoras se identificaron como MinD, MaxD, CV y MCV.
- Dos de siete pupilometrías (MinD y MaxD) mostraron buenos puntajes de confiabilidad test-retest, que se alinearon con investigaciones previas sobre pupilometría en diferentes casos de uso, HQIP y poblaciones.
- Se encontraron fuertes relaciones significativas entre MaxD, MinD y todos los biomarcadores registrados de fatiga inducida por el juego.
- Se encontraron fuertes relaciones significativas entre CV, MCV y biomarcadores de fatiga cognitiva, muscular de las extremidades inferiores y fisiológica.
- Desde la perspectiva del curso del tiempo de recuperación, se pudo detectar una diferencia significativa entre los estados de descanso y fatiga para PC (derecha) y MCV (derecha) desde la línea base hasta GD+2, y para LAT (izquierda) desde GD-1 hasta GD+1 .

XIV – REFERENCES

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XV. - APPENDICES

APPENDIX 1. Study 1: THE NEGATIVE INFLUENCE OF AIR TRAVEL ON HEALTH AND PERFORMANCE IN THE NATIONAL BASKETBALL ASSOCIATION: A NARRATIVE REVIEW.

Reference:

Huyghe T, Scanlan AT, Dalbo VJ, Calleja-González J. The Negative Influence of Air Travel on Health and Performance in the National Basketball Association: A Narrative Review. Sports (Basel, Switzerland). 2018;6(3):E89.

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Article

The Negative Influence of Air Travel on Health and Performance in the National Basketball Association: A Narrative Review

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Abstract: Air travel requirements are a concern for National Basketball Association (NBA) coaches, players, and owners, as sport-based research has demonstrated short-haul flights ($\leq$6 h) increase injury risk and impede performance. However, examination of the impact of air travel on player health and performance specifically in the NBA is scarce. Therefore, we conducted a narrative review of literature examining the influence of air travel on health and performance in team sport athletes with suggestions for future research directions in the NBA. Prominent empirical findings and practical recommendations are highlighted pertaining to sleep, nutrition, recovery, and scheduling strategies to alleviate the negative effects of air travel on health and performance in NBA players.

Keywords: NBA; athletic performance; fatigue; circadian rhythm; injury; sleep

1. National Basketball Association: Schedule and Travel Requirements

The National Basketball Association (NBA) is the premier basketball league in the world [1,2] and in recent years a greater emphasis has been placed on player safety [3,4]. In regard to player safety, there has been increased attention in the areas of training load [3,5] as well as schedule and travel requirements [5]. In an attempt to reduce the training load and schedule requirements of players, the NBA has modified the preseason schedule. Prior to 2017, NBA teams played eight preseason games across 3–4 weeks in preparation for the regular season [6,7]. Since the 2017–2018 season, the NBA season has consisted of four to six preseason games played across 3–4 weeks followed by an 82-game regular season played across 26 weeks (177 days). During the regular season, each team plays two to five games per week (~3.2 games per week) [1] with games lasting an average duration of 2 h and 15 min [2]. NBA teams rarely practice during the season and practices that occur are typically less than 1 h [1,2]. In response to teams resting players during back-to-back (two games within a 2-day span) games [8], the league extended the duration of the regular season by 7 days with the purpose of scheduling fewer back-to-back games [6]. During the 2017–2018 season, NBA teams played an average of 14.4 $\pm$ 0.9 back-to-back games, which was the lowest on record compared to any previous season in the NBA [2]. Furthermore, the 2017–2018 NBA season marked the first season in NBA history in which no team played four games in 5 nights [6]. Despite adjustments to the NBA schedule, air travel demands remain high due to the geographical span of teams across four time zones (eastern, central, mountain, and western). In this regard, NBA players spend more time above 30,000 ft than athletes competing in all other team sports in the United States of America (USA) [7]. Air travel requirements are a concern for NBA coaches, players, and owners, as research has demonstrated short-haul flights ($\leq$6 h) increase injury risk [2,9–13] and impede performance [9,14–20]. Competing in away games has been reported to significantly increase regular season injury risk in a sample of 1443 NBA players between 2012 and 2015 [9]. Specifically, 54% of regular season injuries occurred in players playing games away from home, which was significantly greater than the expected injury rate for away games of 50% ($p < 0.05$) [9]. Furthermore, the direction of air travel should be considered by NBA teams, as traveling westward exacerbates reductions in performance [14,21]. In a sample of 8495 NBA games between 1987 and 1995, west coast teams scored four more points per game ($p < 0.05$) when traveling to the east coast than east coast teams scored when traveling to the west coast [21]. Furthermore, NBA teams traveling eastward had a winning percentage of 45.4% compared with 36.2% for teams traveling westward ($p < 0.001$) between 2010 and 2015 [14]. The increased difficulty of traveling westward across the USA to compete has also been reported in the National Football League and the National Hockey League [14]. Westward travel is likely more difficult since performance tends to peak in the late afternoon and players traveling from west to east tend to play games closer to their circadian peaks given most NBA games are played at night.

2. The Impact of Travel Fatigue on Performance

Frequent air travel can negatively affect hydration status, nutritional behaviors, sleep quality, and sleep quantity, thus extending the time for sufficient recovery between games and/or training in athletes [15]. As a result, air travel should be considered as an additional stressor imposed on NBA players in conjunction with competition and training schedules [15], especially when less than 72 h of rest is experienced between games [21,22].

One of the main consequences associated with frequent air travel exposure is "travel fatigue". Travel fatigue refers to feelings of disorientation, light-headedness, gastrointestinal disruption, impatience, lack of energy, and general discomfort that follow traveling across time zones [13]. The magnitude of travel fatigue depends on many factors such as regularity, duration, and conditions of travel [13]. Specific causes of air-related travel fatigue include:

- Prolonged exposure to mild hypoxia [16,23,24].
- Difficulties in standing, walking, and moving around due to limited room inside the air cabin.
- Reduced air quality in the cabin, which may impair immune function [12].
- Dry cabin air and low hypobaric pressure potentially causing dehydration [25].
- Prolonged sitting in a cramped position reducing mobility and flexibility [10,16].
- Disruption of routines (e.g., eating and sleeping) [26].
- Noise of plane and cabin (e.g., sleep disturbance) [16].
- Formalities of air travel may induce negative mood states [26].

A primary issue regarding air travel occurs as a result of significant reductions in oxygen saturation, which has been found to decrease significantly from 97% at ground level to 93% at cruising altitude ($p < 0.05$) [24]. This finding is significant, as oxygen saturation levels of 93% could prompt physicians to administer supplemental oxygen in hospital patients [24] and thus would slow muscle recovery [27]. One study examined the effects of air travel from the east coast to the west coast of the USA on physiological performance measures, sleep quality, and hormonal alterations [28]. However, it is important to note the following: participants used in this investigation were not athletes, a simulated sporting event most closely related to demands experienced during soccer was administered, and there was no non-exercise (control) group. However, air travel induced jet lag symptoms, which resulted in decreased sleep quality and was paired with significantly increased melatonin levels on flight days (travel from east to west coast and travel from west to east coast) [28]. The authors also examined markers of skeletal muscle damage, but since a non-exercise control was not included in the investigation meaningful interpretations of the data cannot be determined [28].

When flying across two or more time zones, symptoms of travel fatigue can remain up to 2–3 days after arrival [13]. The physiological and perceptual stressors associated with flying across one or more time zones may alter sleep patterns in athletes [12]. In particular, short-haul air travel has been reported to impair athletic performance due to the development of an inefficient internally-driven circadian rhythm (i.e., sleep deprivation or disorientation between the circadian system and the environment) [29]. In this sense, NBA players may experience difficulty sleeping at night and excessive daytime sleepiness when traveling across multiple time zones. Subsequently, the greater the number of time zones travelled, the more difficult it is for an athlete to adapt to a new time zone. For example, a 2-h time zone shift may cause marginal disruption to the circadian rhythm, but a 3-h time zone shift (e.g., NBA players traveling coast to coast within the USA) can cause a significant desynchronization of circadian rhythm [13]. Therefore, it is recommended that NBA players focus on physical activity, eating, and social contact during daylight in their new time zone in order to resynchronize their circadian rhythm, especially when traveling from coast to coast [13].

The circadian rhythm plays a critical role in sports performance [13,19,30,31]. When an athlete's circadian rhythm is synchronized with the environment, the athlete should achieve optimal performance during late afternoons and early evenings [19]. Considering air travel can cause an athlete's circadian rhythm to become unsynchronized with the environment, air travel may contribute to the home court advantage in the NBA [32,33], as the body's core temperature (an endogenous measure of circadian rhythm) takes approximately 1 day for each time zone crossed to adapt completely to the new time zone [13,34]. Consequently, the number of time zones traveled plays a critical role in the magnitude of travel fatigue [13].

The regularity, duration, and direction of air travel, combined with in-cabin conditions, likely predisposes NBA players to travel fatigue [13]. In turn, travel fatigue can have deleterious effects on player recovery and subsequent performance, particularly when scheduled soon after practices or games. Consequently, it is recommended that recovery and practices administered before and after air travel are modified to account for travel fatigue, especially considering the travel direction and flight duration experienced.

3. Scheduling and Recovery Opportunities

Besides the direction and duration of air travel, the home court advantage is also influenced by the quantity of rest NBA teams attain prior to games [35]. In particular, a consistent advantage was recorded when a team had more than 1 day of rest between games (the home team's score increased by 1.1 points per game and the away team's score increased by 1.6 points per game) in a sample of 8495 regular season NBA games between 1987–1995 [21]. Moreover, average total scores (home and away teams) were highest when 3 days of rest were encountered between games with data collected from the 1987–1995 seasons [21]. Consequently, the negative influence of air travel during an NBA season may be mitigated by incorporating supplemental days to recover from games.

An optimal recovery window of 72 h following games and practices is needed for an athlete or team to return to optimal levels of performance [22]. Nevertheless, the NBA schedule dictates condensed game schedules that necessitate compressed training schedules, which may inhibit access to active rest days to fully recover from accumulated physical and psychological stress induced by NBA games and practices. Consequently, NBA teams are often obligated to intervene with various ergogenic practices in an attempt to speed up the recovery process, such as whole body cryotherapy, compression tights, cold water immersion, contrast water therapy, and soft tissue massage [36]. While these commonly employed recovery practices, including compression tights [37], cold water immersion [38], and massage [39], have been investigated in various samples of basketball players, no data are available specifically in NBA players. Therefore, more research is needed to ascertain if these recovery practices benefit NBA players across the season.

Another factor to consider in reducing injury risk and optimizing performance in the NBA is the total amount of in-game minutes accrued by each player. While coaches have presumed withdrawing high-minute players from entire games may reduce injury risk and enhance performance, a tactic which is often seen nearing the conclusion of the regular season, data to support this approach is lacking. In fact, existing data revealed the average minutes played per game did not influence on-court performance or injury risk ($p < 0.001$) in 811 NBA players competing between 2000 and 2015 [8,9]. However, it should be noted these data are not reflective of performance and injury risk in players who were rested for entire games but rather are indicative of players completing reduced game minutes. Subsequently, future studies are needed to examine the consequences and confirm the efficacy of resting high-minute players for entire games in the NBA.

Scientific information about the specific demands of air travel on performance and health in professional team sports is scarce, with research existing in soccer [40] and rugby [41], which may not directly apply to the NBA. Therefore, research is needed to understand the impact of air travel on player health and game performance across the season in the NBA. Future research on the influence of air travel in NBA players should focus on the identification of causes and symptoms of travel fatigue as well as interventions to mitigate the effects of air travel on player health and performance.

4. Conclusions and Future Research

The NBA travel schedule induces misalignments in circadian rhythm that cannot be avoided. Air travel across three time zones has been reported to induce susceptibility to travel fatigue [18,29,42–44], increase injury risk [13,29,41], and reduce game performance [13,14,17,29,32]. NBA schedule-makers and teams may succeed in mitigating the negative effects of air travel from coast to coast on sleep by implementing up-to-date, evidence-based strategies applied in other professional sports, such as blue light exposure in the morning and red light exposure in the evening, in order to resynchronize the circadian rhythms of players [45]. Other strategies include the ingestion of a high-carbohydrate, low-protein meal in the evening, which may enhance serotonin production to promote drowsiness and sleep [19,46], or the ingestion of a high-protein, low-carbohydrate meal in the morning, which may increase the uptake of tyrosine and its conversion to adrenaline, which elevates arousal and promotes alertness [44,46]. However, future studies are required to evaluate the efficacy of the abovementioned strategies in NBA players.

Despite recent schedule modifications and an increased awareness of the potential negative consequences of air travel on the health and performance of NBA players, there is still a need to implement effective strategies to address issues with sleep and travel fatigue to promote greater equity across western and eastern teams. Future research exploring various aspects of regularity, duration, directions, and conditions of air travel [13] in one or multiple NBA seasons can help identify origins of fatigue in players. Consequently, a holistic approach to future research is recommended, with some potential topics of interest encompassing descriptive and intervention-style studies.

First, it is important to understand the impact of air travel on NBA players at an individual level, given that NBA players often experience time zone transitions, which have been found to increase injury risk [9,41] and hinder performance [15,19,21,40,42,47]. Considering frequent time zone transitions often disrupt the circadian rhythm in athletes [15,16,19,26,42,43], future studies may focus on the measurement of salivary melatonin onset, adrenaline concentrations, and body temperature, as these are critical biomarkers of circadian rhythm [19,48]. Measurement of these biomarkers would provide insight into how each player individually adapts to air travel throughout the NBA season. Consequently, NBA performance support staff may then apply individualized approaches to training and game preparation to combat the negative impact of air travel.

Second, examination of various ergogenic aids will provide a better understanding of practices that may enhance physiological and perceptual responses to air travel in NBA players. For instance, nutrition [49] and hydration [49] are fundamental aspects underpinning circadian rhythm. Therefore, analyzing and comparing the hormonal responses of NBA players adopting different diets may provide NBA coaches and support staff with further insight into beneficial nutritional strategies for coping with air travel in the NBA.

Third, in order to mitigate the negative impact of air travel on mood state, it is recommended that each player's psychological and psycho-sociological reactions to air travel should be monitored during the season. For instance, comprehensive psychometric questionnaires such as the Acute Recovery and Stress Scale (ARSS) [50] and the REST-Q Sport [51] have been established as logical, practical, and versatile tools to measure self-perceived travel fatigue in professional team sports [50,51]. Considering the time constraints in the NBA, shorter customized versions of these questionnaires can be completed on a daily basis [52], which have been reported to be valid and reliable in elite Australian Rules Football [53]. However, further research is necessary to provide normative standards, especially with a focus on individual interpretations, recommendations, and compliance in NBA players.

Finally, considering that skeletal muscle and connective tissues become shortened during flights and may stiffen, it is recommended for players to avoid sitting the entire trip, and instead, walk around the cabin every hour, unless they are asleep or advised not to do so by flight staff [46]. With a tentative agreement between the NBA and Delta Airlines charters, walking inside the air cabin should be attainable, as most NBA teams (27 out of 30 teams) fly with private jets of Delta Airlines (including A319s and Boeing 757-200s) with almost 50 percent more cabin space than standard planes [54]. This cabin space allows most NBA players, who possess an average stature of 6 feet and 7 inches, to have more freedom to stand erect during air travel [54]. Additionally, simple stretching exercises can be applied while in the seat or in the cabin, which could help relax muscles while increasing blood flow and delivering oxygen and other nutrients to muscles [27,46]. As a result, stretching may reduce the negative effects of air travel on flexibility and skeletal muscle recovery. Consequently, future studies are encouraged to examine the efficacy of these in-flight travel strategies in NBA players.

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APPENDIX 2. Study 2: THE UNDERPINNING FACTORS OF NBA GAME-PLAY PERFORMANCE: A SYSTEMATIC REVIEW (2001-2020)

Reference:

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REVIEW

The underpinning factors of NBA game-play performance: a systematic review (2001–2020)

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ABSTRACT

Objective: Recognizing the high stakes associated with winning and losing in the National Basketball Association (NBA), a deep understanding of the underlying mechanisms of NBA game-play performance would provide substantial benefit to all stakeholders involved with preparing NBA players and teams for competitive success. To the best of the authors' knowledge, this systematic review presents the first attempt to systematically amalgamate and appraise the scientific literature published in the XXI Century, following a constraints-led approach (CLA). In particular, two underpinning factors of NBA game-play performance were investigated: (1) NBA player constraints (internal variables) and (2) NBA contextual constraints (external variables).

Methods: Databases included PubMed (MEDLINE), Web of Science (WOS), ResearchGate, SPORTDiscus, SCOPUS, Google Scholar, and the World Association of Basketball Coaches' database (WABC). This review followed the Preferred Reporting Items for Systematic Review and Meta-Analyses (PRISMA) model and the Population, Intervention, Comparison and Outcomes (PICOS) guidelines.

Results: Ultimately, 43 articles met the inclusion criteria (*n* = 43). Promisingly, the vast majority of studies were published in recent years (>2016; *n* = 28; 65.1%). Topics related to 'contextual constraints' (*n* = 25; 58.1%) received more attention than topics related to 'player constraints' (*n* = 18; 41.9%). Even though the importance of longitudinal-interventional approaches to applied sports science is well-documented, descriptive-observational research emerged as the most popular method of choice (*n* = 27; 62.8%); interventional studies were absent; and near all researchers merely utilized secondary data sources (*n* = 37; 86.0%).

Conclusions: Taking into account the total body of evidence (2001–2020), NBA practitioners may use this systematic review as a baseline reference to enrich their current knowledge about the nature, demands, and dynamics of the modern-day NBA ecosystem. Finally, adoption of an 'Applied Science Research Framework' is encouraged, fostering clearly outlined project incentives; standardizing taxonomies; sequencing follow-up studies; embracing holistic and cross-disciplinary viewpoints; and integrating longitudinal-interventional projects to increase the reproducibility of their findings.

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Introduction

The National Basketball Association (NBA) is widely recognized as the premier basketball competition in the World and one of the most popular sports leagues in and outside the United States [1]. The typical NBA schedule requires teams to participate in 82 regular season games played across a 5.5-month competition period in which players are exposed to an average of 22.6 ± 10.6 minutes of playing time per game, 3.4 games per week, one game every 2.07 days, 13.3 back-to-back scenarios per season, alongside frequent air travel across four different time zones (e.g. NBA teams flew 250 miles a day for 25 straight weeks during the 2018–2019 season), as well as participation in individual and team practices and workouts amid all these endeavors [1–3]. In addition, players typically go through one month of preseason activities (4–5 games) as well as potentially two months of post-season appearance (4–28 games) [1,4,5].

The monetary value of succeeding in this exceptional environment is substantial, with NBA teams generating a combined revenue of almost $US8.8 billion U.S. dollars (2018–2019) [6], and the 30 ranked teams during the 2019–2020 NBA season payed its 450 players $US3.66 billion in salaries alone [7]. Hence, league executives, teams, coaches, players and support staff personnel are all interested in enhancing and sustaining the performance of teams and players during games to improve the likelihood of competitive success. Given the average margin of victory between NBA teams is considerably small (e.g. the 2018–2019 regular season's margin of victory equaled 11.8 points) [8], the competitive edge would not need to be large to make a difference between winning and losing a game. With significant international, national, and local pride associated with winning games, significant lower-limb injury rates (11.6 lower limb injuries per 1000 game appearances) [2], lack of definitive evidence in recommendations pertaining to

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NBA player training, recovery and injury risk mitigation during the regular season [2], and yet the monetary rewards available [7], an 'evidence-based framework' to precisely prepare NBA players and teams for the subsequent demands of game-play would benefit all club stakeholders involved in this process [9–11]. Notably, according to Pol et al. [12], an evidence-based approach to coaching and training should not be defined as a framework that is 'intrinsically valid' nor 'intrinsically invalid', but instead, 'contextually more (in)appropriate or (un)functional' [12]. Accordingly, within this concept, sports scientists and coaches operating in the NBA environment necessitate a deep understanding of the central properties of complexity during NBA games (i.e. the players and the teams), their interdependence, temporal nestedness, and circular causality acting upon all levels, timescales, and dimensions of game-play [12]. Nevertheless, collecting, storing, organizing, analyzing, interpreting, disseminating, and ultimately taking action upon 'Big Data' remains a difficult task to conquer in the modern era of professional team sports [4]. With the uncontrolled influx of advanced technologies, changes in the NBA's league rules, regulations and collective bargaining agreements, and often lingering conservative approaches toward data-driven decision-making processes in the modern era [1,4], the aforementioned challenges faced upon NBA stakeholders still remains prominent today [1–4].

In an attempt to surmount these challenges [13,14], over the past two decades, projects related to 'game-play performance analysis' has rapidly grown, and continues to surface as a distinct sub-discipline and integral part of numerous applied sport science programs in elite sports (e.g. *'Performance Analysis UK'*), as well as numerous peer-reviewed journals (e.g. *International Journal of Performance Analysis in Sport; Journal of Quantitative Analysis in Sports*), international conferences (e.g.*' World Congress of Performance Analysis in Sport')*, books *(e.g. Routledge Handbook of Sport Performance Analysis*), international scientific societies (e.g. *International Society of Performance Analysis of Sport*), and academic programs (e.g. *M.Sc. in Sports Performance Analysis*) [14]. In turn, the pervasive investments in 'slow' research has already shown its value and viability across a wide range of professional basketball teams and team-sport organizations around the world [15–24]. However, the traditional approach to rudimentary analysis of standalone 'game-play performance indicators' has provoked criticism, because it offered little information about the fundamental mechanisms and behaviors that underpin game-play performance [25]. In response, the principles of 'ecological dynamics' and 'complex systems theory' have been revisited [12–14,20,25] and utilized to construct 'process-oriented analysis' of game-play performance, offering numerous benefits to both researchers and practitioners [25–27], including: generating new insights about the complex dynamics that serve as grassroots for the emergence game-play performance outcomes; gaining multi-level perspectives (inter-individual and intra-individual patterns); facilitating new opportunities for multi-disciplinary departments to collaborate and play a more prominent role in modulating the underpinning factors of game-play performance [25–27].

As a starting point to adopt such process-oriented approach to NBA game-play performance analysis, a well-defined taxonomical classification of factors that 'constrain' NBA game-play performance deems necessary [27–33]. Although a number of different constraint models have been postulated by numerous researchers, the most widely cited model to date is grounded on the concepts of Newell (1989) [28] and later on Newell and Jordan (2007) [29]. Advocated by numerous sports scientists and sport performance analysts, as well as other branches of sciences including mathematics, physics and biology [30,32]. In particular, Newell's Constraints-Led Approach (CLA) constitutes three central constraints that serve as the 'degrees of freedom' or 'boundaries' for the emergence of game-play performance, specifically: (1) player constraints (organismic characteristics), (2) contextual constraints (environmental characteristics), and (3) task constraints (game-play rules and regulations) [27–33]. This triangular framework takes into account the continuous interactions that are predicated on the 'player-task-environment relationship', and the information yielded by this approach could be used to inform real-world practices by manipulating the constraints that impinge on the player-task-environment system (e.g. technical and tactical decision-making, injury risk mitigation protocols, training and recovery prescriptions, talent identification, etc.). Therefore, the authors conceded the CLA as a suitable framework and an appropriate scale of analysis for examination of complex ecological phenomena, such as NBA game-play performance.

Despite the NBA's demanding schedule, risk for injuries, great valuta of players, and major wager associated with winning games, to the best of the authors' knowledge, a comprehensive resource of scientific evidence about the underlying mechanisms and behaviors of NBA game-play performance remains unknown. Therefore, the primary aim of this systematic review is to provide coaches, managers, medics, applied researchers, and support staff personnel with a complete compendium of peer-reviewed research spanning across the past two decades (2001–2020) specifically related to two constraints of NBA game-play performance (i.e. player and contextual constraints), and in turn, help promote the employment of evidence-based guidelines amidst the fast-pace NBA atmosphere. Secondly, the authors aim to provide this information in the most recent, reliable, accurate, and easy-to-understand language for practitioners in order to facilitate transfer of knowledge, and finally, offer short-term and long-term research agendas to promote the evolution of scientific knowledge about the modern-day NBA ecosystem.

Materials and methods

Search strategy and eligibility criteria

A systematic search of peer-reviewed research published between January 2001 and November 2020 was conducted on 2 December 2019; 4 April 2020; 10 October 2020; 14 November 2020 and 31 December 2020 utilizing PubMed (MEDLINE), Web of Science (WOS), ResearchGate, SPORTDiscus, SCOPUS, Google Scholar, and the World Association of Basketball Coaches' database (WABC). This review followed the Preferred Reporting Items for

Systematic Review and Meta-Analyses (PRISMA) guidelines and the PICOS model [34] for the definition of the inclusion criteria: P (Population): 'Healthy AND injury-free NBA players', I (Intervention): 'competed in the NBA regular season or NBA playoff basketball competition', C (Comparators): 'same conditions with comparators', O (Outcome): 'described internal factors related to NBA game-play performance (i.e. structural and/or functional characteristics of NBA players); and/or external factors related to NBA game-play performance (i.e. game location, season period, game period, game status, difference of team quality, momentum effects, playing time, rest days, travel, and/or interactive effects)'; Study design (S): 'quantitative, qualitative, and/or mixed-method model with experimental, quasi-experimental, and/or non-experimental research design, utilizing primary and/or secondary data sources'.

The search terms included a mix of medical subject headings (MeSH) and free-text words for key concepts related to 'NATIONAL BASKETBALL ASSOCIATION', 'PROFESSIONAL BASKETBALL', 'NBA', 'ATHLETIC PERFORMANCE', 'GAME-PLAY PERFORMANCE', 'GAME PERFORMANCE' along with Boolean operators such as 'AND' or 'OR' including ('National Basketball Assocation'[MeSH Terms] OR 'National Basketball Association'[All Fields]) AND (('athletic performance'[MeSH Terms] OR 'athletic performance'[All Fields]) OR ('performance'[MeSH Terms] OR 'performance'[All Fields]) OR OR ('game-play performance'[MeSH Terms] OR 'game-play performance'[All Fields) OR ('game performance'[MeSH Terms] OR 'game performance'[All Fields)) AND (('professional basketball'[MeSH Terms] OR 'professional basketball'[All Fields]) OR ('NBA'[MeSH Terms] OR 'NBA'[All Fields])). Through this equation, relevant articles in this field were obtained applying the snowball strategy. All titles and abstracts from the search were cross-referenced to identify duplicates and any potential missing studies. The titles and abstracts were screened for a subsequent full-text review.

Selection process

Two reviewers (TH, JC-G) independently screened citations and abstracts to detect articles that potentially met the inclusion criteria. Full-text versions of the selected articles were retrieved and independently screened by two reviewers (TH, JC-G) to determine whether they met inclusion criteria. Any disagreements that have occurred with regards to whether an article met the inclusion criteria were resolved through direct communication with the other authors (SB, PA) and a consensual decision was made for each final article through a joint decision-making process (i.e. computer-mediated Delphi process as a tool to scaffold idea generation and evaluation) [35]. Titles and abstracts of publications were obtained in accordance with the search strategy and the two reviewers (TH, JC-G) determined the relevance of the publication for final inclusion. Based on the information within the full-text reports, the inclusion criteria was subsequently used to select the trials eligible for inclusion in the systematic review through discussions and consensus between all authors (TH, JC-G, SB, and PA). There were no filters applied to the NBA players' ethnicity, socio-economic or socio-cultural background, age, and/or training experience to increase the power of the analysis.

Quality assessment and risk of bias

In order to carefully consider the potential limitations of selected studies and obtain reliable conclusions, two authors independently assessed the methodological quality and risk of bias (TH, JC-G), whereas disagreements were resolved by the entire research group (TH, JC-G, SB, and PA). As demonstrated and consented by Faber et al. [36] and Sarmento et al. [20] in appraising the methodological quality of quantitative studies, the 'Critical Review Forms' conceptualized by Law et al. [37] was adopted to critically appraise the methodology of included studies. In particular, the articles were assessed based on the following items: purpose (item 1), relevance of background literature (item 2), appropriateness of study design (item 3), sample studied (items 4 and 5), use of informed consent procedure (item 6), outcome measures (item 7 and 8), intervention details (item 9, 10, and 11), significance of results (item 12), analysis (item 13), practical importance (item 14), description of drop-outs (item 15), and conclusions (item 16). All sixteen quality criteria were scored on a binary scale (0/1), wherein five of those criteria (items 6, 9, 10, 11, and and 15) encompassed the option: 'not applicable' [37]. This 'if not applicable' option was included to account for non-experimental study designs, and studies in which explanation of informed consent and/or drop-outs was not required [20]. Therefore, this tertiary option eliminated the negative effect of assuming '0' on a binary scale when that item was irrelevant to that particular study. Corresponding to previous studies [20,36,38], a final percentage score of methodological quality was calculated in order to compare studies with each other (Table 3). In this regard, the sum of the score of all items was divided by the number of relevant scored items for each research study. All articles were classified as: (1) low methodological quality – with a score ≤50%; (2) good methodological quality – between 51% and 75%, and; (3) excellent methodological quality – with a score>75% [20,37,39].

Outcome measures and data organization

Based upon Newell's CLA and preliminary scientific reports in team-sport game-play performance analysis [25–33], the included studies of this systematic review were presented according to two distinct, yet interdependent, constraints of NBA game-play performance. In particular: (1) player constraints and (2) contextual constraints. Subsequently, the topics and subtopics underlying these constraints were generated based upon Casals' preliminary report in 'NBA basketball game-play performance analysis' [39]. Subsequently, two reviewers (TH, JC-G) independently organized and designated each article resulting from the analysis to their corresponding constraint, topic, and subtopic (Figure 1). Any disagreements were resolved through discussion with the other coauthors (SB, PA) until a consensus was established.

Data extraction

Once the inclusion criteria was applied to each study, the following data were extracted and documented independently by two authors (TH and JC-G) for each article using a spreadsheet (Microsoft Inc, Seattle, WA, USA): main author, year of publication, subjects (sample size), constraint (including topic and subtopic), main variables included in the analysis

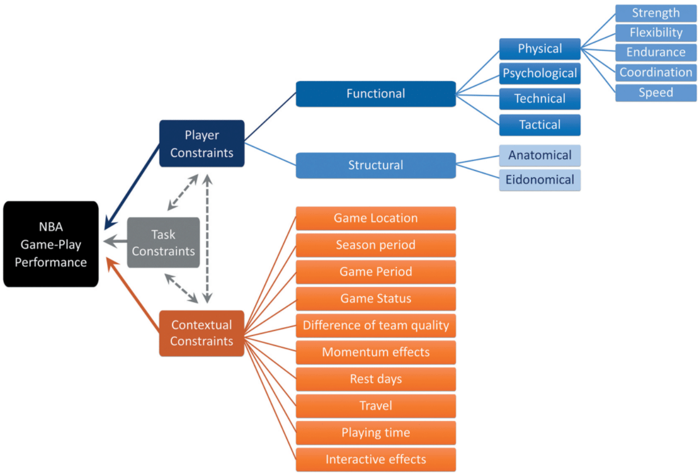

Figure 1. Systematic representation of the underpinning factors of NBA game-play performance.

(independent and dependent variables), type of data employed (secondary or primary data source), main research purpose (descriptive, exploratory, or explanatory), research model (quantitative, qualitative or mixed-method), research design (experimental, quasi-experimental, non-experimental), main findings, and research quality score based on Law's critical appraisal tool [37] (Tables 1 and 2).

Results

The results of the interobserver reliability analysis, calculated by the Kappa index, was 0.93 (95% CI 0.93–0.98), indicating very good agreement between observers. The quality of indicators for the included papers was determined as following: (1) the mean methodological quality score for the 43 selected articles was 82.9%; (2) two articles achieved the maximum score of 100%; (3) three of the articles scored below 50%; (4) eight articles scored between 50% and 75% (good methodological quality); and (5), 32 articles achieved an overall rating of >75% (excellent methodological quality) (Table 3). Possible deficiencies identified in the 43 studies were mainly related to criterion 16 (reporting of drop-outs or missing values), and some studies lacked information in relation to criterion 7 (reliability of reported outcomes) due to either neglecting the computation of the required minimum sample size, involving sample sizes that did not meet the requirements to make the concluded inferences, or neglecting potential biases due to inter-observer or intra-observer reliability.

The initial search process on NBA performance returned 192 articles (Figure 2). From the 103 records that were screened by the authors, a total of 60 studies were excluded due to being off-topic (e.g. salaries, racial differences, ethical issues, entertainment, branding and marketing, player health and injury issues, sports betting, etc.). A total of 43 studies (n = 43) were ultimately selected for final review based upon the authors' criteria to include only peer-reviewed articles from scientific journals between January 2001 and November 2020 simultaneously being most relevant to the main constraints, topics, and subtopics discussed in this systematic review (Figure 2).

The main intention behind the included studies was to describe information (n = 27; 62.8%) rather than explore (n = 15; 34,9%) and/or explain (n = 1; 2.3%) research problems or hypotheses (Table 4). Furthermore, near all researchers employed secondary data sources (n = 37; 86.0%) compared to primary data sources (n = 6; 14.0%) and/or a mixture of both (n = 0; 0.0%). Interestingly, more than half of all researchers utilized an ecological study design (n = 24; 55.8%) encompassing large population-based datasets (e.g. numerous NBA teams across multiple seasons). The ecological study design was especially popular in studies examining contextual constraints (n = 20), while the case report was the preferred study design when examining player constraints (n = 8) (Table 4). Near all studies adhered a quantitative research model (n = 41; 95.3%), while only two studies were qualitative by nature (narrative review articles) (n = 2; 4.7%), and no mixed-method research models were identified. Promisingly, the vast majority of all studies were published in recent years, in particular within the last 4 years (n = 28; 65.1%) (>2016), the last 7 years (>2013) (n = 37; 86.0%), and near all studies were published within the last ten years (n = 41; 95.3%) (>2010). When evaluating the number of studies in each constraint, topic, and subtopic of interest, it appeared that the vast majority of researchers focused on external factors (i.e.

Table 1. Summary of scientific studies (2001–2020) included in this systematic review, specifically related to *player constraints* of NBA game-play performance.

Main Author	Year	Topic	Subjects	Main variables	Data type	Research purpose	Research model	Research design	Main findings	Quality Score
Bakkenbull [53]	2017	Structural (Eidonmical)	2015–2016 NBA regular season players.	Playing Efficiency (PER and PIE), physical characteristics, age, draft selection and player salaries	Secondary	Descriptive	Quantitative	Non-exp Ecological	The relative wingspan is positively associated with performance whereas the vertical jumping influences it in a significantly negative way.	66,7
Cheema [60]	2020	Structural (anatomical)	From 2013 to 2018, all NBA players who attended the NBA Draft Combine's cardiac evaluation (307 players)	Using the P-wave as the reference point, speckle-tracking was utilized to measure left atrial booster, conduit, and reservoir strain over one cardiac cycle. Left atrial volume index (LAVI) of ≥34 mL/m^2 was considered enlarged	Primary	Descriptive	Quantitative	Non-exp Cross-sectional	Mean LAVI was 34.5 mL/m^2 and LAVI was enlarged in 131 (48.2%) athletes. Comparing LA strain in those with enlarged vs normal sized atria, reservoir strain was significantly reduced, with no difference seen in booster strain (9.2% [SD 2.1%] vs 9.4% [SD 2.7%], *P* = .45).	91,7
Courel-Ibáñez [92]	2016	Functional (tactical)	808 inside passes (ball possession score differences below 10 points) from 25 games (NBA Playoffs, 2010)	Players' position, players' actions before and after receiving the ball, game condition and ball possession effectiveness	Secondary	Descriptive	Quantitative	Non-exp Case	The inside pass represents a large potential scoring option with a greater effective rate, even in tight competition situations. Particularly strong side actions (pick and roll, pass and cut) linked with weak side actions (out of ball screen, dive cut) to increase scoring options.	83,3
Cui [51]	2019	Functional (physical)	3,610 players participating in the 2000–2018 NBA draft combine test	height without shoes, weight, wingspan, standing reach, body fat percentage; no step vertical jump, no step vertical reach, max vertical jump, max vertical reach, bench press, lane agility and three-quarter court sprint	Secondary	Exploratory	Quantitative	Non-exp Case-control	The drafted players outperformed the undrafted in height, wingspan, vertical jump height and reach, line agility and three-quarter sprint test ($p < 0.01$, ES = 0.26–0.87). Leg power predicts draft in guards, as did agility and speed for power forwards and centers.	91,7
Engel [59]	2016	Structural (anatomical)	526 NBA players competing during the 2013–2014 and 2014–2015 seasons	Left ventricular (LV) size, mass, wall thickness, and hypertrophy patterns and function; left atrial volume; and aortic root diameter. All dimensions were biometrically scaled	Primary	Descriptive	Quantitative	Non-exp Cross-sectional	LV hypertrophy was present in 144 athletes (27.4%). African American athletes had increased LV wall thickness and LV mass compared with LV wall thickness ($P < .001$) and LV mass ($P = .029$) in white athletes. The maximal aortic root diameter in the cohort was 42 mm. Aortic root diameters reached a plateau at the uppermost biometric variables.	91,7
Jones [78]	2019	Functional (psychological)	112 NBA players actively tweeting between 2009 and 2016.	Time-stamped social media activity and in-game performance (total points scored, shooting percentage, rebounds, turnovers, fouls)	Secondary	Exploratory	Quantitative	Non-expRetrospective cohort	Acute sleep deprivation (Twitter usage between 11:00 PM and 7:00 AM) is associated with changes in next-day game performance in the NBA. In particular, players made shots at 1.7% less points following late-night tweeting.	66,7

(*Continued*)

Table 1. (Continued).

Main Author	Year	Topic	Subjects	Main variables	Data type	Research purpose	Research model	Research design	Main findings	Quality Score
Koster [77]	2018	Functional (psychological)	330 NBA players with Twitter accounts during 2014–2015 season and playoffs	Player status defined as all-star selection, "following" ties of teammates on Twitter, team performance measured as postseason playoffs success	Secondary	Exploratory	Quantitative	Non-exp Case	Average of 11 current players with Twitter accounts (SD = 1.39), as compared to roster sizes of approximately 14 players. Compared to high-status players on successful teams, high-status players on underperforming teams are less likely to follow their teammates.	83,3
Kraus [75]	2010	Functional (psychological)	Players from the National Basketball Association (NBA) during the 2008–2009 regular season	12 distinct types of celebratory touches: fist bumps, high fives, chest bumps, leaping shoulder bumps, chest punches, head slaps, head grabs, low fives, high tens, full hugs, half hugs, and team huddles; team cooperation using a 4-point scale; Win Score, Offensive and defensive EFF were the amount of points a team scores or allows every 100 possessions, assist ratio, rebs ratio, team Win Score and NBA EFF	Secondary	Explanatory	Quantitative	Non-exp Ethological	Early season touch predicted greater performance for individuals as well as teams later in the season. Additional analyses confirmed that touch predicted improved performance even after accounting for player status, preseason expectations, and early season performance	75,0
Laby [72]	2020	Functional (physical)	13 NBA players who competed in 2018–2019 season	Fixation count; visit count; total duration; The "% shots made" defined as a percentage of the fraction of shots successfully made divided by the total number of shots (in this case 30), on-court metrics (FT%, FG3%, ORB%, and USG%)	Primary	Descriptive	Quantitative	Non-exp Case	Percentage of successful FT's and the four measures of visual fixation were correlated (r = 0.539 to 0.687). Shooters who had more frequent, as well as longer, fixations on the rim were more likely to have lower Usage Percentage. Visual Fixation in NBA FT's relates to On-Court Performance (USG%), and Offensive Rebound Percentage (ORB%) as well as higher Three-Point Field Goal Percentage (FG3%).	92,3
Mangine [73]	2014	Functional (physical)	12 NBA players of Orlando Magic 2012–2013 season.	Visual tracking speed, reaction time, player position, in-game variables measured per 100 minutes of play	Primary	Descriptive	Quantitative	Non-expCase	Greater visual tracking time is related to game-related increments in ball control (AST, TO, AST/TO, and STL).	75,0
McLean [4]	2019	Functional (physical)	NBA players (unspecified)	Emerging technologies, impact of specific league rules, steps taken to protect players in the age of Big Data, game demands (travel, training, games)	Secondary	Descriptive	Qualitative	Non-exp Review	Future collaborations between league entities, NBA clubs, commercial partners, and outside research institutions will enhance understanding of the physical demands in the NBA (and other health- and performance-related areas).	91,7
Phatak [91]	2020	Functional (technical)	610,822 free throws from the NBA seasons between 2006 and 2016 (regular and playoffs)	FT success rates	Secondary	Descriptive	Quantitative	Non-exp Ecological	The success rate of the second FT was greater compared to the first FT. For triple FT's, the success rate increased with each successive FT. The results demonstrate differences between consecutive throwing percentages.	91,7

(Continued)

Table 1. (Continued).

Main Author	Year	Topic	Subjects	Main variables	Data type	Research purpose	Research model	Research design	Main findings	Quality Score
Ranisavljev [70]	2020	Functional (physical)	58 NBA players (rookies) who matched the inclusion criterion of average playing time and number games in the period 2012–2015	Lane agility, shuttle run, ¾ court speed, VJ from running, 185 lbs bench press, and key basketball performance variables	Secondary	Exploratory	Quantitative	Non-exp Case	Pre-Draft Combine testing procedures show the highest correlation between upper body strength and number of rebs ($r = .403$, $p = .002$) and blocks ($r = .333$, $p = .011$). Regression model of Combine performance explained 24.7% of basketball performance with three physical performance tests.	91,7
Rauch [71]	2020	Functional (physical)	178 NBA players that were active on an NBA roster	Standing height, playing position, body weight, CMJ's jump height, net relative impulse, relative un-weighting force, sum (left and right) braking force, relative sum (left and right) concentric force, total movement time, maximum joint flexion average, delta joint flexion, joint total range of motion, maximal joint flexion velocity, joint flexion acceleration, joint extension, joint extension velocity, joint extension acceleration, and time to maximum joint flexions and extensions	Primary	Descriptive	Quantitative	Non-exp Case	Lower limb joint angular displacement (i.e. delta flexion) explained the highest portion of point variability (89.3%), and three clusters were recommended (Ball Hall Index). Delta flexion was significantly different between clusters and players were characterized as "stiff flexors", "hyper flexors", or "hip flexors". There were no significant differences in jump height between clusters ($p > 0.05$).	91,7
Sampaio [89]	2015	Functional (technical)	548 NBA players during the 2013–2014 regular season.	Playing positions, pull-up shots, catch and shoot, close shots, drives, passing-variables, touches-variables, speed and distance, rebounds, free-throw percentage	Secondary	Exploratory	Quantitative	Non-exp Ecological	All-star players performed consistently better than non all-star players in elbow touches, offensive rebounds, close touches, close points and pull-up points (within 12 feet of the basket).	91,7
Sedeaud [52]	2014	Structural (eidonomical)	50,736 NBA players from 1987 to 2011.	Player mass, height, body mass index (BMI), age, field goals in relation to players height	Secondary	Descriptive	Quantitative	Non-exp Ecological	In the NBA, a height-attractor at 201.3 ± 6.3 cm for the best scorers is invariant, regardless of the level of play. Discrepancies between some mass and height developments question the (disproportionate) large mass increase (relative to the height increase) during the 1980s and 1990s.	83,3
Teramoto [55]	2018	Structural (eidonomical) and functional (physical)	2010–2015 NBA combine data and subsequent NBA game performances (1–3 years following the combine)	Game-related statistics and NBA combine test results	Secondary	Exploratory	Quantitative	Non-exp Case	H without shoes, standing reach, W, WS, and HL, and subscale of L-S, had positive, medium-to-large-sized correlations (with Defensive Box Plus/Minus. Combine subscale of length-size was a predictor most significantly associated ($p \leq 0.05$) with Win Shares, BPM, and VORP, followed by upper-body strength.	33,3
Xu [76]	2015	Functional (psychological)	NBA players (in the 2012–13 season)	91,659 tweets, game date, game type, home/away, opponent and win/loss (score), age, games started, minutes played, FG, 3PFG, FT's, ±	Secondary	Descriptive	Quantitative	Non-exp Case	Sentiment analysis on NBA players' tweets was directly related to GPP after controlling for other factors affecting performance.	83,3

Table 2. Summary of scientific studies (2001–2020) included in this systematic review, specifically related to *contextual constraints* of NBA game-play performance.

Main Author	Year	Research Topic	Subjects	Variables	Data type	Research purpose	Research model	Research design	Main findings	Quality score
Arkes [40]	2011	Player momentum	3452 NBA games from 2007 season through the 2009 season	Home vs. away team, game outcome, rest days, team records and how they did 3 and 5 games prior to the game	Secondary	Exploratory	Quantitative	Non-exp Ecological	Marginal effects indicate that an extra win in the past 5 games, on average, increases the probability of winning by between 2.2 and 2.8 percentage points using Model A (full season winning percentages) and between 3.3 and 4.0 percentage points using Model B (half season winning percentages).	75,0
Belk [95]	2017	Rest days	811 NBA players (2005–2015) who made the playoffs while playing a minimum of 20 minutes per game.	Playing position, age, regular season minutes per game, player efficiency ratings, shooting percentage, points per game, assists per game, productivity and inefficiency on the court, steals, blocks	Secondary	Exploratory	Quantitative	Non-exp Retrospective cohort	There were no significant differences between players who missed 5 to 9 games due to rest versus players who missed less than 5 games due to rest at any position in terms of points per game, assists per game, player efficiency rating, true shooting percentage, blocks, steals, or number of playoff games missed because of injury.	75,0
Cao [111]	2011	Game period	National Basketball AssociationNBA free throw data from the 2002–2003 through 2009–2010 seasons	Scoring statistics, the time in the game at which the various shots were taken, and the score difference at the time of the shots	Secondary	Descriptive	Quantitative	Non-exp Ecological	NBA players shoot on average 5–10 percentage points worse than normal in the final seconds of very close games. Choking is more likely for players who are worse overall FT shooters, and on the second shot of a pair after the first shot is missed.	83,3
Casals [39]	2013	Interactive effects	27 NBA players competing during the 2007 regular season	Win score, division, conference and team, season period, home advantage, difference of team quality, rest days, game started, player momentum, player wage relative to team salary, teams fighting for playoffs, player position, age, contract condition, minutes played, usage percentage	Secondary	Descriptive	Quantitative	Non-exp Retrospective cohort	Minutes played, the usage percentage and the difference of quality between teams were the main factors for variations in points made and win score. The interaction between player position and age was important in win score.	100
Christmann [113]	2018	Game period	Offense play types in final 120 s of 115 close games (5 points score difference) in the NBA (all 2015 regular season post-Allstar games)	The video-captured frequencies and outcomes of six defined play types: 1 on 1 without isolation; 1 on 1 with isolation; pick-and-roll; complex team play; inbound play; and transition play	Secondary	Descriptive	Quantitative	Non-exp Ecological	During endgame play in the NBA, the pick-and-roll was employed the most and inbound play the least frequently. The 1 on 1 with or without isolation were the least effective play types, averaging 0.9–1.0 pts/possession. In contrast, transition, inbound and complex team plays were the most effective (means 1.3–1.5 pts/possession). Overall, plays led to 0.8 pts/possession when being in the lead vs. 1.4 pts/possession when being down.	91,7

(*Continued*)

Table 2. (Continued).

Main Author	Year	Research Topic	Subjects	Variables	Data type	Research purpose	Research model	Research design	Main findings	Quality score
Dehesa [120]	2019	Difference of team quality	1,311 NBA games (472 players analyzed) during the 2014–2015 season	± On-court and off-court, difference between ± on-court and off-court, maximum negative points difference, maximum positive points difference, PT, team wins, pace, offensive and defensive EFF, FG%, ORB%, TO%, FT's/FG's	Secondary	Descriptive	Quantitative	Non-exp Ecological	NBA performance could be divided into five clusters during the regular season and four clusters during the playoffs. These clusters were mainly characterized by the game quarter, and the negative difference in plus/minus between on-court and off-court play during the season, and the positive difference in plus/minus between on-court and off-court play during the playoffs, as well as second and third game-quarters.	91,7
Entine [96]	2008	Rest days	NBA data for the 2004–2005 and 2005–2006 seasons.	Average margin of victory experienced by home teams over visitors, strengths of each team year, home court advantage for the host team, amount of rest coming into the game.	Secondary	Descriptive	Quantitative	Non-expEcological	Lack of rest for the road team and length of the road trip, while not a dominant factor, are important contributors to the home court advantage in the NBA. However, the bulk of the advantage for home team arises from other, non-related factors.	33,3
Esteves [94]	2020	Rest days	Data from 82 games from all teams participating in NBA 2016–2017 regular season	Playing back-to-back games, playing on one day's rest, playing on two day's rest, playing on three or more day's rest) and performance of NBA basketball teams	Secondary	Exploratory	Quantitative	Non-exp Ecological	Fixture congestion cycles has a significant impact on the game outcome and team performance in the NBA. In particular, the likelihood of winning a game increased significantly from playing back-to-back games to having one day rest in between.	75,0
Flynn-Evans [101]	2020	Travel	499 postseason games played during the 2013–14 to 2018–2019 seasons	Direction of travel and time zones traveled on game outcomes, Elo rating differences, win probability, and team scoring.	Secondary	Exploratory	Quantitative	Non-exp Ecological	Direction and magnitude of travel were related to win probability, team scoring, and game outcomes, whereby teams traveling eastward and within the same time zone gained an advantage over those traveling westward.	91,7
García-Manso [112]	2015	Game period	5 NBA regular seasons	Difference between the last minute and the rest of the game from the collected scores (1, 2, and 3 points), substitutions and timeouts	Secondary	Descriptive	Quantitative	Non-exp Ecological	NBA games during the final moments present typically shorter possessions (especially by the disadvantage team), played with fewer number of passes and participating players, higher number of fouls, higher game stops and number of changes.	91,7

(*Continued*)

Table 2. (Continued).

Main Author	Year	Research Topic	Subjects	Variables	Data type	Research purpose	Research model	Research design	Main findings	Quality score
Gomez [109]	2016	Game location	48 NBA close games (below 10 points difference) during the 2013–2014 season played by 27 teams.	Situational and technical-tactical variables: starting quarter score, game location, quality of opposition, game situation, defense type, outcome, shot type, technical execution, defense on the shooter, play events, mean played clock-time	Secondary	Exploratory	Quantitative	Non-exp Ecological	The main differences between HT's and AT's are starting quarter score, FT's scored, 3 point FG from central positions. During balanced games: defensive fouls, game location, quality of opposition, ball possession success, 2FGIO, 3PFGCR, and defensive rebounds during HT's positive scoring trends.	91,7
Gonzalez [74]	2013	Playing time	7 NBA players from the Orlando Magic (53–30 record, 1st round of playoffs)	Body mass, BF%, vertical jump, quickness, reaction time, squat power	Primary	Exploratory	Quantitative	Non-exp Prospective cohort	NBA players can enhance lower-body power, repetitive jump ability and reaction time during a competitive season, which can be stimulated by playing time (less subjective overall fatigue in starters vs. nonstarters).	100
Guerra [116]	2013	Game status	6150 NBA games between 2005 and 2010	Two and three point shots, free throws, rebounds, steals, turnovers, fouls, substitutions, time between each point	Secondary	Descriptive	Quantitative	Non-exp Ecological	There is no uniform behavior in scoring points in the NBA. However, different behaviors exist depending on the time of scoring. Future research may look at the complexity of the game and analyze whether memory generates different scoring behaviors inside the NBA.	83,3
Harris [107]	2019	Game location	32 seasons (1983–84 to 2017–18)	Home and home opponent 2pt, 3pt, and FT; away and away opponent 2pt, 3pt and FT	Secondary	Descriptive	Quantitative	Non-expEcological	The style of play is a key factor in the home advantage. Teams that make more two point and free-throw shots see larger advantages at home.	91,7
Huyghe [1]	2018	Travel	Studies related to traveling demands in the NBA.	Recommendations pertaining to sleep, nutrition, recovery and scheduling strategies to mitigate the risk involved with frequent air travel in the NBA	Secondary	Descriptive	Qualitative	Non-exp Review	Future research will provide a better understanding of practices that may enhance physiological and perceptual responses to air travel in NBA players.	91,7
Jones [78]	2007	Game location	17 unmatched NBA games in the 2002–2003 and 2003–2004 regular season	Home court advantage factoring in for team quality, average points scored by quarter and overtime	Secondary	Descriptive	Quantitative	Non-expEcological	Home advantage in the NBA is strongly front-loaded. Home teams accumulated two thirds of the home advantage it had at the end of the game in the first quarter. It accumulated less of an advantage in the second and third quarters, and still less in the fourth quarter. Further, the home team does not on average lengthen its lead in quarters which it enters ahead, but gains strongly in any quarter which it enters behind.	75,0

(*Continued*)

Table 2. (Continued).

Main Author	Year	Research Topic	Subjects	Variables	Data type	Research purpose	Research model	Research design	Main findings	Quality score
Mateus [90]	2017	Playing time	NBA Players competing in 2013–2014 season (n = 712).	Player position, player minutes, coefficient of variability from game to game	Secondary	Exploratory	Quantitative	Non-exp Retrospectivecohort	Less PT decreases the probability of maintaining stable performance across games and long PT in away and losing games may vary due to the constraints imposed by opponent teams. FT's seem to be the variables that best discriminate between winning and losing teams.	84,6
Mikolajec [88]	2013	Difference of team quality	2003–2011 NBA seasons (30 teams)	official boxscores of NBA and included 52 variables that characterized offensive and defensive effectiveness of 30 teams	Secondary	Descriptive	Quantitative	Non-exp Ecological	The main factors which influence sports results in the NBA indicated in the present study are much more connected with offense than defense.	91,7
Nutting [100]	2017	Travel	NBA games from 1991 until 2013	Winning percentage, time zone, travel direction, game time, game frequency, distance traveled, length of home stands, and length of road trips	Secondary	Exploratory	Quantitative	Non-exp Ecological	Visiting teams traveling in westwards direction are 7.7% less likely to win for each time zone further away from home. The consequences of travel direction are more prominent in day games (before or at 4:00 pm) rather than night games (after or at 7:00 pm).	25,0
Ribeiro [105]	2016	Game location	16,133 games covering 13 NBA seasons (from the 2001–02 to the 2013–14).	Game place, team names, match date, score evolution $S(t)$ of each team as a function of the game time t	Secondary	Descriptive	Quantitative	Non-exp Ecological	Home advantage affects the microscopic dynamics of the game. However, average differences have slightly decreased over time, suggesting a weakening of the phenomenon.	83,3
Teramoto [87]	2010	Season period	1999–2000 and 2008–2009 seasons	Overall efficiency (offensive and defensive ratings), and effective field goal percentage, turnover percentage, rebound percentage, and free throw rate	Secondary	Descriptive	Quantitative Lastly,	Non-exp Ecological	The importance of defense in winning games may be greater in the playoffs than in the regular season. Fewer TO's could be another key to winning games, especially in the regular season. Lastly, rebounding may play a significant role in deciding the outcome of the Conference Finals where two teams most likely have similar shooting efficiency and TO rates.	91,7
Urban [93]	2018	Rest days	NBA Finals data between 1984 and 2018	Margin of victory for each game in the NBA finals, home court advantage, game to game momentum effects, previous NBA finals experience, and relative team quality	Secondary	Exploratory	Quantitative	Non-expEcological	Additional time between NBA playoff rounds provides a significant advantage, predominantly on the second game of the subsequent round (moderately significant with doubling the odds of winning game two when given supplemental rest between series)	91,7

(*Continued*)

Table 2. (Continued).

Main Author	Year	Research Topic	Subjects	Variables	Data type	Research purpose	Research model	Research design	Main findings	Quality score
Zhang [121]	2018	Difference of team quality	354 players across 699 regular season balanced games (10 points or less) during the 2015–2016 regular season.	Team ranking, game-related statistics, playing experience, height and weight	Secondary	Descriptive	Quantitative	Non-expEcological	Top H and W combined with low experience was associated with 2PFG's made and missed, offensive and defensive rebs, blocks, and fouls; whereas low H and W combined with low PE is associated with the fewest passes and touches. Weaker teams typically demonstrate low H and W combined with low PE, whereas stronger teams are characterized by low H and W with medium PE, and Finals' appearance was associated with medium H and W combined with medium PE.	91,7
Zhang [122]	2019	Difference of team quality	355 players playing in 692 balanced NBA games (final score is equal or less than 10 points difference) of the 2016–2017 season.	Quality of the team and opposition, match outcome, match location, points made in the paint, two point field goals, free throws made, turnovers, assists, touches, passes, offensive rebounds, defensive rebounds, steals, blocks, personal fouls, field goals defended at rim made, deflections, distance run, average speed, playing position	Secondary	Descriptive	Quantitative	Non-exp Ecological	Stronger NBA teams show better performance qualities in defensive rebss, blocked shots, and assists while defensive rebs and TO's determined the outcome of the game for weaker teams. In stronger vs stronger team match-ups, all players from winning teams ran slower in home games than their peers in losing teams, while an opposite trend was found for away games. In stronger versus weaker team match-ups, all players from winning teams in home games covered more distance and ran faster than their peers from losing teams. In weaker versus weaker team match-ups defensive effectiveness determined the outcome of the game.	91,7
Zhang [118]	2019	Season period	30 teams with each participating in 82 games during the NBA regular season (1230 games between 25 October 2016 and 12 April 2017).	Two-point field goals made, wo-point field goals missed, three-point field goals made, three-point field goals missed, free throws made, free throws missed, offensive rebounds, defensive rebounds, assists, turnovers, steals, blocked shots, personal fouls	Secondary	Descriptive	Quantitative	Non-expEcological	NBA team profiles generally presented similarity, while the beginning and ending of the season showed relative dissimilarity. The dominant teams presented similar game styles. In addition, the game-play of the teams evolved into effective interactions in terms of offense and defense as the competition progressed while presenting an increased trend in the number of 3PFG's made.	91,7

Table 3. Critical appraisal (risk of bias) of scientific studies included in this systematic review, related to *player constraints* and *contextual constraints* as underpinning factors of NBA game-play performance.

First Author	PURPOSE	LITERATURE	DESIGN	SAMPLE			OUTCOMES		INTERVENTION			RESULTS				CONCLUSION	Total	
	Purpose	*Relevance background*	*Study design*	*Sample details*	*Sample justified*	*Informed consent*	*Outcomes reliable*	*Outcomes valid*	*Intervention details*	*Contamination avoided*	*Cointervention avoided*	*Statistical significance*	*Analysis methods*	*Clinical importance*	*Drop-outs or missing data*	*Conclusions & Implications*	*Score*	*%*
Player Constraints																		
Bakkenbull	1	1	1	0	0	N/A	0	1	N/A	N/A	N/A	1	1	1	0	1	8/12	66,7
Cheema	1	1	1	1	1	N/A	1	1	N/A	N/A	N/A	1	1	1	0	1	11/12	91,7
Chenyan	1	1	1	1	1	N/A	0	1	N/A	N/A	N/A	1	1	1	0	1	10/12	83,3
Courel-Ibáñez	1	1	1	1	1	N/A	0	1	N/A	N/A	N/A	1	1	1	0	1	10/12	83,3
Cui	1	1	1	1	1	N/A	1	1	N/A	N/A	N/A	1	1	1	0	1	11/12	91,7
Engel	1	1	1	1	1	N/A	1	1	N/A	N/A	N/A	1	1	1	0	1	11/12	91,7
Jones	1	1	0	1	1	N/A	0	0	N/A	N/A	N/A	1	1	1	0	1	8/12	66,7
Koster	1	1	1	1	1	N/A	0	1	N/A	N/A	N/A	1	1	1	0	1	10/12	83,3
Kraus	1	1	1	1	0	N/A	0	1	N/A	N/A	N/A	1	1	1	0	1	9/12	75,0
Laby	1	1	1	1	1	1	0	1	N/A	N/A	N/A	1	1	1	1	1	12/13	92,3
Mangine	1	1	1	1	0	N/A	0	1	N/A	N/A	N/A	1	1	1	0	1	9/12	75,0
McLean	1	1	1	1	1	N/A	1	1	N/A	N/A	N/A	1	1	1	0	1	11/12	91,7
Phatak	1	1	1	1	1	N/A	1	1	N/A	N/A	N/A	1	1	1	0	1	11/12	91,7
Ranisavljev	1	1	1	1	1	N/A	1	1	N/A	N/A	N/A	1	1	1	0	1	11/12	91,7
Rauch	1	1	1	1	1	N/A	1	1	N/A	N/A	N/A	1	1	1	0	1	11/12	91,7
Sampaio	1	1	1	1	1	N/A	1	1	N/A	N/A	N/A	1	1	1	0	1	11/12	91,7
Sedeaud	1	1	1	1	0	N/A	1	1	N/A	N/A	N/A	1	1	1	0	1	10/12	83,3
Teramoto	1	1	0	1	1	N/A	0	0	N/A	N/A	N/A	0	0	0	0	0	4/12	33,3
Contextual constraints																		
Arkes	1	1	1	1	1	N/A	0	0	N/A	N/A	N/A	1	1	1	0	1	9/12	75,0
Belk	1	1	0	1	1	N/A	1	0	N/A	N/A	N/A	1	1	1	0	1	9/12	75,0
Cao	1	1	1	1	1	N/A	1	1	N/A	N/A	N/A	1	1	1	0	0	10/12	83,3
Casals	1	1	1	1	1	N/A	1	1	N/A	N/A	N/A	1	1	1	1	1	12/12	100
Christmann	1	1	1	1	1	N/A	1	1	N/A	N/A	N/A	1	1	1	0	1	11/12	91,7
Dehesa	1	1	1	1	1	N/A	1	1	N/A	N/A	N/A	1	1	1	0	1	11/12	91,7
Entine	1	0	0	0	0	N/A	0	0	N/A	N/A	N/A	1	1	1	0	0	4/12	33,3
Esteves	1	1	1	1	1	N/A	0	1	N/A	N/A	N/A	1	1	1	0	0	9/12	75,0
García-Manso	1	1	1	1	1	N/A	1	1	N/A	N/A	N/A	1	1	1	0	1	11/12	91,7
Gomez	1	1	1	1	1	N/A	1	1	N/A	N/A	N/A	1	1	1	0	1	11/12	91,7
Gonzalez	1	1	1	1	1	1	1	1	N/A	N/A	N/A	1	1	1	1	1	13/13	100
Guerra	1	0	1	1	1	N/A	1	1	N/A	N/A	N/A	1	1	1	0	1	10/12	83,3
Harris	1	1	1	1	1	N/A	1	1	N/A	N/A	N/A	1	1	1	0	1	11/12	91,7
Huyghe	1	1	1	1	1	N/A	1	1	N/A	N/A	N/A	1	1	1	0	1	11/12	91,7
Jones	1	1	1	1	1	N/A	0	0	N/A	N/A	N/A	1	1	1	0	1	9/12	75,0
Mateus	1	1	1	1	1	0	1	1	N/A	N/A	N/A	1	1	1	1	0	11/13	84,6
Mikolajec	1	1	1	1	1	N/A	1	1	N/A	N/A	N/A	1	1	1	0	1	11/12	91,7
Nutting	1	0	0	1	1	N/A	0	0	N/A	N/A	N/A	0	0	0	0	0	3/12	25,0
Flynn-Evans	1	1	1	1	1	N/A	1	1	N/A	N/A	N/A	1	1	1	0	1	11/12	91,7
Ribeiro	1	1	1	1	1	N/A	1	0	N/A	N/A	N/A	1	1	1	0	1	10/12	83,3
Teramoto	1	1	1	1	1	N/A	1	1	N/A	N/A	N/A	1	1	1	0	1	11/12	91,7
Urban	1	1	1	1	1	N/A	1	1	N/A	N/A	N/A	1	1	1	0	1	11/12	91,7
Zhang	1	1	1	1	1	N/A	1	1	N/A	N/A	N/A	1	1	1	0	1	11/12	91,7
Zhang	1	1	1	1	1	N/A	1	1	N/A	N/A	N/A	1	1	1	0	1	11/12	91,7
Zhang	1	1	1	1	1	N/A	1	1	N/A	N/A	N/A	1	1	1	0	1	11/12	91,7

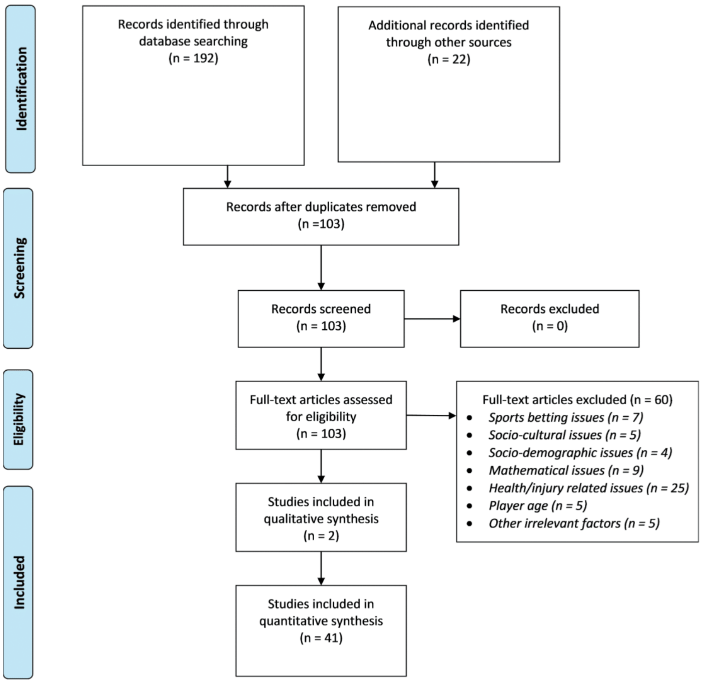

Figure 2. Flow diagram of the systematic review screening process.

contextual constraints) (*n* = 25; 58.1%) rather than internal factors (i.e. player constraints) (*n* = 18; 41.9%). Nevertheless, the most popular research topic was identified as 'functional abilities' of NBA players (*n* = 13; 30.2%), in which 'physical qualities' (*n* = 6) was the most prominent subtopic. The least popular topics were identified as 'game status', 'tactical skills', 'momentum effects', and 'interactive effects', in which each topic accounted for only one study (*n* = 1; 2.3%) (Table 4).

Discussion

This manuscript used systematic review methodology [20,34] to investigate the scientific literature (2001–2020) about two underpinning factors of NBA game-play performance (i.e. player constraints and contextual constraints). Promisingly, the body and scope of research published about this matter has significantly grown in recent years (65.1% of studies published >2016), and at first glance, the number of articles selected in this systematic review (*n* = 43) appears to prevail as a comprehensive resource for evidence-based extrapolations. In the following sections, we discuss the most frequently employed *NBA Game-Play Performance Indicators* first, followed by our main findings and insights about *NBA player constraints* and *NBA contextual constraints*, and finally, we acknowledge the main limitations and present practical suggestions for future research.

NBA Game-Play Performance Indicators

Ultimately, all NBA team stakeholders desire to win as many games as possible. However, utilizing the outcome of a game as the only indicator of 'game-play performance' entails two important limitations. First, this approach disregards underlying behaviors (at the intra-player, inter-player, and inter-team level) that may cooperatively influence the final outcome of a game [25,26,30–33]. Secondly, key stakeholders often prioritize long-term mission, vision, strategy, culture-building, human resources, and organizational efficiency rather than winning one single game [41,42]. Surprisingly, to the best of the authors' knowledge, the majority of researchers solely utilized outcome-based metrics of game-play performance, via open-source box-score statistics, and subsequently analyzed to which extent these box-score statistics retain power in describing, explaining or predicting future game-play performance (e.g. linear and logistic regression techniques) (Tables 3 and 5). Recognizing the rapid advancements in basketball analytics (data-mining and machine learning techniques) [43], numerous sophisticated approaches and algorithms have been applied to personalize the computation of NBA game-play performance indicators to team and players preferences (Table 5) [43]. Unfortunately, as a side effect, the lack of agreement and growing variety of statistical possibilities have evoked discrepancies among researchers, which in turn complicates our ability to compare and express definitive inferences between the included studies because an inherently different dependent variable was determined in an inherently different ecosystem each time.

Generally, researchers favored 'offense-specific' box-score statistics and focused on the team-level of performance, neglecting 'quality of opposition' as a potential confounding variable. Therefore, the 'Factors Determining Production' metric (FDP) [44] may serve as a simple and valuable alternative, because this metric integrates non-scoring box-score statistics across more than one game, incorporates quality of opposition, allows player-level performance analysis, takes into account the final result of each game, relies on a validated statistical procedure, overcomes 'Win Score' from a theoretical viewpoint, and finally, it offers a simple linear weight formula which altogether yields a more holistic and realistic representation of how well an NBA player performs [44].

By understanding the team's strength and weaknesses, as well as the key underpinning fixed and random factors associated with NBA game-play performance, sports scientists and data scientists can generate valuable exploratory, explanatory, and predictive metrics to help practitioners in data-supported decision-making [39,43,44]. However, we encourage future researchers to adopt a structured 'applied science research framework' that sequences research incentives in a scientifically rigorous fashion (e.g. piloting toward randomized control trials), which in turn would foster better reproducibility of their research methods, designs, and results [45]. Finally, future researchers may consider aggregating traditionally used box-score statistics (technical-tactical parameters) with other components of game-play performance behavior, such as physical [46,47], psychological [48] or injury-related determinants [49], because for coaches, managers, medics, and support staff personnel, it is a unique opportunity to improve decision-making specifically concerned with risk mitigation (e.g. mental health issues, nagging pain, energy deficiency) that could ultimately cost in team and player game-play performance.

Table 4. Overview of research trends and methodologies applied in included studies of this systematic review.

	Player constraints		Contextual constraints		Total	
	N	%	N	%	N	%
Research purpose						
Exploratory	6	33.3	9	36.0	15	34.9
Explanatory	1	5.6	0	0.0	1	2.3
Descriptive	11	61.1	16	64.0	27	62.8
Data type						
Secondary	13	72.2	24	96.0	37	86.0
Primary	5	27.8	1	4.0	6	14.0
Combination	0	0.0	0	0.0	0	0.0
Research design						
Experimental	0	0.0	0	0.0	0	0.0
Quasi-experimental	0	0.0	0	0.0	0	0.0
Non-experimental	18	100	25	100	43	100
Prospective Cohort	0	0.0	1	4.0	1	2.3
Retrospective Cohort	1	0.0	3	12.0	4	9.3
Case report	8	44.4	0	0.0	8	18.6
Review	1	5.6	1	4.0	2	4.6
Case-control	1	5.6	0	0.0	1	2.3
Case series	0	5.6	0	0.0	0	0.0
Ecological	4	22.1	20	80.0	24	55.8
Cross-sectional	2	11.1	0	0.0	2	4.7
Ethological	1	5.6	0	0.0	1	2.3
Research model						
Quantitative	17	94.4	24	96.0	41	95.3
Qualitative	1	5.6	1	4.0	2	4.7
Mixed-method	0	0.0	0	0.0	0	0.0
Publication year						
>2016	13	72.2	15	60.0	28	65.1
>2013	17	94.4	20	80.0	37	86.0
>2010	18	100	23	92.0	41	95.3

NBA Player Constraints

The majority of studies related to NBA player constraints focused on functional abilities (n = 13), in which 'physical qualities' emerged as the primary topic of interest (n = 6) (Table 4). However, the proposed research questions were polarized and non-sequential (e.g. quiet-eye training, individual scoring ability, visual tracking speed, combine testing, vertical jumping mechanics, social media influences, etc.). Taking into account the large divergence of topics reported, we organized the most relevant player constraints according to (1) structural characteristics (eidonomical, anatomical) and (2) functional abilities (physical, psychological, technical-tactical) in the following sections respectively. Notably, scientific information related to the biography of NBA players (e.g. age, socio-demographic background, training history, injury history) was excluded from the scope of this systematic review.

Structural aspects

Eidonomical characteristics. Not every eidonomical factor (i.e. factors related to the external appearance of an organism) plays a substantial role in NBA game-play performance, however two discriminative, commonly discussed, and readily available eidonomical variables in NBA players are: 'height' and 'mass' [50–53]. Similar to secular trends in other sports, NBA players are becoming taller and more massive over time with the rates of growth exceeding those predicted by secular trends (Table 6) [50,53]. For instance, an arm length-to-height ratio of 1.01-to-1 is considered as 'normal' in human beings [54], however NBA players generally represent an arm-to-height ratio of 1.06-to-1 [51,53] which meets the diagnostic criteria for Marfan syndrome, a disorder of the body's connective tissues that often results in elongated limbs [54]. Hence, this clearly demonstrates the extreme morphology that typifies playing at the NBA level. Although these measures can be easily obtained from a variety of sources and have been recorded as far back as records

Table 5. Scientific evidence, practical applications, and future research lines specifically related to the computation, analysis, and interpretations of *NBA game-play performance indicators*.

NBA GAME-PLAY PERFORMANCE INDICATORS

Scientific evidence	Practical Applications	Future Research

Frequently generated algorithms
• GmSc[a]
• WinSc[b]
• Win % CG
• UR[c]
• TP[d]
• PER
• BPM
• Adjusted BPM
• Points Differential
• Points Made
• GGV
• TR[f]
• PIE
• Win-S
• HCA
• FDP
 	
Frequently employed statistical-analytical techniques
• Linear and Logistic Regression
• GMLM
• Functional data analysis
• K-means clustering
• PCA and PCR
• NMMS
• MBI
	• Coaches, scouting personnel, and performance analysts may use previously established NBA GPP indicators to analyze and monitor NBA GPP within and across games in their respective team.
	• Underlying methods and variables employed to compute NBA GPP indicators should be well-understood prior to implementation.
		• Which holistic measures of NBA GPP may provide a more complete picture of NBA GPP than previously established?
		  • *Examples:[51] Player Impact Plus Minus, CARMELO, Elo Ratings, Expected Possession Value, Wins Above Replacement, Performance Index Rating, Net Rating, Pythagorean Win Percentage, Value over Replacement Player, Win Shares, Tendex, Exposed position value, Factors determining production*
		• Are any alternative methods of statistical-analytical techniques superior to previously established methods to predict and/or explain NBA GPP?
		  • *Examples:[51] Random Forest, Adaboost, Multilayer Perceptron, Radial Basis Function Networks, Association Rule based models, Neural Networks, Decision Trees, Bayesian Networks, Support Vector Machines, Markov Modeling, Functional data analysis, Archetype Analysis and Archetypoid Analysis*
		• How can NBA GPP be better visualized through a multi-factorial and trans-disciplinary viewpoint, reflecting the player (organism), team (aggregation of organisms), and competition (ecosystem) behaviors?

Algorithms: [a]GmSc = *1.43934 − (.43008 x Lane agility) + (.04234 x VJ from running) − (.06169 x Bench press);*[78] [b]WinSc = *Points + Rebs + Steals + 0.5 Assists + 0.5 Blocks − TO's − FGA's − 0.5 Fouls − 0.5 FTA's;*[41] [c]UR = *[FGA+(FTA×0.44) + (AST ×0.33) +TOV]×40× LP (Minutes × TP);*[42] [d]TP = *[FGA−ORB+TOV + (FTA×0.44)]×48 (Team Minutes × 2);*[42] [f]TR = 22,868 + 59,08 Win % + 0,18 Avg Fouls + 21,33 Offensive EFF + 2,46 Win% CG + 3rd Qrt PPG + 0,28 Avg Steals.[96]

Abbreviations: *GGV = Game-to-game variability; Win-S = Win Shares; BPM = Box Plus/Minus; GPP = Game-play Performance; FT = Free Throw; FTA = Free Throw Attempt; HCA = Home Court Advantage; TR = Team Ranking; Win % CG = Win percentage in close games; GmSc = Game Score; WinSc = Win Score; UR = Usage Rate; TP = Team Pace; PER = Player Efficiency Rating; PIE = Player Impact Estimate; LP = League Pace; PCA = Principal Component Analysis; GMLM = General Mixed Linear Models; NMMS = Non-metric multidimensional scaling techniques; PCR = Principal Component Regression; FDP = Factors Determining Production; MBI = Magnitude-based inferences* allowed [50], to date, only four studies (n = 4) that presented eidonomical characteristics of NBA players could be identified [51–53,55]. In particular, Sedeaud et al. [52] indicated that the 'optimum' wingspan and height in NBA's top scorers (3453 players; 1950–2011) was situated at 201.3 ± 6.3 cm (defined as the 'height-attractor') [52]. Indeed, having a relative longer wingspan and height may increase an NBA player's ability to perform, particularly in blocking shots and taking rebounds, because his arms are longer than his direct opponents [53], and likewise, having a relative long wingspan likely makes it more difficult for the opponents to block his shot when he acquires possession of the ball [53,56–58]. Consistently, height without shoes, standing reach, weight, wingspan, and hand length, and subscale of length-size measured at the 2010–2015 NBA combines, all had a positive medium-to-large-sized relationship (r = 0.313–0.545) with Defensive Box Plus/Minus in the subsequent 1–3 years of NBA competition, and length-size was identified as the main predictor of Win Shares, Box Plus/Minus, and Value Over Replacement Player ($p \leq 0.05$) [55]. However, given the difficulty in modulating a player's height, future studies may focus on eidonomical characteristics that are more tangible and modifiable in relation to NBA game play performance. For instance, whole-body and limb skinfolds, circumferences, and postural deviations have yet to be presented, and may provide unique opportunities for future research to expand upon the current body of evidence. Finally, potential higher-order interactive effects between 'coaching philosophy' (e.g. playing 'small ball', player usage, team style of play), eidonomical characteristics, and game-play performance indicators, may help us better understand how coaches can specifically compensate (smaller roster) or capitalize (taller roster) through opponent-specific in-game coaching tactics as well as technical-tactical training stratagems.

Anatomical characteristics. Concerning the study of anatomical factors of NBA (i.e. factors related to the internal appearance of an organism), only two studies (n = 2) could be identified [59,60] in which both studies focused on the normative values of cardiac morphology through the application of transthoracic echocardiograms (ECG). In particular, the authors consented that NBA players tend to have a significant enlargement of the left atrium (LA) and left ventricle (LV) [59,60]. Although this information enables medics and paramedics to better understand what the 'normal' and 'abnormal' heart morphology entails in NBA players, the cross-sectional design of the study prevents the possibility to draw inferences upon 'heart function' (e.g. adaptability to specific imposed stressors). Hence, repeated measurements at specific time-point intervals (e.g. pre-post training, pre-post flights) would allow practitioners to better understand how the heart of NBA players adapt and respond to specifically imposed stressors, and subsequently, create individualized training and recovery stimuli targeting optimal athletic cardiac remodeling trends in each NBA player respectively [61,62]. For instance, Stanley et al. [61] reported that the time required for complete cardiac autonomic nervous system (ANS) recovery after a single bout of aerobic training equals 24 h following low-intensity exercise, 24–48 h following threshold-intensity exercise and at least 48 h following high-intensity exercise [61]. However, ANS recovery occurs more rapidly in individuals with greater aerobic fitness, thus the importance of maintaining an adequate level of aerobic fitness in NBA players is an important discussion point, especially during potentially detrimental periods of inactivity (e.g. offseason, transition period, injury) [63,64]. Therefore, future applied sport scientists may consider examining the cardiac responses in NBA players following exercise (e.g. games, practices, workouts), travel (international and domestic flights), or following COVID-19 contraction, in order to better prepare players for the cardiorespiratory demands of the NBA ecosystem. At this point, NBA coaches and support staff may refer to the general scientific insights and proposed guidelines about cardiac parasympathetic recovery kinetics in elite athletes by Stanley et al. [61], Kovacs et al. [62] and Baggish et al. [64], while maintaining a critical viewpoint given this preliminary body of evidence has yet to be confirmed or disputed in NBA players most specifically.

Finally, recognizing that cardiac musculature has been the only topic of interest thus far, atomic, cellular, and tissue-level analyses of other organs are needed in order to gain more context and insights into how training and recovery prescriptions can be individualized in NBA players to evoke optimal adaptations at the micro-level. For instance, the growing technological advancements in noninvasive neuroimaging devices [65] facilitate brain-focused research as they become more readily available in applied sciences, enabling real-time and/or quasi real-time feedback during practices or games [65,66]. Similarly, advancements in monitoring exercise-induced adaptations at the local innate muscles, tendons, cartilage, and/or bones (e.g. tensiomyography, sonography, thermography, elastography, dynamometry, digital palpation) [67–69] may continue help researchers to collect and examine primary datasets on a wide spectrum of anatomical variables in NBA players, in a frequent and consistent manner (e.g. Achilles and Patellar tendon viscosity), hence promoting the ability to establish normative scales of 'functional status' (adaptability), rather than only 'structural status' in NBA players.

Functional aspects

Physical qualities. From a general perspective, physical qualities can be classified into five components of 'physical condition' (i.e. bio-motor abilities: speed, strength, endurance, flexibility, and coordination) [63]. In the NBA, these components of physical condition are typically measured during the NBA combine [51,55,70]. Consequently, three studies examined the physical condition of NBA players during the pre-draft combine and examined its predictive value on future on-court performance (n = 2) and/or odds of getting drafted (n = 1) [51,55,70]. In particular, the regression model by Ranisvavlev et al. [70] demonstrated that three physical tests (i.e. lane agility, vertical jump, and bench press) explained 24.7% of future game-play performance in NBA prospects who competed at least 30 games and averaged at least 16 minutes of playing time per game in the first year of entering the NBA [70]. These findings partially align with the results from principal-component regression (PCR) analysis by Teramoto et al. [55] (2010–2015 NBA combine), in which upper-body strength was determined to be the second most influential component

Table 6. Scientific evidence, practical applications, and future research lines specifically related to *player constraints of NBA game-play performance.*

PLAYER CONSTRAINTS OF NBA GAME-PLAY PERFORMANCE				
		Scientific Evidence	**Practical Applications**	**Future Research**
STRUCTURAL	Eidonomical	• ↗ 14.2 kg of Avg M from 1950 to 2011. [58] • Avg A-to-H ratio of 1.06-to-1.59 • Median H of 204 cm, Avg H of 198.62 cm, Avg WS of 209.57 cm, Avg SR of 263.24 cm, Avg HL of 22.31 cm, Avg HS of 23.93 cm. [59] • Avg H of top scorers = 201.3 ± 6.3 cm (1950-2011). [59] • HWS, SR, MM, WS, HL, and L-S at 2010-2015 NBA combines is associated with GPP in <3 subsequent years. [60] • L-S predicts BPM and VORP. [58]	• Managers may use historical data regarding secular in NBA players' Eidonomical characteristics as a benchmark for talent identification purposes. • Combining anthropometric and biomechanical testing protocols can help coaches evaluate, profile, and compare players to optimize the safety and efficiency of inherited movement mechanics.	• What are the characteristics of whole-body and limb skinfolds, circumferences, length ratios, and postural deviations in NBA players? • Does coaching philosophy (e.g., playing "small ball") compensate for a lack of high-eidonomical profile players?
	Anatomical	• LA and LV hypertrophy can be expected. [65,66] • Heart ventricles augmented normally with exercise. [65,66]	• Cardiorespiratory profiling is an important task for NBA support staff given the importance of aerobic condition, especially during and following the COVID-19 pandemic. [90] • At present, scientific reports on EI cardiac parasympathetic recovery kinetics in elite athletes [67,68] may help NBA coaches design appropriate training stimuli according to players' cardiac adaptability to EI demands.	• What is the cardiac remodelling process in NBA players following training, games, and/or air travel? • How do NBA players (mal)adapt to the demands of NBA games at the atomic, cellular, and tissue level? *E.g., local innate muscles, tendons, cartilage, and bones* • How does the cerebellum of NBA players respond to visual, auditory, and somatosensory (tactile) stimulation?
FUNCTIONAL	Physical	• Bench press and PQA ↗ → rebs and blocks ↗. [61,77] • Lane agility, VJR, and bench press explained 24.7% of variance in NBA GPP. [77] • ↗ VJHR, ↗ lane agility, and ↗ ¾ sprint → ↗ odds of being drafted (2000-2018). [57] • ↗ "quiet eye" = ↙ USG%, ↙ ORB% and ↗ FG3%. [79] • ↗ VTS → ↗ assists , ↗ steals and ↗ A-to-T ratio. [80] • Overall PT ↗ → likely ↗ ability to stustain of VJP. [81]	• The protocol of Rauch et al. provides a viable and valuable blueprint to standardize and implement movement profiling in NBA players. • Individualized training and recovery prescriptions for players receiving less overall PT is warranted to avoid potential detriments in LBSP, RT, VJP, alertness, and subjective feeling of fatigue accumulating during the regular season.	• What is the difference in VTS between rookies and veterans? • How do baseline markers of 'fitness' fluctuate during the season and how does season period, playing experience, position, and playing time interact with these variances? • How does the "quiet eye" differ between contested, semi-contested, and non-contested shot situations, and how does this impact scoring?
	Psychological	• Tactical communication in the beginning of the season ↗ → ↗ NBA GPP later in the season (2008-2009 season). [82] • 79% of players used Twitter (2012 till 2015). [83,84] • Twitter "teammate following behavior" of NBA star players impacts their team GPP.85 • Tweeting between 11:00 PM and 7:00 AM = ↙ next-day GPP, in particular ↙ points, ↙ rebounds, ↙ PT. [85]	• Practice scenarios that stimulate tactile communication and behavior is encouraged, especially in the first phase of the season. • SMHAT-1 and SMHRT-1 may help design individual mental preparedness profiles. [93] • Regular implementation of player-centred educational programs to help support a performance-friendly, sustainable, and healthy approach to using social media is warranted.	• What is the impact of the "NBA Bubble" on the psycho-social behaviour of NBA players, factoriong in their age, playing experience, and personality type? • What is the impact of social media based mood state scores on future team and player NBA GPP? • What is the most common personality types in successful or high-achieving NBA players?
	Technical & Tactical	• All-star NBA players → ↗ scoring <12 ft (366 cm), ↙ velocities in defense ↗ elbow touches, ↗ defensive rebounds, ↗ close touches, ↗ close points and ↗ pull-up points. [96] • FT's ↗ with each successive FTA. [98] • Outside-inside coordination ↗ → NBA team GPP ↗. [99]	• Practice scenarios in which high-post and low-post interactions are stimulated, as well as concurrent interplay between the weak side is recommended when aiming at enhancing inside pass and scoring options, especially in close (balanced) games.	• What actions typically occur during the FT calibration phase? *e.g., ball tracking systems, change of position, body language or interaction with other players* • How are teams and players employing inside passing situations against various types of defensive team tactics that are used to disrupt them?

Abbreviations: *MM = mean mass; A-to-H = arm-to-height ratio; H = height; SR = standing reach; HS = hand size; HL = hand length; LA = left atrium; LV = left ventricle; HWS = height without shoes; WS = wingspan; L-S = length-size; VORP = value over placement player; GPP = game-play performance; EI = exercise-induced; NI = neuro-imaging; UB = upper body; power-quickness ability; PT = playing time; BPM = box-score plus/minus; CMJ = countermovement jump; LBSP = lower-body squat power; RT = reaction time; VJP = vertical jump power; SMHAT-1 = ; Sport Mental Health Assessment Tool 1; SMHRT-1 = Sport Mental Health Recognition Tool 1; FT = free throw; FTA = free throw attempt; VJR = vertical jump from running; VJHR = vertical jump height and reach; VTS = visual tracking speed; USG% = usage percentage; FG3% = 3-point field goal percentage; ORB % = offensive rebound percentage; VJR = vertical Jump from running; PT = playing time; PQA = power, quickness, and agility; Rebs = rebounds.*

of future NBA game-play performance, followed by their power-quickness ability [55]. Finally, Cui et al. [51] examined near two decades of combine data (2000–2018) and concluded vertical jump height and reach, lane agility, and three-quarter sprint as the most determining parameters for increasing an NBA player's odds of being selected in the annual NBA draft [51]. Given upper-body strength (185-lbs bench press test) seems to play a significant role in future game-play performance, but not in getting drafted, managers may reconsider their approach and take this parameter into account. However, it is important to note that the combine testing data employed by these researchers are a static reflection of the players' physical characteristics (one-time measurement), thus 'physical progress' was not considered when computing the predictive value on any dependent variable. In turn, these findings cannot be regarded as a true reflection of an NBA player's 'physical work capacity' or 'physical adaptability' to the NBA ecosystem. Hence, regular physical testing in NBA players is required in order to gain insights into how physical strengths can be maximized, and conversely, how physical shortcomings can be compensated, in an evidence-based manner. In this sense, extended partnerships with internal and external academic and commercial entities may support and enforce this process. Promisingly, four studies have already demonstrated the viability and value of adopting such collaborative efforts in repeated physical testing in NBA players, and have disseminated useful findings based on primary data that can immediately help improve the practices and decision-making of NBA strength and conditioning (SC) coaches [71–74]. In particular, Rauch and colleagues [71] conducted a biomechanical assessment (utilizing force plates and 3D motion capture suits) in 178 NBA players, which resulted in a detailed report of movement mechanics applied during the 'descent phase' of three maximal-effort countermovement jumps (CMJ) [71]. Given the relative large sample size and robust methodology applied in their investigation, this study offers an insightful and useful framework to help profiling NBA players according to their recurrent movement patterns and jumping styles, and in turn, allowing to construct player-centered plyometric and coordination exercises that help them better produce ground-based forces in an efficient and ergonomic manner [71].

Besides jumping mechanics, two researchers focused on visuomotor skills in NBA players [72,73]. In particular, Laby [72] demonstrated that NBA players who tend to have more frequent and longer visual fixations on the rim ('quiet eye') are more likely to have a higher Three-Point Field Goal Percentage (FG3%) [72], which aligns with previous findings in basketball shooting [72]. Notably, this initial report included a relative small sample size and utilized a controlled testing environment (30 practice free-throw attempts wearing eye-tracking glasses in an uncontested situation), thus future studies may consider larger sample sizes, incorporating contested and semi-contested shot situations. Ultimately, randomized controlled trials may be considered to evaluate the effects of quiet-eye training regimen to improve shooting skills in NBA players. Aside of the quiet eye in NBA players, Mangine et al. [73] demonstrated that 'visual tracking speed' is positively related with assists, steals, and assist-to-turnover ratio in NBA players [73]. Unfortunately, in this study, visual tracking speed was measured only once in also a relative small sample size (n = 12), thus future studies are required on this matter to draw more conclusive inferences across players and teams.

Finally, to the best of the authors' knowledge, Gonzalez et al. [74] were the only staff members of an NBA team that followed a cohort of NBA players during the course of a season and subsequently published their findings on the 'physical progress' of their players (i.e. the 2012–2013 Orlando Magic team) [74]. This baseline report indicated that playing time (average of 27.8 ± 6.9 minutes per game compared to 11.3 ± 7.0 minutes per game) likely promotes the sustainability of vertical jump power (5 consecutive countermovement jumps), reaction time (20-seconds reaction time), and alertness in NBA players [74]. Nevertheless, this single study, involved a relative small sample size (7 players, tested twice), and previous playing experience and age were not accounted as potential co-factors in their analysis. In turn, this limits our ability to draw conclusive inferences across players and teams, as well as determine which particular factors (e.g. playing experience, coaching philosophy, player usage, etc.) and mechanisms (e.g. training and recovery regimen) were most relevant to maintaining the physical ability of their players throughout the season. Therefore, follow-up studies encompassing a broader context, larger sample size, and more frequent testing administrations is required.

Psychological aspects

Based upon all studies related to psychological factors of NBA players included in this systematic review (n = 4), it appears that all researchers focused on 'psycho-social' factors. In particular, 'touching behavior among teammates' (n = 1) [75] and 'social media usage' (n = 3) [76–78]. Specifically, Kraus et al. [75] were able to propose 12 distinct behaviors of 'teammate touching' (e.g. fist bumps) that provided predictive value for future NBA game-play performance, even after accounting for player status, preseason expectations, and early season performance (2008–2009) [75]. However, other contextual factors (e.g. cumulative fatigue, age, playing experience, personality type) and potential variations among different events (e.g. team practices vs games) were not considered as potential confounding variables. Recognizing the COVID-19 pandemic has enforced social distancing regulations (i.e. restricting or reducing tactile communication for player health and societal safety purposes) [79] resulting into well-documented mental health issues across the elite sport and public landscape [3,79–83], future research aimed at investigating tactile communication and psychological function of players in the NBA's post-COVID-19 era is an important research line to consider.

Besides touching behavior, the remaining researchers focused on social media behavior in NBA players and its relation to game-play performance (n = 3) and were all published within the last five years [76–78]. Considering a total of 330 million active Twitter users (San Francisco, CA, United States) were reported in 2019 [84], while 79% of NBA players had a Twitter account between 2012 and 2015 [76,77], the social media space has clearly grown into an inseparable part of the modern NBA player's lifestyle. In response, sentiment analyses (i.e. text and emoticon tagging and labeling of Tweets according to individual mood state) has become a research strategy to evaluate psychological status in NBA player [76,77]. For instance, Xu et al. [76] defined NBA players' pre-game 'mood states' (scale from −5 to +5) of 353 NBA players (2012–2013 season), and in turn, investigated how these mood states impacted future NBA game-play performance [76]. Hence, this data-mining technique has the possibility to be continuously implemented by NBA organizations to support their game-day player assessments, administrative and operational decision-making, and proactively educate players on the potential negative effects of social media mis-usage or over-usage [77]. Interestingly, social media behavior may not only relate to NBA players' mood states, but also their own team's chemistry and performance [77]. For instance, online teammate Twitter unfollowing behavior of high-status players (e.g. NBA all-stars) has demonstrated to be significantly associated with underperformance of their respective team [77], which aligns with research on status inconsistency, suggesting that individuals deemphasize their group affiliation when it jeopardizes their individual status [77]. Interestingly, this finding also aligns with recent anecdotal reports, such as the 2019–2020 NBA's Most Valuable Player who unfollowed all of his teammates on Instagram (Menlo Park, CA, United States) after his team was eliminated during the 2019–2020 playoffs. Nevertheless, future research is needed to make it possible for cause-effect inferences as well as enable deeper insights into how these specific psycho-social behaviors on social media channels can be properly addressed to improve the overall team chemistry and performance in their team respectively.

Besides 'Tweeting content' and 'following of teammates', the 'timing' of social media behavior has been examined by one research group, indicating that Tweeting between 11:00 PM and 7:00 AM is negatively associated with next-day game-play performance in 122 NBA players (2009–2016) as represented by fewer points scored, fewer rebounds, and less time played [78]. Although this study did not directly address the question of whether late-night and mid-night social media usage affects sleep quality or sleep quantity, a recent meta-analysis demonstrates that time spent watching mobile devices at night is associated with inadequate sleep duration, poor sleep quality, and excessive daytime sleepiness among youth [85], thus future studies have an opportunity to examine to what extent late-night tweeting behavior in NBA players impact sleep quality and/or quantity. In turn, this may help NBA coaches and support staff personnel to make proactive player-centered efforts to mitigate the associated risk that may come with uncontrolled, mis-used, or over-used social media activities. Additionally, validated comprehensive psychological assessment tools recently developed by the International Olympic Committee (IOC) (Table 6) [86] may serve as a starting point to identifying and stratifying (modifiable and non-modifiable) psycho-sociological risk factors in NBA players.

Technical and tactical aspects

NBA coaches routinely teach technical and tactical skills to enhance player and team success. Hence, analyzing tactical and technical skills according to various levels of play (e.g. all-stars vs non all-stars, professional vs amateur, etc.) can help determine which skills are most important for success at the NBA level. Given NBA team salaries are associated with offensive quality and not defensive quality, and offensive quality is correlated with team winning percentage [87,88], it is non-surprising that all studies included in this systematic review concentrated on offensive technical-tactical factors of NBA game-play performance (n = 3). In particular, Sampaio and colleagues reported that all-star players performed better in points within 12 ft (366 cm) away from the basket compared to non-all-star players [89]. However, it is important to acknowledge that all-star players typically play more minutes accumulated over the season compared to non-all-star players, thus limiting our ability to determine whether the differences were attributed to playing time or inherent motor ability [90].

With specific attention to free-throw (FT) shooting, Phatak et al. [91] demonstrated that NBA players may benefit from the 'calibration effect' (i.e. the success rate of the second FT attempt is typically greater compared to the first FT, and for triple FT's, the success rate increased with each successive FT) [91]. Given the dataset used within this study included more than 610,000 FT's from over ten NBA seasons [91], the 'calibration effect' during FT shooting is a well-documented phenomenon in the NBA. However, the behavior between two subsequent FT's was not described, nor examined. Therefore, future studies may investigate behavioral indicators (e.g. ball tracking systems, change of position, body language or interaction with other players) in order to gain a better understanding of how and why this calibration effect takes place, as well as how it can be entrained to promote successful acquisition of this skill.

From an offense tactical skill standpoint, only one study could be identified. In particular, Courel-Ibanez et al. [92] described the inside-outside configurations according to playing position in NBA Playoff contenders, and highlighted the value of employing concurrent strong side (pick and roll, pass and cut) actions with weak side (out of ball screen, dive cut) actions to increase scoring options when using the inside pass [92]. Consequently, these preliminary findings may support coaches in designing player development plans that align with the offensive collective dynamics that can be expected during NBA playoff games. Nevertheless, given only 8 teams in a total of 25 NBA Playoff games (2011) were examined in this initial sample, the final outcomes may not automatically replicate to other team settings and coaching philosophies. Hence, future studies examining larger sample sizes, while factoring in the defensive team tactics that are specifically constructed to disrupt the offensive team tactics, would likely provide more context and insights in the future.

NBA contextual constraints

Taking into account the individual strengths and limitations of each included study, this section provides a discussion on the following topics respectively: rest days, travel, game location, game period, game status, season period, difference of team quality, momentum effects, playing time, and finally, interactive effects. Notably, socio-cultural and socio-demographic constraints, including family support, demographic backgrounds, peer pressure, as well as public norms and expectations, were not included in the scope of this systematic review.

Rest days

All researchers (*n* = 4) consented that the number of rest days leading up to a game is positively correlated with an NBA team's ability to win that game [93–96]. In particular, when additional rest days were offered between playoff series, a two-fold increase in the odds of winning the second game in the next NBA playoff series (1984–2018 Finals) has been reported [93]. Similarly, during the regular season, Esteves et al. [94] revealed that having at least one day of rest between games increased the likelihood of winning the next regular season game by 37.6% [94]. Interestingly, when coaches voluntarily decided to rest players, a potential 'rust' phenomenon may emerge (i.e. trade-off effect on individual fitness and/or performance level) once more rest days are offered than what their players actually need in order to recover from previous stressors [95]. In particular, coaches who rested players for preventive reasons lasting five-to-nine games during the regular season (811 players; 2005–2015) did not display any benefits (i.e. points per game, assists per game, player efficiency rating, true shooting percentage, blocks, steals, or number of playoff games missed because of injury) over coaches who rested players for less than five games [95]. Hence, a quarter-by-quarter minute-restriction plan during games to avoid full 'under-loading' or 'detraining status' may likely present a better alternative than eliminating game-play opportunities entirely. Although evidence supports the positive relationship between rest days and subsequent game-play performance, future research is needed to disseminate more conclusive findings on this subject matter, especially regarding which in-game and between-game resting strategies likely evoke the greatest benefit on subsequent game-play performance in teams and players individually.

Travel

In the NBA, air travel demands remain high due to the obligatory geographical span (four different time zones) and time spent above 30,000 ft [1]. Consequently, air travel requirements have been a concern for NBA coaches, players, and owners, given research in team sports have demonstrated short-haul flights (e.g. domestic ≤6 h flights) increase injury risk and impede performance [1,5,97–99]. Surprisingly, only three studies (*n* = 3) specifically focused on the role of air travel on NBA game-play performance [1,100,101]. In particular, researchers generally consented that traveling in westward direction is likely more demanding than traveling in eastward direction, as demonstrated by points scored and winning percentage at the NBA team level [1], which also aligns with previous reports in the National Football League and the National Hockey League [1]. Westward travel is likely more difficult since alertness and focus tends to peak in the late afternoon and players traveling from west to east tend to play games closer to their circadian peaks given most NBA games are played at night [1]. Subsequently, NBA teams should carefully and proactively map out their travel schedule when flying westward at any point of the season or playoffs and recognize that NBA players are typically handling night games better than day games [1,101]. Noteworthy, the abovementioned findings were derived from observational-descriptive research studies, thus clearly defined protocols that would help mitigate potential negative consequences associated with air travel demands in NBA players remains unknown. Subsequently, the lack of longitudinal-interventional research on this topic forces NBA practitioners to employ cross-contextual inferences based on other elite sport populations that may not automatically apply to the NBA. Therefore, pre and post flight data collection involving physiological, psychological, and environmental parameters, through clinically validated self-reported questionnaires [102,103] and user-friendly mobile applications [104] would allow coaches and support staff to create individual player profiles according to their 'travel-adaptability' against various stressors (e.g. temperature, travel distance, travel duration, travel direction, altitude, humidity, and ultraviolet radiation) that are typical for the NBA ecosystem [1,102–104]. In this sense, the 2020 NBA playoffs, which began on 17 August 2020, offers an exceptional opportunity for comparative research purposes, because this new competition format eliminated short and long haul travel entirely due to the COVID-19 pandemic [83,101].

Game location

In alignment with previous studies in professional basketball, the home court advantage in the NBA is a well-documented phenomenon (*n* = 4), verified in over 7000 games spanning across 14 seasons (2004–2018) altogether [96,105–109]. However, to what extent lack of rest, travel duration and direction, time zone differential, stadium attendance, altitude, and team market size influenced these home court advantages remains ambiguous territory [96,105–107,110]. Thus, future studies have an opportunity to unravel these potential co-factors in order to help coaches better understand how the home court advantage can be modulated in their favor. Interestingly, one particular study examined the home court advantage from a 'microscopic dynamics' perspective [109]. In particular Gomez et al. [109] evaluated the impact of game location (alongside quality of opponent and starting quarter score) on final point differential in 48 NBA close games (below 10 points of difference) during the 2013–2014 season [109]. More specifically, the authors distinguished these games according to three different game types: (1) equal scoring trend between teams; equal outcome at the end of the 3rd and 4th quarter (n = 29) (type 1), (2) home team positive trend: home team winning by less than 10 points or even outcome at the end of the 3rd quarter and winning at the end of the 4th quarter (n = 10) (type 2), and (3) away team positive trend: away team winning by less than 10 points or even outcome at the end of the 3rd quarter and winning at the end of the 4th quarter (n = 9) (type 3). Through the assurance of good intra-observer reliability (values greater than .86) and inter-observer reliability (values greater than .81) by the authors (Graduated in Sports Sciences and certified as basketball coaches with a minimum of ten years of experience), they revealed that game location had the greatest impact on NBA game-play performance during type 2 (p = 0.007) and type 3 (p = 0.001) games [109]. Hence, these findings can help support NBA coaches to better understand which type of games are most susceptible to impact their team's game-play performance due to changing locations, and conversely, which variables of game-play performance should be prioritized in this particular case (Table 7). Finally, even though the home court advantage has been examined at the macro level predominantly (team analyses), future studies may consider investigations at the micro level (player analyses) given this would allow NBA coaches and support staff personnel to generate player-centered incentives, especially for players who are most susceptible to rapidly changing game locations during the season.

Game period

In general, game period can be defined as: the beginning (first quarter), middle (second and third quarter), and end (4th quarter and last 5 minutes) of an NBA game [25]. Among these periods, the final moment has been the most popular timeframe of investigation [111–113]. For instance, shorter possessions [113], fewer number of passes and participating players [112], higher number of fouls [112], and higher game stops and number of changes [112] can be expected during the final moments of an NBA game. More specifically, one-on-one isolation plays tend to generate the least team possessions, while inbound and complex team plays tends to generate the most team possessions [113], thus advocating collective-driven tactics as a profitable strategy during 'money time' [112,113]. Nevertheless, future studies are needed to examine how these findings are influenced by co-factors, such as: player status (e.g. all-star vs non all-star players), playing time, player usage, game location, fan attendance, and whether or not previous trends during the regular season may or may not transcend to post-season games. Finally, preliminary evidence in youth basketball players have indicated that playing after prolonged periods of sitting (up to 20 minutes) decreased their subsequent jumping height during simulated basketball games [114], thus the first moments following 'tip-off' as well as the 'halftime break' may add broader insights into how game periods influence game-play performance in NBA players and teams [115].

Game status

Game status can be defined as: the time a specific behavior is recorded in which an NBA team or player is losing, winning, or drawing [25]. Hence, game status can be viewed as a measure of 'interim performance', thus potentially impacting the effort made by a player [25,39]. For instance, during a specific moment of a positive point differential, teams may change their tactics, or players may adopt a ball retention strategy, slowing down the game, resulting in lower running speeds [25]. Surprisingly, Guerra et al. [116] were the only researchers (n = 1) to explore this underpinning factor of game-play performance in the NBA setting. In particular, they were able to identify in-game 'tipping points' (i.e. the non-equilibrium state when the slightest change causes a significant difference in the game score) (Table 7) [116]. Although these tipping points may help coaches understand what particular moments of the game are most critical in the performance of their team, the underlying tactics (e.g. time-outs) employed to counteract (nearby) tipping points is yet to be explored. Hence, it is important to recognize that tipping points may result from numerous underlying physiological and psychological processes [117], shaped by individual (e.g. personality type) and situational forces (e.g. referee disagreements) [117], which are yet to be discovered in the NBA. Hence, with only one study to date on this matter, follow-up studies are required to formulate more clear and conclusive inferences.

Season period

Previous evidence suggests that key moments arise during the NBA season in which game-play performance significantly changes at the individual and/or team level [25,39]. In this sense, the comparison between regular season games and playoff games have been the most popular type of investigation (n = 2) [25,87,118]. Unfortunately, all researchers solely focused on outcome-based metrics (box-score statistics), thus neglecting potential underlying mechanisms for how seasonal variations influenced variations in NBA game-play performance [87,118], hence potential biases in outcomes may exist, and thus conclusive inferences remain limited at this moment. Finally, considering that the timeframe of the regular season and playoffs are inherently imbalanced (e.g. 5.5 months versus 2 months), researchers may instead consider adopting a split-series comparison of four different periods (i.e. 21, 20, 20, and 21 games) across the season [119]. Consequently, this approach would help us better understand the impact of season period on NBA game-play performance across consistent time intervals throughout the year, hence providing a better reference point for annual planning and periodization strategies respectively.

Difference of team quality

Some teams are inherently better than others, and has been frequently defined by the team's 'winning percentage' or 'team ranking at the end of the season' [39]. Four studies (n = 4) aimed to better understand the quantification of an NBA team's inherent quality compared to other teams [88,120–122]. Interestingly, researchers were mainly concerned with the following parameters: playing experience, height, weight, and traditional box-score statistics, disregarding potential internal factors (e.g. physiological and psychological parameters). Nevertheless, irrespective of the internal factors, regression techniques enabled researchers to explain 86% of variances in team quality by only six key variables derived from box-score statistics (Table 7) [88]. Conversely, Zhang et al. [122] determined the 'difference of NBA team quality' based on other box-score statistics, and mapped out the most important variables according to various possible confrontation types (i.e. strong vs weak, strong vs strong, weak vs weak teams) [122]. Although these preliminary findings can help support coaches to highlight specific technical-tactical variables that best explain the 'difference of quality of their team', the ability to determine how these outcomes have accumulated and emerged over time remains limited, thus restricting our ability to modulate these outcomes accordingly (Table 7). Therefore, it is recommended that future researchers take into account behavioral parameters (e.g. coaching philosophy, personality type), combine qualitative and quantitative datasets, and regularly repeat their analyses throughout the season, in order to gain a picture of when and how 'difference of team quality' can be built and/or maintained.

Momentum effects

The belief of a 'momentum effect' in professional team sports is evident and can be defined as: a team gaining a higher chance of winning in a game because they had been playing well in the few games leading up to that game [123]. However, to the best of the authors' knowledge, only one study focused on the investigation of the momentum effect in the NBA in particular [123], indicating that winning in the past 5 games significantly increases the odds of winning the subsequent game, even after controlling for difference of team quality [123]. Although these early findings tend to align with the literature on momentum effects in elite sports, future studies are warranted to control for other potential confounding variables (e.g. abrupt changes in team's composition due to injury or trades, game location, season period, leadership and personality traits, coaches' tactical strategies, etc.). Finally, as highlighted by Crust et al. [124], future researchers may consider focusing on the players' personal experiences and employing qualitative data collection methods [124] in order to help NBA coaches and support staff personnel develop a clearer conceptualization of momentum effects from a cognitive and behavioral-change viewpoint, as well as, paint a more a holistic picture about the impact of momentum effects on subsequent NBA game-play performance at the individual level [124].

Playing time

To the best of the authors knowledge, only two studies ($n = 2$) were concerned with examining NBA players' playing time and their subsequent ability to perform during games [74,90]. In particular, Mateus et al. [90] utilized a statistical clustering technique to categorize players according to 'short playing minutes' (11.5 ± 5.3 minutes), 'medium playing minutes' (25.2 ± 3.5 minutes), and 'long playing minutes' (36.8 ± 3.9 minutes), demonstrating that NBA players who played more overall minutes during the 2012–2013 season are less likely to present game-to-game variances in performance (i.e. box-score statistics), mainly in offensive statistics [90]. On the other hand, Gonzalez et al. [74] compared starters (27.8 ± 6.9 minutes per game) with nonstarters (11.3 ± 7.0 minutes per game), and used a much smaller sample size (7 players, 2 moments of observation) than Mateus et al. (474 players, 712 games played, 14,150 performance records). Nevertheless, to the best of the authors' knowledge, to date, Gonzalez et al. [74] were the first and only researchers to quantify the impact of NBA players' playing time on 'physical performance' rather than the traditionally used box-score statistics to evaluate game-play performance [74]. In particular, their findings implied that NBA players who gained more overall playing time during the season are better equipped to maintain and/or enhance their vertical jump power, reaction time, energy, focus, and control perceptual fatigue throughout the regular season [74]. At first glance, these findings tend to align with trends reported in similar investigations completed in European basketball [125]. Nevertheless, it is important to acknowledge that the underlying mechanisms of how and why less playing time plays a role in an NBA player's ability to maintain their fitness levels over the course of the season is yet to be explored. Interestingly, seasonal mood fluctuations (perceptual fatigue and tension related) has been displayed in other professional basketball competitions [126], hence advocating for including psychological measures when evaluating the impact of playing time on game-play performance in NBA players. Recognizing that inter-personal relationships between players, coaches, and support staff members play an integral part and important catalyst in driving motivation and mental well-being in professional basketball players [126], future studies may also consider investigating when, how, and why training, recovery, and mindfulness strategies specifically aimed at compensating a dearth of playing time can accommodate NBA players to stay physically and mentally ready for game-play demands throughout the season.

Interactive effects

With the exception of Casals et al. [39], to the best of the authors' knowledge, possible higher-order interactive effects (e.g. the role of momentum effects on playing time and playing time on home court advantage) has been frequently neglected. As previously reported, scientific research practices in elite sports are generally dominated by quantitative types of research (63.3%), while qualitative (36.2%), and mixed-method type of research (0.5%) are scarce (221 articles reviewed) [127], thus aligning with the outcomes reported in this systematic review. Given the scarcity of published mixed-model and mixed-method research in the sciences related to NBA game-play performance analysis, adopting a pragmatic, pluralistic, sequential, and multiphase research philosophy in future investigations is recommended [128,129], while simultaneously respecting the design, analytical, and statistical procedures that are required to implement a robust mixed-method and mixed-model research project [127–131].

Table 7. Scientific evidence, practical applications, and future research lines specifically related to the *contextual constraints of NBA game-play performance.*

	CONTEXTUAL CONSTRAINTS OF NBA GAME-PLAY PERFORMANCE		
	Scientific Evidence	**Practical Applications**	**Future Research**
Rest Days	• Rest days between playoff series → $\boxed{\nearrow}$ chance of winning Game 2 in subsequent series. [100] • For each day of rest between games → winning odds $\boxed{\nearrow}$ by 37.6%. [101] • NBA GPP when resting players 5-9 days ≈ resting players <5 days. [102]	• To avoid potential "rust" effects, coaches may consider quarter-by-quarter minute-restriction plans to promote recovery in key players, rather than completely eliminating them from games.	• How does active recovery days differ from passive recovery days with regards to subsequent NBA GPP? • How does gradual reduction, exponential reduction, and steady reduction of PT influence future NBA GPP?
Travel	• Following westward travel → $\boxed{\swarrow}$ chance of winning, especially in evening games. [1,108,109]	• Adjust to the timing, duration, and intensity of activities before, during, and following short and long haul flights, in order to support optimal hormonal regulation and secretion before, at, and following game tip-off time.	• How does the complete elimination of air travel during the "NBA Bubble" relate to retrospective and prospective measures of NBA GPP? • How does air travel impact sleep, mental health, energy, focus, alertness, and training attractiveness in NBA players in the short term (acute) and long term (chronic)?

Game Location	• The HCA is a well-documented phenomenon in the NBA.41,104,115–[117]
	• Particularly in <u>type 2</u> game scenarios:
	  ○ HT's = $\boxed{\nearrow}$ BPS and $\boxed{\nearrow}$ 2PFGIO. [117]
	  ○ AT's = $\boxed{\nearrow}$ 3PFGCR and $\boxed{\nearrow}$ defensive rebs. [117]
	• Particularly in <u>type 3</u> game scenarios:
	  ○ HT's = $\boxed{\nearrow}$ BPS, penetrations and 2 or >2 on the shooter. [117]
	  ○ AT's = $\boxed{\nearrow}$ missed FT's. [117]
		• Testing and profiling players according to their level of "travel-adaptability" may help detect players who are most susceptible to changing environments.
		• The technical-tactical factors established as distinctive between HT's and AT's can be mapped out against game type, and subsequently prioritized in training when aiming to improve T-POS effectiveness. [117]
			• What are the differences in "microscopic" dynamics between AT's and HT's?
			• What individual factors magnify or alleviate the HCA in NBA players respectively?
			• How does lack of rest, long road trips, stadium attendance, altitude, and team market size influence team-level and player-level HCA?

Game Period	• Final seconds of CG → $\boxed{\swarrow}$ 5-10% points, [118] and $\boxed{\swarrow}$ possessions (especially by the disadvantage team), $\boxed{\swarrow}$ passes, $\boxed{\swarrow}$ fouls, $\boxed{\nearrow}$ game stops and $\boxed{\nearrow}$ number of changes. [120] • Final seconds of CG → 1v1 play = $\boxed{\swarrow}$ T-POS, while transition, inbound and complex team plays = $\boxed{\nearrow}$ T-POS. [119]	• Coaches may benefit from creating "late-game" practice scenarios in which transition, inbound, and complex team plays are enforced. • Coaches may benefit from late-game practice scenarios in which shooting accuracy in pressured situations are challenged.	• What are the differences in microscopic dynamics between the AT and HT during the 1st quarter? • What is the impact of team playing style in the 1st quarter on subsequent team playing style in the 4th quarter, as well as the outcome, and overall GPP of the game?

Game Status	• Most critical moments during NBA games: [123]
	  ○ *≤10 points*
	  ○ *10-28 points*
	  ○ *≥28 points*
		• Coaches may strategically construct their tactics (e.g., time-outs) based upon previously established game tipping points.	• What are the effects of technical fouls, ejections, TO's, slam dunks, buzzer beaters, and/or alley-oops on the microscopic dynamics of NBA games?

Season Period	• 3PT FGM $\boxed{\nearrow}$ as the season evolves. [125] • Importance of defense → $\boxed{\nearrow}$ during playoffs. [126] • $\boxed{\swarrow}$ TO's → $\boxed{\nearrow}$ winning during the regular season. [126] • $\boxed{\nearrow}$ Rebs → $\boxed{\nearrow}$ winning during Conference Finals when facing teams with similar shooting efficiency and TO rates. [126]	• Coaches may benefit from focusing on defensive tactics during the playoffs, limit TO's during the season, and focus on rebounding skills during the Conference Finals, especially when the opponent has similar shooting efficiency and TO rates.	• What are the most important factors of NBA winning games during the first 21 games, second 20, third 20, and final 21 games of the season, taking into account technical, tactical, mental, and physical parameters?

Difference of Team Quality	• 86% of variances in 'difference of NBA team quality' can be explained by the following equation: [128]
	  ○ *22,868 + 59,08 Win % + 0,18 Avg Fauls + 21,33 Offensive EFF+ 2,46 Win% CG + 3rd Qrt PPG +0,28 Avg Steals*
	• <u>Strong teams</u> are characterized by: [131]
	  ○ $\boxed{\nearrow}$ *Defensive rebs,* $\boxed{\nearrow}$ *blocked shots and* $\boxed{\nearrow}$ *assists*
	• <u>Weak teams</u> are characterized by: [131]
	  ○ $\boxed{\nearrow}$ Defensive rebs and $\boxed{\nearrow}$ TO's
	• <u>Strong team match-ups</u>: [131]
	  ○ *Winning teams in home games =* $\boxed{\swarrow}$ *running speed than losing teams, while opposite in away games.*
	• <u>Strong vs weak team match-ups</u>: [131]
	  ○ *Winning teams in home games =* $\boxed{\nearrow}$ *distance and* $\boxed{\nearrow}$ *running speed than losing teams.*
	• <u>Weak team match-ups</u>: [131]
	  ○ *"Defense wins the game".*
		• Managers and coaches may benefit from mixing up various line-ups to earlier in the season to evaluate which line-up possesses the greatest potential to winning games according to specific match-ups according to the quality of opposition in the upcoming game.
		•
			• Which physical and mental variables complement or contradict 'difference of team quality'?
			• What are the most important factors of 'team quality' during the NBA playoffs according to rank position?
			• How does 'difference in team quality' affect the GPP of NBA players individually?

Momentum Effects	• NBA winning % in the last 5 games → $\boxed{\nearrow}$ odds of winning the subsequent game.	• Coaches can expect and prepare for increased match difficulty when playing against teams that have accumulated wins preceding the game.	• Does abrupt changes in team's composition due to injury or trades, preceding travel, season period, leadership and personality traits, and coaching philosophy influence momentum at the team and player level? • Are NBA team-level momentum effects similar to player-level momentum effects?
Playing Time	• NBA players who $\boxed{\nearrow}$ PT = $\boxed{\nearrow}$ consistency of GPP across games, particularly in offensive box-score statistics.	• Coaches should carefully weight down the risks versus benefits of selecting players who are not used to play substantial minutes given they are more likely to present game-to-game variance in GPP.	• Which training, mindfulness, and education methodologies are best equipped to alleviating any of the previously reported disadvantages in players who receive little PT in the NBA?
Interactive Effects	• The scarcity of current evidence restricts our ability to draw any conclusive inferences.	• The scarcity of current evidence restricts our ability to draw any conclusive inferences.	• Longitudinal mixed-method and mixed-model research designs are required in order to help us understand the underpinning factors of NBA GPP from a holistic and pragmatic viewpoint.

Abbreviations: *Avg = average; GPP = game-play performance; PT = playing time; Offensive EFF = offensive efficiency rate; Win % CG = win percentage in close games; PPG = points per game; H = height; W = weight; PE = playing experience; HCA = home court advantage; Rebs = Rebounds; 3PT FGM = 3-point field goals made; TO's = turnovers; PPG = points per game; EFF = efficiency rating; T-POS = team possessions; AT = away team; HT = home team; CG = close games; starting quarter score; FTS = free throws scored; 3PFGC = 3-point field goals from central positions; 2PFGIO = 2-point field goals from inside and outside the central positions; 3PFGCR = 3-point field goals from central and right court positions; BPS = ball possession success.*

Limitations

First, although the research articles included in this systematic review (n = 43) represented a substantial source of information, we recommend the readers to take caution in externalizing these findings given the research questions and hypotheses were largely heterogeneous (i.e. all studies aimed at answering a distinctive question rather than sequentially following up on preliminary evidence). Hence, the totality of information tends to lack consistency in research interests, terminology, and methodology, which in turn, may jeopardize the reproducibility of its findings to the real-world milieu. Second, the vast majority of studies followed an ecological study design, examining multiple NBA teams at once and altogether, however none of these articles were encompassed recent competitions (>2017), thus inferences on player and team specific inner variables with similar conditions for the outer variables in the modern NBA competition cannot be automatically assumed. Third, the procedures in which 'indicators' of game-play performance were determined by the authors were non-uniform (e.g. margin of victory in one single game vs. team ranking at the end of the regular season), thus clarity and uniformity in determining what 'NBA game-play performance' represents from a holistic and multi-disciplinary viewpoint, is an important challenge facing upon future sport scientists and performance analysts. In general, the selected indicators of NBA game-play performance were outcome-driven, thus lacking the ability to draw inferences on how teams and/or players may change their behaviors during the course of a game to ultimately arrive at successful game-play outcomes. Therefore, future studies concerned with a behavioral-driven approach to examining NBA game-play performance in-game and end-game statistics is warranted. As an illustration, by factoring in player-specific covariates (position, usage rate, and average minutes played per game), Page et al. [132] were able to apply a hierarchical Gaussian regression process to compute critical NBA game-play performance indicators that were more comprehensive in nature than previously proposed [132]. Fourth, the vast majority of findings were descriptive-observational designs (n = 27; 62.8%), hence lacking the ability to draw hypotheses generating (exploratory), causal-comparative (explanatory), predictive, and/or prescriptive inferences. Consequently, the absence of interventional research inhibited the ability to draw causal-comparative conclusions between independent and dependent variables due to the lack of manipulation, control, and randomization of subjects, and may complicate future research due to potential intra and inter-observer biases in observations, recording, and interpreting previously reported information. Fifth, near all studies neglected reporting of subject drop-outs and/or missing values, which tends to be a common problem across social sciences research [133]. Therefore, the authors recommend to consider and address missing values at each stage of the research process (design, data collection, analysis, and reporting) to prevent missing data, define the estimand, and specify primary and sensitivity analyses [134]. Sixth, because linear models (e.g. linear and logistic regression) are relatively simple to execute, it is not surprising that the majority of researchers have favored this particular method of statistical analysis to try answering various proposed research questions. Unfortunately, this type of analysis may overlook random effects by treating each variable as a 'fixed effect', thus undervaluing the importance of variability in NBA basketball and the inherent complexity of team-sport research in general [39]. Therefore, if and when variances of errors in the datasets are normally distributed, mixed-model research (e.g. Generalized Linear Mixed Model) may serve as an adequate and parsimonious alternative to investigating relationships among key underpinning factors inside complex systems such as NBA games [20,25–27,39]. Seventh, near all researchers analyzed secondary data sources. Unfortunately, this type of data limits the researchers' ability to gain control over potential risks of biases during the data collection process (observers' inter-observer and intra-observer reliability), as well as establish targeted research questions to elicit the data that will help them with their specific purpose of the study, gain ownership of on-demand data, and generate real-time and/or quasi-real-time feedback to help players and coaches better adapt the contemporary demands within the course of NBA games [135]. Therefore, we encourage future researchers and practitioners to collaborate with both internal and external parties (e.g. academic institutes, player agencies, data science consultants, sports technology companies, data protection officers, league executives, national and international Olympic committees, etc.) to facilitate the storage, modeling, aggregation, and replication of various data sources.

Considering the main limitations described above, the authors encourage future researchers to embrace a stepwise framework, such as the Applied Research Model for Sport Sciences (ARMSS) conceptualized by Bishop et al. [45] because it sequentially integrates descriptive, exploratory, and explanatory study designs, and links them altogether in a progressive manner (8-step process) [45]. In turn, this approach would foster the reproducibility and transferability of scientific findings to the real-word NBA settings (i.e. dynamic correspondence). Recognizing the complexity of NBA games and lack of consistency in research over the past two decades, we also encourage the full integration of NBA coaching staffs and key decision-makers to support new research thrusts, facilitate inter-staff and cross-disciplinary discussions, to create worthwhile research lines that would help build theoretical and practical grounds for future sport scientists [45,136,137]. Consequently, this joint approach to more applied research would foster new insights that may not only be 'statistically significant', but perhaps more importantly, 'clinically useful' to act upon new insights [45,136,137].

In summary, adhering to our inclusion criteria, a total of 43 articles could be identified. Piloting of the search strategy and subjunction of outcomes generated by electronic databases with hand searching the reference lists of each article, permitted our confidence in ensuring that all relevant studies were included in this systematic review, and that suppositions arising from this systematic review can be based on the synthesis of all available evidence up to this date. With respect to the overall strengths and limitations of included studies, as well as procedures applied in systematically reviewing them, our main findings, practical applications and new future research line proposals are presented in the following sections. Specifically, the first section presents a discussion of research trends regarding the popular computations and analyses of 'NBA game-play performance indicators', followed by their underpinning factors ('NBA player constraints' and 'NBA contextual constraints') (Tables 5,6 and 7).

Noteworthy, prior to applying the information generated from our discussion as an immediate source of knowledge, it is important that readers take into account the unique and ever-changing dynamics and demands of the NBA ecosystem (e.g. post-COVID-19 era); various individual differences that may exist across players, teams, and generations; and the administrative and operational resources that may or may not be available within their respective team setting.

Conclusions

To the best of the authors' knowledge, this systematic review presents the first attempt to disseminate a comprehensive portfolio of scientific information about the underpinning factors of NBA game-play performance. Taking into account the total body of evidence (2001–2020), and respecting the strengths and limitations of included studies, NBA coaches and support staff members may use this systematic review as a baseline reference point to explore and enrich their current knowledge about the NBA ecosystem. Acknowledging the vast majority of included studies were disseminated in recent years, the future of applied science in the NBA deems promising. However, given the polarization of research topics and popularity in descriptive-observational oriented research designs up to this date, future researchers may consider the employment of an applied science research framework that fosters (1) clearly outlined incentives (time frame, objectives, organizational and operational demands, strengths, limitations, and outcomes); (2) standardization of taxonomies; (3) sequential follow-up of research projects; (4) holistic, pragmatic, and trans-disciplinary viewpoints; and (5) implement longitudinal-interventional, mixed-method, and mixed-model research designs to increase the overall ecological validity and reproducibility of their findings.

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Authors' contributions

Conceptualization, T.H. and J.C-G.; methodology, S.B., J.C-G. and P.A.; resources, T.H., S.B. and J.C-G.; writing and original draft preparation, T. H.; review and editing, T.H., S.B., J.C-G. and P.A. All authors have read and agreed to the published version of the manuscript.

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APPENDIX 3. Study 3: PUPILLOMETRY AS A NEW WINDOW TO PLAYER FATIGUE? A GLIMPSE INSIDE THE EYES OF A EURO CUP WOMEN'S BASKETBALL TEAM.

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Pupillometry as a new window to player fatigue? A glimpse inside the eyes of a Euro Cup Women's Basketball team

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ABSTRACT: A rapidly emerging area of interest in high-pressure environments is that of pupillometry, where handheld quantitative infrared pupillometers (HQIPs) are able to track psycho-physiological fatigue in a fast, objective, valid, reliable, and non-invasive manner. However, the application of HQIPs in the context of athlete monitoring is yet to be determined. Therefore, the main aim of this pilot study was to examine the potential usefulness of a HQIP to monitor game-induced fatigue inside a professional female basketball setting by determining its (1) test-retest repeatability, (2) relationship with other biomarkers of game-induced fatigue, and (3) time-course from rested to fatigued states. A non-ophthalmologic practitioner performed a standardized Pupil Light Reflex (PLR) test using a medically graded HQIP among 9 professional female basketball players (2020–2021 Euro Cup) at baseline, 24-h pre-game (GD-1), 24-h post-game (GD+1) and 48-h post-game (GD+2). This was repeated over four subsequent games, equalling a total of 351 observations per eye. Two out of seven pupillometrics displayed good ICCs (0.95–0.99) (MinD and MaxD). Strong significant relationships were found between MaxD, MinD, and all registered biomarkers of game-induced fatigue ($r = 0.69$–0.82, $p < 0.05$), as well as between CV, MCV, and cognitive, lower-extremity muscle, and physiological fatigue markers ($r = 0.74$–0.76, $p < 0.05$). Three pupillometrics were able to detect a significant difference between rested and fatigued states. In particular, PC (right) ($F = 5.173$, $\eta^2 = 0.115$ $p = 0.028$) and MCV (right) ($F = 3.976$, $\eta^2 = 0.090$ $p = 0.049$) significantly decreased from baseline to GD+2, and LAT (left) ($F = 4.023$, $\eta^2 = 0.109$ $p = 0.009$) significantly increased from GD-1 to GD+2. HQIPs have opened a new window of opportunity for monitoring game-induced fatigue in professional female basketball players. However, future research initiatives across larger and heterogenous samples, and longer investigation periods, are required to expand upon these preliminary findings.

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INTRODUCTION

In high-performance sports, excessive levels of fatigue can inhibit the desired adaption to training, increase injury risk, and potentially hinder athletic performance [1]. Therefore, continuously exploring new ways to quantify player readiness is considered a priority within elite sporting organizations [1, 2]. In light of this pursuit, numerous fatigue monitoring tools have emerged [1, 2]. However, from a practical perspective, traditional fatigue monitoring tools often remain exhaustive (e.g., maximal-effort physical testing) [2, 3], subjective (e.g., self-reported questionnaires) [2, 4], invasive (e.g., blood sampling) [2, 5], expensive (e.g., electroencephalogram) [2, 6], or relatively slow to conduct (e.g., 5-min recordings of heart rate indices in standing and lying postures) [7]. Hence, there's an ongoing need for innovative solutions that enable real-time, multi-modal, non-invasive, cost-effective, valid, and reliable insights into player fatigue, and in turn, improve the day-to-day decision-making processes of coaches and support staff personnel [1, 2].

Some of the most promising innovations to date in this space have emerged from collaborative initiatives between engineers, developers, scientists, and practitioners who operate in high-pressure environments (i.e., transatlantic flights, space shuttle missions, military combat, medical surgery, long-haul truck driving, etc.) as a lack of operational readiness in these positions could lead to lethal consequences [8, 9, 10]. Consequently, pupillometry has gained a rapid surge in interest by the research community across high-stake industries [9, 10]. Pupillometry can be defined as the study of the the central opening of the iris through which light passes before reaching the lens and being focused onto the retina [11]. Because the pupils are directly innervated by the second cranial nerve (CN II) and third cranial nerve (CN III) [11], measuring pupil reflexes provides an objective representation of the autonomic nervous system (ANS) [12–15] as well as cognitive, emotional, physical, and physiological status in real time [16, 17, 18]. Since the first discovery of pupillometry as a human fatigue detection tool in 1936 [19], the field has rapidly advanced in recent years due to the emergence of Handheld Quantitative Infrared Pupillometers (HQIPs) [19, 20, 21, 22]. In particular, HQIPs are now able to repeatedly measure the pupil diameter (1 measurement every 30 ms) with a minimum detectable change of < 0.03 mm (i.e., practical error of 0.88% in relation to the average pupil diameter) [22, 23]. Consequently, a vast range of Intensive Care Units (ICUs) settings [24] and high-stake occupations are progressively integrating HQIPs as a first-point-of-care instrument [25, 26, 27].

Surprisingly, the use of modern HQIPs in professional sports remains bounded by a few use cases (e.g., concussion-related diagnostics [28, 29, 30] and "quiet eye" analytics [31]). While some researchers have introduced HQIPs as a method to evaluate ANS function in athletes [12, 14, 15], the validity and reproducibility of their methods and findings remains unclear. For instance, the investigations typically followed a cross-sectional study design, adopted non-standardized and non-validated pupil testing procedures, executed in laboratory conditions, and involved only amateur and sub-elite athletes. Besides the application of HQIPs to monitor ANS function, researchers have also demonstrated its effectiveness to monitor cognitive effort (i.e., pupil dilation can be viewed as an indirect index of effort in cognitive control tasks across the domains of updating, switching and inhibition) [32]. This could imply an important discovery as player performance and fatigue originates from the complex state of both physiological and psychological processes [33]. Hence, HQIPs may potentially reveal itself as a multi-model at monitoring instrument.

Acknowledging the inherent potential of HQIPs, and appreciating the efforts made by previous researchers on this research line, this pilot study aims to explore the potential usefulness of a medically graded HQIP to monitor game-induced fatigue in nine professional female basketball players by determining (1) the test-retest repeatability, (2) the relationship between pupillometrics and other biomarkers of game-induced fatigue, and (3) the time-course of pupillometrics from baseline and 24 h before games up to 24 h and 48 h following games. In turn, the reported baseline findings and methodological framework may serve as a valuable reference for future research initiatives on this topic.

MATERIALS AND METHODS

Experimental approach to the problem

This pilot study followed a prospective observational study design and was conducted in non-experimental conditions, so the coaching staff, support staff personnel, and participants did not receive any input from the research team. Training data, competitive schedule and fixture outcomes were supplied by the coaching staff of the team. Two weeks prior to the investigation period, a baseline pupil test was performed after two consecutive off days (i.e., no scheduled or organized practices or workouts during these days) to optimize physical and psychological recovery. Subsequently, the participants played four home games over a 5-week investigation period (1 week apart, all games commenced between 8:00 – 8:30 PM). For each game, a pupil testing sequence was executed at the following timepoints: 24-h pre-game (GD-1), 24-h post-game (GD+1), and 48-h post-game (GD+2). All pupil tests were completed and performed inside a standard clinical testing room during regular pre-practice physiotherapy session hours (6:00 PM – 7:30 PM) to emulate a standardized clinical testing time and environment.

Participants

Nine female Belgian professional basketball players (n = 9) competed in the 2020–2021 Euro Cup Women's Basketball Tournament and voluntarily participated in this study. All participants were aged 18 years or older (range: 18–33 years; mean age: 21.20 ± 4.92 years), with a mean height of 181 ± 5.36 (cm) and body mass of 80.61 ± 10.73 (kg). Based on positional groupings: 45% were grouped as Posts, 33% as Guards, and 22% as Wings. Based on the role: 55% were starters and 45% non-starters.

Players were not eligible to participate when they encountered at least one of the following criteria: < 18 years of age; unable to participate in individual and/or team practices due to injury or illness at any point of the investigation period; unable to sit for testing; history in genetic syndromes, neurologic pathologies (including intracranial masses) or intraocular pathologies that would affect pupillary function (e.g. uveitis, cataracts, diabetes, glaucoma, optic nerve dysfunction); ingestion of alcoholic and/or caffeinated foods, drinks, or substances within < 12 h of any pupil examinations; use of ergogenic aids and/or medical support that may have altered the neurophysiological state of the athlete at any point of the investigation period. Prior to the investigation, this study was approved by the Institutional Review Board of UCAM University, Murcia, Spain (code: CE122002) and conformed to the requirements of the European Union General Data Protection Regulation and United States Health Insurance Portability and Privacy Act with adherence to the tenets of the Declaration of Helsinki with Fortaleza actualization 2013 [34]. All test procedures strictly adhered to the World Health Organization (WHO), European Commission, and local government safety guidelines regarding scientific research during the COVID-19 pandemic.

Testing procedure

To verify whether any pupillometrics could detect a significant change in game-induced fatigue and recovery, participants were instructed to go through a comprehensive fatigue test battery at each allocated timepoint (i.e., baseline, GD-1, GD+1, GD+2). The fatigue test battery consisted of the pupil test in combination with four other fatigue tests: cognitive fatigue test (i.e., visuomotor reaction time) [35, 36], lower-extremity muscle fatigue test (standing postural sway) [37, 38], perceptual fatigue test (self-perceived exertion) [38], and ANS fatigue test (heart rate variability indices) [40–44]. More specifically, upon arrival to the clinical testing room, the player was instructed to wear the Polar H10 heart rate chest strap (Polar

Electro Oy, Kempele, Finland) and complete a 5-min heart rate variability (HRV) test in rested condition and seated posture using the EliteHRV software (Asheville, NC, United States) [44] on an iPhone SE (Apple Inc., Los Altos, California, United States). The Polar H10 was selected based on its underlying support as a medically graded heart rate sensor [40, 41] and the EliteHRV was selected based on its ability to record, store, and export HRV data in a secure and user-friendly manner [44]. Particularly, the natural log of the root-mean-square difference of successive normal RR intervals (ln-RMSSD) was used for HRV analyses given its well-documented support for monitoring physiological fatigue in young female basketball players [41] as well as numerous other sport athletes [43]. Following the HRV test, the player completed two subsequent Sway tests using the Sway Medical, Inc. software (Tulsa, Oklahoma, United States) [35–38] via touch screen display as well as tri-axial accelerometry (i.e., motion detection) on an iPad (6^{th} generation) by Apple Inc. (Los Altos, California, United States). The Sway test protocols have been established as an objective and reliable method for assessing reaction time, impulse control, timed visual processing, and working memory [35–38]. Particularly, the first Sway test examined the cognitive fatigue status through the Simple Reaction Time (SRT) test (ms) [35]. During this test, the player held the iPad horizontally (landscape mode) and moved it as fast possible in any direction when the screen display changed from a white to orange color. Each SRT test started after a variable delay of 2–4 s in order to prevent the player from anticipating the stimulus ahead of time. Each player completed five trials. The fastest and the slowest SRT scores were excluded in order to remove outliers and reflect only the typical response times of the player [34]. Subsequently, the scores of the three remaining trials were averaged to calculate the individual score for each player. Following the SRT test, the player performed the Sway Balance test, which quantified postural sway during the performance of a series of tasks to reflect lower-extremity muscle fatigue [45]. Specifically, the Sway Balance test consisted of five stance conditions (10-s in duration per stance) on a firm surface and with the eyes closed. The postural sway was quantified through the iPad's triaxial accelerometer, and the units that corresponded with the accelerations were used to calculate the final proprietary Sway Balance score [38].

Subsequently, the test administrator manually performed the standard Pupil Light Reflex (PLR) test [12, 28] in each player's eye respectively, using the NeurOptics NPi-200 pupillometer (NeurOptics, Laguna Hills, CA, U.S.A.), a medically graded HQIP (Class I medical device as listed under 21CFR 886.1700) [11, 46]. More specifically, this HQIP integrated a calibrated full-field white light stimulus with peak wavelengths comprised of red, green, and blue at a fixed intensity (1000 Lux) and fixed flash duration (0.8 s) to simulate a standard pupil light reflex (PLR) [11, 46]. Subsequently, this HQIP digitally registered the pupil light response as a video (sampling rate of 30 Hz) for a duration of 3.5 s, followed by a display of numeric results on a screen for each eye respectively [11, 46]. The device highlighted an outline of the pupil and graphed its displacement over time with an accuracy of 0.03 mm (i.e., practical error of 0.88% in relation to the average pupil diameter) [11, 46]. Scotopic lighting conditions (434–440 lumen/m^2) were verified prior to each pupil exam by measurement of luminance of less than 2 Lumens with a luminometer (Dr. Meter LX1330B Digital Illuminance/Light Meter, Hisgadget, Union City, CA, U.S.A.) at the level of the players' eyes. Furthermore, normal forehead temperature was measured and controlled (35.4 °C to 37.4 °C) prior to each test via a forehead thermometer (iProven DMT-489, Beaverton, Oregon, U.S.A.). Each pupil test was conducted sitting stationary looking straight ahead. Each player was prompted to maintain a forward head posture and binocular viewing conditions in a seated position throughout the test. The non-test eye was fixated on a neutral wall at 3-m distance to the chair's front leg. The right eye was tested first, immediately followed by the left eye. This sequence was completed three consecutive times using 60-s intervals to allow sufficient recovery of the pupil before the next light stimulus [11, 46, 47]. A retest was taken

TABLE 1. Descriptions of All Pupillometrics.

	Pupillometrics	Units	Description
MaxD	Maximum Diameter	Mm	Maximum pupil size before constriction.
MinD	Minimum Diameter	Mm	Pupil diameter at peak constriction.
PC	Percentage of Change	%	The change in pupil size over time, computed as: $PC = \left(\frac{MaxD - MinD}{MaxD}\right) * 100$
LAT	Latency	mm/s	Time of onset of constriction following initiation of the light stimulus.
CV	Constriction Velocity	mm/s	Average of how fast the pupil is constricting after exposure to light.
MCV	Maximum Constriction Velocity	mm/s	Represents the maximum velocity of pupil constriction.
DV	Dilation Velocity	mm/s	The average pupillary velocity when, after having reached the peak constriction, the pupil tends to recover and dilate back to the initial resting size.

whenever the HQIP was held incorrectly, or blinking was detected by the HQIP. All pupil tests were relatively quick to conduct and did not exceed ~4 min in duration per player, and ~60 min in total duration for the entire team. Notably, ease of use was reported by the test administrator (i.e., performance coach without previous clinical experience in using HQIPs). In particular, a total of 351 pupillary measurements were recorded in each eye, without any interference with the daily predetermined schedule of the team.

The selected HQIP extracted seven pupillometrics, which represented parameters of both the Sympathetic Nervous System (SNS) function and Parasympathetic Nervous System (PNS) function [11]. Furthermore, the HQIP used an algorithm to calculate the overall reactivity of the pupil (proprietary score), called the Neurological Pupil Index (NPi) [11]. However, the authors excluded the NPi pupillometric from the final analyses as the company did not publicly provide any details on the computation of the NPi. Descriptions and calculations for the seven remaining pupillometrics are presented in Table 1.

Finally, within < 1 h following any practice or game, the players completed an online survey to record their RPE score based on Borg's rate of perceived recovery status scale of 100 points [38], in which 0 means 'very poorly recovered/extremely tired,' 20 represents 'poorly recovered/very tired,' 40 means 'minimally recovered/ tired,' 50 denotes 'slightly recovered/somewhat tired,' 60 signifies 'moderately recovered,' 80 represents 'well recovered,' and 100 represents 'very well recovered/highly energetic' [39].

Statistical Methods

Prior to the statistical analyses, normal distribution of the dataset was confirmed (Shapiro-Wilkinson test; $n > 50$). Participant demographic information, including: age, height, body mass, playing position and role were calculated using descriptive statistics. The pupillometrics were compared between the left and the right eye through a paired t-test. The intraclass correlation coefficients (ICCs) were computed to examine test-retest reliability for each pupillometric using the thresholds outlined by Martins et al. (2014) for the assessment of technological equipment in research and clinical practice: very poor: ICC < 0.70, poor: ICC = 0.70–0.90, moderate: ICC = 0.90–0.95, good: ICC = 0.95–0.99, and very good: ICC > 0.99 [48]. The Pearson's Product Moment Correlation (r) examined the linear relationship between each pupillometric and various other measures of game-induced fatigue and recovery, including: perceptual fatigue (i.e., average daily Borg Rating of Perceived Exertion scores) [39], lower-extremity muscle fatigue (i.e., Sway Balance Error Scoring System test scores) [45]; cognitive fatigue (i.e., Sway reaction time score) [34], and ANS fatigue (i.e., lnRMSSD) [42]. The Pearson's correlation coefficients were interpreted using the reference standards by Hopkins et al. (2009): trivial: $r < 0.1$; small: $0.1 < r < 0.3$; moderate: $0.3 < r < 0.5$; large: $0.5 < r < 0.7$; very large: $0.7 < r < 0.9$; nearly perfect: $r > 0.9$; perfect: $r = 1$ [49, 50]. To explore whether any pupillometrics differed between rested conditions (baseline and GD-1) and fatigued conditions (GD+1 and GD+2) at the group level, the Levene test was applied as a derivation of the classical one-way analysis of the variance (ANOVA) to compute the F-statistics, Effects sizes (expressed as "η^2" or Eta Squared), Coefficient of Variation (CV), absolute and relative differences, Confidence Intervals at 95% (CI95), and p-values. The post-hoc Tukey test was examined for pairwise comparisons. The η^2 was interpreted with the following thresholds: small effect: $\eta^2 = 0.01$; medium effect: $\eta^2 = 0.06$; large effect: $\eta2 = 0.14$ [49, 50]. Additionally, the magnitude of these differences were visually presented by a 'percentage difference' in which postgame data (value) was subtracted by either baseline data or pregame data (value) represents, and divided by the baseline or pregame data (value). The significance of all inferential statistics was set for $p < 0.05$. All analyses were performed at 95%-Confidence Interval. All statistical tests were performed using IBM SPSS Version 28.0.0.0.

RESULTS

Descriptive statistics

A paired sample t-test revealed statistically significant difference between left and right eye pupillometrics at the group level (mean difference = -0.034; p-value < 0.001). Therefore, all statistical tests and analyses were performed and analyzed for each eye separately. The normative data (means and standard deviations) of all pupillometrics (at the group level) of both eyes are displayed in Table 2.

Test-retest repeatability

Table 3 displays the ICC's of all pupillometrics, which range from very poor to good (0.286 to 0.963). Particularly, LAT, DV, and MCV showed very poor ICCs (< 0.70), whereas CV and PC showed poor ICCs (0.70–0.90). However, MinD (left eye), and MaxD (both eyes) showed good ICCs (0.95–0.99). Minimal measurement bias was detected for all pupillometrics with the maximum bias for the left eye being +2.9% (MaxD) and right eye being +1.98% (MaxD). The average bias across all pupillometrics was 0.001 ± 0.450. When comparing baseline (BL) to post-game (GD+1 and GD+2) timepoints, the smallest read difference (SRD) was widest for MaxD (R = 0.340; L = 0.318) and MCV (R = 0.304; L = 0.263), and least for LAT (R = 0.005; L = 0.005) and DV (R = 0.074; L = 0.085). When comparing pre-game (GD-1) to post-game (GD+1 and GD+2) timepoints, the SRD was widest for MaxD (R = 0.285; L = 0.266) and MCV (R = 0.249; L = 0.199) and least for LAT (R = 0.007; L = 0.007) and DV (R = 0.066; L = 0.068).

Relationships with other biomarkers of game-induced fatigue

With regards to perceptual fatigue, the findings demonstrated a very large positive significant correlation between average RPE and MinD ($r = 0.78$, $p < 0.05$) and MaxD ($r = 0.77$, $p < 0.05$). With regards to lower-extremity muscle fatigue, Sway Balance (left and right) showed a very large positive significant association with MaxD, MinD,

TABLE 2A. Descriptive statistics of all pupillometrics (right eye).

		N	Mean	Std. Deviation	Std. Error	95% CI		Min	Max
						Lower Bound	Upper Bound		
MaxD (right)	GD-1	35	6.3223	1.02479	.17322	5.9703	6.6743	4.01	8.11
	GD+1	35	6.3500	1.01662	.17184	6.0008	6.6992	3.97	7.91
	GD+2	34	6.3224	1.06745	.18307	5.9499	6.6948	4.16	8.22
	Baseline	8	6.4775	1.06054	.37496	5.5909	7.3641	4.63	7.97
	Total	112	6.3421	1.02446	.09680	6.1502	6.5339	3.97	8.22
MinD (right)	GD-1	35	3.9794	.76203	.12881	3.7177	4.2412	2.58	5.85
	GD+1	35	3.9837	.69930	.11820	3.7435	4.2239	2.58	5.23
	GD+2	34	4.0256	.73358	.12581	3.7696	4.2815	2.62	5.65
	Baseline	8	3.8788	.76868	.27177	3.2361	4.5214	2.74	5.38
	Total	112	3.9876	.72542	.06855	3.8518	4.1234	2.58	5.85
PC (right)	GD-1	35	.3720	.03437	.00581	.3602	.3838	.28	.44
	GD+1	35	.3769	.03151	.00533	.3660	.3877	.32	.44
	GD+2	34	.3703	.03389	.00581	.3585	.3821	.27	.42
	Baseline	8	.4013	.03796	.01342	.3695	.4330	.32	.43
	Total	112	.3751	.03404	.00322	.3687	.3815	.27	.44
CV (right)	GD-1	35	3.2737	.46457	.07853	3.1141	3.4333	2.38	4.37
	GD+1	35	3.3029	.42080	.07113	3.1583	3.4474	2.37	4.23
	GD+2	34	3.2750	.45240	.07759	3.1171	3.4329	2.42	4.13
	Baseline	8	3.4250	.46605	.16477	3.0354	3.8146	2.65	4.08
	Total	112	3.2940	.44317	.04188	3.2110	3.3770	2.37	4.37
MCV (right)	GD-1	35	5.3266	.77629	.13122	5.0599	5.5932	3.49	6.52
	GD+1	35	5.1871	1.10929	.18750	4.8061	5.5682	.63	7.04
	GD+2	34	5.2035	.66672	.11434	4.9709	5.4362	4.02	6.37
	Baseline	8	5.7250	.66002	.23335	5.1732	6.2768	4.85	6.61
	Total	112	5.2741	.86056	.08132	5.1130	5.4352	.63	7.04
LAT (right)	GD-1	35	.2131	.02898	.00490	.2032	.2231	.17	.30
	GD+1	35	.2223	.02787	.00471	.2127	.2319	.17	.27
	GD+2	34	.2147	.02135	.00366	.2073	.2222	.17	.27
	Baseline	8	.2150	.01604	.00567	.2016	.2284	.20	.23
	Total	112	.2166	.02573	.00243	.2118	.2214	.17	.30
DV (right)	GD-1	31	1.4132	.25639	.04605	1.3192	1.5073	1.02	2.28
	GD+1	34	1.3756	.20289	.03480	1.3048	1.4464	.90	1.82
	GD+2	32	1.3850	.24336	.04302	1.2973	1.4727	.97	2.14
	Baseline	7	1.4343	.24845	.09391	1.2045	1.6641	1.18	1.84
	Total	104	1.3937	.23263	.02281	1.3484	1.4389	.90	2.28

TABLE 2B. Descriptive statistics of all pupillometrics (left eye).

		N	Mean	Std. Deviation	Std. Error	95% CI		Min	Max
						Lower Bound	Upper Bound		
MaxD (left)	GD-1	35	6.0817	.99069	.16746	5.7414	6.4220	3.49	7.68
	GD+1	35	6.0891	.95812	.16195	5.7600	6.4183	3.65	7.56
	GD+2	34	6.1238	.97442	.16711	5.7838	6.4638	3.94	7.85
	Baseline	8	6.2650	1.03907	.36737	5.3963	7.1337	4.39	7.73
	Total	112	6.1099	.96662	.09134	5.9289	6.2909	3.49	7.85
MinD (left)	GD-1	35	3.7314	.64574	.10915	3.5096	3.9532	2.34	5.21
	GD+1	35	3.6911	.60097	.10158	3.4847	3.8976	2.45	4.92
	GD+2	34	3.7662	.63090	.10820	3.5460	3.9863	2.48	5.20
	Baseline	8	3.7687	.66827	.23627	3.2101	4.3274	2.77	4.95
	Total	112	3.7321	.62115	.05869	3.6157	3.8484	2.34	5.21
PC (left)	GD-1	35	.3851	.03568	.00603	.3729	.3974	.30	.44
	GD+1	35	.3929	.03259	.00551	.3817	.4041	.32	.47
	GD+2	34	.3847	.02339	.00401	.3765	.3929	.34	.44
	Baseline	8	.3975	.02964	.01048	.3727	.4223	.36	.44
	Total	112	.3883	.03087	.00292	.3825	.3941	.30	.47
CV (left)	GD-1	35	3.3491	.56844	.09608	3.1539	3.5444	1.60	4.21
	GD+1	35	3.2971	.45486	.07689	3.1409	3.4534	2.18	4.16
	GD+2	34	3.3165	.46990	.08059	3.1525	3.4804	2.17	4.32
	Baseline	8	3.4075	.56835	.20094	2.9323	3.8827	2.23	3.96
	Total	112	3.3271	.49930	.04718	3.2337	3.4206	1.60	4.32
MCV (left)	GD-1	35	5.4780	.81903	.13844	5.1967	5.7593	3.20	6.67
	GD+1	35	5.3737	.77775	.13146	5.1065	5.6409	3.45	6.77
	GD+2	34	5.3509	.73337	.12577	5.0950	5.6068	3.64	6.91
	Baseline	8	5.6800	1.02745	.36326	4.8210	6.5390	3.94	7.18
	Total	112	5.4213	.79076	.07472	5.2732	5.5693	3.20	7.18
LAT (left)	GD-1	35	.2320	.02753	.00465	.2225	.2415	.20	.27
	GD+1	35	.2186	.02992	.00506	.2083	.2288	.17	.27
	GD+2	34	.2118	.02167	.00372	.2042	.2193	.17	.27
	Baseline	8	.2063	.03420	.01209	.1777	.2348	.13	.23
	Total	112	.2198	.02828	.00267	.2145	.2251	.13	.27
DV (left)	GD-1	34	1.3765	.24277	.04164	1.2918	1.4612	.96	1.84
	GD+1	33	1.3009	.21842	.03802	1.2235	1.3784	.87	1.79
	GD+2	33	1.3936	.24903	.04335	1.3053	1.4819	.94	2.09
	Baseline	7	1.5057	.43412	.16408	1.1042	1.9072	.82	2.04
	Total	107	1.3669	.25499	.02465	1.3180	1.4158	.82	2.09

TABLE 3. ICC scores for all 7 pupillometrics

Pupillometrics	ICCs (CI_{95})	
	Right	Left
MaxD (mm)	0.955 (0.937–0.968)**	0.963 (0.949–0.974)**
MinD (mm)	0.945 (0.920–0.962)**	0.955 (0.935–0.970)**
PC (%)	0.756 (0.680–0.819)**	0.749 (0.674–0.813)**
CV (mm/sec)	0.755 (0.679–0.818)**	0.827 (0.770–0.873)**
MCV (mm/sec)	0.626 (0.528–0.714)**	0.667 (0.575–0.748)**
LAT (sec)	0.452 (0.335–0.566)**	0.287 (0.165–0.413)**
DV (mm/sec)	0.501 (0.379–0.616)**	0.656 (0.558–0.742)**

** p < 0.001

TABLE 4. Pearson's correlation coefficients between the 7 pupillometrics and other biomarkers of game-induced fatigue and recovery.

Pupillometrics	Sway SRT	lnRMSSD	Sway Balance (Right)	Sway Balance (Left)	Average RPE
MaxD	**0.70***	**-0.82***	**0.77***	**0.79***	**0.77***
MinD	**0.69***	**0.77***	**0.78***	**0.78***	**0.78***
PC	-0.17	0.22	-0.28	-0.20	0.28
CV	-0.62	**0.74***	**-0.75***	**-0.75***	0.45
MCV	-0.62	**0.74***	**-0.75***	**-0.76***	0.44
Lat	0.14	-0.22	-0.10	-0.10	0.10
DV	-0.20	0.22	-0.10	0.00	0.24

* Coefficients presented in bold are significant (p < 0.05)

CV, and MCV ($r = 0.75–0.78$, $p < 0.05$). With regards to cognitive fatigue, a large significant positive relationship was identified between Sway SRT scores and MinD ($r = 0.69$, $p > 0.05$) and a very large significant positive relationship between Sway SRT scores and MaxD ($r = 0.70$, $p > 0.05$). Finally, with regards to physiological fatigue, a very large positive significant relationship was detected between lnRMSSD scores and MinD ($r = 0.77$, $p < 0.05$), CV ($r = 0.74$, $p < 0.05$), and MCV ($r = 0.74$, $p < 0.05$) whereas a very large inverse significant relationship was found between MaxD and ln-RMSSD ($r = -0.82$, $p < 0.05$) (Table 4). All significant correlations have been highlighted in bold in table 4. Overall, the combination of MaxD, MinD, CV and MCV demonstrated to be the most representative of overall game-induced fatigue.

Time course of pupillometrics following games (at the group level)

Initially, the ANOVA analysis revealed that there was no statistically significant difference in pupillometrics between rested states (baseline and GD-1) and fatigued states (GD+1, GD+2) ($p < 0.05$), except for LAT (left) in which a medium-to-large difference was detected ($F = 4.023$, $\eta^2 = 0.109$ $p = 0.009$). In particular, a post-hoc Tukey HSD test revealed that LAT (left) on GD-1 (0.232 ± 0.027 mm/s) was significantly higher than on GD+2 (0.212 ± 0.216 mm/s) (mean difference = 0.202, std. error = 0.006, $p = 0.013$, $\eta^2 = 0.101$), thus the time from onset of the light stimulus to pupil constriction in the left eye typically took longer on GD-1 than on GD+2. Although LAT (left) was the only pupillometric that could detect a statistically significant change between rested conditions and fatigued conditions ($p < 0.05$), small-to-moderate effect sizes were detected for PC (right) ($\eta^2 = 0.052$, $p = 0.121$), MCV (right) ($\eta^2 = 0.026$, $p = 0.410$), LAT (right) ($\eta^2 = 0.023$, $p = 0.470$), PC (left) ($\eta^2 = 0.021$, $p = 0.518$), and MCV (left) ($\eta^2 = 0.013$, $p = 0.587$). All other pupillometrics showed very small ($\eta^2 < 0.01$) and non-significant effects ($p > 0.05$) across all timepoints. With regards to the magnitude of change between timepoints (% difference using Equation 1), the largest differences were found between baseline and GD+2, in which MCV (both eyes) represented the largest relative difference (left = -7.77%; right = -5.64%) (Table 5a and 5b; Figure 1).

TABLE 5A. ANOVA results of the pupillometric changes between baseline (BL) and post-game timepoints (GD+1 and GD+2)

ANOVA results	BL to GD+1					BL to GD+2				
	Mean Difference	*Std. Error*	*F*	η^2	*p*	*Mean Difference*	*Std. Error*	*F*	η^2	*p*
MaxD (mm) (R)	.127	.406	.101	.002	.752	.155	.407	.137	.003	.713
MinD (mm) (R)	-.104	.287	.142	.003	.709	-.146	.288	.255	.006	.616
PC (%) (R)	.024	.013	3.623	.081	.064	**.030**	**.013**	**5.173**	**.115**	**.028**
CV (mm/s) (R)	.122	.175	.528	.013	.472	.150	.175	.704	.017	.406
MCV (mm/s) (R)	.537	.337	1.884	.040	.197	**.521**	**.338**	**3.976**	**.090**	**.049**
LAT (s) (R)	-.007	.010	0.502	.012	.483	.000	.010	.001	.000	.971
DV (mm/s) (R)	.058	.097	.451	.011	.506	.049	.981	.234	.006	.631
MaxD (mm) (L)	.175	.383	.213	.005	.647	.141	.384	.133	.003	.718
MinD (mm) (L)	.077	.246	.104	.003	.748	.002	.247	.000	.000	.992
PC (%) (L)	.004	.012	.136	.003	.714	.012	.012	1.752	.042	.193
CV (mm/s) (L)	.110	.197	.350	.008	.557	.091	.198	.225	.006	.638
MCV (mm/s) (L)	.306	.312	.896	.021	.349	.329	.312	1.116	.027	.297
LAT (s) (L)	-.012	.010	1.050	.025	.312	-.005	.010	.333	.008	.567
DV (mm/s) (L)	.204	.168	3.464	.084	.070	.112	.169	.885	.023	.353

* Coefficients presented in bold are significant ($p < 0.05$)

TABLE 5B. ANOVA results of the pupillometric changes between pre-game (GD-1) and post-game timepoints (GD+1 and GD+2)

ANOVA results	GD-1 to GD+1					GD-1 to GD+2				
	Mean Difference	*Std. Error*	*F*	η^2	*p*	*Mean Difference*	*Std. Error*	*F*	η^2	*p*
MaxD (mm) (R)	-.028	-.248	.013	.000	.910	-.000	.249	.000	.000	1.000
MinD (mm) (R)	-.004	.175	.001	.000	.981	-.046	.176	.066	.001	0.799
PC (%) (R)	-.004	.008	.380	.006	.540	.001	.008	.430	.001	0.836
CV (mm/s) (R)	-.029	.106	.076	.001	.784	-.001	.107	.000	.000	0.991
MCV (mm/s) (R)	.139	.205	.371	.005	.544	.123	.207	.498	.007	0.483
LAT (s) (R)	-.009	.006	1.810	.026	.183	-.001	.010	.065	.001	0.800
DV (mm/s) (R)	.037	.058	.435	.007	.512	.028	.059	.201	.003	0.656
MaxD (mm) (L)	-.007	.233	.001	.000	.975	-.042	.235	.032	.000	0.859
MinD (mm) (L)	.040	.150	.073	.001	.788	-.034	.151	.051	.001	0.822
PC (%) (L)	-.007	.007	.892	.013	.348	.000	.007	.004	.000	0.952
CV (mm/s) (L)	.052	.120	.179	.003	.674	.032	.121	.068	.001	0.796
MCV (mm/s) (L)	.104	.190	.298	.004	.587	.104	.190	.460	.007	0.500
LAT (s) (L)	.013	.006	3.819	.053	.055	**.020**	**.006**	**11.469**	**.146**	**0.001**
DV (mm/s) (L)	.075	.061	1.790	.027	.186	-.017	.061	.82	.001	0.776

* Coefficients presented in bold are significant ($p < 0.05$).

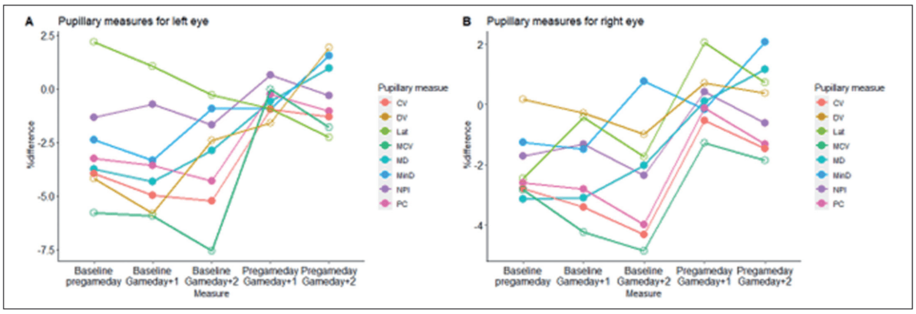

FIG. 1. The percentage difference of pupillometrics between test moments.

DISCUSSION

The main purpose of this pilot study was to explore the potential usefulness of HQIPs in the context of monitoring game-induced fatigue in professional female basketball players. The reported findings may not only serve as a benchmark for future comparisons and hypothesis testing in athletic populations that includes PLR data from automated pupillometry, but also provide point estimates and variance for PLR measures, as well as inferential statistics to describe the effect of game-induced fatigue on pupillary behaviour, when used in naturalistic elite sports environment. Overall, the main findings of this pilot study suggest that (1) two out of seven pupillometrics represented good repeatability scores (MinD and MaxD) (ICC = 0.95–0.99), (2) Statistical significant relationships were found between MaxD, MinD, and all other biomarkers of game-induced fatigue ($r = 0.69–0.82$, $p < 0.05$), as well as between CV, MCV, and biomarkers of cognitive, lower-extremity muscle, and physiological game-induced fatigue ($r = 0.74–0.76$, $p < 0.05$), and (3) Statistically significant differences were found between rested and fatigued states for three pupillometrics: PC (right) and MCV (right), and LAT (left) ($p < 0.05$).

The test-retest repeatability

In response to the first research question, good ICCs were reported for two out of seven pupillometrics, in particular: MinD (left) and MaxD (left and right) (0.95–0.99). Conversely, poor ICCs were reported for CV and PC (0.70–0.90) and very poor ICCs were reported for LAT, DV, and MCV (< 0.70). Nevertheless, the smallest read difference was extremely narrow for LAT in both eyes (0.005–0.007) as well as DV in both eyes (0.066–0.085). Therefore, the quantification of the maximum and minimum pupil diameter seem to be least prone to errors or noise due to external factors when examining professional female basketball players. However, this remains to be questioned as to the best of the authors knowledge, Swanson et al. (2017) [51] were the only researchers that provided open access to ICC results from PLR tests using the Neuroptics NPi-200 in an athletic population (i.e., 186 collegiate athletes across eight sports) [51]. Unfortunately, the only pupillometric reported in their investigation was the Neurological Pupil Index (NPI) (i.e., a proprietary score generated by the manufacturer). Furthermore, the PLR tests were completed at different time intervals, executed by multiple trained test administrators, and focused on a different use case (i.e., the detection of traumatic brain injury instead of fatigue monitoring). In turn, meta analyses and comparative inferences remain challenging. From a general viewpoint, the ICCs reported in this pilot study tend to follow the trend of various HQIPs applied in different use cases. For instance, Zheng et al. (2022) [52] also reported that LAT was the least reliable of all pupillometrics (i.e., very poor ICC of 0.65) using the RAPDx pupillometer (Konan Medical, Irvine, California, USA) and Chopra et al. (2020) [53] reported moderate to good ICCs for MinD and MaxD (ICC > 0.90) using the same RAPDx pupillometer.

Taking into account the abovementioned limitations, combined with the overall lack of consistency and transparency in pupillometric research over the past 50 years (as recently highlighted by an international panel of pupillometry experts across disciplines) [47], future researchers may use this pilot study as a baseline framework and prioritize transparency and standardization when executing their initiatives on this research topic.

The relationship between pupillometrics and other biomarkers of game-induced fatigue

In response to the second research question, four pupillometrics were identified as the strongest indicators of game-induced fatigue in professional female basketball players. In particular, MaxD and MinD represented the strongest indicators for all other biomarkers of game-induced fatigue ($r = 0.69–0.82$, $p < 0.05$), whereas CV and MCV were identified as the strongest indicators for cognitive, lower-extremity muscle, and physiological biomarkers of game-induced fatigue

($r = 0.74–0.76$, $p < 0.05$). Hence, keeping track of these four pupillometrics on a daily basis may present a multi-modal solution to better understanding the psycho-physiological processes that underpin game-play fatigue in elite sports settings. However, the lack of existing literature on pupillometry in relation to sports-specific fatigue creates barriers for deeper comparative analyses. From a general perspective, the reported findings in this pilot study tend to align with previous investigations that examined the role of pupillometry in acute human fatigue. For instance, previous researchers have revealed strong relationships between multiple pupillometrics and biomarkers of HRV indices (e.g., lnRMSSD) [12, 14, 15, 54], as well as lower-extremity muscle fatigue (e.g. Postural Sway) [55, 56], subjective ratings of effort and tiredness from prolonged listening and attentional efforts) [57], subjective ratings of perceived exertion from muscular contraction during a power grip task [58]. Neverthelesss, there was a clear lack of consistency in terms of the selected testing timeframes (i.e., measuring before, during, or after given tasks or events), testing conditions (i.e., naturalistics vs. laboratory settings), selected HQIPs (i.e., self-engineered vs. commercial instruments), extracted pupillometrics (i.e., standard vs. proprietary scores and algorithms), and none of the investigations involved professional basketball competition. Acknowledging these limitations, and given that pupil responses vary based on the sport and context in which players participate in [kaltsatou, filipe], more detailed comparative analyses remain inappropriate at this point of time. Hence, a vigilant, transparent, and consistent research strategy is required to expand upon our existing knowledge regarding this use case.

The time-course of pupillometrics from rested to fatigued states

In response to the third research question, three pupillometrics were capable of detecting a significant change from rested states (baseline and GD-1) to fatigued states (GD+1 and GD+2). In particular, PC (right) ($F = 5.173$, $\eta^2 = 0.115$ $p = 0.028$) and MCV (right) ($F = 3.976$, $\eta^2 = 0.090$ $p = 0.049$) significantly decreased from baseline to GD+2, while LAT (left) ($F = 4.023$, $\eta^2 = 0.109$ $p = 0.009$) significantly increased from GD-1 to GD+2. Hence, at timepoints where residual fatigue was expected to remain present (48 h following games), the pupils constricted slower (MCV), with a smaller magnitude (PC), while it took longer to begin its constriction phase (LAT). This further supports the underlying physiological concept of pupillary behavior as LAT can be regarded as an index of sympathovagal balance (i.e., higher values indicate sympathetic dominance) [14], whereas PC and MCV can be regarded as an index of parasympathetic activity (i.e. higher values indicate parasympathetic dominance) [14]. Hence, this confirms, at least in part, that the players' ANS were not fully reverted to normal levels 48-h following games. Interestingly, this trend of LAT, PC, and MCV is inconsistent with earlier findings by Kaltsatou et al. [14] who examined the immediate effects of physical exertion (maximal ergometer stress test) on pupillary behavior in power -and endurance-trained athletes. Specifically, in their investigation, LAT decreased, while MCV and PC increased from peak exertion to 5-min following the test (when heart rate return to baseline levels). Consequently, similar to how sports scientists typically evaluate traditional game-induced fatigue markers (e.g. Heart Rate Variability indices) [59, 60, 61], the before-after, day-to-day, and week-to-week fluctuations in pupillometics should be analyzed distinctively and individually, and contextualized against other external factors.

It is also important to acknowledge that the reported findings in this pilot study does not inform about the underlying factors that may have contributed to its overall acute fatigue state, nor does it imply the practical relevance of it. For instance, in a recent systematic review on post-game recovery kinetics in team ball sport athletes, Doeven et al. [62] highlighted the many covariables that play an influential role on the recovery dynamics of each player (e.g., menstrual cycle, physical fitness, role within the team, playing time, exertion, playing level, playing style, age, gender, genetic make-up, game location, preceding travel duration, opponent quality, imposed workload, lifestyle habits, sleep quantity and quality) [62]. Hence, future researchers are encouraged to integrate these cofactors in future investigations in order to pinpoint the underlying mechanisms for pupillary change following games. Additionally, to determine the practical relevance of these changes, future researchers may include predetermined anchor points that are practically relevant to their organization (e.g., specific injury occurrence per minute of activity exposure, on-court game-play performance metrics, pre-game alertness levels) [1, 59, 60]. This anchoring approach, often referred to as the Minium Clinical Important Difference (MCID), would allow practitioners to track pupillometrics per player over time and transform them into a prediction or prescription tool informing the onset to critical states via real-time alerting or traffic-light based visualization systems [59, 60, 61, 62]. For instance, Umesh et al. (2015) [63] were able to predict a self-reported Visual Analogue Scale (VAS) state of sleepiness score of ≥ 6 (the target variable) by using a MCV threshold value (age adjusted) of 2.8, with a sensitivity of 83% and specificity of 84%. Similarly, future researchers could determine the MCID's for MaxD, MinD, CV, and MCV against their self-determined threshold values.

Finally, emerging technologies may enable faster interventions in the future. For instance, Stoeve et al. (2022) [64] created a VR-based stress test during a football goalkeeping scenario, and achieved a performance of 87.3% accuracy through the Random Forest classifier, claiming a comparable outcome to state-of-the-art approaches fusing eye tracking data and additional biosignals. Given the strong resurgence and further democratization of VR, Mixed Reality (MR) and augmented reality (AR) based eye-tracking applications in recent years [65–68], new opportunities may arise to accelerate pupillometric research in the context of real-time athlete monitoring.

In summary, the findings of this pilot study promotes HQIPs as a potential instrument for monitoring game-induced fatigue in female professional basketball players. From an ergonomic standpoint, the PLR testing routine took little time and effort on the practitioner's side, and good test-retest repeatability scores were reported for two pupillometrics (MaxD and MinD). Additionally, strong relationships were found for four pupillometrics (MaxD, MinD, CV, and MCV) and all other biomarkers of game-induced fatigue, and three pupillometrics were able to distinguish rested states from fatigued states (LAT, PC, and MCV). Although these preliminary findings tend to support the potential adoption of pupillometry as an athlete monitoring tool in elite sports settings, researchers should remain cautious when drawing conclusive inferences as the dataset was extracted from a relatively small and homogenous sample, tracked over a relatively short timeframe (4 games across 5 weeks). Therefore, future researchers should aim to cover a larger and more heterogenous sample across various time intervals to allow for more precise estimations of "normal pupillary behaviour" in elite athletes. The recent technological advancements in HQIPs that are compact and versatile (e.g., smartphone-based and VR-based pupillometers) [63–70] may further accelerate and facilitate investigations on this topic.

CONCLUSIONS

HQIPs have opened a new window of opportunities for sports practitioners given its ease of use and ability to extract objective insights on player fatigue in a quick, reliable, valid, and non-invasive character. Overall, the pupillometrics MinD, MaxD, CV, and MCV were identified as the most promising indicators of game-induced fatigue in female professional basketball players. However, it's important to acknowledge that this research line is still in its infancy, and the findings stem from a small homogenous sample, thus the statistical inferences remain indicative rather than confirmative or directive. However, future researchers are encouraged to leverage this pilot study as a baseline framework for future investigations, and ensure standardization is prioritized throughout the process in order to maximize the reproducibility of findings across a variety of sports, timeframes, contexts, and use cases.

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The UCAM University Institutional Review Board (code: CE122002) approved this study in accordance with the Helsinki Declaration and researchers were provided de-identified data to analyze.

Conflicts of interest

The authors declare no conflict of interest.

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