UNIVERSIDAD POLITÉCNICA DE MADRID

Facultad de Ciencias de la Actividad Física y del Deporte (INEF)

Modelling and Simulation in Game Performances of Basketball Players and Teams in the National Basketball Association

Tesis Doctoral

D. Shaoliang Zhang

张绍良

Madrid, 2019

UNIVERSIDAD POLITÉCNICA DE MADRID

Facultad de Ciencias de la Actividad Física y del Deporte (INEF)

MODELLING AND SIMULATION IN GAME
PERFORMANCES OF BASKETBALL PLAYERS
AND TEAMS IN THE NATIONAL BASKETBALL
ASSOCIATION

TESIS DOCTORAL

D. Shaoliang Zhang

Madrid, 2019

DEPARTAMENTO DE CIENCIAS DE LA ACTIVIDAD FÍSICA, DEL
DEPORTE Y DEL OCIO

Facultad de Ciencias de la Actividad Física y del Deporte (INEF)

MODELLING AND SIMULATION IN GAME
PERFORMANCES OF BASKETBALL PLAYERS
AND TEAMS IN THE NATIONAL BASKETBALL
ASSOCIATION

AUTOR:
D. Shaoliang Zhang

DIRECTOR:
Dr. Alberto Lorenzo Calvo, Professor en Ciencias de la Actividad
Física y del Deporte, Universidad Politécnica de Madrid.

Dr. Miguel Ángel Gómez Ruano, Doctor en Ciencias de la Actividad
Física y del Deporte, Universidad Politécnica de Madrid.

Madrid, 2019

Tribunal nombrado por el Magfco. y Excemo. Sr. Rector de la Universidad Politécnica de Madrid, el díade.....de 2019.

Presidente: D.....	Vocal:
D.....	Vocal:
D.....	Vocal:
D.....	Secretario:
D.....	

Realizando el acto de defensa y lectura de la Tesis el día.....de..... de 2019.
En.....
Calificación.....

EL PRESIDENTE

LOS VOCALES

EL SECRETARIO

*“TRAVEL AND CHANGE OF PLACE
IMPART NEW VIGOR TO THE
MIND.” – SENECA*

Abstract

The National Basketball Association (NBA) is commonly regarded as the most popular and competitive basketball league in the world. Basketball players and teams respond to the stress of practice and competition, there remains a clear need to use updated sports performance models to inform starting points for player preparation. One of the most common methods of monitoring sports performance is using game-related statistics to evaluate technical and tactical behaviours, as well as the efficiency of players and teams throughout the season. The application of new training and competing interventions from statistical models can optimise training process and enhance technical-tactical and physical development.

Purpose: The general aim of the thesis is to model and simulate the game performances of basketball players and teams based on game-related statistics integrating with influencing factors in the National Basketball Association. To achieve the aims of this research, this thesis can be summarized in the five chapters and separated into the following three sections. Firstly, the aim of the first section was to explore the (dis)similarity of game-play characteristics throughout in-season period in the National Basketball Association (Chapter 2). Secondly, the aim of the second section was to group basketball players into similar clusters based on a combination of anthropometric characteristics and playing experience (Chapter 3) or different levels of scoring production (Chapter 4); and then explore the distribution of basketball players from different levels of teams within the obtained clusters. Finally, the aim of the third section was to examine the independent and interactive influences of situational variables on technical and physical performances according to playing position (Chapter 5 and 6).

Methods: Thirteen performance-related indicators of all the 1230 games of regular season

2016–2017 in the National Basketball Association were analysed by Non-metric multidimensional scaling (Chapter 2). Twenty performance-related indicators from 699 balanced games of 2015-2016 regular season were analysed using a two-step cluster model and a discriminant analysis (Chapter 3). Thirteen performance-related indicators of all the 1230 games of regular season 2015–2016 were analysed by using a two-step cluster model, a discriminant analysis, and K-nearest neighbour analysis (Chapter 4). Seventeen performance-related indicators of all the 699 matches of regular season 2015–2016 were performed using magnitude-based inferences (Chapter 5). Twenty performance-related indicators of all the 692 balanced games of regular season 2016–2017 in the National Basketball Association were conducted by decision tree algorithm (exhaustive CHAID) and magnitude-based inferences (Chapter 6).

Study 1: The two-dimensional multivariate matrix showed multivariate team profiles generally presented similarity while the beginning and ending of the season (October and April) showed relatively dissimilarity. Although each team presents unique paths throughout in-season period, the dominant teams in the NBA may uncover the similar game styles. In addition, the game-play of the teams evolves into effective interactions in terms of offence and defence as the competition progresses whilst presenting an increased trend in the number of three-point field goals throughout in-season period.

Study 2: The clustering process allowed identifying five different player profiles: Top height and weight (HW) with low experience, TopHW-LowE; Middle HW with middle experience, MiddleHW-MiddleE; Middle HW with top experience, MiddleHW-TopE; Low HW with low experience, LowHW-LowE; Low HW with middle experience, LowHW-MiddleE. Discriminant analysis showed that TopHW-LowE group was highlighted by two-point field

goals made and missed, offensive and defensive rebounds, blocks, and personal fouls; whereas the LowHW-LowE group made fewest passes and touches. The players from weak teams were mostly distributed in LowHW-LowE group, whereas players from strong teams were mainly grouped in LowHW-MiddleE group; and players that participated in the finals were allocated in the MiddleHW-MiddleE group.

Study 3: In the first step, the obtained results provided an automatically determined solution with two clusters, with a good silhouette measure of cohesion and separation (average silhouette=0.7). A new categorical variable was saved in the database with these classification results. For designation purposes, one of the clusters was labelled as “lower-scoring players” and gathered 258 players (53%) averaging 0.30 ± 0.06 points per minute (range 0-0.38) and the other cluster was labelled as “higher-scoring players”, gathering 230 players (47%) that averaged 0.49 ± 0.09 points per minute (range 0.39-0.85). In the second step, the obtained discriminant functions were all significant ($p \leq 0.001$) with chi-square values of 119.7 for guards, 105.9 for forwards and 42.8 for centres. There were variables achieving high discriminant status for all positions, such as the free-throws and turnovers, and more moderate variables, such as the assists and the defensive rebounds. Interestingly, distance covered and running speed were the only variables with no substantial discriminant status. In addition, the guards’ discriminant variables were related to field-goals (two and three-point), the forwards to free throws, and the centres to three-point field goals, touches and steals.

Study 4: As could be expected, results showed that players’ technical and physical performances differed between strong and weak teams. In technical aspect, forwards and centres from strong teams made more three point field goals, but fewer two-point field goals, than their counterparts from weak teams. Interestingly, forwards and guards from strong

teams covered shorter distances and lower speeds than their peers from weak teams. In addition, the three point field goals presented high variability compared with other performance indicators. Game location generally had no significant impact on the players' performance. Guards exhibited relatively lower variability in technical and physical variables in comparison with forwards and centres.

Study 5: Our study indicated that defensive rebounds, blocked shots, and assists determined between winning and losing games for strong teams while defensive rebounds and turnovers were the key performance indicators for weak teams. Subsequently, in strong vs strong games, players from winning teams in home games ran slower than their peers from losing teams, whereas an opposite trend was found in away games. In strong vs weak games, players from winning teams in home games covered more distance and ran faster than their peers from losing teams. In weak vs weak games, effective defence played an important role in winning the games.

Conclusions: A similarity of team profiles was presented in the middle of the regular season while a relative dissimilarity was discovered at the beginning and end of the season. Besides, defensive rebounds were the common KPIs that discriminated between winning and losing games for strong and weak teams in the current NBA. Further, three point field goals made and assists showed increased trend as the competition progressed whilst LowHW-MiddleE players, high-scoring guards, and forwards and centres from strong teams have better performance in three point field goals. Importantly, game performance was influenced by the situational variables, either independently or interactively. Hence, this thesis emphasized the need to consider the potential interactive effects of situational variables during the assessment of tactical, technical and physical performances in the future research.

Declaration

I, Shaoliang Zhang, declare that the Doctor of Philosophy thesis titled “Modelling and simulation in game performances of basketball players and teams in the National Basketball Association” is no more than 100,000 words in length including quotes and exclusive of tables, figures, appendices, bibliography, references and footnotes. This thesis contains no material that has been submitted previously, in whole or in part, for the award of any other academic degree or diploma. Except where otherwise indicated, this thesis is my own work.

Signature:

Date:

Sponsorship

This doctoral thesis was sponsored by the China Scholarship Council (CSC) from the
Ministry of Education of P.R. China under Grant [(2015) 3022]

Dedication

To my grandfather who passed away

To my grandmother, my parents, uncles and relatives

To my future wife and children

Dedicación

A mis abuelo, que ya murieron

A mi abuela, mis padres, tíos y familiares

A mi futura mujer y a mis hijos venideros

谨献给

我逝去的祖父

为我无私奉献的祖母 父母 叔叔及亲人

我未来的妻子和儿女

Acknowledgement

When I write the following text, it means that my student career is coming to an end. For my dreams, I used to study in different countries and cities. Apart from my personal efforts, I know I cannot realise dream without the concern and support from the following people. At this moment, I have sincere gratitude with highest respect, paying tribute to those who helped me and made contribution to my thesis.

I have to admit that studying in Spain makes me fall in love with scientific research. I can closely connect my favourite interests from a young age, which made me more clear future direction. I am undoubtedly a lucky person, thanking for everything God grant me.

During the period of studying in Spain, I firstly should thank my first supervisor, Alberto Lorenzo. He is very strict and patient with me because I am his first Asian student. During every conversation, he always reminded me of the order of the events at each stage, and planned a clear development path. He taught me a lot of basketball technical and tactical skills so that I can learn to think independently; he allowed me to watch the basketball games with free tickets in the ACB and European Basketball League; he recommended me to study at the famous laboratory of sports performance analysis in Portugal; he provided me free account of the Synergy Sports Technology so that I can enjoy the abundant resources in the basketball; he taught me to use Nacsport software for notational analysis; he provided Real Madrid and Spanish U18 physical data, allowing me to take charge of all scientific research in person; he always told me what is most important thing in the life; he is just like a father who helps me to be great! In his words, I am watching you to grow up!

Secondly, I want to thank the second tutor Miguel-Ángel Gómez, who made me realise the

importance of the creative and critical thinking. He often finds inspiration to explore new research fields or make a breakthrough in original scientific research. His style has a huge influence on scientific research during the period of doctoral career. He taught me to study statistics and provided me a MAC computer to learn R language programming which allowed me to enter a higher ladder in sports data visualization; He also provides me with sports data from other sport fields such as football, badminton which allows me to open my mind and broaden my horizons.

In addition, I thank Miguel introducing me to recognise Professor Anthony Leicht. He told me that academic rigor allows me to take scientific writing to new levels. Every time I study from his retouching articles, I usually feel the disparity between my English level and mother tongue. In the process of repeated revisions, I learned to think in English and replace the complicated and long expressions with authentic and simple words which made me deeply understand that good articles are revised rather than written. I really appreciate to Professor Anthony for the careful guidance that is benefit for scientific writing.

During my study in Portugal, I would like to thank my third mentor, Jaime Sampaio and all the members of the team. This is undoubtedly huge fortune for me to study in the one of the top of sports performance analysis laboratory in the world. When I recalled the studying time in Portugal, I had to admit that this was one of the most exciting part of studying abroad. After studying in Portugal, I not only understood the overall framework and core content of the theory of sports performance analysis but also realise the research frontiers and major trends in this discipline, which allows me to be more interested in the profession. It was the most unforgettable time for me to study and explore sports science. I love the human geography, I love the enthusiastic people, and I love the red wine and squid in the Portugal!

During the period of the master in China, I would like to thank professor Yongbo Guo, Professor Fei Deng, and Professor Aiguang Zhou. At that time, I was very maverick. They gave me a lot of love and support and allow me do at all costs to overcome the English. I also thank to my good friend Hongyou Liu giving me encouragement during the application of studying abroad. I have to say that recognising him is an important turning point in my life. In addition, I would like to appreciate to two girls – Xuemeng Du and Xia Zhong. One made me realise the importance of the lifelong learning, and one taught me life and responsibility. They made me who I am today.

I would like to express my special thanks to the Chinese Scholarship Council (CSC) of the Ministry of Education of the People's Republic of China. My country allowed me to visit the cities in Europe to experience different human geography and also allowed me to concentrate all my thoughts on scientific research. I will be self-reliant, ideal, capable, and a responsible young generation making contribution to my country. I really appreciate to my prosperous motherland allowing me to have the opportunity to realise the dream of studying abroad.

Finally, I want to give my deepest gratitude to my family. My grandmother, father and mother, and uncle give me education and love from a young age that is the driving force to overcome various difficulties in the life. Their behavioural models in life have deeply influenced on my life. Thanks to their selfless dedication and nurture. Growing up in such a family is the greatest pride in my life. In addition, the special thanks to my grandfather. Although he left us when I was four years old, he left me the most precious gift - my name, I wrote this name on the top international journals of sports science. I cannot erase the picture for a lifetime when he sat on a brown-red sofa and quietly smoked to look into the distance. I miss him very much and love him deeply. I hope that my international doctoral degree can

satisfy with his last wish!

Special thanks to the teachers, friends and classmates I met in different countries and cities. Although I can't mention your names one by one, I would like to express my deep gratitude for their guidance and help.

My mother and father used two sentences to admonish the life of studying abroad. One sentence from Psalms of the Bible is “the seeds of tears will be harvested.” One sentence comes from the "Warnings of the World" is “No pain, No gain.”

Beautiful Spain and Portugal, one is the passionate fire, one is the romantic sea

My life memories on the Iberian Peninsula.....

Written in Prague, Czech Republic, 02/10/2019

End in Madrid, Spain

Agradecimientos

Mientras escribo estas líneas los hechos indican que va a acabar mi vida como estudiante. Para realizar este sueño he estudiado en diferentes países y ciudades. En el camino académico, aparte de mi esfuerzo y del empeño que he puesto, debo reconocer que no lo habría podido conseguir sin el amor y apoyo de las siguientes personas. En este momento, con la mayor sinceridad, me siento honrado en agradecer a los que me ayudaron y contribuyeron durante mi proceso de aprendizaje.

Tengo que admitir que la vida como estudiante en España me ha permitido verdaderamente amar la investigación científica, que me ha dado la oportunidad de aunar el trabajo al que me he dedicado con la pasión que he tenido desde muy pequeño. Esto no sólo me ha proporcionado la tranquilidad de hacer lo que me apetece, sino también que me ha confirmado la orientación de mi futuro. Sin duda alguna, soy una persona con suerte. Le agradezco mucho a Dios que me haya dado todo esto.

Durante la estancia de estudio en España, le quiero agradecer, en primer lugar, a mi director Alberto Lorenzo. Como yo soy su primer alumno que viene de Asia me ha tratado con mucha paciencia y con severidad. Me ha ayudado no sólo a orientar la investigación sino también a simplificar los asuntos que me parecían más complicados. En cada conversación mantenida, siempre me ha permitido ordenar las distintas cuestiones de mayor a menor importancia, me ha planificado la rutina de trabajo y también me ha enseñado a pensar de forma independiente. Me dio entradas gratuitas para ver la Liga ACB y la Euroliga de Baloncesto, con el objetivo de seguir aprendiendo, así como me ofreció la oportunidad, aprovechando sus contactos, de estudiar en el laboratorio de análisis de la actividad física más conocido en el mundo, y compartió las cuentas gratuitas de acceso a todas las plataformas de datos de

baloncesto a nivel mundial. Además, me enseñó cómo analizar los vídeos con Nacsport. Con su apoyo pude redactar todos los artículos científicos yo mismo. Siempre me expuso cuáles son las cosas más importantes en la vida, mostrando gran humanidad conmigo. Como diría mi padre, desde el fondo de corazón: “¡Yo te vi crecer!”

En segundo lugar, quiero dar mi agradecimiento a mi tutor Miguel-Ángel Gómez. Es él quien me enseñó a pensar, y ser creativo y crítico. Siempre mostró el entusiasmo para explorar nuevas áreas de investigación, y la capacidad para criticar más formas tradicionales de afrontar este tópico de investigación; influyendo profundamente en la creación y el desarrollo de mis estudios de doctorado. Le agradezco muy especialmente su ayuda en el estudio de la Estadística (ofreciéndome incluso un MAC para que estudiar programación con el lenguaje R), así como también me ayudó a interpretar mejor el análisis de los datos y la visualización de los mismos.

Del mismo modo, me gustaría agradecer su ayuda al profesor Anthony Leicht de Austria. Su meticulosidad en su trabajo se ha podido ver reflejada en mis publicaciones; agradeciéndole muy especialmente su aportación en la redacción en inglés de los artículos publicados. Esta mejora se ha podido ver reflejada en el proceso de redacción y corrección de la tesis doctoral. Creo que de esta experiencia es importante la idea que me llevo conmigo, según la cual “un buen artículo no se hace por redacción sino por corrección”. Muchas gracias al Profesor Anthony por dirigir y corregir una y mil veces mi tesis. Sin duda alguna, ¡soy y seré beneficiario para toda la vida en la redacción en inglés!

De mi estancia de estudio en Portugal, quisiera agradecer al Profesor Jaime Sampaio y a todos los miembros del grupo su apoyo y ayuda constante y decisiva en mi proceso formativo. Ha

sido una fortuna para mí haber tenido la oportunidad de estudiar en su laboratorio de análisis de la actividad física. Cuando recuerdo el tiempo que pasé, tengo que admitir que ha sido la parte más maravillosa de todas mis experiencias de estudio. Es en dicha estancia donde llego a conocer con profundidad y de forma completa el marco teórico, así como el estado actual de desarrollo de mi disciplina y las tendencias prioritarias de investigación, lo cual contribuyó a incrementar mi amor por lo que he estudiado. En Portugal no sólo aprendí a manipular distinta tecnología, sino también la importancia de trabajar en equipo. Ha sido el tiempo más precioso estudiando y explorando las Ciencias de los Deportes. ¡Me encantan los paisajes de Portugal, la pasión que tienen los portugueses, los vinos y el bacalao!

En cuanto al periodo de master en Guangzhou, quisiera dar las gracias al Profesor Guo Yongbo y al Profesor Deng Fei y al Zhou Aiguang. En aquel entonces me mostraron su apoyo y me dieron soporte y ayuda para aprender el idioma inglés. Gracias a mi amigo Liu Hongyou, por su apoyo y ánimos constantes cuando decidí estudiar en el extranjero. No podría ser yo mismo sin él. Él ha sido un punto de inflexión en mi vida. Y durante mi estudio fuera de casa, he conocido a dos mujeres—Du Xuemeng y Zhongxia,- gracias a las cuales, reconozco la importancia de estudiar sin desánimo, y aprendí a vivir siendo responsable. Me ayudaron a ser el yo de ahora.

Particularmente, quiero dar mis agradecimientos al CSC, a mi país, que me financió para hacer posible mis viajes y formación, permitiéndome explorar diferentes culturas y tradiciones; así como también me permitió vivir sin preocuparme por la comida ni la ropa con el fin de concentrarme plenamente en el estudio científico. Nuestra generación tiene que hacer todos los esfuerzos necesarios para superarse y mejorar, siendo una generación de capacidad y responsabilidad. Probablemente, gracias a lo aprendido, pueda contribuir en la construcción

de mi país. Ha sido mi patria quien me dió la oportunidad de realizar mi sueño de estudiar en un país extranjero, por lo tanto, gracias CHINA Finalmente, quiero dar mis más sinceros agradecimientos a mi familia, a mi abuela, mi padre, mi madre y mi tío. Su enseñanza y su amor incondicional son la motivación que me ayuda a superar todo tipo de dificultades. Sus ejemplos de comportamiento siempre han influido decisivamente en mi camino de la vida. Gracias por sus contribuciones y cuidados con todo el corazón. Me siento muy orgulloso de crecer en esta familia. Además, gracias especialmente a mi abuelo porque, aunque falleció siendo yo muy niño, me dio lo más importante de mi vida — mi nombre. Siempre me he esforzado para que apareciese reflejado a nivel internacional en las revistas más prestigiosas de nuestro campo de investigación. Su imagen sentado en casa, en el sofá marrón, pensando mientras fumaba con la vista perdida en el horizonte nunca se me olvidará. Siempre, le extraño y extrañaré. Él siempre fue un ejemplo para mí, y espero que pueda cumplir su último deseo adquiriendo el título de doctor con mención internacional.

Quiero dar gracias a los profesores, amigos y compañeros con los que me he encontrado en los diferentes países y ciudades. Si bien no puedo mencionar todos sus nombres aquí, les agradezco mucho por orientar y ayudarme a superar muchas dificultades. ¡Muchísimas gracias! Mi madre y mi padre, durante este tiempo, han utilizado dos ideas o frases reflexionando sobre esta etapa. La primera viene de la *Biblia* y dice dice: “Los que derramaron lágrimas saludarán la cosecha”, y la otra viene de los *Cuentos que Advierten el Mundo*, y dice: “No hay ganancia sin dolor.” ¡Animo!

Bonita España, maravillosa Portugal, apasionante como el fuego, romántica como el mar. En la península ibérica flota una parte de la memoria de mi vida...

Escrito en Praga, Chequia; Terminado en Madrid, España, 02/10/2019

致谢

当我写下如下文字时，意味着我学生生涯即将结束。为了我的梦想，我曾经求学于不同的国家和城市，这一路走来除了我个人的努力和付出之外，也离不开以下人们对我的关爱和支持，此刻我带着真诚的谢意和最崇高的敬意，致敬曾经在我求学过程中给予我帮助和做出贡献的你们。

我不得不承认在西班牙的留学让我真正的爱上了科学研究，我可以把我从小的兴趣爱好和所从事的工作紧密的联系在一起，这不仅让我可以踏下心来做自己最爱的事情，也让我明确和坚定了未来的发展方向，我无疑是个幸运的人，感谢上天给予我的一切

在西班牙的留学过程中，我首先应该感谢我的第一导师Alberto Lorenzo，我是他第一个来自于亚洲的学生，他对我很严厉又很耐心，他一直帮我明确方向化繁从简，在我们每次的交谈过程中，他总是提醒我每个阶段事情的主次顺序，给我规划了清晰的发展路线。他教会了我很多的篮球技战术，让我学会独立思考；他给我免费的球票让我去观摩西甲和欧冠的篮球比赛；他利用他的人脉推荐我去世界著名的运动表现分析实验室学习；他提供给我终身免费使用的账号，让我可以享用世界上最全的篮球数据平台里的所有资源；他手把手教我使用Nacsport软件做视频分析；他提供我皇家马德里和西班牙U18的体能数据，让我亲自执笔负责所有的科学研究。他始终告诉我人生中哪些是最重要的，他就像一个父亲对我苦口婆心教我成人，用他的话说，我是看着你长大的！

其次，我想要感谢的第二导师 Miguel-Ángel Gómez, 他让我意识到了创新思维和批判思维的重要性，他总是能够找到创新的灵感去开拓新的研究领域或者在原有的科学研究上进行大胆的批判否定，这些思维深深的影响了我博士期间的创作和发展。他教我学习统计学并且提供给我MAC电脑让我学习R语言编程，让我在运动数据的清理和分析以及运动数据可视化上进入了更高的阶梯，他告诉我体育运动是共通的，并提供给我足

球，羽毛球等其他领域的运动数据练笔，讲解他的想法教我扩展思维和开阔眼界！

此外，我要感谢我的第二导师引领我认识澳大利亚的Anthony Leicht教授，Anthony教授在学术上的严谨影响了我的学术写作，每次经过他润色的文章，我都会感觉到自己在科学写作上与英语为母语的创作者之间的差异，在反复修改的过程中，让我学会了用英式思维去表达我的思想并且用地道简洁的词语去替换繁杂冗长的表达，也让我深深的体会到好的文章“不是写出来的而是改出来的”，感谢Anthony教授不厌其烦对我文章的反复修改和详细指导，这让我在英文写作上受益终生！

在葡萄牙的留学过程中，我要感谢我的第三导师Jaime Sampaio以及团队的所有成员，有机会在世界顶级的运动表现分析实验室学习，这无疑是我一辈子的财富。当我回忆那段游学时光时，我不得不承认这是我留学过程中最精彩的部分。在葡萄牙学习以后，我才真正的了解了运动表现分析理论的整体框架和核心内容，让我认识到我所学学科的研究前沿和发展的主要趋势，这让我更加深爱我所学的专业。在那里不仅让我学习了世界顶尖实验设备的操控也让我认识到了团队的重要性，与团队其他成员翱翔在体育科学的前沿领域进行学习和探索是我留学最宝贵的时光。我爱葡萄牙的人文地理，爱那里人民的朴实热情，爱那里的红酒和鳕鱼！

在中国广州的硕士期间，我要感谢我的导师郭永波和邓飞教授以及我的院长周爱光教授，那时的我很特立独行，他们给予我很多的关爱和支持，让我全力以赴攻克语言关，我还要感谢我的好朋友刘鸿优，在国外留学申请过程中给我的支持和鼓励，没有他没有现在的我，不得不说认识他是我人生的一个重要转折点。在我离家求学的过程中，我认识两个女孩--杜雪朦和仲夏，我要感谢生命中她俩的出现，一个让我认识到终身学习的重要性，一个教会了我生活和责任，她们成就了现在的我。

需要特别提出感谢的是中华人民共和国教育部国家留学基金委（CSC），我的祖国对我博士期间的资助，让我可以游览欧洲的所有国家和城市，去体验不同的人文地理，开

阔眼界，增长见识，也让我衣食无忧将全部的心思都集中在科学研究上。吾辈当自强，做个有理想，有本领，有担当的青年一代，在我专业领域用我所学的知识报效我的国家，感谢我祖国的繁荣昌盛，让我有机会实现我留学的梦想！

最后，我要把我最深深的感激送给我的家人。我的奶奶，父亲和母亲，叔父他们对我从小的教导和疼爱是我克服各种困难的原动力，他们在生活中的行为典范深深的影响了我的人生，感谢他们无私的奉献和养育，生活在这样家庭是我这辈子最大的骄傲。此外，特殊的感谢送给我的爷爷，虽然在我四岁时他就离开了我们，但是他留给了我了最宝贵的礼物-我的名字，我通过自身努力将这个名字写在了我专业领域所有的国际顶级期刊上。他坐在棕红色沙发上，静静的抽烟看向远方思考的样子是在我脑海里一辈子无法抹去的，我相信那是他对我的憧憬，我很想念他，深深的爱着他，他是我为人的典范，希望我获得的国际博士学位能满足他的遗愿！

特殊的感谢给予我在不同的国家和城市求学过程中遇到的老师，朋友和同学，尽管无法一一提及你们的名字，我也要在此对他们表示感激，是他们的指导和帮助让我顺利的通过很多难关，表示深深的感激！

我的母亲和父亲曾经用两句话，告诫我的求学之路，一句来自于《圣经》诗篇，留泪撒种的，必欢呼收割。一句来自于《警世通言》吃得苦中苦，方为人上人，共勉！

美丽的西班牙和葡萄牙，一个热情似火，一个浪漫如海
在伊比利亚半岛上我一生的回忆.....

2019.2.10 写于捷克 布拉格

结于西班牙 马德里

Table of Contents

Abstract	I
Declaration	V
Sponsorship	VI
Dedication	VII
Acknowledgement.....	X
List of Tables.....	XXVI
List of Figures	XXVII
List of Abbreviations.....	XXIX
Chapter 1 General Introduction	3
1.1 Research background.....	3
1.2 State of the problem.....	5
1.3 The aim of the study	8
1.4 The structure of the thesis.....	9
Chapter 2 Evolution of Game-play Characteristics Within-season for the National Basketball Association	13
2.1 Introduction	13
2.2 Method.....	15
2.2.1 Data sample	15
2.2.2 The reliability and validity of data	17
2.2.3 Statistical analysis	17
2.3 Result.....	18

2.3.1	Multivariate team performance dynamics.....	19
2.3.2	Individual performance indicators dynamics	19
2.4	Discussion.....	20
2.4.1	Multivariate team performance dynamics.....	20
2.4.2	Individual performance indicator dynamics.....	26
2.5	Conclusion.....	27
2.6	Limitations.....	28
Chapter 3 Clustering Performances in the NBA according to Players' Anthropometric Attributes and Playing Experience..... 31		
3.1	Introduction	31
3.2	Methods	33
3.2.1	Sample and variables.....	33
3.2.2	Statistical analysis	36
3.3	Results	37
3.3.1	Discriminant variables from each cluster group	40
3.3.2	The specific distribution of all players (included starters and non-starters) from different levels of teams within five cluster group.....	40
3.4	Discussion.....	41
3.4.1	Describing different game performance profiles	41
3.4.2	The specific distribution of all players (included starters and non-starters) from different levels of teams within five cluster group.....	47
3.5	Conclusion.....	49

3.6	Practical applications and limitations	49
Chapter 4	Modelling of Playing Process and Tactical Behaviour in the NBA.....	52
4.1	Introduction	52
4.2	The current problem of the existing analysis method.....	55
4.3	Concepts and methods of modelling	58
4.4	Methodological experience.....	60
4.5	Results	62
4.5.1	Determining different levels of scoring	62
4.5.2	Identifying a smaller subset of important variables	62
4.5.3	Identifying the most similar player	67
4.6	Practical application	75
Chapter 5	Players' Technical and Physical Performance Profiles and Game-to-game	
	Variation in the NBA	78
5.1	Introduction	78
5.2	Methods	81
5.2.1	Sample.....	81
5.2.2	Data source and validity.....	81
5.2.3	Variables.....	82
5.2.4	Statistical analysis	84
5.3	Results	85
5.4	Discussion.....	92
5.5	Conclusion.....	96

Chapter 6	Performance Profiles and Opposition Interaction during Game-play in Elite Basketball Evidence from National Basketball Association.....	100
6.1	Introduction	100
6.2	Method.....	102
6.2.1	Sample and variables.....	102
6.2.2	Data source reliability and validity	105
6.2.3	Statistical analysis	107
6.3	Results	109
6.3.1	Performance profiles from strong and weak teams	109
6.3.2	Opposition interaction: Strong teams vs Strong teams	111
6.3.3	Opposition interaction: Strong teams vs Weak teams.....	112
6.3.4	Opposition interaction: Weak teams vs Weak teams	113
6.4	Discussion.....	114
6.4.1	Performance profile from strong and weak teams	114
6.4.2	Opposition interaction: Strong teams vs Strong teams	118
6.4.3	Opposition interaction: Strong teams vs Weak teams.....	119
6.4.4	Opposition interaction: Weak teams vs Weak teams	121
6.5	Conclusion	122
6.6	Practical applications and limitations	122
Chapter 7	General Discussion.....	126
7.1	Summary and discussion of main findings.....	126
7.1.1	Section 1 - Team performance profiles (Chapter 2).....	126

7.1.2	Section 2 - Player performance profiles (Chapter 3 and 4).....	129
7.1.3	Section 3 - Situational variables (Chapter 5 and 6).....	132
7.2	Novel perspectives.....	136
7.3	Limitations.....	137
7.4	Future Directions	138
Chapter 8	Overall conclusion.....	142
8.1	Overall conclusion.....	142
Bibliography		147
Appendix		169

List of Tables

Table 3.1 Descriptive statistics of different performance profiles groupings	37
Table 3.2 The distribution of all players (included starters and non-starters) from different levels of teams in the five cluster groups	38
Table 4.1 Linear classification function coefficients for higher and lower scoring players and structure coefficients for each position.	63
Table 5.1 Descriptive statistics of players' performance between strong and weak teams	85
Table 5.2 Descriptive statistics of the variability of performance variables of players from different positions according to game location and game outcome	88
Table 5.3 Descriptive statistics of the variability of performance variables of players from different positions according to team and opposition quality	89
Table 6.1 Descriptive statistics of the strong and weak teams between winning and losing games.....	106
Table 6.2 Descriptive statistics of guards, centres and forwards considering game outcome between home and away game when strong teams played against strong teams	115
Table 6.3 Descriptive statistics of guards, centres and forwards considering game outcome between home and away game when strong teams played against weak teams	116
Table 6.4 Descriptive statistics of guards, centres and forwards considering game outcome between home and away game when weak teams played against weak teams.....	117

List of Figures

Figure 1.1 Overview of the structure of the thesis	10
Figure 2.1 An ordination plot using non-metric multidimensional scaling of a distance matrix calculated based on the team performance indicators throughout in-season period.	21
Figure 2.2 Non-metric multidimensional scaling plot for each team over the observational period.....	22
Figure 2.3 A box and whisker plots with median values interquartile ranges and outliers for performance indicators in games across 7 months of the National Basketball Association. ...	23
Figure 3.1 The distribution of all players from different levels of teams (included each team in NBA) within five cluster groups.	42
Figure 3.2 The distribution of starters from different levels of teams (included each team in NBA) within five cluster groups.	43
Figure 3.3 The distribution of non-starters from different levels of teams (included each team in NBA) within five cluster groups.	44
Figure 3.4 Territorial map from the cases and classified clusters.	45
Figure 4.1 Depiction from the three steps of a possible approach.	57
Figure 4.2 Histograms of teams' constitution profile according to high-scoring players (upper panel) and low-scoring players (lower panel)	64
Figure 4.3 Teams' constitution profile according to high-scoring players (upper panel) and low-scoring players (lower panel) for each playing position: Centres (C); Forwards (F); Guards (G).....	65
Figure 4.4 Lower-dimensional projection of the predictor space, containing the six predictors: free-throws (FT_percent), 2-point field-goals (FG_percent), turnovers, 3-point field-goals, assists and defensive rebounds (DREB_mean).	68
Figure 4.5 Target values by predictors for initial focal cases and nearest neighbors.	69

Figure 4.6 Lower-dimensional projection of the predictor space, containing the nine predictors: free-throws (FT_percent), defensive rebounds, turnovers, 2-point field goals, Touches (touches_min), offensive rebounds, blocks (BLK_mean), assists and committed fouls.	70
Figure 4.7 Target values by predictors for initial focal cases and nearest neighbors.	71
Figure 4.8 Lower-dimensional projection of the predictor space, containing the seven predictors: free-throws (FT_percent), touches, turnovers (TOV_mean), 3-point field-goals, assists (AST_mean), defensive rebounds (DREB_mean) and steals.	72
Figure 4.9 Target values by predictors for initial focal cases and nearest neighbors.	73
Figure 5.1 Comparison of the performance profiles of overall and different position's players from Strong and Weak teams.	86
Figure 5.2 Effect sizes of differences in mean of CV of each match action or event.	90
Figure 6.1 Correlation matrix of the variables.	105
Figure 6.2 Full exhaustive CHAID classification tree model results explaining balanced game outcome for strong teams	109
Figure 6.3 Full exhaustive CHAID classification tree model results explaining balanced game outcome for weak teams.	110
Figure 6.4 Comparison of the performance profiles of different position's players when strong teams played against strong teams.	111
Figure 6.5 Comparison of the performance profiles of different position's players when strong teams played against weak teams.	112
Figure 6.6 Comparison of the performance profiles of different position's players when weak teams played against weak teams.	113
Figure 7.1 Overview of influencing factors considered in this thesis	127

List of Abbreviations

AST	Assists
ATL	Atlanta Hawks
BLK	Blocked Shots
BOS	Boston Celtics
BKN	Brooklyn Nets
CHA	Charlotte Hornets
CHI	Chicago Bulls
CLE	Cleveland Cavaliers
DREB	Defensive Rebounds
DEFLEC	Deflections
DFGM	Field goals defended at rim made
DAL	Dallas Mavericks
DEN	Denver Nuggets
DET	Detroit Pistons
DIST	Distance Run
FTA	Free Throws attempted
FTM	Free Throws made
FTMs	Free Throws missed
GSW	Golden State Warriors
HOU	Houston Rockets
IND	Indiana Pacers
LAC	Los Angeles Clippers
LAL	Los Angeles Lakers
MEM	Memphis Grizzlies

MIA	Miami Heat
MIL	Milwaukee Bucks
MIN	Minnesota Timberwolves
NOP	New Orleans Pelicans
NYK	New York Knicks
OKC	Oklahoma City Thunder
ORL	Orlando Magic
OREB	Offensive Rebounds
PHI	Philadelphia 76ers
PHX	Phoenix Suns
PASS	Passes Made
PF	Personal Fouls
PITPM	Points made in the paint
POR	Portland Trail Blazers
STL	Steals
SPD	Average Speed
SAC	Sacramento Kings
SAS	San Antonio Spurs
TCHS	Touches
TOV	Turnovers
TOR	Toronto Raptors
UTA	Utah Jazz
WAS	Washington Wizards
2PA	Two-point field goals attempted
2PM	Two-point field goals made

2PMs	Two-point field goals missed
2PM-RM	Two-point field goals made in the middle range
3PA	Three-point field goals attempted
3PM	Three-point field goals made
3PMs	Three-point field goals missed

Tesis Doctoral

D. Shaoliang Zhang

CHAPTER 1

General Introduction

Chapter 1 General Introduction

1.1 Research background

Basketball is one of the most widely popular team sports all over the world characterised by highly dynamic and complex interactions of strategic, tactical and technical dimensions at team level and physical, psychological, and technical skills and actions at individual player level (Courel-Ibáñez, McRobert, Toro, & Vélez, 2017; Fox, Scanlan, & Stanton, 2017; Stojanović et al., 2017). Basketball has millions of fans around the world with the biggest fan-bases mainly in North and South America, Europe, Oceania and Asia (Huang and Hong, 2015). The National Basketball Association (NBA) is the premier men's professional basketball league in North America which is also widely considered to be the most immense and prestigious basketball leagues in the world; composed of 30 teams (29 in the United States and 1 in Canada) (McLean, Strack, Russell, & Coutts, 2018; Sampaio et al., 2015). Additionally, The National Basketball Association (NBA) has a demanding competition schedule, encompassing 82 regular season games played from late October to mid-April each year (~ 3.4 games per week), followed by up to 28 playoff games over a two-month period for teams who advance in the post-season (McLean, et al., 2018). During the season, NBA athletes also travel and compete in four different time zones across the continental United States and Canada (with several teams also traveling to Mexico and Europe each season) to play approximately half of their games in the home cities of opposing teams. The coaching staffs have to prepare and design the training loads on players throughout the entirety of the competition period, a complex process that places a great amount of technical, tactical, physical, physiological and psychological stress on the basketball players (Mikolajec, Maszczyk, & Zajac, 2013; Sampaio, et al., 2015). This process also requires managing the significant differences in work demands introduced by position-specific (e.g. guards, forwards

and centres) game behaviours and player status (e.g. starters and non-starters) as well as adjusting throughout the season to several changing unpredictable constraints such as player injuries (Gonzalez et al., 2013; Sampaio et al., 2008; Sampaio, Janeira, Ibáñez, & Lorenzo, 2006). Thus, the ongoing planning and monitoring of training sessions and game performance is critical for optimising the decisions on individual training loads taken by coaching staff.

Although each player responds individually to the stress of practice and competition, it is necessary to use updated sports performance models to optimise the preparation of teams and players. One of the most common methods of evaluating game performances and the efficiency of players and teams is using game-related statistics throughout the season (Ibáñez et al., 2003; Leicht, Gomez, & Woods, 2017; Lorenzo et al., 2010). Game-related statistics can represent duality of the performer and the environment in order to understand how players engage with others by detecting affordances (Gómez, Lorenzo, Barakat, et al., 2008). In other words, game-related statistics can provide insight on both perception and action of the players and may provide a measure of co-adaptation, in the way that players function as part of a larger system (the team) co-adapting to small but important changes in each structure and function (Sampaio, et al., 2015). Quantitative analysis of basketball performance in the NBA, particularly through game-related statistics, is being widely used among coaches in order to analyse game events with more valid and reliable data. The previous NBA research on this subject is mainly focused on the identification of the most discriminant statistics according to game final outcome - winning and losing teams (Courel-Ibáñez, McRobert, Toro, & Vélez, 2016; Mikolajec, et al., 2013; Paulauskas et al., 2018; Taylor and Trogon, 2002), game final score differences - close, balanced and unbalanced games (Gómez, Gasperi, & Lupo, 2016; Zhang et al., 2017), game location - home and away games (Jones, 2007; Kotecki, 2014; Mateus et al., 2015) and game type - regular and play-off season (Galily, 2018; Teramoto and

Cross, 2010; Zimmer and Kueth, 2009). Accepting the differences between samples studied and methodological approaches between researchers, it seems clear that winning teams in the NBA exhibit a higher offensive quality that is well expressed by higher two point field-goal percentages and a higher number of defensive rebounds (Sampaio, et al., 2015; Teramoto and Cross, 2017). This evidence is more powerful in close games (Zhang, et al., 2017). On the other hand, home advantage in the NBA is well documented (Gómez, et al., 2016; Kotecki, 2014). In basketball, this phenomenon is explained through different game statistics. Finally, it seems clear that play-off games are more slowly paced than regular season games; a fact that seems to contribute to the establishment of different game statistics profiles between these game types (Teramoto and Cross, 2010).

The above research reporting these variables frequently uses data from NBA team-level but not from the NBA player-level analysis, meaning that little information exists on what performance variables mostly discriminate position-specific game behaviours in the NBA. Thus, it is necessary to complete related research to address this imbalance in the basketball science.

1.2 State of the problem

With all above-mentioned research in mind, it is undeniable that the analysis of basketball performance actual competition setting has created ecological and meaningful information related to basketball game behaviours. However, there is a lack of depth in the information and limited the application of the theory into practice scenes if we consider the following aspects.

Firstly, basketball game play is characterized by brief bouts of high-intensity linear and

multidirectional activity interspersed with recovery periods. There is a commonly held belief amongst coaches and players that there has been an increase in both the technical and tactical demands of the game throughout in-season period (Ibáñez et al., 2008; Staunton et al., 2018). Technical and physical variables have been shown to better differentiate between competitive standards in elite basketball (Conte, Kolb, Scanlan, & Santolamazza, 2018; Drinkwater et al., 2005). There is, however, a lack of research to map the evolution of the game play throughout in-season period and to quantify whether the perception of technical and tactical evolution is indeed a reality. Thus, assessing temporal changes in critical performance indicators throughout the in-season period may therefore assist in coaches to inform periodization plans that maintain technical output.

Secondly, team success used to depend on the recruitment and selection of the valuable players. Existing research only takes into account the contribution of the position-specific players (e.g. guards, forwards and centres) and player role (e.g. starters and non-starters) to team success (Gonzalez, et al., 2013; Mateus, et al., 2015; Sampaio, et al., 2008; Sampaio, Ibáñez, Lorenzo, & Gómez, 2006; Sampaio, Janeira, et al., 2006). In fact, game performance not only requires technical and tactical coordination among position-specific players, but also depends on players' own characteristic (such as players' anthropometric attributes and playing experience or scoring ability). There is a wide recognition that extensive experience in a sport is necessary to reach the highest levels of performance (Agloti, Cesari, Romani, & Urgesi, 2008; Scanlan, Dascombe, & Reaburn, 2011; Tarlow, 2012; Williams and Ford, 2008). Similarly, anthropometric characteristics of an athlete are important predictors of whether the athlete will reach the top level of their chosen sport (Gabbett, Kelly, Ralph, & Driscoll, 2009; Strumbelj and Erculj, 2014). In basketball, there appears to no doubt that greater height and body sizes are significant contributors to better performance (Drinkwater, Pyne, & McKenna,

2008; Strumbelj and Erculj, 2014). Thus, consideration of a combination of anthropometric characteristic and playing experience may contribute to the selection of talented players and improve team performance. Also, team success used to depend on players' scoring ability. An alternative solution to refine performance metrics can be proposed by classifying players into different levels of point production. This way, lower-scoring players would improve their chances of having their performance evaluated and recognized and coaching staffs can access objective data to provide suggestions for improvement. Following up this idea of analysing different levels of scoring production, there is a clear need to identify the subset of game statistics that discriminate these levels of point production, when accounting for specific game positions (guards, forwards and centres) that probably have different action requirements. Obtained results would likely contribute to help understanding the complex interactions that determine successful performances in the game.

Thirdly, existing notational analysis has provided preliminary information on the effects of situational variables such as match location, match status, quality of the opponent and game period on sports performance at a behavioural level (Gómez, Lorenzo, Ibanez, & Sampaio, 2013; Gómez, Lorenzo, Sampaio, et al., 2008; Sampaio, Drinkwater, & Leite, 2010; Sampaio, Lago, Casais, & Leite, 2010). In basketball, the related research mainly focused on the effects of situational variables on the whole team performance (García, Ibáñez, Gómez, & Sampaio, 2014; Sampaio and Janeira, 2003), which means that the applicability of the research findings from position-specific player analysis is limited. Another issue worthy of attention is that previous research has examined the independent influence of situational variables on game performance at individual player level (Sampaio, et al., 2008), not accounting for the possibility of higher-order interactions (e.g. home advantage and quality of opponent). The examination of situational variables in isolation would appear to provide limited insight into

the complex nature of team sports performance (McGarry, O'Donoghue, & Sampaio, 2013; Trewin, Meylan, Varley, & Cronin, 2017). For example, Mateus, et al. (2015) demonstrated that players' technical and physical performance was influenced by the situational variables, either independently or interactively. Thus, it is necessary to for coaches and performance analysts to explore the potential interactive effects of situational variables during the assessment of tactical, technical and physical performances at individual player level.

1.3 The aim of the study

Based on the above discussions, the main aims of the studies contained in the current thesis include as follows:

- (1) To explore the (dis)similarity of game-play characteristics throughout an in-season period within the National Basketball Association (NBA).
- (2) To group basketball players into similar clusters based on a combination of anthropometric characteristics and playing experience; and (ii) explore the distribution of players (included starters and non-starters) from different levels of teams within the obtained clusters.
- (3) To group basketball players into similar clusters based on different levels of scoring production; and (ii) to explore the distribution of position-specific players from each team within the obtained clusters.
- (4) To identify technical and physical performances of basketballers according to playing position considering team quality, and (ii) to describe variability in game-to-game performance according to game outcome, location, quality of team and opposition.

(5) To explore the key performance indicators (KPIs) that determined between winning and losing games integrating with team quality; and (ii) to examine the interactive effects of situational variables on the players' technical and physical performances according to playing position.

1.4 The structure of the thesis

The structure of this doctoral thesis included general introduction in Chapter 1, the specific studies from Chapter 2 to Chapter 6, general discussion in Chapter 7, and overall conclusions in Chapter 8 (See Figure 1.1). The specific studies of this thesis were mainly comprised of five inter-linking sections. The first section focused on the evolution of game-play characteristics with-in season for National Basketball Association (Chapter 2). The second section assessed the effects of player's anthropometric characteristics and playing experience on game performance in the NBA (Chapter 3). The third section assessed the effects of different levels of scoring production on game performance in the NBA (Chapter 4). The fourth and fifth sections examined the isolated and interactive influences of situational variables on game performance at individual player level in the NBA (Chapter 5 and 6). Additionally, the above studies have been specifically written for publication in peer-review scientific journal. For the consistency and ease of reference, all citations have been presented in American Psychological Association (APA) referencing format using a single bibliography at the end of thesis.

Figure 1.1 Overview of the structure of the thesis

Tesis Doctoral

D. Shaoliang Zhang

CHAPTER 2

Evolution of Game-play Characteristics Within-season for the National Basketball Association

*Shaoliang Zhang, Alberto Lorenzo, Carl T. Woods
Anthony S. Leicht & Miguel-Angel Gómez*

Chapter 2 Evolution of Game-play Characteristics Within-season for the National Basketball Association

2.1 Introduction

The National Basketball Association (NBA) is commonly regarded as the most popular and competitive basketball league in the world. The typical competitive NBA season consists of 82 regular season games per team over a five to six month period (resulting in two to five games per week), with players also undertaking a month of preseason games and practice (Gonzalez *et al.*, 2013; Teramoto *et al.*, 2017). The competition stress accumulated over this season may lead to a decline in technical and tactical performances if the appropriate adjustments are not made to training programs (Gonzalez *et al.*, 2013). Assessing temporal changes in critical performance indicators throughout the in-season period may therefore assist coaches with informed periodization plans that maintain technical output.

Teams in the NBA often focus their attention towards technical and tactical parameters throughout the in-season period in order to maintain a winning percentage prior to the play-offs (Teramoto & Cross, 2010). Previous research has illustrated that season-long performance may be supported by players' and teams' passing skills and defensive preparation (Ibáñez *et al.*, 2008). Moreover, Klusemann *et al.* (2013) revealed that ball reversals, indirect screens, dribble penetration and ball screens were the four most frequently executed offensive tactics as the competition progressed during the season. The high number of ball reversals indicated the importance of shifting the ball from one side of the court to the other in order to disrupt the opposition's defence while the higher frequency of dribble penetration may be related to a faster style of play allowing players to attack the basket more frequently (Klusemann *et al.*, 2013). Further, the study from Sampaio *et al.* (2010) highlighted that

game-related statistics (offensive and defensive rebounds, free throws, two-and-three point field-goals, passing skills and turnovers) did not vary significantly from the first month to the eight month within the Spanish professional basketball league. Despite the above studies describing some aspects of game-play across the in-season period, these studies did not examine the multivariate and individual performance profiles to explore in-seasonal (dis)similarity in their respective basketball leagues. Consequently, it is difficult to discuss the evolution of game-play style within a season or illustrate the dynamicity with which teams appear to evolve. In order to reveal (dis)similarity of the multivariate performance profiles throughout the in-season period, Woods, Robertson, *et al.* (2018) acknowledged that nuanced analyses are required, drawing on analytical methods infrequently used within the sport sciences.

Indeed, it is unlikely that univariate analytical approaches offer comprehensive insight into the profiles of teams within a season given the dynamic nature of game-play in basketball (Bruce *et al.*, 2018; Woods, Robertson, & Collier, 2017; Woods, Robertson, *et al.*, 2018). Thus, a promising analytical approach to consider game-play in basketball may be non-Metric Multidimensional Scaling (nMDS), as previously employed by Woods, Robertson, *et al.* (2018). This technique is an indirect gradient analysis which produces an ordination based on a distance or dissimilarity matrix (Kenkel & Orlóci, 1986). Unlike methods which attempt to maximise the variance or correspondence between samples in an ordination, nMDS attempts to represent, as closely as possible, the pairwise dissimilarity between samples (e.g. team performance indicators) in a low-dimensional space. Simply, nMDS offers a map that spatially conveys the relationships between samples in a reduced two-dimensional space (Woods, Leicht, *et al.*, 2018). Similar samples are located proximal to one another while dissimilar samples are located relatively further apart on the ordination surface (Woods,

Robertson, Sinclair, *et al.*, 2017). The interpretation of the map affords practitioners with objective insights into item (dis)similarity and could offer key insight for NBA coaches to design game-plans or to select rostered players that explicitly express (dis)similarity to an opposition game type (Woods, Leicht, *et al.*, 2018). In addition, this analysis may illustrate how the dynamics of game-play across an entire competition have altered which may provide administrators with objective support surrounding team and/or organisational modifications for prospective seasons (Woods, Robertson, *et al.*, 2018).

The nMDS technique has been applied in studies of team sports including rugby league (Woods, Robertson, & Collier, 2017; Woods, Robertson, Sinclair, *et al.*, 2017) and netball (Bruce *et al.*, 2018) but is lacking for one of the prominent global sports such as basketball. Thus, the aim of this study was to explore the (dis)similarity of game-play characteristics throughout the in-season period of the world's premier basketball league, the National Basketball Association.

2.2 Method

2.2.1 Data sample

Team performance indicators were collected from a commercially accessible provider (<https://corp.synergysportstech.com/>; Synergy™ Sports Technology system, Washington, USA). A total of 1,230 regular season games were examined during the 2016-2017 NBA season. There were a total of 30 teams with each participating in 82 games during the NBA regular season over the observational period from October 25, 2016 to April 12, 2017. In accordance with prior studies (Gómez, Lorenzo, Barakat, *et al.*, 2008; Ibáñez *et al.*, 2009; Lorenzo *et al.*, 2010; Sampaio & Janeira, 2003; Zhang *et al.*, 2018), a total of thirteen performance indicators were selected to explore the evolution of team multivariate profiles

throughout the in-season period. All procedures were approved by the local Institutional Research Review Board. The operational define of performance indicators were described as follows:

- Two-point field goals made: The number of two-point field goals that a player or team has successfully made.
- Two-point field goals missed: The number of two-point field goals that a player or team has missed.
- Three-point field goals made: The number of three-point field goals that a player or team has successfully made.
- Three-point field goals missed: The number of three-point field goals that a player or has missed.
- Free Throws made: The number of free throws that a player or team has successfully made.
- Free Throws missed: The number of free throws that a player or team has missed.
- Offensive Rebounds: The number of rebounds that a player or team has collected while they were on offense.
- Defensive Rebounds: The number of rebounds that a player or team has collected while they were on defense.
- Assists: An assist occurs when a player completes a pass to a teammate that directly leads to a field goal.
- Turnovers: A turnover occurs when the team on offense loses the ball to the defense.
- Steals: A steal occurs when a defensive player takes the ball from a player on offense, causing a turnover from offensive players.
- Blocked Shots: A block occurs when an offensive player attempts a shot, and a defensive

player tips the ball, blocking their chance to score.

- **Personal Fouls:** The total number of fouls that a player or team has committed.

2.2.2 The reliability and validity of data

As performance indicator data were provided by a commercially accessible provider (Synergy™ Sports Technology system, Washington, USA), the reliability and validity of such information was not publicly available. In order to assess the validity of data sets, a sub-sample of 10 games was randomly selected and observed by two experienced analysts (basketball coaches with more than 5 years of experience in basketball performance analysis) who recorded key performance indicators. These results were contrasted with those gathered within the Synergy™ Sports Technology system and perfect Intra-class Correlation Coefficients (ICC=1.0) were obtained for free-throws, two-and-three point field-goals (both made and missed), offensive and defensive rebounds, turnovers, steals, blocked shots, personal fouls. A lower but very acceptable ICC (0.91) was obtained for the final performance indicator, assists.

2.2.3 Statistical analysis

A multivariate distance-based analytical approach was used to explore the evolution of team performance profiles throughout the in-season period. Specifically, nMDS was used, which is the preferred ordination technique that visualises team profiles in sports sciences (Woods, Robertson, *et al.*, 2018). Further, nMDS is an analysis of similarity of a $n \times p$ data matrix where the n rows represent the samples (e.g., teams) and the p columns (e.g., performance indicators) represent the variables measured within each sample. From the $n \times p$ data matrix, a distance matrix was calculated based on the ranked similarities. Ranked similarities are preferred when no assumptions are made about the underlying distribution of the data.

A distance matrix based on thirteen team performance indicators was built-up using the metaMDS function from the “vegan” package in the computing environment R (Wood, 2003). The method of Bray-Curtis dissimilarity measure was used to calculate the dissimilarity matrix. The dissimilarity matrix was then visualised in two-dimensional space and convex hulls were used to show the team profiles grouped throughout the in-season period. Two ordination plots were built, the first plot presented the evolution of the NBA competition, while the second plot highlighted the temporal change of each team profile throughout the in-season period. In addition, the dynamic shifts of the winner (Golden State Warriors) and runner-up (Cleveland Cavaliers) of the 2016-2017 NBA finals were also plotted throughout the in-season period. This comparison allowed an examination of the team profiles for the ‘dominant’ and rest of the NBA teams within the observational period (Woods, Robertson, & Collier, 2017).

Then, one-way, independent-measures, analysis of variance (ANOVA) tests with Bonferroni post-hoc tests were used to compare group (month) differences. Statistical significance was set at $p < 0.05$. Effect size (ES) was calculated to determine the meaningfulness of the difference and magnitudes were expressed as partial eta-squared (η^2) with the following threshold values employed: >0.01 (small), >0.06 (moderate), and >0.15 (large) (Cohen, 1988). Data visualization was carried out using the “ggplot2” package accessed via the Deducer Interface for the R statistical programming language. All analyses were conducted using R version 3.5.0 (R Core Team, 2015).

2.3 Result

2.3.1 Multivariate team performance dynamics

The ordination plot in Figure 2.1 displayed the (dis)similarity scores in two -dimensional

space for NBA team's multivariate profiles throughout the in-season period. The (dis)similarity matrix solution was reached after twenty runs (stress=0.20, root-mean-square error [rmse]= 3.02×10^{-4} , maximum residual= 2.97×10^{-4}). The ordination plot showed general similarity over the observational period given their clustered positioning on the plot, but some dissimilar profiles were discovered for certain teams during specific months (i.e. presented on the perimeters of the convex hulls). Specifically, the dynamics of the competition evolved month-to-month, and the overlapping part of the ordination plot and convex hulls indicated that team profiles remained generally similar over the observational period. In addition, the beginning and end of the season (October and April) showed relatively dissimilarity for team's multivariate profiles compared with other periods of the regular season. However, a notable feature was that the performance profiles of the dominant teams in the NBA (e.g. Golden State Warriors and Cleveland Cavaliers) generally clustered closer toward the right area of the ordination surface whilst these teams generally crossed paths along the right boundary of the multivariate team matrix during the observational period.

The ordination plot of each team was presented in Figure 2.2. These plots indicated that each team displayed unique profile paths throughout the in-season period. The direction that team profiles were progressing across the ordination surface demonstrated relatively (dis)similar trends amongst teams. It was worth noting that the Denver Nuggets possessed the most dynamic path with large month-to-month dissimilarity relative to the remaining teams.

2.3.2 Individual performance indicators dynamics

The month-to-month difference and temporal change in performance indicators were presented in Figure 2.3. The following key performance indicators were significantly altered during the in-season period: two-point field-goals missed decreased ($p < 0.006$, ES=0.012)

from the start to the end of the in-season period while three-point field-goals made increased ($p<0.000$, $ES=0.011$); free-throws missed during a game were higher ($p<0.011$, $ES=0.007$) in October compared to April; assists gradually increased ($p<0.005$, $ES=0.007$) between October and April while a decreased trend were found for personal fouls ($p<0.001$, $ES=0.018$).

2.4 Discussion

The aim of this study was to explore the (dis)similarity of game-play characteristics throughout the in-season period within the NBA. Multivariate analysis revealed (dis)similarity across team profiles during the observational period. The changing profile of the dominant teams over the analysed period may highlight the emergence of innovative game styles implemented. Each team presented unique paths in the ordination space, which can provide a valued reference for coaches and coaching staff to design game strategies that reflect nuanced team idiosyncrasy.

2.4.1 Multivariate team performance dynamics

The ordination plot showed a similarity of team profiles from November to March, while a relative dissimilarity were discovered between the beginning (October) and end (April) of the season. A possible explanation would be that the tactical coordination and game styles of the team were constantly evolving during the season as a result of changing team cohesion, a well reported unstable phenomenon (Carron *et al.*, 2002; Muthiane *et al.*, 2015). Additionally, this evolution may have resulted from adaptation of adjusting their style of playing at the start of the season and coaches alterations in their playing rosters of teams at the end the season to maximise player performance in the upcoming playoffs (Belk *et al.*, 2017).

Figure 2.1 An ordination plot using non-metric multidimensional scaling of a distance matrix calculated based on the team performance indicators throughout in-season

period.

Figure 2.2 Non-metric multidimensional scaling plot for each team over the observational period.

Figure 2.3 A box and whisker plots with median values interquartile ranges and outliers for performance indicators in games across 7 months of the National Basketball Association.

The relative positioning of the winner (Golden State Warriors) and runner-up (Cleveland Cavaliers) in the NBA finals was predominantly clustered in the right area of the ordination plot and the paths of dynamic shift were mostly presented along the edge of the multivariate team matrix from the beginning to the end of the regular season. Clustering in the ordination plot illustrated that the dominant teams were able to be successful based on similar game styles over the course of a season (Bruce *et al.*, 2018). Indeed, Teramoto and Cross (2017) pointed out that ‘small ball’, a style of play that sacrifices height, physical strength and low post offence/defence in favour of a line-up of smaller players for speed, agility and increased scoring (often from the three-point line), was exhibited by the Golden State Warriors in recent years and the dominating style during the regular season in the NBA. The ‘small-ball’ style challenges the conventional concept that height and weight are an important aspect of the game with the roles of players dramatically different in ‘small-ball’; all players are required to have perimeter shooting skills, including three-point shooting, as well as to guard the opposition on the perimeter (Teramoto & Cross, 2017). The recent emergence of ‘small-ball’ appears to be a critical factor in the NBA as this style was more common in dominant teams during the ‘current’ evolution of the NBA. In addition, the winner (Golden State Warriors) and runner-up (Cleveland Cavaliers) of the NBA finals possessed pre-eminent or ‘all-star’ players with excellent coaching staff, components of a "Superteam" (Losada *et al.*, 2016). Sampaio *et al.* (2015) noted that ‘all-star’ players were more efficient than others as they were able to perceive environmental information and adapt their behaviour accordingly with less mistakes when deciding offensive and defensive actions. Thus, the highly competitive and effective playing styles of ‘all-star’ players likely influenced the whole team’s style of play throughout the season (Ruiz *et al.*, 2014).

During the in-season period, all 30 teams displayed unique and specific paths (Figure 2.2)

with some dissimilarities presented for certain teams. Of note was that the Denver Nuggets showed the greatest dissimilarity throughout the in-season period. Studies in netball and rugby league have reported that the larger dissimilarity may be attributed to changes in coaching and playing personnel (Bruce *et al.*, 2018). The Denver Nuggets experienced a significant restructure of coaching staff (included assistant coaches, player development coaches and assistant video coordinator) before the start of the season compared with the remaining teams in the NBA; potentially explaining their unique profile relative to the competition

2.4.2 Individual performance indicator dynamics

A number of the individual team performance indicators exhibited a trend with two-point field-goals and free-throws missed decreasing while three-point field-goals made increased throughout the in-season period. These results indicated that long distance shooting had a greater influence on the game dynamics throughout the in-season period with players becoming specialists and focusing their performance in terms of long distance shooting. A strong three-point attack option has been suggested to be key for excellent offence because its existence provides opportunities for dribbling penetration, creates space for operation in the post, and forces defenders into difficult choices between current assignments and helping others (Garcia *et al.*, 2013; Teramoto & Cross, 2010). Moreover, Teramoto and Cross (2017) pointed out that the playing style of ‘small-ball’ had gained popularity within the current NBA because it increased the number of three-point shots taken, which would result in better offensive efficiency when shots were made. Similarly, others have highlighted that playing positions such as Centres, typically the tallest players, in the NBA were diversifying their role and increasing their opportunities for three-point field-goals (Gómez *et al.*, 2016; Mateus *et al.*, 2015; Zhang, Lorenzo, Gómez, Liu, *et al.*, 2017). Thus, the constant evolution of the game across the in-season period appeared to impact players who now tended to perform non-

traditional actions, further adding to the evolution of game-play.

Interestingly, the number of assists displayed an increased trend over the in-season period while a decreased trend was evident for personal fouls. Previously, assists and personal fouls were reported to reflect team cohesion and maturity in terms of offense and defense (Gómez, Lorenzo, Sampaio, *et al.*, 2008; Ibáñez *et al.*, 2008; Lorenzo *et al.*, 2010; Sampaio & Janeira, 2003; Zhang, Lorenzo, Gómez, Mateus, *et al.*, 2017). Specifically, increasing assists would be a reflection of the fluency of the team's overall tactics with ball handlers making informed decision to assists teammates scoring by monitoring the movements (planned and unplanned) of the teammates, and analysing the positioning of the defenders as movement progresses (Mangine *et al.*, 2014). In addition, personal fouls gradually reduced throughout in-seasonal period that may reflect effective team defensive communication, which requires positive and complementary participation between teammates (Gómez, Lorenzo, Sampaio, *et al.*, 2008; Leicht *et al.*, 2017; Sampaio *et al.*, 2010). Thus, the current results indicated that as the season progresses, the tactical strategies of teams evolve into more effective interactions between players and team coordination in terms of offence and defence.

2.5 Conclusion

In summary, this study explored the evolution of game-play characteristics throughout the in-season period in the NBA based on a novel data visualization approach to the sport sciences. The interpretation of multivariate team profiles across the in-season period demonstrated that team profiles generally presented a similar trend while the beginning and end of the season (October and April) showed relatively dissimilarity compared with the other analysed periods. The 2016-2017 NBA Finals' winner (Golden State Warriors) and runner-up (Cleveland Cavaliers) clustered together indicating similar evolutionary changes to their game-styles. The

interpretation of individual team profiles across the in-season period displayed that the Denver Nuggets possessed the most dynamic path, possibly as a result of coaching changes. Finally, effective team interactions (offence and defence) developed as the competition progressed concurrently with an increased trend in the number of three-point field-goals made. Beyond the implications this research holds for the NBA league, it also presented a novel data visualization approach for explaining dynamic trends in multivariate datasets within sport. The clear results objectively demonstrated the capability of nMDS to simultaneously analyse and visualize nonlinear behaviours extracted from longitudinal multivariate datasets. Thus, the application of nMDS in basketball and other sports may reveal new trends and allow coaching staff and performance analysts to improve fine-tuning periodization and game performance rather than making inferences based on traditional univariate model sets.

2.6 Limitations

Despite a strong analytical study design and large dataset, some limitations in the current research should be considered for further studies. Firstly, the results were based upon our current professional basketball knowledge within the NBA during one season with future work recommended to examine the evolution of game-play characteristics across multiple seasons. Secondly, the current research did not consider the influence of the situational variables on nonlinear behaviours which means that future studies are encouraged to examine multivariate and individual team performance profiles under different contextual variables (e.g. game location, the quality of team and opponent). Finally, the descriptive design of this work generates speculative limitations when discussing multivariate team performance dynamics. Future work may wish to integrate with other statistical technique to present clear and detailed results.

Tesis Doctoral

D. Shaoliang Zhang

Volume 36(22), 2511-2520

CHAPTER 3

Clustering Performances in the NBA according to Players' Anthropometric Attributes and Playing Experience

*Shaoliang Zhang, Alberto Lorenzo, Miguel-Angel Gómez
Nuno Mateus, Bruno Gonçalves & Jaime Sampaio*

Chapter 3 Clustering Performances in the NBA according to Players' Anthropometric Attributes and Playing Experience

3.1 Introduction

The recruitment of basketball players is regarded as a key factor to achieve successful game performances. In the National Basketball Association (NBA), a component of this information may relate to anthropometric attributes and player experience (Drinkwater *et al.*, 2008; Tarlow, 2012), as identified in available research (Alejandro *et al.*, 2015; Popovic *et al.*, 2013; Štirn *et al.*, 2016; Tomovic *et al.*, 2016; Torres-Unda *et al.*, 2013). Dežman *et al.* (2001) suggested that the specific-position of basketball players were traditionally determined by their weight and height. Specifically, the tallest and heaviest players tend to play the role of the key positions close to the basket, while smaller players are placed in perimeter positions (Latin *et al.*, 1994; Ostojic *et al.*, 2006; Sallet *et al.*, 2005). This basic spatial distribution allows the smaller players to move quickly the ball down the court, as the larger and strong players take advantage of height and weight close to the basket to perform the high efficacy shots during the basketball game (Drinkwater *et al.*, 2008).

Players' experience may be another important factor to be considered in the selection process. Multiple studies have suggested that playing experience is related to performance in team sports (Black *et al.*, 2016; Ozmen, 2012; Swann *et al.*, 2012; Williams & Ford, 2008). In particular, expert players set more specific goals, selected more technique-oriented strategies, made more strategy attributions, and displayed higher levels of self-efficacy than non-experts and novices (Cleary & Zimmerman, 2001; Kitsantas & Zimmerman, 2010). In addition, research has identified that experts have better performance than novices in using advance visual cues to guide their anticipatory responses (Williams, 1993). Similarly, more

experienced soccer referees appeared better at anticipating and reading play and ultimately were more economical with their movements (Weston *et al.*, 2010). Some research has also summarized from psychological perspectives that expert players have an advantage over novice players in: i) reading game ability (Livingston *et al.*, 2011); ii) decision-making ability (Travassos *et al.*, 2013); and iii) anticipation ability (Gabbett & Abernethy, 2013; Rowe *et al.*, 2009).

In basketball, previous studies suggest that early sport experiences may affect basketball skill acquisition (Santos *et al.*, 2016). The expert players probably have better performances in assists, free throws and three point field goals than novice players (García *et al.*, 2010; Ibáñez *et al.*, 2015; Sampaio *et al.*, 2004). Besides, the expert players are better able to deal with both moderate and high intensity fatigue conditions and maintain a higher level of performance (Ibáñez *et al.*, 2009; Lyons *et al.*, 2006; Sampaio *et al.*, 2009). Moreover, Tarlow (2012) suggested postseason experience has a positive impact on a team success in the play-off season. Therefore, the development of technical and physical performance profiles considering anthropometric characteristics and playing experience can help reveal new trends to recruit valuable players. Similarly, it can allow coaching staffs to make well-informed decisions, in particular by using different line-ups combinations in different match-ups. In addition, the process of selecting players also considers the complementary roles of starter and non-starter players. In fact, when the starter players do not perform as expected, are fatigued or in foul trouble, non-starter players play a key role in maintaining performance levels (Clay & Clay, 2014; Gómez *et al.*, 2017; Sampaio *et al.*, 2009). In the NBA, the competitive season imposes a great amount of psychological and physiological stress on players because the typical competitive 82 regular season games over a time span of 5.5 months (2–5 games per week). Considering the length of the basketball season in the NBA,

the starters may experience greater accumulated fatigue than those who are not playing so consistently (nonstarters) (Gonzalez *et al.*, 2013). Thus, coaches have to deal with the management of on-court and bench players and anticipate substitutions caused by fatigue, foul trouble, poor performance, defensive changes and critical moments (Clay & Clay, 2014; Gómez *et al.*, 2009; Sampaio, Ibáñez, *et al.*, 2006).

Based on the above considerations, the aim of the present study was to (i) group basketball players' into similar clusters based on a combination of anthropometric characteristics and playing experience and then identifying a small subset of performance variables that discriminate between the previous clusters; and (ii) explore the distribution of players (included starters and non-starters) from different levels of teams within the obtained clusters.

3.2 Methods

3.2.1 Sample and variables

This study used a descriptive design (Thomas *et al.*, 2015).

Archival data were obtained from open-access official NBA records during the 2015–2016 regular season (available at <http://stats.nba.com>). A total of 699 regular season games were selected based on the balance score inclusion criteria with final score differences equal to or less than 10 points. This criteria is based on the available literature that considers this scoring margin as recoverable for any of the confronting teams and, therefore, denoting that the game was not unbalanced to a way that one team was clearly superior to the opponent (Ferreira *et al.*, 2014). The game-related statistics were transformed to per-minute statistics (original statistics/min $\times$ 40) according to players' game duration on the court (Kubatko *et al.*, 2007). The players who played less than 500 minutes in the whole season were excluded from the sample because those players' transformed data were regarded as unreliable per-minute

statistics (Kubatko *et al.*, 2007). In addition, the players who played less than five minutes were also excluded from the sample (Sampaio, Janeira, *et al.*, 2006), which finally limited the sample to 354 players with 12724 performance records (the current sample selected accounts for the 57% of the total sample). The team quality was decided by final team ranking in the NBA league (Sampaio, Lago, *et al.*, 2010). The weak teams were the ones that only played the regular season stage whereas the strong teams were the ones that played the play-off season but did not enter the conference finals. The final teams played the conference finals and final.

According to the available literature (Gómez *et al.*, 2008; Lorenzo *et al.*, 2010; Mateus *et al.*, 2015; Sampaio & Janeira, 2003; Zhang, Lorenzo, Gómez, Mateus, *et al.*, 2017), a total of twenty variables were selected for analysis as follows:

- Anthropometric attributes: Height and Weight
- Experience: The player accumulated experience on the court from the first year of entering NBA to the last year of professional career (limited the whole NBA phase).
- Two-point field goals made (2PM): The number of two-point field goals that a player or team has successfully made.
- Two-point field goals missed (2PMs): The number of two-point field goals that a player or team has unsuccessfully made.
- Three-point field goals made (3PM): The number of three-point field goals that a player or team has successfully made.
- Three-point field goals missed (3PMs): The number of three-point field goals that a player or team has unsuccessfully made.
- Free Throws made (FTM): The number of free throws that a player or team has successfully made.

- Free Throws missed (FTMs): The number of free throws that a player or team has unsuccessfully made.
- Offensive Rebounds (OREB): The number of rebounds that a player or team has collected while they were on offence.
- Defensive Rebounds (DREB): The number of rebounds that a player or team has collected while they were on defence.
- Assists (AST): An assist occurs when a player completes a pass to a teammate that directly leads to a field goal.
- Turnovers (TOV): A turnover occurs when a player on offense loses the ball to the defence.
- Steals (STL): A steal occurs when a defensive player takes the ball from a player on offence, causing a turnover from offensive players.
- Blocked Shots (BLK): A block occurs when an offensive player attempts a shot, and a defensive player tips the ball, blocking their chance to score.
- Personal Fouls (PF): The total number of fouls that a player has committed.
- Touches (TCHS): The number of times a player touches and possesses the ball during the game.
- Passes Made (PASS): The total number of passes a player made during the game.
- Distance Run (DIST): The total distances in miles that a player covered while on the court.
- Average Speed (SPD): The average speed in miles per hour of all movements (standing, walking, jogging, running, and sprinting) by a player while on the court.

In order to test the validity of data sets, a sub-sample of 20 games (final score differences equal to or less than 10 points) was randomly selected and observed by two experienced

analysts (basketball coaches with more than 5 years of experience in basketball performance analysis). The results were contrasted with the gathered data in the website and perfect Intra-class Correlation Coefficients (ICC=1.0) were obtained for free-throws, two and three-pointers (both made and missed), offensive and defensive rebounds, turnovers, steals, blocked shots, personal fouls. For the assists, pass made and touches, the results were lower but still very acceptable (ICC = 0.91). There was a formal approval of all procedures from the Local Institution of Research Review Board.

3.2.2 Statistical analysis

Records were screened for univariate outliers (cases outside the range Mean $\pm$ 3SD) and distribution tested in order to proceed to the inferential analysis (Kerlinger & Pedhazur, 1973). A two-step cluster with log-likelihood as the distances measure and Schwartz's Bayesian criterion was carried out to group basketball players into the different groups (Gómez *et al.*, 2013; Gómez *et al.*, 2017; Mateus *et al.*, 2015; Sampaio, Drinkwater, *et al.*, 2010), using experience, weight and height as variables. A descriptive discriminant analysis was conducted to identify which variables best discriminate the previously obtained clusters. Discriminant analysis is robust for these derived rate variables (Norusis & Inc, 2004). Interpretation of the obtained discriminant function was based on examination of structure coefficients greater than |0.30|, which means that variables with higher absolute values were best placed to discriminate between groups (Kerlinger & Pedhazur, 1973). Validation of discriminant models conducted using the leave-one-out method of cross-validation (Norusis & Inc, 2004). Cross-validation analysis evaluated the usefulness of discriminant functions when classifying new data. This method involved generating the discriminant function on all but one of the participants (n-1) and then testing for group membership on that participant. The process was repeated for each participant (n times) and the percentage of correct

classifications was taken as the mean for the n trials. Moreover, the distribution of all players, starters and non-starters from different levels of teams (included each team in NBA) within obtained cluster groups were performed by separately setting up custom and cross tables using IBM SPSS Statistics for Windows (Armonk, NY: IBM Corp). Statistical significance was set at 0.05.

3.3 Results

The two-step cluster analysis allowed obtaining five different groups of players: Top height and weight with low experience (TopHW-LowE); Middle height and weight with middle experience (MiddleHW-MiddleE); Middle height and weight with top experience (MiddleHW-TopE); Low height and weight with low experience (LowHW-LowE); Low height and weight with middle experience (LowHW-MiddleE). Table 3.1 contains the means and standard deviations from the variables according to the cluster solutions and the structure coefficients from both functions. In addition, the discriminant analysis revealed three statistically significant functions ($P < 0.001$), however, the first two yielded 88.8% of cumulative variance (canonical correlations of 0.80 and 0.51, respectively). The reclassification of the cases in the original groups was moderate (59%). The first function had strong emphasis on offensive ($SC=0.63$) and defensive rebounds ($SC=0.65$), whereas the second function was mainly emphasized by performance obtained in passing-related variables like touches ($SC=-0.82$), passes made ($SC=-0.81$). Additionally, in shooting aspects, three-point field goals made ($SC=-0.41$) and missed ($SC=-0.41$) were emphasized in the function 1, while two-point field goals made ($SC=-0.34$) and missed ($SC=-0.34$) were highlighted in the function 2. Furthermore, blocked shots ($SC=0.58$), personal fouls ($SC=0.32$) and turnovers ($SC=-0.45$) were also respectively emphasized in the function 1 and function 2. The assists were the only variable commonly highlighted in both functions.

Table 3.1 Descriptive statistics of different performance profiles groupings

Variables	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Function1 (73.2%)	Function2 (15.6%)
	TopHW-LowE	MiddleHW-MiddleE	MiddleHW-TopE	LowHW-LowE	LowHW-MiddleE		
Height	210.61±3.62	202.73±4.03	204.97±5.27	198.02±4.79	187.72±3.99	-	-
Weight	112.97±6.08	101.74±5.69	106.98±9.04	93.10±5.85	85.28±4.99	-	-
Experience	3.41±2.54	5.98±1.81	12.79±2.47	1.52±1.17	6.63±3.28	-	-
2PM	5.77±1.86	4.33±1.80	4.49±2.19	3.74±1.40	4.23±1.65	0.26	-0.34*
2PMs	5.74±2.18	4.58±1.72	4.95±2.42	4.28±1.52	4.99±1.78	0.13	-0.34*
3PM	0.45±0.75	1.40±0.87	1.10±1.02	1.49±0.69	1.65±0.72	-0.41*	0.23
3PMs	0.98±1.47	2.92±1.66	2.37±2.15	3.11±1.25	3.31±1.36	-0.41*	0.28
FTM	2.74±1.24	2.62±1.57	2.49±1.55	2.14±1.08	2.75±1.68	0.03	-0.21
FTMs	1.19±0.93	0.79±0.40	0.93±0.69	0.72±0.48	0.64±0.36	0.25	-0.12
DREB	7.33±1.72	5.52±1.67	6.00±2.06	4.31±1.34	3.69±0.97	0.65*	-0.11
OREB	2.83±1.00	1.61±1.10	1.74±1.06	1.08±0.66	0.75±0.47	0.63*	-0.19
AST	2.10±1.06	2.87±1.71	2.97±1.25	3.10±1.74	5.59±2.20	-0.49*	-0.57*
BLK	1.31±0.64	0.66±0.43	0.78±0.55	0.50±0.37	0.30±0.23	0.58*	-0.17
STL	0.97±0.46	1.16±0.44	1.06±0.39	1.19±0.44	1.37±0.53	-0.22	-0.07
TOV	2.11±0.65	1.95±0.74	1.99±0.70	1.96±0.78	2.61±0.93	-0.14	-0.45*
PF	4.23±0.91	3.30±0.86	3.69±1.12	3.43±0.95	3.10±0.77	0.32*	-0.12
TCHS	68.88±11.56	63.60±14.28	66.16±12.18	61.81±18.37	85.94±18.39	-0.21	-0.82*
PASS	50.08±9.72	44.75±12.54	47.50±10.51	43.57±16.01	63.66±15.67	-0.19	-0.81*
DIST	2.75±0.14	2.78±0.12	2.67±0.30	2.88±0.10	2.84±0.13	-0.29	0.23
SPD	4.11±0.20	4.16±0.18	4.01±0.19	4.32±0.15	4.25±0.19	-0.29	0.23

Means ± Standard deviations and structure coefficients (SC) of technical and physical performance for five clusters. **Abbreviations:** 2PM = Two-point field goals made; 2PMs = Two-point field goals missed; 3PM = Three-point field goals made; 3PMs = Three-point field goals missed; FTM = Free Throws made; FTMs = Free Throws missed; DREB = Defensive Rebounds; OREB = Offensive Rebounds; AST = Assists; BLK = Blocked Shots; STL = Steals; TOV = Turnovers; PF = Personal Fouls; TCHS = Touches; PASS = Passes Made; DIST = Distance Run (Miles); SPD = Average Speed (MPH).

Table 3.2 The distribution of all players (included starters and non-starters) from different levels of teams in the five cluster groups

Player	Team	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
		TopHW-LowE	MiddleHW-MiddleE	MiddleHW-TopE	LowHW-LowE	LowHW-MiddleE
All players	Weak teams	44 (26%)	32 (19%)	14 (8%)	48 (28%)	31 (18%)
	Strong teams	29 (21%)	31 (23%)	24 (18%)	18 (13%)	35 (26%)
	Final teams	10 (21%)	13 (27%)	8 (17%)	8 (17%)	9 (19%)
Starters	Weak teams	10 (25%)	11 (28%)	6 (15%)	5 (13%)	8 (20%)
	Strong teams	7 (17%)	11 (26%)	9 (21%)	2 (5%)	13 (31%)
	Final teams	3 (17%)	6 (33%)	3 (17%)	2 (11%)	4 (22%)
Non-starters	Weak teams	34 (26%)	21 (16%)	8 (6%)	43 (33%)	23 (18%)
	Strong teams	22 (23%)	20 (21%)	15 (16%)	16 (17%)	22 (23%)
	Final teams	7 (23%)	7 (23%)	5 (17%)	6 (20%)	5 (17%)

3.3.1 Discriminant variables from each cluster group

The top height and weight with low experience group (TopHW-LowE) presented highest association with discriminant variables (two-point field goals made and missed, offensive and defensive rebounds, blocks, personal fouls) from both functions. The middle height and weight with middle experience group (MiddleHW-MiddleE) presented lowest association with explained variables (turnovers) from both functions. The middle height and weight with top experience group (MiddleHW-TopE) showed a similar profile as (TopHW-LowE) group. The low height and weight with low experience group (LowHW-LowE) presented lowest association with discriminant variables (passes made and touches). The low height and weight with middle experience group (LowHW-MiddleE) presented highest association with explained variables (three-point field goals made and missed and passing-related variables).

3.3.2 The specific distribution of all players (included starters and non-starters) from different levels of teams within five cluster group (see Table 3.2)

In general, all players from weak teams are mainly distributed in the LowHW-LowE group. All players from strong teams are allocated in the LowHW-MiddleE group while those from final teams are mainly grouped in the MiddleHW-MiddleE group. In addition, starters and non-starters from weak teams were mostly grouped in the MiddleHW_MiddleE and LowHW_LowE group. Starters and non-starters from strong teams were mainly grouped in the LowHW_MiddleE group while their counterparts from final teams were mostly grouped in the MiddleHW_MiddleE group. It is worth noting that strong and final teams tend to put more -bench players from TopHW_LowE group.

Besides, the detailed describe of the proportion of the five cluster groups in each team in the NBA is also presented for descriptive purposes (see Figure 3.1, Figure 3.2 and Figure 3.3).

Figure 3.4 presents the territorial map from the cases and created clusters within the space from the first and second discriminant functions. The players from TopHW-LowE group had better performances in explained variables related to function 1.

3.4 Discussion

The aim of the present study was to (i) group basketball players' into similar clusters based on a combination of anthropometric characteristics and playing experience and then identifying a small subset of performance variables that discriminate between the previous clusters; and (ii) explore the distribution of players (included starters and non-starters) from different levels of teams within the obtained clusters.

3.4.1 Describing different game performance profiles

The top height and weight with low experience group (TopHW-LowE) presented highest association with discriminant variables (two-point field goals made and missed, offensive and defensive rebounds, blocks, personal fouls) from both functions. The findings of our study are in line with several studies (Erculj & Strumbelj, 2015; Gómez *et al.*, 2016; Sampaio, Janeira, *et al.*, 2006) suggesting that the tallest and heaviest players are highly specialized in rebounding, blocking and inside shooting, likely because the use of 1 on 1 situations to solve the possessions with players close to the basket is much required. Additionally, players from this group committed more fouls in comparison with other groups. A possible explanation would be that players with lower experience are not able to accurately predict and anticipate the behaviour of the opponents (Aglioti *et al.*, 2008), while another possibility would be that tallest and heaviest players often defend 1-on-1 penetrations at the rim, which increases the probability of committing fouls (Koh *et al.*, 2011).

The middle height and weight with middle experience group (MiddleHW-MiddleE) presented lowest association with discriminant variables (turnovers) from both functions. In fact, more experienced athletes are able to correctly assess and respond to a dynamic environment to avoid unforced errors or make mistakes (Mori *et al.*, 2002). Additionally, previous research has shown that ideal average playing experience level in the NBA league would be 4.33 seasons for each player because these players who maintain peak performance can have better collective performance and success (Tarlow, 2012).

The middle height and weight with top experience group (MiddleHW-TopE) presented association with discriminant variables (two-point field goals made and missed, offensive and defensive rebounds, blocks, personal fouls) from both functions. This is supported by Ibáñez *et al.* (2009) believed that the expert players maintain a higher defensive intensity during the game than the inexperienced players and they can select optimal moment and reach a better position in which the defensive pressure is less to shoot through perceiving environmental information and adapting their behaviour accordingly.

The low height and weight with low experience group (LowHW-LowE) presented lowest association with explained variables in passes made, and touches, whereas the low height and weight with middle experience group (LowHW-MiddleE) presented highest association with discriminate variables in passing-related variables. Moreover, players from both groups comprised of point guards or shooting guards with extremely high values in three-point field goals made and missed.

Weaker teams

Stronger teams

Final teams

Figure 3.1 The distribution of all players from different levels of teams (included each team in NBA) within five cluster groups. **Note:** TopHW-LowE: Top height and weight with low experience; MiddleHW-MiddleE: Middle height and weight with middle experience; MiddleHW-TopE: Middle height and weight with top experience; LowHW-LowE: Low height and weight with low experience; LowHW-MiddleE: Low height and weight with middle experience.

Weaker teams

Stronger teams

Final teams

Figure 3.2 The distribution of starters from different levels of teams (included each team in NBA) within five cluster groups. **Note:** TopHW-LowE: Top height and weight with low experience; MiddleHW-MiddleE: Middle height and weight with middle experience; MiddleHW-TopE: Middle height and weight with top experience; LowHW-LowE: Low height and weight with low experience; LowHW-MiddleE: Low height and weight with middle experience.

Weaker teams

Stronger teams

Final teams

Figure 3.3 The distribution of non-starters from different levels of teams (included each team in NBA) within five cluster groups. **Note:** TopHW-LowE: Top height and weight with low experience; MiddleHW-MiddleE: Middle height and weight with middle experience; MiddleHW-TopE: Middle height and weight with top experience; LowHW-LowE: Low height and weight with low experience; LowHW-MiddleE: Low height and weight with middle experience.

Figure 3.4 Territorial map from the cases and classified clusters.

In fact, guards play a central role in ball handling and distribution in the NBA league, especially in game pace control, passing and organizing offensive tactics, and keeping a higher long-range shooting ability (Fewell *et al.*, 2012; Gómez *et al.*, 2016; Sampaio *et al.*, 2009). However, our study noticed that despite the super athleticism of NBA players, players with lower height and weight remain the one that prefer to perform offensive tasks in the perimeter position and the abilities of organizing and reading game improved as playing experience increased. Indeed, Sampaio *et al.* (2004) suggested that passing-related variables discriminated between senior and junior basketball players' performances, which are a

measure of playing experience and maturity. Besides, the previous studies showed that younger players lack cooperation with teammates and do not show tactical intention or involvement, mainly watching the other players' performance during the game, due to their self-centred personalities and their limited attention spans (Diaz del Campo *et al.*, 2011). Thus, younger players with low height and weight should invest enough time to join in collective tactical activities to learn how to create space and explore optimal passing timing to help teammates to score.

3.4.2 The specific distribution of all players (included starters and non-starters) from different levels of teams within five cluster group

In general, all players from weak teams are distributed in the LowHW-LowE group. All players (included starters and non-starters) from strong teams are allocated in the LowHW-MiddleE group while their counterparts from final teams are mainly grouped in the MiddleHW-MiddleE group.

All players (especially for non-starter players) from weak teams are generally distributed in the LowHW-LowE group. Our findings indicated that weak teams tend to select younger players with low height and weight. In fact, according to the rule of draft system in the NBA league, the 14 teams (weak teams) who did not qualify for the Playoffs have priority to select best players, and then the rest of the teams (strong and final teams) choose in reverse order of the regular season ranking (the team with the best record goes last) (Taylor & Trogon, 2002). However, although NBA draft order appeared to value anthropometric and athletic variables, players with heavier and higher anthropometric characteristics are negatively related to draft status (Moxley & Towne, 2015). Thus, younger players with lower height and weight may be

selected preferentially by weak teams.

In addition, all players (included starters and non-starters) from strong teams are mostly allocated in the LowHW-MiddleE group, which means that strong teams tend to select and possess the players (especially for shooting and point guards) with the abilities of the excellent organizing and shooting out of three-point line. In fact, Zhang, Lorenzo, Gómez, Liu, *et al.* (2017) demonstrated that players from strong teams have better performance in terms of three-point field goals than weak teams in the NBA. Furthermore, Mateus *et al.* (2015) highlighted that with the development of the modern basketball game, three-point field goals play a key role in team success. Thus, this might be important information for coaches and scouts to select and evaluate players.

Finally, all players (included starters and non-starters) from final teams are mainly grouped in the MiddleHW-MiddleE group, which means that final teams seem to be more willing to select basketball players who make fewer turnovers during game. Indeed, Teramoto and Cross (2010) suggested that the teams that played in the Conference Finals make better shooting efficiency and fewer turnover rates because these factors are particularly related to winning the series in the First Rounds and the Conference Semifinals. Thus, it is necessary to select basketball players making a correct response for complex tactics strategy when setting up the final teams. In addition, it is worth noting that strong and final teams tend to put more bench players from TopHW_LowE group. It is possible that strong and final teams do not give priority to select players, which lead these teams to take the challenge to select and recruit some younger players with taller and heavier physical advantage into bench position in order to secure rebounds in offence and defence and increase inside shooting (Gonzalez *et al.*, 2013; Sampaio, Ibáñez, *et al.*, 2006; Soebbing & Mason, 2009).

3.5 Conclusion

In summary, five different performance profiles were obtained by cluster analysis. TopHW-LowE group highlighted two-point field goals made and missed, offensive and defensive rebounds, blocks, personal fouls; MiddleHW-MiddleE group made fewest turnovers; MiddleHW-TopE group covered shortest distance and the lowest speed; LowHW-LowE group made fewest passes and touches; LowHW-MiddleE group emphasized three-point field goals made and missed and passing-related variables. Furthermore, all players from weak teams are mainly distributed in the LowHW-LowE group. All players from strong teams are allocated in the LowHW-MiddleE group while their counterparts from final teams are mostly grouped in the MiddleHW-MiddleE group. These findings can be used to set up teams and optimize preparation for individual player groupings in order to improve game performances of the players and teams.

3.6 Practical applications and limitations

The findings of this study contribute to understanding the influence of players' anthropometric characteristics and playing experience on technical and physical performance. Therefore, the obtained results provide a strong and direct basis to guide both players' recruitment strategies and interventions aimed at improving team rosters in the NBA or even other league. There are limitations in the current research that should be considered in further studies concerning player's performance profile. Firstly, our study considered playing experience as NBA playing experience, meaning that in the future, the previous years of playing experience in other leagues can also be accounted. Secondly, the criterion of evaluating team quality is based on the final ranking in the NBA league, which might be a criterion of lacking temporal sensitivity, thus, future studies can be developed upon a more longitudinal assessment.

Tesis Doctoral

D. Shaoliang Zhang

Book Chapter

CHAPTER 4

Modelling of Playing Process and Tactical Behaviour in the NBA

*Jaime Sampaio, Bruno Gonçalves, Nuno Mateus
Shaoliang zhang & Nuno Leite*

Chapter 4 Modelling of Playing Process and Tactical Behaviour in the NBA

4.1 Introduction

Performance in high-level basketball is a very complex process to understand, mainly due to its dependency of a substantial number of dynamical interactions between technical, tactical, fitness and anthropometric characteristics of players (Sampaio *et al.*, 2013). In general, available research has used the game-related statistics to identify the most important performance indicators (Ittenbach *et al.*, 1992; Karipidis *et al.*, 2001; Sampaio & Janeira, 2003b; Trninic *et al.*, 1999) and, afterwards, has modelled performance with the help of several situational variables such as game location, quality of opponent or scoring line (Gómez *et al.*, 2013; Gomez *et al.*, 2013). In addition, it has been possible to understand the effects of using alternative defensive strategies, such as individual or zone defence (Gómez *et al.*, 2006) or to comprehend how the defensive pressure (full or half court press) affects technical actions (Sampaio, Leser, *et al.*, 2015). Results available are mainly based on samples from European competitions and suggest that basketball performance depends offensively on shooting field-goals and defensively on securing defensive rebounds (Karipidis *et al.*, 2001; Malarranha *et al.*, 2013; Sampaio & Janeira, 2003b). However, in more specific contexts such as close contested games, the fouls and the free-throws might exhibit higher importance (Kozar *et al.*, 1994; Sampaio & Janeira, 2003b). Most of these results can also be identified during the playoffs stages of the competition, where players are required to respond to critical moments and circumstances that are substantially different from the regular season (García *et al.*, 2013).

The other game-related statistics such as offensive rebounds, turnovers, steals or assists, seem

to be inconsistently reported as discriminators between winners and losers. There are also results that relate the best performances to assists, steals and blocks, denoting the importance from passing skills as long as exterior and interior defensive intensity (Ibanez *et al.*, 2008). Most recently, players' external load started to be measured more accurately, providing important information not only about performance (Sampaio, McGarry, Calleja-Gonzalez, Jimenez Saiz, *et al.*, 2015), but also about the risk of injury (Caparrós *et al.*, 2017).

Playing time and player status have also drawn attention from researchers. Unsurprisingly, turnovers seem to be the most important factor when contrasting important and less important players, with fewer errors being made by important players (Sampaio *et al.*, 2010). Recent studies performed with NBA (National Basketball Association from the United States of America) players added that that playing time seem to have a key role in enhancing lower-body power, repetitive jump ability, and reaction during the competitive season (Gonzalez *et al.*, 2013).

One of the most recent trends in sports science is the individualization of all protocols for training and monitoring, especially in NBA, where the highly-congested schedule can directly affect the players' performance (Teramoto *et al.*, 2017). In fact, it seems clear that each player responds individually to the stress of practice and competition, whereby it seems to be a need to use updated performance models to act as starting points in players' preparation, as well as fine-tuned measurements of their performance (Sampaio *et al.*, 2014b). Several approaches were done using NBA games attempting to fine-tune the models that can serve this purpose for high-level basketball. For example, it has been shown that NBA all-star players perform consistently better within 12 feet of the basket and it was possible to identify groups of performers, particularly related to roles of scoring, passing, defensive and all-round tasks in

the game (Sampaio, McGarry, Calleja-Gonzalez, Saiz, *et al.*, 2015). These performance differences are influenced by players' court-position and have a straight repercussion on their playing time (Mateus, Gonçalves, *et al.*, 2015). Nonetheless, caution seems necessary in potential assumptions relating players' court-positions and game-statistics, particularly in guards and centres, since the continuous evolution of the game and the players' athleticism levels are probably increasing within-position variability (Mateus, Gonçalves, *et al.*, 2015). The problem of individualization contrasts with the obvious need of considering the players as part of a team. On one hand, the coaches need to individualize preparation but, on the other hand, they also need to pull the team together. Available research tries to minimize the individualization problem by grouping players using their game specific positions, using three or five different levels (Calleja-Gonzalez *et al.*, 2016; Mateus, Goncalves, *et al.*, 2015; Pojskic *et al.*, 2015; Shaoliang *et al.*, 2017). However, considering the above-mentioned evidences, there is always criticism to these standardized and subjective grouping procedures. Therefore, the possibility of using methodologies that are capable of extending the stage of playing position analysis and provide information about individual performance that might be very helpful to reveal new insights about the true value of players. Finally, evaluating players by individual performance profiles is too much dependent on their scoring capabilities (Mertz *et al.*, 2016), that is, point production might obscure all the other positive and negative actions from the players. This way, basketball analysis could provide clearer results by using different levels of point production in the games.

Based on the above consideration, the current exercise of modelling will try to provide an individualized perspective of performance in the basketball games having in mind the differences in point production from the players and their specific positions.

4.2 The current problem of the existing analysis method

Basketball is a team sport where box-score statistics are often used to help identifying the reason that explains the game outcome (Sampaio & Janeira, 2003a). However, the box-scores only contain information that describes the frequency of actions performed by players of both teams in a game. This description can be often considered as a complete representation of the game, however, measuring performance is still a never-ending problem for basketball coaches, trainers or recruiters (Shea & Baker, 2013). Player tracking technology is one of the most recent technological advances in basketball (Sampaio, McGarry, Calleja-Gonzalez, Jimenez Saiz, *et al.*, 2015). Powerful computer vision systems were designed with fine-tuned algorithms capable of tracking with relatively high accuracy the players' positioning and, subsequently, all derived variables such as distance covered and speed (Sampaio, McGarry, Calleja-Gonzalez, Jimenez Saiz, *et al.*, 2015). A very interesting advance is the combination of performance dimensions, such as the physiological and technical throughout the usual notational analysis. Therefore, it is possible, for example, to analyse the distance covered by the players when the team is attacking and when the team in defending. The studies focused on positional-derived variables in basketball are still very limited to small samples of young basketballers, by examining physical demands (Ben Abdelkrim *et al.*, 2007), effects of defensive pressure on movement behaviour (Leite *et al.*, 2014) and effects of activity workload in tactical performances (Sampaio *et al.*, 2014a).

Nowadays, there is an urgent need to develop and implement the use of adequate performance indicators. In fact, sports organizations are collecting substantial amounts of game-related data, however, most frequently there is no certainty that these measures are really linked with performance and with success (McLean *et al.*, 2018). The gathered data needs to be transformed into performance indicators, with the aim of producing measures linked to

performance processes and outcomes (McLean *et al.*, 2018). Basketball performance is complex in a way that interactions between players and opponents provide for emergent behaviour to occur. Conversely, performance is also dynamic, meaning that most interactions can be time dependent and, finally, performance have substantial non-linear properties, because the output of the system is almost never directly proportional to its input. Therefore, theoretically, the performance indicators should be able to capture most global or partial aspects of the complex, dynamic and non-linear properties as required.

Current research has used several criteria to approach validity of performance indicators such as contrasting between winners and losers (Gómez *et al.*, 2008) elementary and advanced statistical techniques. The actual holistic understanding of the game often requires analysing several sets of (dependent) variables simultaneously and, therefore, the use of statistical procedures such as multivariate analysis of variance, principal components analysis, discriminant analysis, cluster analysis or artificial neural networks may be the most appropriate to be used (Bracewell, 2003).

In all professional and developmental basketball leagues, the data gathering process is standardized and regulated by the operational definitions and criteria published in the Basketball Statisticians Manual (FIBA, 2009). This is a very important point that ensures intra and inter-operator reliability; however, by having reliable data, the assumption of validity is not necessarily comprised, i.e., although the data may be consistent it is not obvious that most of these actions are really transmitting information about performance. Nevertheless, the game actions presented in the box-scores and defined in this official manual are the following: free throws, field goals, rebounds, assists, steals, turnovers, blocked shots and fouls. Using these actions, there has been an intensive search for an accurate group of performance

indicators (Oliver, 2004), so it has been suggested that the best breakdown of offensive and defensive performances can be obtained by analysing four factors in the following order of importance: (1) effective field-goal percentage, (2) offensive rebounding percentage, (3) turnovers per ball possession, and (4) free-throw rate (Kubatko *et al.*, 2007; Oliver, 2004). Offensively, a team wants to minimize turnovers per possession and maximize all the other factors. These factors are not all equivalent, meaning that for NBA games the relative weights of these are approximately 10, 6, 3, and 3, respectively for each factor, but that might change in other competitions (Kubatko *et al.*, 2007).

In a basketball team, point scoring often obscures other key determinants of collective success that supposedly can be measured using other box-score statistics (Zuccolotto *et al.*, 2017). A possible alternative solution to refine performance metrics can be proposed by classifying players into different levels of point production. This way, lower-scoring players would improve their chances of having their performance evaluated and recognized and, later, coaching staffs can access objective data to provide suggestions for improvement. Following up this idea of analysing different levels of scoring production, there is a clear need to identify the subset of other game statistics that discriminate these levels of point production, when accounting for specific game positions (guards, forwards and centres) that probably have different action requirements. At the end, an optimized model can be built by comparing players' performances in a multidimensional space containing the most important variables and accounting for their point production and specific court position. Obtained results would likely contribute to help understanding the complex interactions that determine successful performances in the game.

4.3 Concepts and methods of modelling

A possible approach to the problem will require the sequential usage of three different techniques: (i) cluster analysis, (ii) discriminant analysis and (iii) nearest neighbor analysis.

Figure 4.1 Depiction from the three steps of a possible approach

Figure 4.1 presents the depiction of a possible approach. The first step to accomplish the analysis consisted of using a two-step cluster analysis, a technique designed to reveal natural groupings within large datasets that would otherwise not be apparent. The log-likelihood is used as distance measure and the Schwarz's Bayesian Criterion as clustering criterion. The log-likelihood places a probability distribution on the variables in a way that continuous variables are assumed to be normally distributed, while categorical variables are assumed to be multinomial. In addition, all variables are assumed to be independent, however, empirical internal testing indicates that the procedure is fairly robust to violations of these assumptions. This method is a scalable cluster analysis algorithm designed to handle very large data sets (both continuous and categorical variables or attributes). The two steps consist of pre-clustering the cases into many small sub-clusters and then cluster the sub-clusters resulting from pre-cluster step into the desired number of clusters (Chiu *et al.*, 2001; Zhang *et al.*, 1996).

The descriptive discriminant analysis aims to identify a smaller subset of variables able to discriminate between *a priori* defined groups, in this case, using the categories obtained by the previous cluster analysis as the levels from the grouping variable. This technique seeks out a linear combination of large amounts of variables for each group that maximizes their differences for proper classification. The analysis provides a classification function that determines to which groups an individual belongs. All independent variables enter the model together and the prior probabilities of classification were entered according to the size of the groups (Cooley & Lohnes, 1971; Tatsuoka, 1971). The obtained classification function coefficients can be used to develop predictive equations from the level of scoring in each playing position. The most important variables are identified by the structure coefficients who reached values above |0.30| and the precision of the models are evaluated by the leave-one-out method (Pedhazur, 1982).

The nearest neighbour analysis (kNN) is a non-parametric technique that can be used for classification, where the input consists of the k closest training examples in the feature space. A case is classified by a majority vote of its neighbours, with the case being assigned to the class most common among its k nearest neighbours (k is a positive integer, typically small). For example, if k=1, the case is simply assigned to the class of that single nearest neighbour. The kNN can be using as features the most important variables identified by the discriminant analysis and as target the levels identified by the cluster analysis. The number of neighbours (k) can be automatically determined, after testing a minimum of 3 and maximum of 20. Usually, only the model with less error rate is selected and presented. The Euclidean metric is used to compute distances weighted by the importance of the features (Arya & Mount, 1993; Cunningham & Delaney, 2007; Friedman *et al.*, 1977). In addition, there is a training and a holdout partition that comprised 70% and 30% of the sample, respectively.

4.4 Methodological experience

Data analysis was performed in the NBA database containing all players' performances from the 2015-2016 regular season. The raw data file contained originally 27966 cases, but was transformed in order to aggregate each player performance into a single profile row, by averaging the values from all the available game variables. The experience can be done with these average values, but researchers can also use other approaches such as standard deviations, coefficient of variation, 25th percentile or 75th percentile. For example, using the coefficient of variation can be appropriate to approach variability and obtain information about how players adapt to the different environments and perform. Additionally, using the 25th percentile can allow to obtain information about the worst performance scenarios, whereas using the 75th percentile can allow to describe the best performance scenarios.

From the original database, there were forty-three players averaging less than half-quarter of play (6-min) during the season and they were removed from the database. The final number of players in the file was 488 from the 30 participating teams.

Figure 4.1 presents the depiction of the proposed approach. The two-step cluster analysis was carried out using the continuous variable points scored per minute of play and the number of clusters will be determined automatically. Expectably, this procedure will enable to classify players according to their different levels of scoring and, afterwards, this new categorical variable will allow understanding better players' performance contributors.

The discriminant analysis was the second step in the analysis, allowing identifying the smaller subset of game variables that can discriminate players' different levels of scoring, but also according to their court positions (guards, forwards and centres).

The independent variables were a set of thirteen game variables:

- 2-point field-goal percentages
- 3-point field-goal percentages
- Free-throw percentages
- Average defensive rebounds per game
- Average offensive rebounds per game
- Fouls committed
- Turnovers
- Blocks
- Assists
- steals
- speed
- distance covered
- touches per minute of play

At the end of this stage, it was possible to identify the most powerful game actions in discriminating different levels of scoring for guards, forwards and centres. Also, the obtained equations can help in classifying new cases into the scoring groups.

The third step, nearest neighbour analysis (kNN), consisted of classifying the players' performances based on their similarity to other players and was performed for each playing position, using as features the most important variables identified by the discriminant analysis and as target the levels of scoring determined by the cluster analysis. The kNN technique will allow identifying the most similar players using the most important game variables according

to the level of scoring and playing positions. All the analyses were performed using IBM SPSS software (release 22.0, SPSS Inc., Chicago, IL).

4.5 Results

4.5.1 Determining different levels of scoring

In the first step, the obtained results provided an automatically determined solution with two clusters, with a good silhouette measure of cohesion and separation (average silhouette=0.7). A new categorical variable was saved in the database with these classification results. For designation purposes, one of the clusters was labelled as “lower-scoring players” and gathered 258 players (53%) averaging 0.30 ± 0.06 points per minute (range 0-0.38) and the other cluster was labelled as “higher-scoring players”, gathering 230 players (47%) that averaged 0.49 ± 0.09 points per minute (range 0.39-0.85). Cross-tabulations between the obtained cluster solution and playing positions produced very similar distributions (lower-scoring guards – 52.9%, higher-scoring guards – 47.1%; lower-scoring forwards – 54.9%, higher-scoring forwards – 45.1% and lower-scoring centres – 51.3%, higher-scoring centres – 48.7%).

4.5.2 Identifying a smaller subset of important variables

In the second step, the obtained discriminant functions were all significant ($p \leq 0.001$) with chi-square values of 119.7 for guards, 105.9 for forwards and 42.8 for centres. The canonical correlations were of 0.66 for guards, 0.66 for forwards and 0.68 for centres. Table 1 presents the linear classification function coefficients and structure coefficients for each playing position and scoring level. Concerning the structure coefficients, there were clear differences between playing positions. Nevertheless, there were variables achieving high discriminant status for all positions, such as the free-throws and turnovers, and more moderate variables, such as the assists and the defensive rebounds. Interestingly, distance covered and running

speed were the only variables with no substantial discriminant status. In addition, the guards' discriminant variables were related to field-goals (two and three-point), the forwards to many other variables and the centres to three-point field goals, touches and steals (see Table 4.1).

The linear classification function coefficients allow calculating the discriminant scores for a given case (see Table 4.1). The case example data (Stephen Curry) was used to calculate the discriminant score for each possibility of classification (Discriminant score = $\text{Variable1} * \text{Coefficient1} + \text{Variable2} * \text{Coefficient2} + \dots + \text{constant}$). Afterwards, the higher discriminant score will correspond to the higher probability of being classified in that group. In the case example, the player will be classified as a higher scoring guard (Discriminant score_{lower scoring}=696 vs Discriminant score_{higher scoring}=708).

The leave-one-out classification allowed to test the accuracy of these models and for each playing position the obtained results were high (guards=80.2%, forwards=80.1% and centres=79.5%).

The discriminant scores can be used to analyse several aspects of performance. For example, Figure 4.2 presents the distribution of discriminant scores per player and per team, according to high and low-scoring players. Each of the panels allows identifying the teams' homogeneity in each situation.

Table 4.1 Linear classification function coefficients for higher and lower scoring players and structure coefficients for each position.

Variables	Case Example	Guards			Forwards			Centres		
		Lower scoring	Higher scoring	SC	Lower scoring	Higher scoring	SC	Lower scoring	Higher scoring	SC
Assists	6.39	0.48	-0.01	0.36	1.08	-0.05	0.35	8.75	7.07	0.32
Blocks	0.21	-7.01	-9.33	0.03	4.21	4.54	0.37	-19.72	-20.54	0.16
Distance covered	0.07	1920	1867	-0.20	2818	2837	-0.22	1155	928	-0.28
Def rebounds	4.61	1.57	1.23	0.32	1.57	1.25	0.55	12.41	12.30	0.33
2-pt field goals	48.78	0.32	0.43	0.55	1.01	1.09	0.44	0.89	0.99	0.17
Free-throws	81.42	0.38	0.46	0.74	0.02	0.11	0.73	-0.37	-0.27	0.63
Off rebounds	0.85	-4.87	-5.16	0.13	-13.11	-12.59	0.39	-26.08	-26.91	0.16
3-pt field goals	43.41	0.06	0.09	0.37	-0.06	-0.01	0.18	-0.75	-0.71	0.31
Com fouls	2.06	4.23	3.15	0.20	7.10	6.31	0.33	7.04	6.68	0.25
Speed	4.28	68.78	68.78	-0.18	72.53	70.90	-0.22	163.56	163.14	-0.25
Steals	2.01	-3.50	-3.80	0.28	-17.85	-18.98	0.23	-24.24	-23.10	0.34
Touches	2.48	-1.29	-0.74	0.21	19.61	22.79	0.40	-14.68	-10.33	0.37
Turnovers	3.47	-4.66	-2.89	0.52	7.45	8.96	0.52	26.31	28.00	0.52
(Constant)		-228.19	-231.31	-	-286.84	-292.28	-	-386.53	-382.93	-
Discriminant score		696	708							

Note: the case example provided in the second column refers to the game average performance of the guard Stephen Curry.

Figure 4.2 Histograms of teams' constitution profile according to high-scoring players (upper panel) and low-scoring players (lower panel)

In high-scoring players, for example, SAC has one player that clearly detaches positively from the rest of the team, whereas LAC has one player that detaches negatively (Figure 4.2). WAS seems a very homogeneous team and OKC players are much more spread, showing more inter-players' differences in performance. In low-scoring players, several teams show at least one player much detached from the rest (BOS, CHI, HOU, MEM, MIN, NOP, ORL, PHI, SAC, TOR). The player from NOP had the smaller discriminant score in the whole sample.

Figure 4.3 Teams' constitution profile according to high-scoring players (upper panel) and low-scoring players (lower panel) for each playing position: Centres (C); Forwards (F); Guards (G). The discriminant scores are the sum for the players in the specific positions.

Complementary to the previous information, the Figure 4.3 depicts the teams' constitution profile, according to high and low-scoring players for each playing position. This visualization allows to understand how the previous discriminant scores for each specific position help to identify teams' relative strengths and weaknesses. For example, SAC, OKC, MEM and GSW are identified as teams most represented by discriminate scores from high-scoring centres. Conversely, there are no players from CLE, DET, LAL, NYK and POR in this group, meaning that these teams have different scoring and playing profiles. By analyzing the forwards' performance, NOP, NYC and OKC were the top teams from the high-scoring group and TOR, SAC, ORL the top teams from the lower-scoring group. This last result denotes the problems from these teams in scoring and performing in these positions, when compared to the other teams. Finally, GSW, HOU and PHI were the teams with higher performance in guards from the high-scoring group and NOP denoting performance problems as seen by the lower-scoring discriminant scores. This analysis can be useful to evaluate teams by their complementary performance profiles, as well as to scout the opponents and recruit new prospects.

4.5.3 Identifying the most similar player

In the third step, the analysis from the guards yielded good percentages of correct classifications for training (76.4%) and holdout (70.0%). Nevertheless, lower scoring players had better percentages of correct classifications (83.3% vs 68.5% in training and 78.6% vs 62.5% for holdout).

Figure 4.4 presents a lower-dimensional projection of the predictor space, that contains six predictors ($k=7$ error=0.22). In addition, the quadrant map presented in Figure 4.5 compares the most point productive guard (focal case: Stephen Curry) with their seven neighbours when

performing in the most important predictors. The analysis from the forwards yielded good percentages of correct classifications for training (75.8%) and holdout (76.2%). Again, the lower scoring players had better percentages of correct classifications (90.4% vs 56.4% in training and 93.5% vs 59.4% for holdout).

Figure 4.6 presents a lower- dimensional projection of the predictor space that contains nine predictors ($k = 4$, error = 0.20). In addition, the quadrant map from Figure 4.7 compares the most point- productive forward (Kevin Durant) with their four neighbours. The analysis from the centres yielded good percentages of correct classifications for training (69.1%) and holdout (82.6%). In contrast to the other playing positions, the higher- scoring players had better percentages of correct classifications (67.9% vs. 70.4% in training and 75.0% vs. 90.9% for holdout).

Figure 4.8 presents a lower- dimensional projection of the predictor space that contains seven predictors ($k = 11$, error = 0.29). The quadrant map presented in Figure 4.9 refers to the comparison from the center with higher values of points scored per minute of play (DeMarcus Cousins) and their k - neighbors concerning four predictors. There was one case of a player classified as low- scoring (Rudy Gobert) that reached similar performances of the other peers.

Figure 4.4 Lower-dimensional projection of the predictor space, containing the six predictors: free-throws (FT_percent), 2-point field-goals (FG_percent), turnovers, 3-point field-goals, assists and defensive rebounds (DREB_mean). The focal case is the guard with higher points scored per minute of play (Stephen Curry). Circles represent training cases, and triangles holdout cases. The higher-scoring players have dark filling and the lower-scoring players light filling.

Figure 4.5 Target values by predictors for initial focal cases and nearest neighbours. The focal case is the guard with higher points scored per minute of play (Stephen Curry). Circles represent training cases and triangles holdout cases. The higher scoring players were allocated with a score of 2 and lower- scoring players with a score of 1 (dummy variable).

Figure 4.6 Lower-dimensional projection of the predictor space, containing the nine predictors: free-throws (FT_percent), defensive rebounds, turnovers, 2-point field goals, Touches (touches_min), offensive rebounds, blocks (BLK_mean), assists and committed fouls. The focal case is the forward with higher points scored per minute of play (Kevin Durant). Circles represent training cases and triangles holdout cases. The higher-scoring players have dark filling and the lower-scoring players light filling.

Figure 4.7 Target values by predictors for initial focal cases and nearest neighbours. The focal case is the guard with higher points scored per minute of play (Kevin Durant). Circles represent training cases and triangles holdout cases. The higher- scoring players were allocated with a score of 2 and lower- scoring players with a score of 1 (dummy variable).

Figure 4.8 Lower-dimensional projection of the predictor space, containing the seven predictors: free-throws (FT_percent), touches, turnovers (TOV_mean), 3-point field-goals, assists (AST_mean), defensive rebounds (DREB_mean) and steals. The focal case is the center with higher points scored per minute of play (DeMarcus Cousins). Circles represent training cases and triangles holdout cases. The higher- scoring players have dark filling and the lower- scoring players light filling.

Figure 4.9 Target values by predictors for initial focal cases and nearest neighbours. The focal case is the guard with higher points scored by per minute of play (DeMarcus Cousins). Circles represent training cases and triangles holdout cases. The higher- scoring players were allocated with a score of 2 and lower- scoring players with a score of 1 (dummy variable).

4.6 Practical application

Accessing basketball performance requires using holistic perspectives and, therefore, several questions can be explored at the level of critical thinking and decision making, such as:

- (i) Using variables that provide information from several different dimensions (tactical, technical and physical aspect);
- (ii) Using variables that isolate individual performance and variables that are related to collective behaviour;
- (iii) Using variables that describe the performed actions, but also variables or procedures that explore interactions;
- (iv) Using variables that describe game macro-structures (5x5) and micro-structures (1x1,...);
- (v) Using combined static, dynamic and self-organized perspectives of complexity;
- (vi) Using combined statistical techniques.
- (vii) Design a model of basketball performance by describing different levels of analysis and the situational variables that might influence the coupling subject/team-task-environment at each level.
- (viii) Reinforce the proposed model, by designing an adequate evaluation method for each level.

Tesis Doctoral

D. Shaoliang Zhang

Volume 36(22), 2511-2520

CHAPTER 5

Players' Technical and Physical Performance Profiles and Game-to- game Variation in the NBA

*Shaoliang Zhang, Alberto Lorenzo, Miguel-Angel Gómez
Hongyou Liu, Bruno Gonçalves & Jaime Sampaio*

Chapter 5 Players' Technical and Physical Performance Profiles and Game-to-game Variation in the NBA

5.1 Introduction

The process of preparing basketball teams at the highest standard of competition is complex and depends upon the interactions of technical, tactical, physical, psychological and physiological characteristics of available players (Csataljay *et al.*, 2009; Sampaio *et al.*, 2015). Currently, performance analysis provides information on both the physical activity, the technical and tactical responses of each player and team during the games (Hughes & Franks, 2004). The available research has clarified the relationship between players' technical performances and game final outcome (Gómez *et al.*, 2009; Sampaio, Drinkwater, *et al.*, 2010; Sampaio, Janeira, *et al.*, 2006). For instance, defensive rebounds and two point field goals would be commonly regarded as discriminant variables between winning and losing teams (Csataljay *et al.*, 2009; Gómez *et al.*, 2008; García *et al.*, 2014). However, contrasting winners' and losers' performance can only provide limited information for teams' success at a given instant, because successful teams can also lose some games and vice-versa. Therefore, some studies have used different methods to evaluate and compare the quality of teams and their opponents, such as multi-criteria assessing methods like TOPSIS and AHP (Dadelo *et al.*, 2014; Kiani Mavi *et al.*, 2012) or cluster analysis (Marcelino *et al.*, 2011; Sampaio, Drinkwater, *et al.*, 2010). Besides, teams' quality has either been subjectively categorized as "successful" or "unsuccessful" according to their standings or winning percentage within a particular tournament (Gómez *et al.*, 2017; Ibáñez *et al.*, 2008; Pollard & Gómez, 2007; Sampaio, Ibáñez, *et al.*, 2006) or classified as "strong" or "weak" and "top half" or "bottom half" based on symmetric division of end-of-season classification (Doğan *et al.*, 2016; Sampaio, Lago, *et al.*, 2010). However, there is less available research about exploring the

difference of technical and physical performances of players according to the specific position between different levels of teams. Therefore, the development of technical and physical performance profiles considering team quality would be necessary to reveal new trends and also to provide useful information to support coaching staffs tailoring optimal strategies and training plans.

Another important issue that has been given limited attention is the concept and interpretation of the game-to-game variation of the technical and physical performances of basketball players (Mateus *et al.*, 2015; Pinilla Arbex *et al.*, 2015). As a matter of fact, one of the most common features of human movement is its variability. It is suggested that better performances can be achieved when variability increases to a point of higher instability, followed by an automatic switch to a new and more stable movement pattern with less variability (Stergiou & Decker, 2011; Thelen, 1995). In other words, biological systems self-organize according to environmental, biomechanical, and morphological constraints to find the most stable solution for producing a given movement (Clark & Phillips, 1993; Hamill *et al.*, 1999). Thus, increased variability in a movement pattern generally indicates loss of stability, while decreased variability generally demonstrates a highly stable behaviour (Stergiou & Decker, 2011). In fact, movement execution will inevitably give rise to movement variability because motor output (motor commands, muscle contractions, or muscle torques) is inherently variable (van Beers *et al.*, 2004). In order to more effectively execute movement pattern in a given environment, decreasing variability seem to be commonly regarded as the best ideal solution (Newell & Corcos, 1993; Stergiou *et al.*, 2006). In team sports, players maintain stable performance and effectively perform technical and tactical strategies on the court, leading to the success of the teams in a long term performance (Liu *et al.*, 2016).

In particular, the basketball games can be considered as complex, unstable, adaptive and dynamic systems in which players try to keep lower variability of their own attacking and defending balance and to destabilize the balance of the opposition (Guerra *et al.*, 2013; Oliver, 2004). Several situational variables such as game outcome, game location, quality of opposition or team quality, are considered as very important variables that influence individual and collective performances (Gómez *et al.*, 2008; García *et al.*, 2013; Ibáñez *et al.*, 2003; Lorenzo *et al.*, 2010). For example, due to the effect of crowd factors, learning/familiarity factors, travel and rule factors on players' performance (Carron *et al.*, 2005), players are likely to display lower variability in technical and physical performances in home games than away games. In fact, Sampaio *et al.* (2008) have identified that the game context, such as game location, has a huge impact on performance of basketball players from different positions. However, there is still a lack of understanding for the variability of players' performances from different positions under different situational variables. Consequently, analysing the variation of players' performances from different positions incorporating possible influences of different environmental constraints (game contextual variables) would make a very important contribution to a better understanding of the basketball game (Mateus *et al.*, 2015).

Based on previous considerations, the aims of the current study were to compare the between-player differences in technical and physical performances of strong and weak teams according to players' specific field positions and, to explore the within-player game-to-game variation of technical and physical performances taking consideration of four contextual variables, i.e., team and opposition quality, match outcome and match location. We hypothesized that there may be the differences in terms of game statistics and physical aspects for players from different positions between strong and weak teams and game-to-game variation in technical

and physical aspects across different playing positions would be influenced by situational variables.

5.2 Methods

5.2.1 Sample

Archival data were obtained from open-access official NBA records during the 2015–2016 regular season (available at <http://stats.nba.com>). A total of 699 games were selected based on the balance score inclusion criteria during the regular season, i.e., games that ended with final score differences equal to or less than 10 points (Ferreira *et al.*, 2014). The game-related statistics were transformed to per-minute statistics ($\text{original statistics}/\text{min} \times 40$) according to players' game duration on the court (Kubatko *et al.*, 2007). The players with less than 500 minutes played in the whole season were excluded from the sample, as those players' transformed data were regarded as unreliable per-minute statistics (Kubatko *et al.*, 2007). In addition, the players who played only one game or less than five minutes were also excluded from the sample (Sampaio, Janeira, *et al.*, 2006), which limited the sample to 354 players with 12724 performance records. Players were divided by three different categories based on playing positions: Guards ($n = 155$ players, observations = 5453), Centres ($n = 59$, observations = 2148), and Forwards ($n = 140$, observations = 5123). In order to precisely make sure the players' position, playing certain position was determined by referring to the NBA official website (<http://stats.nba.com>).

5.2.2 Data source and validity

In order to test the validity of data sets, a sub-sample of 20 games (final score differences equal to or less than 10 points) were randomly selected and observed by two experienced analysts (basketball coaches with more than 5 years of experience in basketball performance

analysis). The results were contrasted with the gathered data in the website and perfect Intra-class Correlation Coefficients (ICC=1.0) were obtained for free-throws, two-and three-pointers (both made and attempted), offensive and defensive rebounds, turnovers, steals, blocked shots, personal fouls, passes made. For the assists and touches, the results were lower, but still very acceptable as valid (ICC = 0.91). There was a formal approval of all procedures from the Local Institution of Research Review Board.

5.2.3 Variables

A total of seventeen game actions and events were selected as variables in the analyses (Mateus *et al.*, 2015; Sampaio *et al.*, 2015). Analysed variables included non-tracking variables, tracking variables and situational variables per game.

Non-tracking variables

- Two Pointers made (2PM): The number of two point field goals that a player or teams has made.
- Two Pointers attempted (2PA): The number of two point field goals that a player or teams has attempted.
- Three pointers made (3PM): The number of three point field goals that a player or teams has made.
- Three pointers attempted (3PA): The number of three point field goals that a player or teams has attempted.
- Free Throws made (FTM): The number of free throws that a player or teams has successfully made.
- Free Throws attempted (FTA): The number of free throws that a player or teams has taken.
- Offensive Rebounds (OREB): The number of rebounds that a player or teams has

collected while they were on offense.

- Defensive Rebounds (DREB): The number of rebounds that a player or teams has collected while they were on defence.
- Assists (AST): An assist occurs when a player completes a pass to a teammate that directly leads to a made field goal.
- Turnovers (TOV): A turnover occurs when the teams on offense loses the ball to the defence.
- Steals (STL): A steal occurs when a defensive player takes the ball from a player on offense, causing a turnover from offensive players.
- Blocked Shots (BLK): A block occurs when an offensive player attempts a shot, and a defensive player tips the ball, blocking their chance to score.
- Personal Fouls (PF): The total number of fouls that a player or teams has committed.
- Touches (TCHS): The number of times a player touches and possesses the ball during the game.
- Passes Made (PASS): The total number of passes a player made during the game.

Tracking variables

- Distance Run (DIST): The total distances in miles that a player covered while on the court.
- Average Speed (SPD): The average speed in miles per hour of all movements (sprinting, jogging, standing, walking, backwards and forwards) by a player while on the court.

Situational variables

- Quality of the team and opposition. The teams that entered into the play-off season were defined as strong teams/oppositions and the teams that did not enter into the next phase were classified as weak teams/oppositions (Doğan *et al.*, 2016; Ibáñez *et al.*, 2008; Sampaio, Lago, *et al.*, 2010).

- Match outcome (win and lose).
- Match location (home and away).

5.2.4 Statistical analysis

Records were screened for univariate outliers (cases outside the range $\text{Mean} \pm 3\text{SD}$) and distribution tested in order to carry the inferential analysis (Kerlinger & Pedhazur, 1973).

The first phase was to set up the performance profiles of players between strong and weak teams by using profiling techniques (Butterworth *et al.*, 2013; O'Donoghue, 2005). Count values of the seventeen performance-related game actions and events of all players were transformed into standardized scores (Z-Score, Z) and were unified into the same scale by the formula " $T = 10Z + 50$ " (O'Donoghue, 2013). Using median to compare performances of all players and different position players (i.e. guards, centres and forwards) and represented by plotting into radar charts (Liu *et al.*, 2016).

The second phase was to explore the variation of players' game performance from different positions under four different situational variables (i.e. teams and opposition quality, match outcome and match location). The within-player game-to-game variation was measured by the coefficient of variation (CV) of each game action or event. The differences of variation in performance were compared for (a) winning games and losing games, (b) home games and away games (c) strong teams and weak teams, and (d) strong opposition and weak opposition. For example, if one player performed in 50 games at home and 45 games away, the CV was calculated separately for each condition and compared. In order to calculate the within-player CV ($(\text{standard deviation}/\text{mean}) * 100\%$), only the players who played at least two entire matches were selected in each game context. When the mean of an action or event was 0 (e.g.

0 three point field goals made in 20 games), the CV of this single action or event was defined as a missing value. The software used for these calculations was IBM SPSS Statistics for Windows (Armonk, NY: IBM Corp.) and the radar charts were drawn in the Microsoft Excel (Redmond, Washington: Microsoft). Comparisons of performance profile and variation of match performance were carried using the spreadsheet developed by Hopkins (2007). Nonclinical magnitude-based inferences were applied and were evaluated by using the smallest worthwhile difference, calculated by 0.2 times the standardization estimated from between-subject standard deviation. For the comparison of players' performance profile and variation of match performance, the 90% confidence intervals were used to make the inferences (Hopkins, 2007). Magnitudes of clear differences were assessed as follows: <0.20, trivial; 0.20–0.60, small; 0.61–1.20, moderate; 1.21–2.0, large; >2.0, very large (Batterham & Hopkins, 2006). Differences were defined as unclear when the confidence limits for the effect size include both substantial positive and negative values ($\pm 0.2 \times \text{standardization}$) (Hopkins *et al.*, 2009). Likelihood of the magnitude to be clear was defined as follows: <0.5% most unlikely; 0.5-5 very unlikely; 5-25%, unlikely; 25-75%, possibly; 75-95%, likely; 95-99.5%, very likely; >99.5%, most likely (Hopkins *et al.*, 2009).

5.3 Results

The comparison of performance variables between players from strong and weak teams can be found in Table 5.1 and Figure 5.1. There were some clear differences in terms of technical variables in centres and forwards position and physical variables in guards and forwards position between strong teams and weak teams.

Table 5.1 Descriptive statistics of players' performance between strong and weak teams

Variable	All performances (n=12724)		Guards (n=5453)		Centres (n=2148)		Forwards (n=5123)	
	Strong	Weak	Strong	Weak	Strong	Weak	Strong	Weak
2PM	4.54±3.26	4.69±3.31	4.35±3.16	4.02±2.87	5.81±3.31	6.40±3.67	4.19±3.22	4.71±3.35
2PA	9.38±5.36	9.84±5.49	9.30±5.23	8.89±4.78	11.4±5.35	12.8±6.07	8.58±5.26	9.67±5.55
3PM	1.27±1.64	1.16±1.56	1.64±1.70	1.61±1.64	0.23±0.79	0.16±0.58	1.32±1.65	1.10±1.56
3PA	4.00±3.61	3.53±3.37	5.12±3.41	4.87±3.11	0.74±1.91	0.52±1.26	4.24±3.54	3.34±3.39
FTM	2.62±2.98	2.59±2.93	2.83±3.15	2.53±2.90	2.85±2.93	2.86±3.05	2.29±2.78	2.54±2.90
FTA	3.51±3.74	3.46±3.68	3.53±3.77	3.24±3.54	4.46±4.09	4.06±3.93	3.09±3.45	3.45±3.68
OREB	1.64±2.03	1.60±2.01	0.87±1.33	0.70±1.15	3.34±2.48	3.18±2.35	1.76±2.01	1.94±2.11
DREB	5.39±3.67	5.35±3.62	3.85±2.82	3.89±2.82	8.01±3.88	7.82±3.78	5.95±3.60	5.90±3.62
AST	3.28±3.06	3.28±3.06	4.49±3.37	4.64±3.44	1.91±2.20	2.33±2.43	2.58±2.52	2.29±2.26
TOV	2.09±1.98	2.22±2.02	2.34±2.05	2.45±2.08	1.97±1.91	2.28±2.07	1.86±1.90	1.96±1.89
STL	1.20±1.44	1.13±1.39	1.36±1.46	1.28±1.44	0.94±1.36	0.95±1.33	1.13±1.43	1.06±1.35
BLK	0.70±1.16	0.70±1.20	0.40±0.84	0.32±0.77	1.41±1.52	1.55±1.52	0.74±1.18	0.78±1.24
PF	3.47±2.51	3.50±2.49	3.08±2.29	3.10±2.28	4.17±2.64	4.25±2.70	3.59±2.60	3.63±2.53
DIST	2.77±0.18	2.81±0.18	2.81±0.17	2.86±0.17	2.70±0.18	2.70±0.17	2.75±0.18	2.80±0.17
SPD	4.15±0.26	4.20±0.26	4.20±0.25	4.27±0.24	4.05±0.26	4.05±0.25	4.13±0.26	4.18±0.25
TCHS	69.2±21.0	69.7±21.7	74.7±24.3	76.0±24.4	67.0±16.3	67.6±17.8	64.3±17.3	64.0±18.0
PASS	49.6±17.7	50.0±18.9	53.0±20.5	55.0±21.6	49.1±14.1	48.1±15.0	46.2±14.9	45.5±15.8

Note: (Values are mean ± S.D. Per- × 40 statistics, except for SPD). Abbreviations: = Two Pointers made; 2PA = Two Pointers attempted; 3PM = Three pointers made; 3PA = Three pointers attempted; FTM = Free Throws made; FTA = Free Throws attempted; OREB = Offensive Rebounds; DREB = Defensive Rebounds; AST = Assists; TO V = Turnovers; STL = Steals; BLK = Blocked Shots; PF = Personal Fouls; DIST = Distance Run (Miles); SPD = Average Speed (MPH); TC HS = Touches; PASS = Passes Made.

Figure 5.1 Comparison of the performance profiles of overall and different position's players from Strong and Weak teams. Notes: Letters in parentheses denote the magnitude: t = trivial; s = small; m = moderate; l = large. Asterisks indicate the likelihood for the magnitude of the true difference in means as follows: *possible; **likely; ***very likely; ****most likely.

The differences were clear in physical variables when comparing all players together; players from strong teams covered shorter distances (possibly small difference; ES=0.21) and lower speeds (possibly small difference; ES=0.20) than weak teams. The comparisons of players from different positions between strong and weak teams showed different results. Firstly, there were main differences in physical variables for guards between strong and weak teams. Guards from strong teams covered less distances (most likely small difference; ES=0.28) and lower speeds (very likely small difference; ES=0.27). Secondly, centres presented the biggest

difference in terms of shooting ability. Centres from strong teams made less two-point field goals (likely small difference; $ES=0.25$) and attempted (likely small difference; $ES=0.24$), but made more three-point field goals (very likely small difference; $ES=-0.46$) and attempted (most likely moderate difference; $ES=-0.73$) comparing to their peers from weak teams. Finally, there were clear differences for forwards in technical and physical variables between strong and weak teams. In technical aspect, forwards from strong teams shot more three-point field goals (possibly small difference; $ES=-0.20$) but fewer in two-point field goals (possibly small difference; $ES=0.21$). In physical aspect, forwards from strong teams run less distances (very likely small difference; $ES=0.25$) and kept lower speeds (likely small difference; $ES=0.24$) comparing to their counterparts from weak teams.

The comparison on the difference of within-player game-to-game variation of technical and physical performances in different positions under different situational variables is presented (in Table 5.2 and Table 5.3 and Figure 5.2). Three point field goals made (3PM) and attempted (3PA) were the most unstable technical game actions that showed substantial differences in variation in all the four situational contexts (Figure 5.2). Almost all of performance variables of players from different positions presented lower variation between home game and away game, and only personal fouls showed higher variation, in forwards position (possibly small difference; $ES=-0.26$), and in centres position (possibly small difference; $ES=-0.20$). Additionally, guards showed lower variation when facing with different levels of opposition.

Table 5.2 Descriptive statistics of the variability of performance variables of players from different positions according to game location and game outcome

Variables	Guards		Forwards		Centres		Guards		Forwards		Centres	
	Win	Lose	Win	Lose	Win	Lose	Home	Away	Home	Away	Home	Away
2PM	71±32 (155)	72±32 (155)	71±34 (140)	72±32 (139)	55±24 (59)	53±20 (58)	72±29 (155)	69±30 (154)	71±29 (140)	71±31 (139)	55±22 (59)	55±22 (59)
2PA	48±21 (155)	48±24 (155)	51±21 (140)	51±25 (140)	42±19 (59)	38±14 (58)	48±21 (155)	47±22 (155)	51±21 (140)	51±21 (140)	40±15 (59)	40±15 (59)
3PM	113±67 (154)	110±49 (154)	142±93 (117)	149±101(120)	269±155(15)	194±130(13)	114±62 (153)	111±52 (154)	145±96 (119)	149±101(121)	246±144(15)	177±84 (12)
3PA	63±38 (155)	60±40 (155)	91±76 (126)	104±100(135)	217±159(22)	240±154(26)	63±49 (155)	62±35 (155)	100±95 (130)	99±91 (132)	224±139(26)	236±152(25)
FTM	125±67 (155)	126±65 (155)	124±56 (138)	141±68 (138)	108±51 (59)	125±60 (58)	125±63 (153)	128±69 (155)	129±54 (139)	133±63 (137)	115±62 (59)	111±42 (59)
FTA	120±64 (155)	119±63 (155)	116±56 (139)	126±61 (137)	95±46 (59)	109±57 (58)	117±59 (153)	123±66 (155)	117±50 (139)	123±61 (138)	101±57 (59)	99±40 (59)
OREB	165±66 (152)	165±60 (152)	120±58 (140)	112±43 (139)	76±26 (59)	77±29 (58)	161±59 (153)	170±64 (151)	115±51 (140)	116±47 (140)	79±32 (59)	78±39 (59)
DREB	72±24 (155)	70±25 (155)	57±20 (140)	60±22 (140)	48±18 (59)	48±18 (58)	72±22 (155)	71±26 (155)	58±18 (140)	59±21 (140)	47±15 (59)	48±22 (59)
AST	70±38 (155)	69±33 (155)	101±50 (139)	97±37 (140)	108±46 (59)	115±51 (57)	71±33 (155)	69±36 (155)	98±41 (140)	99±40 (140)	114±46 (59)	109±47 (59)
TOV	89±35 (155)	91±40 (155)	105±39 (139)	105±41 (138)	92±26 (59)	99±36 (57)	94±44 (155)	88±32 (155)	108±45 (139)	105±44 (140)	97±26 (59)	99±43 (59)
STL	121±51 (155)	119±47 (155)	137±54 (139)	146±61 (139)	150±50 (58)	159±70 (56)	119±42 (155)	118±47 (152)	141±65 (138)	141±65 (137)	152±56 (58)	163±61 (58)
BLK	230±96 (133)	236±92 (133)	172±79 (135)	185±82 (135)	107±39 (59)	112±46 (57)	244±103(137)	233±95 (136)	174±82 (135)	183±76 (136)	107±43 (59)	112±51 (58)
PF	75±23 (155)	70±22 (155)	69±21 (140)	65±19 (140)	61±15 (59)	61±18 (58)	73±23 (155)	71±21 (155)	70±20 (140)	65±20 (140)	61±15 (59)	59±16 (59)
DIST	3.9±1.1 (155)	4.0±1.1 (155)	4.1±1.2 (140)	4.2±1.1 (140)	4.0±1.2 (59)	4.1±1.0 (58)	3.9±1.1 (155)	4.0±1.1 (155)	4.0±1.0 (140)	4.2±1.2 (140)	3.9±0.9 (59)	4.1±1.0 (59)
SPD	3.8±1.0 (155)	3.9±1.0 (155)	4.0±1.1 (140)	4.0±0.9 (140)	3.8±0.9 (59)	4.0±1.0 (58)	3.8±0.9 (155)	3.8±0.9 (155)	4.0±1.0 (140)	4.0±0.9 (140)	3.9±0.9 (59)	3.9±0.8 (59)
TCHS	18±8 (155)	17±7 (155)	20±6 (140)	19±6 (140)	17±5 (59)	18±4 (58)	18±8 (155)	17±7 (155)	19±6 (140)	19±6 (140)	18±4 (59)	18±5 (59)
PASS	22±11 (155)	21±9 (155)	23±7 (140)	23±7 (140)	21±6 (59)	22±5 (58)	23±10 (155)	21±9 (155)	23±7 (140)	23±7 (140)	22±5 (59)	21±5 (59)

Note: (values are mean ± S.D. CV = (Standard deviation/Mean)*100%). Abbreviations: 2PM = Two Pointers made; 2PA = Two Pointers attempted; 3PM = Three pointers made; 3PA = Three pointers attempted; FTM = Free Throws made; FTA = Free Throws attempted; OREB = Offensive Rebounds; DREB = Defensive Rebounds; AST = Assists; TOV = Turnovers; STL = Steals; BLK= Blocked Shots; PF = Personal Fouls; DIST = Distance Run (Miles); SPD = Average Speed (MPH); TCHS = Touches; PASS = Passes Made.

Table 5.3 Descriptive statistics of the variability of performance variables of players from different positions according to team and opposition quality

Variables	Guards		Forwards		Centres		Guards		Forwards		Centres	
	Strong	Weak	Strong	Weak	Strong	Weak	Strong Opp.	Weak Opp.	Strong Opp.	Weak Opp.	Strong Opp.	Weak Opp.
2PM	73±32 (84)	71±25 (79)	73±28 (76)	70±28 (70)	54±14 (31)	57±28 (28)	73±33 (155)	71±33 (155)	71±31 (139)	71±30 (140)	55±23 (59)	56±25 (59)
2PA	50±22 (84)	48±18 (79)	51±17 (76)	51±23 (70)	40±10 (31)	40±18 (28)	48±21 (155)	47±20 (155)	50±20 (139)	50±22 (140)	40±16 (59)	40±16 (59)
3PM	119±72 (83)	106±36 (79)	132±72 (68)	174±147(61)	321±224(10)	293±216(7)	109±47 (152)	114±62 (154)	147±98 (121)	144±98 (117)	253±144(16)	192±108(12)
3PA	65±49 (84)	59±19 (79)	93±101 (73)	138±148(69)	339±233(17)	306±204(15)	64±50 (155)	60±35 (155)	96±81 (130)	98±93 (130)	254±158(27)	224±153(25)
FTM	124±62 (83)	130±76 (79)	132±50 (76)	131±60 (70)	108±50 (31)	119±52 (28)	125±66 (153)	127±61 (154)	135±62 (138)	130±60 (139)	111±44 (58)	113±54 (59)
FTA	118±60 (83)	122±67 (79)	120±47 (76)	120±58 (70)	96±48 (31)	104±46 (28)	120±65 (154)	121±59 (154)	123±58 (139)	118±56 (139)	97±41 (58)	100±53 (59)
OREB	166±68 (83)	170±50 (79)	116±41 (76)	113±42 (70)	74±22 (31)	79±25 (28)	170±70 (154)	166±62 (152)	113±51 (139)	119±51 (140)	81±36 (59)	74±26 (59)
DREB	73±24 (84)	71±20 (79)	59±19 (76)	58±17 (70)	47±14 (31)	48±15 (28)	72±25 (155)	70±22 (155)	56±18 (140)	60±22 (140)	47±16 (59)	47±18 (59)
AST	72±34 (84)	68±30 (79)	95±36 (76)	101±35 (70)	113±36 (31)	109±50 (28)	71±35 (155)	69±35 (155)	100±43 (140)	99±42 (140)	113±45 (59)	107±41 (58)
TOV	91±33 (84)	87±29 (79)	107±37 (76)	104±34 (70)	97±21 (31)	95±31 (28)	91±40 (155)	89±34 (155)	106±46 (139)	106±37 (139)	97±30 (59)	97±32 (59)
STL	116±44 (84)	119±37 (79)	140±65 (75)	141±51 (70)	159±52 (31)	160±82 (28)	120±44 (155)	119±46 (154)	140±57 (138)	141±65 (138)	154±61 (57)	160±62 (59)
BLK	239±108(81)	280±130(74)	176±65 (76)	188±92 (70)	115±43 (31)	103±38 (28)	236±97 (138)	246±104(140)	190±99 (136)	174±74 (137)	115±51 (59)	111±54 (59)
PF	73±21 (84)	72±16 (79)	67±17 (76)	67±18 (70)	61±11 (31)	60±13 (28)	71±25 (155)	75±24 (155)	67±18 (140)	67±19 (140)	61±15 (59)	60±15 (59)
DIST	4.0±0.9 (84)	4.0±0.9 (79)	4.1±0.8 (76)	4.2±0.9 (70)	3.9±0.7 (31)	4.2±0.7 (28)	3.9±1.0 (155)	4.0±1.1 (155)	4.1±1.0 (139)	4.1±1.1 (140)	4.1±1.0 (59)	4.0±0.9 (59)
SPD	3.9±0.8 (84)	3.8±0.7 (79)	4.0±0.8 (76)	4.1±0.7 (70)	3.8±0.7 (31)	4.0±0.6 (28)	3.8±0.9 (155)	3.9±0.9 (155)	3.9±1.0 (139)	4.0±0.9 (140)	4.0±1.0 (59)	3.9±0.8 (59)
TCHS	17±6 (84)	19±8 (79)	19±6 (76)	20±5 (70)	18±4 (31)	18±4 (28)	18±7 (155)	18±8 (155)	19±6 (139)	19±6 (140)	18±5 (59)	18±5 (59)
PASS	21±8 (84)	23±10 (79)	23±6 (76)	24±6 (70)	21±6 (31)	22±4 (28)	22±9 (155)	22±10 (155)	23±7 (139)	23±7 (140)	22±6 (59)	22±6 (59)

Note: (Values are mean ± S.D. CV= (Standard deviation/Mean) *100%). Abbreviations: 2PM = Two Pointers made; 2PA = Two Pointers attempted; 3PM = Three pointers made; 3PA = Three pointers attempted; FTM = Free Throws made; FTA = Free Throws attempted; OREB = Offensive Rebounds; DREB = Defensive Rebounds; AST = Assists; TOV = Turnovers; STL = Steals; BLK= Blocked Shots; PF = Personal Fouls; DIST = Distance Run (Miles); SPD = Average Speed (MPH); TCHS = Touches; PASS = Passes Made.

Figure 5.2 Effect sizes of differences in mean of CV of each match action or event. of (a) players in winning games and in losing games; (b) players playing at home and playing at away; (c) players from strong teams and weak teams; (d) players playing against strong teams and weak teams. Notes: Asterisks indicate the likelihood for the magnitude of the true differences in mean as follows: *possible; **likely; ***very likely; ****most likely. Asterisks located in the trivial area denote for trivial differences.

5.4 Discussion

The aim of the present study was to (i) identify the difference of technical and physical performance variables for basketball players in the different positions between strong teams and weak teams, and (ii) explore the variability of players' performance across different playing positions when considering four different situational variables (i.e. game outcome, game location, team quality and quality of opposition). The previous basketball studies have clearly stated the influence of situational variables (Gómez, Lorenzo, *et al.*, 2013; Gómez, Prieto, *et al.*, 2013), playing positions (Sampaio *et al.*, 2008; Sampaio, Janeira, *et al.*, 2006) and performance variability (Mateus *et al.*, 2015; Pinilla Arbex *et al.*, 2015) as explanatory factors on teams' and players' performances. Accordingly, the current findings may enhance the importance of some variables when analysing the players' performances. Our results allow supporting the previous hypothesis that the players from strong teams, especially in guards and forwards position, covered shorter distances and lower speeds, and centres and forwards from strong teams have better performance in three point field goals than their counterparts from weak teams. Situational variables generally have an impact on game-to-game variation across different playing positions, but game location had no significant impact on performance variability of the players from different positions. Firstly, when comparing with the difference of all players between strong teams and weak teams, our results indicated that players from strong teams covered shorter distances and lower speeds than their counterparts from weak teams. The previous study has identified that seasonal variation of the game events and actions was likely to depend on team quality because the best teams had the best players in training and game environments, which had an impact on game performances (Sampaio, Drinkwater, *et al.*, 2010). Moreover, Sampaio, Drinkwater, *et al.* (2010) have identified strong teams outperform weak teams in terms of two point field goals and passes, which means that best players from strong teams possibly get better control of the game pace and utilise more

passes to complete technical and tactical strategies instead of covering more distance. This is possibly a result of having higher quality performers that take more informed decisions on when and where to run in offence and defence; therefore, those players possibly covered shorter distances at lower average velocities to reach their destinations (Sampaio *et al.*, 2015). Furthermore, our performance profiles also identified differences in the technical and physical demands of players from different playing positions. Previous studies have presented substantial differences for players fitness in a different position in terms of height (Cormery *et al.*, 2008; Sallet *et al.*, 2005), anthropometric features and body composition (Ostojic *et al.*, 2006; Tomovic *et al.*, 2016), aerobic and anaerobic capacity (Hoffman *et al.*, 1999), speed and distances covered (Tsitskaris *et al.*, 2003), agility (Alemdaroğlu, 2012), muscular strength (Willoughby & Simpson, 1996), and heart rate variability (Paul & Garg, 2012). Although these studies have provided important information on the fitness of guards, forwards, and centres, to date, the difference on the physical aspects of the specific individual roles are not available between strong and weak teams. Our study found that guards and forwards showed small differences in physical variables between strong and weak teams. Specifically, guards and forwards from strong teams covered shorter distances and lower speeds than those from weak teams. As stated before, strong teams can effectively perform tactical strategies by passing and shooting instead of running too much during the game. In fact, in basketball games, guards and forwards mainly play the most important role in shooting and passing, because guards are in charge of organizing the attacking process, and dominate passing and ball dribbling skills (particularly in 1vs1 and screens situations) and forwards are responsible for shooting from long and medium distances and play an important role during fast break situations (either shooting or passing) (Courel-Ibáñez *et al.*, 2017). However, there was a trivial difference when comparing with centres between strong and weak teams. In fact, Abdelkrim *et al.* (2010) found that guards and forwards spent a similar percentage of time

performing high-intensity movements compared with centres (17.1%, 16.6%vs 14.7%, respectively). Miller and Bartlett (1994) also identified that centres spent more time stationary and less get involved in significantly high-intensity movements in comparison with guards and forwards during the game. Thus, these seem to be the reason that centres between strong and weak teams presented trivial differences in physical variables in comparison with guards and forwards.

Sampaio, Lago, *et al.* (2010) and Ibáñez *et al.* (2008) have suggested that strong teams in the overall standings were the most effective at scoring points. Specifically, the effect of both two and three point field goals shooting was identified as “trivial” between strong and weak teams. Indeed, our results also demonstrated that there were small and moderate differences in terms of two and three point field goals for players in centres and forwards position between strong and weak teams. The previous studies of Fotinakis *et al.* (2002) have suggested that one of the main characteristics of the NBA league is the use of 1 on 1 situation to solve the possessions with the centre close to the basket. This is a specific characteristic of the athleticism of the NBA players that allow them to shoot near the basket and make dunks with a higher rate of effectiveness (Erculj & Strumbelj, 2015). However, what is interesting about our findings is that centres and forwards from strong teams shot more three point field goals, but fewer two point field goals, than their counterparts from weak teams. In fact, the importance of three point field goals reflects the game-play based on inside-outside passes that create open space for shooting and 1 on 1 situation (Gómez *et al.*, 2016). Moreover, our results seem to imply that the future development of basketball games will need more skilled and versatile players, which means that players not only perform tasks at their primary position and would satisfy performance criteria on two or even more playing positions (Trninić *et al.*, 2008). For example, centres and forwards can create more space playing in the

paint zone, and also create danger out of the three-point line.

Analyses on the game-to-game variation of individual players' technical and physical actions can get a further understanding of the game performance when considering effects of contextual variables (i.e. team and opposition quality, match outcome and match location). A recent study of Mateus *et al.* (2015) identified three point field goals made and attempted were un-ideal performance variables to discriminate the variability of the players from the specific position. Indeed, our results also found that three point field goals made and attempted were only technical game actions that displayed high game-to-game variation in all situational contexts. The higher variability in three point field goals may be affected by the diversity of the position-specific (Mateus *et al.*, 2015) and similar attributes players with different and specific roles on the court (Carter *et al.*, 2005; Sampaio, Janeira, *et al.*, 2006). Furthermore, shooting distance may also have an impact on the variability, because long-range shots displayed greater variation than short-range shots (Miller, 2002; Robins *et al.*, 2006).

Previously, game location was regarded as an important factor influencing both offensive and defensive performances of basketball (Carr, 2015; Gómez & Pollard, 2011; Pollard & Gómez, 2013; Sampaio *et al.*, 2008). Specifically, the available research has identified that players playing away get worse field goal percentages, less defensive rebounds and more committed fouls than playing at home (Sampaio & Janeira, 2003). By contrast, the present research identified that personal fouls were only game actions that showed greater variation when playing away than when playing at home. It is possible that players committed more fouls and presented higher variation in personal fouls in order to overcome game unexpected factors (e.g. more aggressive techniques and tactics from opposition, negative psychological and

behavioural states, crowd pressure, less protection by the referees) in away games (García *et al.*, 2014; Mateus *et al.*, 2015). However, those influencing factors may gradually decrease in the future with the development of basketball game, because our results are in line with the previous results that showed that game location generally has a little impact on the variability of players' performance as opposed to our assumption in the introduction (Mateus *et al.*, 2015).

Guards exhibited relatively lower variability in technical and physical variables in comparison with players from other positions under four situational variables. The main reason would be that guards are the central role for ball distribution especially in game control, ball handling and controlling the game rhythm, passing and organizing offensive tactics and keeping higher long-range shooting ability in the NBA (Fewell *et al.*, 2012). Managers and coaching staffs often supervise and control guards' physical load in the regular season in order to maintain stable performance and avoid sport injuries. The second reason would be that travel had an influence on players' performance in NBA owing to the lack of time for physical recovery (Steenland & Deddens, 1997). However, guards may be smaller affected by this factor, because guards generally were shorter and lighter and also had lower body fat percentages than players from other position (Abdelkrim *et al.*, 2010; Sallet *et al.*, 2005).

5.5 Conclusion

The current study indicated that players (especially in guards and forwards position) from strong teams covered less distances and lower speeds than players from weak teams, possibly because strong teams are characterized by better tactical discipline and that can imply less high intensity effort. For instance, players from strong teams do not need constantly quick responses to recover the defensive position or to force the final actions during attacking ball

possessions. What is more, coaches should develop shooting ability of forwards and centres in out of three-point line or select players with this ability, because players (especially in centres and forwards position) from strong teams have a significant advantage over their peers from weak teams in three point field goals. Finally, game location had no significant impact on the variability of players' performance, but it is worth noting that three point field goals show higher variation when controlling for different situational variables. These findings would be used to optimize preparation for individual player, leading to improve game performances of the players and teams.

Tesis Doctoral

D. Shaoliang Zhang

Volume 19(1), 28-48

CHAPTER 6

Performance profiles and opposition interaction during game-play in elite basketball: evidences from National Basketball Association

Shaoliang Zhang, Alberto Lorenzo, Changjing Zhou, Yixiong Cui, Bruno Gonçalves, Miguel-Angel Gómez

Chapter 6 Performance Profiles and Opposition Interaction during Game-play in Elite Basketball Evidence from National Basketball Association

6.1 Introduction

In the last decade has seen a growth in the performance analysis across team sports, as it can provide information that enhances the training and competition process (Hughes & Franks, 2015; O'Donoghue, 2009). Sport technology has made it possible to collect and analyse more detailed game-related statistics on the basketball court. In the NBA, the application of the SportVU spatial tracking system allows basketball coaches and support stuffs to gather more game-related statistics (e.g. score in the paint area and middle-range, passing-related variables, covered distance as well as running speed) (Sampaio, McGarry, et al., 2015).

Winning or losing in a basketball game under different situational variables has been explained by the game-related statistics. In fact, two-and-three point field goals (Çene, 2018; Ibáñez et al., 2008), free throws (Conte et al., 2018; Csataljay, O'Donoghue, Hughes, & Dancs, 2009), offensive and defensive rebounds (Sampaio, Godoy, & Feu, 2004; Zhang et al.), turnovers (Sampaio, Drinkwater, & Leite, 2010; Teramoto & Cross, 2010), steals (Gómez, Lorenzo, Sampaio, Ibanez, & Ortega, 2008), blocked shots (Gómez, Lorenzo, Jiménez, Navarro, & Sampaio, 2015; Zhang et al., 2018), personal fouls (Gómez, Gasperi, & Lupo, 2016; Leicht, Gomez, & Woods, 2017a), and assists (Ibáñez et al., 2008; Puente, Coso, & Salinero, 2015) were found as the key performance indicators associated to winning basketball games considering different situational variables. However, the game-related statistics in sport are not stable properties of individual players or teams, as a single player's

performance will vary from game to game (O'Donoghue, 2005). Thus, it is necessary to establish normative performance profiles which can represent not only the typical performance of a team or individual, but also the spread of performances from multiple games (Butterworth, O'Donoghue, & Cropley, 2013; Hughes, Evans, & Wells, 2001; O'Donoghue, 2005).

Recently, non-linear data mining techniques are widely used for describing the normative profiles of game-related statistics. These statistical approaches (multivariate techniques with non-parametric data) in basketball have been identified as an optimal resource to explain relationships between predictor variables (team's performance indicators) and a dependent variable (match outcome) in contrast to traditional linear techniques in a way (Çene, 2018; Gómez, Ibáñez, Parejo, & Furley, 2017; Leicht, Gomez, & Woods, 2017b; Lorenzo Calvo, Menéndez García, & Navandar, 2017). However, to date, the application of these techniques did not take into consideration the team quality. Thus, the application of the non-linear data mining techniques considering the team quality based on modern detailed basketball game-related statistics may help basketball coaches make well-informed decision in order to better optimize training load patterns, and then improve players' performance during the game.

Performance profiles can be produced for teams and individual player in sport. However, a team or individual player never plays against themselves. Indeed, the Interacting Performances Theory (O'Donoghue, 2009) states that the process and outcome of performance are influenced by the quality and type of opposition. Similarly, McGarry, Anderson, Wallace, Hughes, and Franks (2002) also stated that individuals and teams exhibit unique traits in their playing patterns when playing against different opponents at different times. In addition, the performance of a player or team might be better explored as the result

of interactions of players and teams, with the interactions being considered as indivisible for the purpose of analysing game behaviours (Bourbousson, Seve, & McGarry, 2010). In basketball, Sampaio, Lago, Casais, and Leite (2010) demonstrated that a small effect from the quality of the opponent was found in the second and third quarters during the game. Moreover, the team quality main effect was identified in all variables with the exception of free-throws, offensive rebounds, and errors in the Spanish professional basketball league (Sampaio, Drinkwater, et al., 2010). In addition, Gómez et al. (2016) stated that the best teams in the NBA league are less affected by the game location and quality of opposition, which are time-dependent variables in basketball. Although the above researches emphasised on the importance of quality of opposition when analysing game events and actions, the effects of opposition interaction on position-specific players are still unknown by far (Franks & McGarry, 1996; Reed & O'Donoghue, 2005). Thus, it is necessary for coaches and supporting staffs to explore the influences of the opposition interaction on position-specific players during the assessment of tactical, technical and physical performances (McGarry, O'Donoghue, & Sampaio, 2013).

Based on the above considerations, the aim of the present study was: (i) to explain the relationships between game-related statistics and game outcome based on team quality; and (ii) to explore the effects of opposition interaction on the players' technical and physical performance according to specific playing position.

6.2 Method

6.2.1 Sample and variables

Data used in the study were made available by Beitai Digital China Company (Beijing). The Company maintained the anonymity of players and teams complying with European General

Data Protection Regulation. A total sample of 692 games were selected based on the balance score inclusion criteria (final score differences equal to or less than 10 points). This criteria is based on the available literature that considers this scoring margin as recoverable for any of the confronting teams and, therefore, denoting that the game was not unbalanced to a way that one team was clearly superior to the opponent (Ferreira, Volossovitch, & Sampaio, 2014). The game-related statistics were transformed to per-minute statistics (original statistics/min $\times$ 40) according to players' game duration on the court (Kubatko, Oliver, Pelton, & Rosenbaum, 2007). The players who played less than 500 minutes during the whole season were excluded from the sample, since those players' standardized data were regarded as unreliable per-minute statistics (Kubatko et al., 2007). In addition, the players who played less than five minutes were also excluded from the sample (Sampaio, Janeira, Ibáñez, & Lorenzo, 2006), which finally limited the sample to 355 players with 12,597 performance records. The team quality was decided by team ranking in the NBA league (Sampaio, Lago, Casais, et al., 2010). The weak teams were the ones that only played the regular season stage whereas the strong teams were the ones that classify to the play-off season stage. Players were divided by three different categories based on playing positions: Guards (n = 151 players, observations = 5259), Centres (n = 65, observations = 2319) and Forwards (n = 145 observations = 5018). In order to precisely make sure the players' position, playing certain position was determined by referring to the NBA official website (<https://stats.nba.com>).

A total of twenty variables were selected in the analyses (Mateus et al., 2015; Sampaio, McGarry, et al., 2015). Analysed variables included offensive, defensive, physical and situational variables. The detailed explanation was presented as follows:

Situational variables

- Quality of the team and opposition: The teams that entered into the play-off season were

defined as strong teams/oppositions and the teams that did not enter into play-offs were classified as weak teams/oppositions.

- Match outcome: winning game and losing game
- Match location: home game and away game

Offensive variables

- PITPM - Points made in the paint: The number of points scored by a player or team in the paint area.
- 2PM-RM - Two-point field goals made in the middle range: The number of points scored by a player or team outside of the paint area but inside of the three-point line.
- FTM - Free throws made: The number of free throws that a player or team has made.
- 3PM - Three-point field goals made: The number of three-point field goals that a player or team has made.
- TOV - Turnovers: A turnover occurs when the player or team on offense loses the ball to the defence.
- AST - Assists: An assist occurs when a player completes a pass to a teammate that directly leads to a field goal.
- TCHS - Touches: The number of times a player or team touches and possesses the ball during the game.
- PASS - Passes: The total number of passes a player or team made during the game.
- OREB - Offensive rebounds: The number of rebounds a player or team has collected while they were on offense.

Defensive variables

- DREB - Defensive Rebounds: The number of rebounds a player or team has collected while they were on defence.
- STL- Steals: A steal occurs when a defensive player takes the ball from a player on

offence, causing a turnover from offensive players.

- BLK – Blocks: A block occurs when an offensive player attempts a shot, and the defence player tips the ball, blocking their chance to score.
- PF - Personal fouls: The total number of fouls that a player or team has committed.
- DFGM - Field goals defended at rim made: Field goals made by the opponent while the player or team was defending the rim.
- DEFLEC - Deflections: The number of times a defensive player or team gets his hand on the ball on a non-shot attempt.

Physical variables

- DIST - Distance Run: The total distances in miles that a player covered while on the court.
- SPD - Average Speed: The average speed in miles per hour of all movements (Standing, Walking, Jogging, Running, and Sprinting) by a player or team while on the court.

6.2.2 Data source reliability and validity

In order to test the validity of data sets, a sub-sample of 10 games (final score differences equal to or less than 10 points) was randomly selected and observed by two experienced analysts (basketball coaches with more than 5 years of experience in basketball performance analysis). The results were contrasted with the gathered data in the system and perfect Intra-class Correlation Coefficients (ICC=1.0) were obtained for two point field goals made in the paint area (PITPM) and in the middle range (2PM-RM), free throws made (FTM), three point field goals made (3PM), offensive (OREB) and defensive (DREB) rebounds, turnovers (TOV), steals (STL), blocked shots (BLK), personal fouls (PF), assists (AST), and field goals defended at rim made (DFGM). For the deflections (DEFLEC), pass made (PASS), and touches (TCHS), the results were lower, but still very acceptable (ICC = 0.89). In addition, in order to further increase data reliability, our study made a preliminary exploration of the data

based on the correlation matrix (Çene, 2018). Inter-class Correlation Coefficients indicates the linear relationship between two variables and takes values between -1 and 1 where 0 indicates no linear relationship and -1 or 1 indicates full linear relationship. Most of the variables exhibit negligible or small value of Inter-class Correlation Coefficients which is below 0.20 . On the contrary, strong relationships between independent variables can be observed as initially maybe expected such as between pass made (PASS) and touches (TCHS), between steals (STL) and deflections (DEFLEC), and between distances run (DIST) and average speed (SPD) (See Figure 6.1). Correlation matrix is produced with “corrplot” function with R programming language (R Core Team, 2015). All procedures were formally approved by the Local Institution of Research Review Board in accordance with the Helsinki Declaration.

Figure 6.1 Correlation matrix of the variables.

6.2.3 Statistical analysis

The first aim was to explore the relationships between game-related statistics and game outcome considering team quality. To fulfil this purpose, the effect of number of possession on game statistics were eliminated by normalising all the game statistics according to team's number of possessions. The number of possessions in a game is estimated with the following equation as suggested from Kubatko et al. (2007).

$$\text{Possessions} = 0.976 \times (\text{Field Goal Attempt} + 0.44 \times \text{Free Throw Attempt} - \text{Offensive Rebounds} + \text{Turnovers})$$

Next, descriptive statistics and independent samples t-test results are reported to understand the pattern on game-related statistics for strong and weak teams between winning and losing games. Mean, standard deviation and Cohen's *d* effect size are also reported. Cohen's *d* effect size was interpreted as follows: $d < 0.5$ = small effect, $0.5 < d < 0.8$ = medium effect, and $d > 0.8$ = large effect. Both p and Cohen's *d* values are used to determine prominent variables.

Table 6.1 Descriptive statistics of the strong and weak teams between winning and losing games

Variables	Strong teams				Weak teams			
	Winning	Losing	P	ES	Winning	Losing	P	ES
PITPM	3.40±2.99	3.34±2.88	0.418	0.02	3.54±3.04	3.42±2.95	0.115	0.04
2PM-RM	1.18±1.76	1.11±1.64	0.090	0.04	1.21±1.67	1.15±1.63	0.239	0.03
FTM	2.82±3.46	2.72±3.42	0.241	0.03	3.00±3.38	2.69±3.21	0.000	0.09
3PM	1.59±1.99	1.45±1.86	0.002	0.07	1.55±1.86	1.45±1.79	0.060	0.05
TOV	2.11±2.12	2.17±2.22	0.270	0.03	2.18±2.17	2.26±2.19	0.041	0.04
AST	3.58±3.46	3.29±3.23	0.000	0.09	3.65±3.49	3.46±3.3	0.036	0.06
TCHS	65.7±23.6	66.1±22.4	0.455	0.02	64.9±27.4	65.1±27.5	0.793	0.01
PASS	47.1±18.8	47.0±18.1	0.846	0.00	46.5±22.1	46.7±22.4	0.796	0.01
OREB	1.67±2.26	1.77±2.42	0.084	0.04	1.68±2.27	1.72±2.31	0.500	0.02
DREB	5.65±3.84	5.24±3.8	0.000	0.11	5.74±4.00	5.41±3.91	0.002	0.08
STL	1.25±1.59	1.21±1.57	0.275	0.03	1.25±1.58	1.20±1.51	0.257	0.03
BLK	0.82±1.43	0.72±1.32	0.003	0.07	0.85±1.46	0.78±1.38	0.088	0.05
PF	2.74±1.66	2.84±1.72	0.013	0.06	2.73±1.66	2.94±1.69	0.000	0.12
DFGM	2.55±2.82	2.65±2.81	0.167	0.03	2.38±2.80	2.66±2.95	0.000	0.10
DEFLEC	2.56±2.45	2.52±2.49	0.536	0.02	2.49±2.37	2.49±2.32	0.968	0.00
DIST	2.80±0.26	2.79±0.25	0.041	0.03	2.86±0.28	2.86±0.28	0.586	0.09
SPD	4.16±0.26	4.15±0.26	0.046	0.33	4.22±0.27	4.23±0.27	0.479	0.40

Then, decision tree analysis with the exhaustive CHAID algorithm was conducted to yield a hierarchical classification of team's performance according to team quality. Exhaustive CHAID algorithm, a modification to the basic CHAID algorithm, performs a more thorough merging and testing of predictor variables. Specifically, the merging of categories continues (without reference to any alpha-to-merge value) until only two categories remain for each predictor. The program then proceeds as described above in the selecting the split variable step, and selects among the predictors the one that yields the most significant split. Additionally, In order to prevent over-fitting of the tree, a minimum of 10 cases were required in order for a node to split (Robertson, Back, & Bartlett, 2016). A significance level of $P < 0.05$ was also limited in order for inclusion of a given game-related statistics. The software used for the above calculations was IBM SPSS (IBM Corporation, Somers, New York, USA).

The second aim was to explore the effects of opposition interaction on the players' technical and physical performance according to playing position. Comparisons were conducted by the spreadsheet developed by Hopkins (2007). Nonclinical magnitude-based inferences were applied by using the smallest worthwhile difference, calculated by 0.2 times the standardization estimated from between-subject standard deviation, and the 90% confidence intervals were used to make the inferences (Hopkins, 2007). Magnitudes of clear differences were assessed as follows: <0.20 , trivial; $0.20-0.60$, small; $0.61-1.20$, moderate; $1.21-2.0$, large; >2.0 , very large (Batterham & Hopkins, 2006). Differences were defined as unclear when the confidence limits for the effect size include both substantial positive and negative values ($\pm 0.2 \times \text{standardization}$) (Hopkins, Marshall, Batterham, & Hanin, 2009). Likelihood of the magnitude was defined as follows: $<0.5\%$ most unlikely; $0.5-5\%$ very unlikely; $5-25\%$, unlikely; $25-75\%$, possibly; $75-95\%$, likely; $95-99.5\%$, very likely; $>99.5\%$, most likely (Hopkins et al., 2009).

6.3 Results

6.3.1 Performance profiles from strong and weak teams

Descriptive statistics, independent t-test and Cohen's *d* statistics results are presented in Table 6.1. Variables related with assists (AST), personal fouls (PF), and defensive rebounds (DREB) are commonly found significant in all two groups with small effect size. Besides, some of the game-related statistics displayed the difference in all two groups. For example, three-point field-goals made (3PM) and blocked shots (BLK) are found significant for strong teams, but actually these variables are insignificant for weak teams. These examples confirm the necessity to divide groups into separate categories.

Then, the relationships between game-related statistics and game outcome according to team quality can be found in Figure 6.2 and Figure 6.3. The decision tree with the exhaustive CHAID algorithm revealed a moderate ability of explaining match outcome for strong teams (69.2%) whilst showing similar overall classification performance for weak teams (66.3%). Performance profile for strong teams showed that defensive rebounds, blocked shots, and assists were the main three components of the classification tree. If a team's defensive rebounds were lower or equal than 34.5 and the game outcome would be decided with blocked shots. Subsequently, if team secured defensive rebounds between 34.5 and 40.6 and then assists would decide a win of the game. It is worth noting that the winning percentage of the teams was 81.1% when strong teams secured defensive rebounds more than 40.6. Performance profile for weak teams showed that the team winning percentage were 65.6% when team secured defensive rebounds more than 40.6. Furthermore, if team secured defensive rebounds between 35.9 and 40.6 and then turnovers would decide a win of game. A team's turnovers were lower or equal than 12.7, and the winning percentage of the team were 65.3%.

Figure 6.2 Full exhaustive CHAID classification tree model results explaining balanced game outcome for strong teams

Figure 6.3 Full exhaustive CHAID classification tree model results explaining balanced game outcome for weak teams.

6.3.2 Opposition interaction: Strong teams vs Strong teams

It is worth noting that all position-specific players from winning teams in home game ran slower ($ES_G=0.42$; $ES_C=0.47$; $ES_F=0.33$) than their peers from losing teams, whereas there is an opposite trend in running speed ($ES_G=-0.34$; $ES_C=-0.46$; $ES_F=-0.29$) for winning game when playing at away game. For home game, guards and centres from winning games made more blocks ($ES_G=-0.21$; $ES_C=-0.21$) than their counterpart from losing games while forwards and centres from winning teams made more two-point field goals in the middle-range area ($ES_F=-0.30$; $ES_C=-0.22$) compared with forwards and centres from losing teams. For away game, forwards from winning games made more assists ($ES=-0.22$) and free throws ($ES=-0.20$) than their peers from losing games. (See Table 6.2 and Figure 6.4)

Figure 6.4 Comparison of the performance profiles of different position's players when strong teams played against strong teams. Asterisks indicate the likelihood for the magnitude of the true differences in mean as follows: *possible; **likely; ***very likely; ****most likely.

6.3.3 Opposition interaction: Strong teams vs Weak teams

For home game, guards from winning team made more steals (ES=-0.22) and centres made more defensive rebounds (ES=-0.23) and blocks (ES=-0.24) in contrast to players from the same position in losing teams. It is worth noting that all position-specific players from winning teams in home game covered more distance (ES_G=-0.23; ES_C=-0.24; ES_F=-0.35) and ran faster (ES_G=0.68; ES_C=0.72; ES_F=0.62) than their peers from losing teams. For away game, centres from winning teams made more assists (ES=-0.26) and steals (ES=-0.37) than centres from losing game while forwards from winning teams made more free throws (ES=-0.25) than their peers from losing teams. (See Table 6.3 and Figure 6.5)

Figure 6.5 Comparison of the performance profiles of different position's players when strong teams played against weak teams. Asterisks indicate the likelihood for the magnitude of the true differences in mean as follows: *possible; **likely; ***very likely; ****most likely. Asterisks located in the trivial area denote for trivial differences.

6.3.4 Opposition interaction: Weak teams vs Weak teams

For home game, guards from winning teams made less fouls (ES=0.43), centres made more steals (ES=-0.31), forwards allow opponents to made less two-point field goals (ES=0.24) at the rim in contrast to the corresponding position players from losing teams. For away game, the main difference between winning and losing games was identified in the position of centres. In offensive aspects, centres from winning teams made more two point field goals in the paint area (ES=-0.36) than centres from losing teams. In defensive aspects, centres from winning teams made more defensive rebounds (ES=-0.24) and deflections (ES=-0.26) and allow opponents made less two- point field goals (ES=0.48) at the rim than centres from losing teams. (See Table 6.4 and Figure 6.6)

Figure 6.6 Comparison of the performance profiles of different position's players when weak teams played against weak teams. Asterisks indicate the likelihood for the magnitude of the true differences in mean as follows: *possible; **likely; ***very likely; ****most likely. Asterisks located in the trivial area denote for trivial differences.

6.4 Discussion

The aim of this study was two folds: (i) to explain the relationships between game-related statistics and game outcome based on team quality; and (ii) to explore the effects of opposition interaction on the players' technical and physical performance according to specific playing position.

6.4.1 Performance profile from strong and weak teams

Performance profiles for strong and weak teams showed that defensive rebounds were the common key performance indicators (KPI) that discriminated between winning and losing games. The present study pointed out that when strong and weak teams secured defensive rebounds more than 40.6 during the game-play, the winning percentage for strong and weak teams were 81.1% and 65.6%, respectively. This means that strong teams have the better ability to convert acquired ball possession into scoring after securing defensive rebounds (Sampaio, Drinkwater, et al., 2010). Performance profile for strong teams also showed that blocked shots and assists discriminated between winning and losing games. These variables along with the aforementioned defensive rebounds may be related to fast-paced rhythms that lead to better offensive (i.e. quick attacks and high shooting accuracy) because this playing style generates more opportunities for fast-breaks when securing defensive rebounds, blocking shots and assisting to an open player in easy field-goal positions without defensive pressure (Çene, 2018; Conte et al., 2018; Gómez et al., 2017; Ibáñez, García, Feu, Lorenzo, & Sampaio, 2009; Sampaio, Lago, & Drinkwater, 2010). This also may be as a result of the effective team defensive communication, which requires positive and complementary participation between teammates, such as guards' ability of stealing and passing the ball and centres' ability of blocking shots and securing defensive rebounds (Leicht et al., 2017a; Sampaio, Drinkwater, et al., 2010).

Table 6.2 Descriptive statistics of guards, centres and forwards considering game outcome between home and away game when strong teams played against strong teams

Variables	Strong teams Vs Strong teams											
	Home game						Away game					
	Guards		Centres		Forwards		Guards		Centres		Forwards	
	Win	Lose	Win	Lose	Win	Lose	Win	Lose	Win	Lose	Win	Lose
PITPM	2.97±2.56	3.11±2.63	4.91±3.53	5.05±3.16	3.00±2.52	2.99±2.79	2.79±2.72	3.07±2.58	4.62±3.43	4.58±2.90	3.13±2.88	3.16±2.71
2PM-RM	1.27±1.67	1.28±1.89	0.98±1.52	0.74±1.27	1.18±1.76	0.87±1.33	1.45±2.03	1.18±1.65	0.92±1.90	0.87±1.33	1.00±1.67	1.07±1.67
FTM	3.46±4.00	3.37±3.98	2.40±2.86	3.12±4.02	2.38±2.84	2.55±3.41	3.14±3.81	3.10±3.50	2.58±3.21	2.57±2.73	2.34±2.95	2.11±3.03
3PM	2.13±1.95	1.80±1.93	0.59±1.43	0.30±0.93	1.63±1.79	1.44±1.74	2.07±2.20	2.04±2.04	0.66±1.45	0.53±1.35	1.66±2.01	1.43±1.92
TOV	2.35±2.14	2.48±2.47	1.89±1.89	2.35±2.18	1.85±2.02	1.83±1.91	2.50±2.46	2.53±2.38	2.40±2.12	2.23±1.96	1.83±1.94	1.87±1.97
AST	5.28±4.06	4.66±3.44	2.04±2.36	2.22±2.12	2.77±2.85	2.32±2.38	4.73±3.66	4.62±3.63	2.68±2.66	2.51±2.81	2.77±2.70	2.44±2.49
TCHS	72.3±24.6	73.9±23.9	62.3±17.4	64.4±15.1	61.1±19.3	61.5±17.5	73.7±24.2	74.1±24.3	66.6±16.9	65.3±17.0	63.8±18.5	61.1±18.6
PASS	50.6±20.1	51.7±19.7	45.2±13.1	47.0±12.6	44.0±15.5	43.76±14.1	52.3±19.6	52.1±20.5	49.7±13.2	48.4±14.6	46.3±15.7	43.6±15.3
OREB	0.97±1.44	0.90±1.39	3.58±2.97	3.62±3.03	1.60±1.89	1.95±2.41	0.72±1.32	0.94±1.39	3.28±2.95	3.41±2.96	1.81±2.40	1.89±2.35
DREB	4.11±3.20	3.62±2.67	7.51±3.95	7.76±4.17	6.06±3.58	5.70±3.85	3.90±2.90	3.57±2.61	7.94±4.34	7.59±4.30	5.89±3.40	5.54±3.54
STL	1.27±1.50	1.29±1.50	0.84±1.30	1.24±1.54	1.28±1.53	1.21±1.60	1.48±1.69	1.39±1.73	0.84±1.57	0.78±1.18	1.20±1.60	1.21±1.65
BLK	0.43±0.89	0.29±0.64	1.60±2.09	1.29±1.44	0.92±1.47	0.79±1.48	0.32±0.76	0.34±0.78	1.64±1.95	1.31±1.67	0.96±1.51	0.75±1.33
PF	2.83±2.11	3.25±2.56	4.12±3.15	4.10±2.71	3.65±2.96	4.01±2.95	3.26±2.69	3.23±2.61	4.80±3.28	4.28±3.25	3.98±3.22	3.89±2.94
DFGM	1.57±1.84	1.63±1.90	4.89±3.57	5.39±3.25	2.86±2.82	2.61±2.38	1.48±1.94	1.58±1.71	5.36±3.39	5.07±3.47	2.93±2.72	2.63±2.60
DEFLEC	2.78±2.45	2.59±2.39	1.90±2.16	2.02±2.15	2.58±2.30	2.49±2.33	2.64±2.35	2.95±2.71	1.63±1.96	1.61±1.97	2.38±2.30	2.63±2.59
DIST	2.80±0.23	2.81±0.25	2.74±0.21	2.72±0.18	2.78±0.24	2.79±0.22	2.84±0.27	2.81±0.26	2.74±0.22	2.73±0.22	2.78±0.22	2.79±0.26
SPD	4.15±0.27	4.17±0.26	4.07±0.24	4.08±0.22	4.12±0.25	4.15±0.25	4.20±0.26	4.16±0.26	4.07±0.25	4.06±0.26	4.14±0.25	4.13±0.26

Table 6.3 Descriptive statistics of guards, centres and forwards considering game outcome between home and away game when strong teams played against weak teams

Variables	Strong teams Vs Weak teams											
	Home game						Away game					
	Guards		Centres		Forwards		Guards		Centres		Forwards	
	Win	Lose	Win	Lose	Win	Lose	Win	Lose	Win	Lose	Win	Lose
PITPM	2.82±2.41	2.86±2.81	5.29±3.78	4.87±3.48	3.19±2.71	3.09±2.73	2.94±2.65	2.89±2.60	5.54±3.92	4.74±3.68	3.15±2.74	2.93±2.81
2PM-RM	1.42±1.80	1.49±1.89	0.98±1.54	1.01±1.74	1.05±1.67	1.20±1.88	1.37±1.89	1.39±1.59	1.06±1.69	0.85±1.41	1.05±1.76	1.04±1.63
FTM	3.35±3.89	2.91±3.55	2.67±2.97	2.76±2.78	2.44±3.31	2.38±3.12	3.17±3.72	3.08±3.79	2.76±3.19	2.94±3.33	2.70±3.46	2.21±3.07
3PM	2.10±2.25	1.86±1.93	0.55±1.45	0.58±1.45	1.46±1.88	1.56±1.89	2.02±1.99	1.75±1.81	0.60±1.47	0.44±1.36	1.58±2.00	1.41±1.74
TOV	2.57±2.18	2.54±2.32	2.10±2.00	1.77±2.01	1.83±1.95	1.83±1.77	2.35±2.26	2.53±2.38	2.08±2.23	2.58±3.07	1.77±1.95	1.65±2.16
AST	5.09±4.01	5.01±3.91	2.70±2.68	2.07±2.61	2.87±2.89	2.67±2.62	5.02±3.83	4.71±4.09	2.52±2.67	2.11±2.09	2.43±2.76	2.16±2.32
TCHS	72.5±26.6	74.5±23.1	64.8±23.4	64.3±16.0	60.2±21.5	64.2±17.4	69.4±28.5	67.9±29.2	61.2±23.2	59.7±26.0	59.3±22.4	56.7±22.6
PASS	51.1±21.4	52.5±19.7	47.6±18.4	46.9±13.9	43.6±17.3	45.9±14.3	49.4±22.5	47.2±22.6	44.7±18.6	43.6±21.2	42.8±18.2	40.2±18.0
OREB	0.87±1.31	0.84±1.64	3.69±3.04	3.34±3.14	1.77±2.19	2.03±3.40	0.76±1.17	0.77±1.22	3.11±2.85	3.17±2.62	1.57±2.17	1.85±2.27
DREB	4.13±2.99	3.72±2.93	8.32±4.17	7.33±4.69	6.24±3.83	5.64±3.54	4.13±2.97	3.92±3.11	8.29±4.22	8.66±5.17	6.02±3.96	5.71±3.37
STL	1.47±1.71	1.10±1.64	1.19±1.70	0.94±1.27	1.20±1.57	1.25±1.57	1.34±1.61	1.35±1.50	1.27±1.85	0.78±1.25	1.17±1.47	1.26±1.59
BLK	0.40±0.85	0.47±0.89	1.81±1.90	1.53±1.88	0.82±1.49	0.85±1.37	0.37±0.82	0.34±0.73	1.50±1.70	1.63±2.22	0.81±1.37	0.78±1.36
PF	3.00±2.43	3.04±2.83	4.17±2.86	4.40±3.01	3.47±2.72	3.93±3.06	2.91±2.29	3.35±2.69	4.66±3.26	4.26±2.90	3.75±2.96	3.66±3.16
DFGM	1.19±1.36	1.58±1.88	4.48±3.21	5.33±3.68	2.40±2.73	2.70±2.85	1.33±1.69	1.41±1.66	4.61±3.21	4.67±3.75	2.50±2.78	2.61±2.71
DEFLEC	2.86±2.61	2.55±2.88	2.28±2.44	2.23±2.16	2.72±2.65	2.65±2.71	2.87±2.48	2.84±2.45	2.41±2.35	1.67±1.90	2.44±2.51	2.56±2.40
DIST	2.84±0.26	2.81±0.23	2.80±0.27	2.74±0.19	2.83±0.27	2.80±0.22	2.84±0.29	2.82±0.26	2.75±0.28	2.73±0.23	2.80±0.28	2.81±0.29
SPD	4.21±0.26	4.18±0.27	4.14±0.24	4.08±0.24	4.18±0.26	4.17±0.25	4.21±0.28	4.19±0.26	4.11±0.26	4.08±0.23	4.17±0.26	4.19±0.26

Table 6.4 Descriptive statistics of guards, centres and forwards considering game outcome between home and away game when weak teams played against weak teams

Variables	Weak teams Vs Weak teams											
	Home game						Away game					
	Guards		Centres		Forwards		Guards		Centres		Forwards	
	Win	Lose	Win	Lose	Win	Lose	Win	Lose	Win	Lose	Win	Lose
PITPM	2.78±2.41	2.75±2.56	6.13±3.42	5.70±4.08	3.18±2.82	3.32±2.78	2.82±2.37	2.76±2.38	6.14±3.89	4.79±3.67	3.40±2.89	3.17±2.58
2PM-RM	1.18±1.47	1.24±1.60	0.86±1.37	0.78±1.47	1.11±1.79	0.97±1.56	1.53±1.75	1.33±1.65	0.80±1.44	0.80±1.60	1.09±1.51	1.20±1.60
FTM	3.04±3.37	2.70±3.20	3.70±4.03	3.05±3.50	2.83±3.12	2.49±3.23	3.13±3.50	2.43±2.92	3.36±3.35	2.73±3.85	2.62±3.11	2.72±3.12
3PM	1.99±1.93	2.02±2.01	0.62±1.46	0.58±1.32	1.55±1.86	1.49±1.81	1.95±1.94	1.79±1.89	0.43±1.08	0.60±1.19	1.72±1.88	1.47±1.78
TOV	2.41±2.37	2.44±2.36	2.47±2.41	2.69±2.32	1.91±1.98	1.96±1.93	2.42±2.33	2.33±2.06	2.42±2.20	2.13±2.24	1.84±1.86	1.90±2.01
AST	5.26±4.09	4.84±3.75	2.58±2.67	2.40±2.77	2.39±2.33	2.25±2.23	4.90±3.72	5.02±3.65	2.75±2.98	2.37±2.89	2.46±2.14	2.37±2.11
TCHS	68.8±32.3	66.1±32.1	63.7±26.3	62.3±28.0	58.9±25.4	57.5±24.8	67.6±32.1	69.9±31.5	65.0±26.0	60.0±26.2	57.5±24.2	58.2±24.3
PASS	49.9±26.3	47.2±25.9	45.1±20.3	44.0±21.3	42.0±20.3	41.1±20.2	48.3±25.8	50.5±25.4	46.2±19.4	43.0±19.8	41.0±19.1	41.5±19.6
OREB	0.71±1.24	0.71±1.13	4.03±3.27	3.65±2.86	1.84±2.06	1.75±1.86	0.67±1.22	0.74±1.17	3.65±3.29	3.90±3.19	1.82±1.99	1.63±1.92
DREB	4.11±3.35	3.72±2.74	8.46±4.69	8.33±5.01	6.47±3.89	5.89±3.80	3.96±2.76	3.73±2.57	9.35±4.41	8.06±4.92	6.06±3.47	6.02±3.78
STL	1.34±1.60	1.24±1.45	1.18±1.66	0.88±1.32	1.09±1.62	1.09±1.49	1.24±1.51	1.30±1.49	1.16±1.67	0.99±1.63	1.19±1.51	1.22±1.54
BLK	0.45±0.95	0.39±0.89	2.25±2.42	1.89±2.21	0.90±1.39	0.86±1.48	0.35±0.77	0.29±0.70	1.68±1.71	1.80±1.92	1.02±1.50	0.88±1.35
PF	2.47±2.01	3.21±2.33	4.71±2.79	4.81±3.60	3.62±3.32	3.69±2.79	2.82±2.28	3.10±2.38	4.87±3.02	5.26±3.38	3.81±3.05	3.73±2.92
DFGM	1.25±1.75	1.36±1.68	4.84±3.83	5.40±4.46	2.31±2.41	3.09±3.15	1.14±1.51	1.39±1.84	4.20±2.87	5.38±3.55	2.26±2.56	2.71±2.69
DEFLEC	2.80±2.43	2.75±2.49	2.34±2.52	2.31±2.26	2.45±2.55	2.43±2.32	2.63±2.31	2.62±2.36	2.42±2.48	2.16±2.62	2.41±2.30	2.47±2.18
DIST	2.96±0.32	2.92±0.25	2.79±0.27	2.79±0.26	2.87±0.26	2.87±0.28	2.94±0.28	2.93±0.29	2.74±0.21	2.76±0.23	2.86±0.24	2.90±0.30
SPD	4.31±0.25	4.31±0.24	4.12±0.30	4.15±0.29	4.23±0.26	4.23±0.26	4.31±0.26	4.30±0.24	4.08±0.24	4.10±0.27	4.23±0.24	4.25±0.28

Performance profile for weak teams emphasized that reducing turnovers are the key to winning games. In fact, the turnovers that are considered as a consequence of playing style of aggressive suppressing and controlling in offence and defence, which may indicate the effective teamwork, and more experienced players and high fitness (Ibáñez et al., 2009; Ibáñez et al., 2008; Lorenzo, Gómez, Ortega, Ibáñez, & Sampaio, 2010; Teramoto & Cross, 2010). Thus, weak teams should pay more attention to increases collective play and reduces frequency of turnovers, such as passing turnovers, player's losing balance due to inadequate foot-work or poor dribbling (Koster & Aven, 2018; Lorenzo et al., 2010).

6.4.2 Opposition interaction: Strong teams vs Strong teams

It is highly worth noting from physical perspective that all position-specific players (guards, centres and forwards) from winning teams in home games ran speed lower than their peers from losing teams, whereas there is an opposite trend for all position-specific players in running speed when playing away. On the one hand, Bray and Widmeyer (2000); Ribeiro, Mukherjee, and Zeng (2016); Sampaio, Ibáñez, Gómez, Lorenzo, and Ortega (2008) stated that the home teams present less competitive anxiety and are more motivated and concentrated than visiting teams because crowd support helps to reduce the negative stress and anxiety levels for home players. These facts allow local players with greater auto-effectiveness and self-confidence to have better performances in passing and assisting and team cohesion, which means that local players possibly covered shorter distances at lower average velocities during game-play (Zhang et al., 2017). On the other hand, results showed that due to the lack of home advantage, winning teams tend to keep fast tempo and positive running to suppress and break opposing tactics when playing away games. This result is supported by Sampaio, Lago, and Drinkwater (2010) who suggested that effective offence (e.g. fast break) and high-pressure defence strategies (e.g. full court press) require much

greater expenditure of energy, which force players to cover longer distances at higher average velocities for a greater proportion of the game.

From a technical perspective, in home games the results corroborate with those obtained by Courel-Ibáñez, McRobert, Toro, and Vélez (2016) that pointed out the effective interaction between inside (centres) and outside players (guards) in defence, which results in blocking more shots from the opponent. Furthermore, winning teams in offence made more two-point field goals in the middle range area. It is possible that the tactical strategies of strong teams evolve into dynamic interactions such as inside-outside game coordination. In particular, in the NBA the inside game takes a relevant importance, which forces players to cut and shoot in the middle range area (Courel-Ibáñez et al., 2016). In away games, forwards from winning games made more assists and free-throws than their peers from losing games. This is linked with the study of Sampaio et al. (2008) that highlighted that guards in away games are subjected to increased pressure from opponents, which lead the guards to choose offensive patterns and force the forwards to participate more in the game.

6.4.3 Opposition interaction: Strong teams vs Weak teams

For home games, our study found that guards made more steals and centres made more defensive rebounds and blocks from winning team in contrast to players from the same position in losing teams. In addition, all position-specific players (guards, centres and forwards) from winning teams covered longer distances at higher average velocities than their peers from losing teams. These technical and physical variables may imply that defensive systems with constant pressure on the opponents are effective strategies to win a game (Gómez, Evangelos, & Alberto, 2006; Leite et al., 2014; Sampaio, Leser, et al., 2015). An optimal defensive system (i) can control the pace of play by forcing the opponent's attack to

play outside of their usual rhythm of play; (ii) can prevent the best scoring options of the opposing team during competition by defensive pressure or stopping the individual penetrations and denying passing line to the best scorers or the free players closer to the basket; and (iii) can extend the man-to-man defence to a full court level, aiming to delay the ball transition from defence to offense and impair the opponents concentration in offence (Sampaio, Leser, et al., 2015; Wissel, 2008).

Meanwhile, the system of aggressive defence is particularly related to player fitness variables as high-level defensive performances seem to require higher energy demands and these kinds of tasks are therefore particularly related to players' quick reaction ability, high speed and repeated high-intensity sprint ability (Sampaio, McGarry, et al., 2015). In addition, the present results study support the study of Pollard and Gómez (2007) that emphasized the need to adjust for team ability when quantifying the magnitude of home advantage for individual teams in basketball because when a strong team plays against a weak team, their difference in ability is likely to outweigh the relatively small effect of home advantage when influencing the game outcome.

For away games, centres from winning teams made more assists and steals than losing game while forwards from winning teams made more free throws than their peers from losing teams. These evidences may reveal a typical strategy of offensive-defensive coordination such as centres take advantage of height and weight trying to competitively protect their basket and dominating the restricted area while guards and forwards move quickly the ball down the court (Drinkwater, Pyne, & McKenna, 2008; Zhang et al., 2018).

6.4.4 Opposition interaction: Weak teams vs Weak teams

For home games, results showed that guards from winning teams made less fouls, centres made more steals, forwards allow opponents made less two point field goals at the rim in contrast to the corresponding position players from losing teams. These defensive variables further highlighted that effective defensive tactics may be the key to winning the game when weak teams played against weak teams. In fact, the available research Gómez et al. (2006); Gómez et al. (2016); and Gómez *et al.* (2010) found that winning teams used more man-to-man defence than away teams, and this defensive strategy allows a team to made less fouls and may generate more steals and consequently easy field-goal positions near the basket. For away game, it is highly worth noting that centres play an important role in winning the game. In offensive aspects, centres from winning teams made more two point field goals in the paint area than centre from losing teams. In defensive aspects, centres from winning teams made more defensive rebounds and deflections and allow opponents to made less two-point field-goals at the rim than their counterpart from losing teams. These results are supported by the studies of Sampaio et al. (2006) and Erculj and Strumbelj (2015) who indicated that NBA centres seem to be larger (height and mass) than the other players, and these characteristics suggest that they are highly specialized in rebounding, inside shooting, screening or drawing fouls. Additionally, it suggests that their participation in offence and defence is confined to play close to the basket (Sampaio *et al.*, 2006). In fact, shooting from the low post is the dominant offensive strategy for NBA teams, known as "inside game", which is one of the options of control offence and requires individual (centres and power forwards) offence near the basket (Courel-Ibáñez, Suárez-Cárdenas, & Cárdenas-Vélez, 2017; George, Evangelos, Alexandros, & Athanasios, 2009). Therefore, the defence of weak teams in away games should primarily prevent the offence's centre from receiving a pass in the low post because supplying the ball to the player near the basket correctly is a determinant for success (George

et al., 2009).

6.5 Conclusion

In summary, performance profile for strong teams showed that defensive rebounds, blocked shots, and assists were the key performance indicators while defensive rebounds and turnovers determined between winning and losing games for weak teams. Subsequently, in strong vs strong games; all of position-specific players from winning teams in home game ran slower than their peers from losing teams, whereas an opposite trend were found in running speed at away games. In strong vs weak games; all of position-specific players from winning teams in home games covered more distance and ran faster than their peers from losing teams. In weak vs weak games; effective defence played an important role in winning the game. These findings may be useful for coaches, physical trainers and performance analysts when evaluating team and player performance or tailoring plans according to the quality of teams and oppositions.

6.6 Practical applications and limitations

The findings of this study contribute to a better understanding of the relationships between game-related statistics and game outcome and the importance of team quality and the effects of opposition interaction on the players' technical and physical performances according to playing position. Therefore, the obtained results provide a strong and direct basis to guide both line-up rotation strategies and game tactics interventions aimed at improving team rosters in the NBA.

There are some limitations in the current research that should be considered in further studies. On the one hand, the criterion of evaluating team quality is based on the final ranking in the NBA league, which might be a criterion of lacking temporal sensitivity, thus, future studies

can be developed upon a longitudinal assessment. On the other hand, the current research only considers the influences of the external environment and opposition interaction on team and individual's performances which means that future studies are supposed to integrate with player's own characteristics (such as players' anthropometric characteristics and playing experience) to evaluate game performance.

Tesis Doctoral

D. Shaoliang Zhang

CHAPTER 7
General Discussion

Chapter 7 General Discussion

The general aim of the thesis is to model and simulate the game performances of basketball players and teams based on game-related statistics integrating with influencing factors in the National Basketball Association. Figure 7.1 may be seen as an overview about influencing factors considered in this thesis. To achieve the aims of this research, this thesis can be mainly summarized into the five interlinking Chapters from Chapter 2 to Chapter 6 and separated into following three sections; each section focusing on a different aspect of the basketball performance analysis in National Basketball Association.

This Chapter of the thesis summarizes and links together the main findings from each section. Importantly, innovative opinion was also given to the classification of the player type with potential avenues for future research discussed. Finally, the limitations and future directions of the studies in this thesis are discussed in depth.

7.1 Summary and discussion of main findings

7.1.1 Section 1 - Team performance profiles (Chapter 2)

From the team perspective, multivariate and individual team performance dynamics throughout in-season period are described in Chapter 2. In multivariate team performance profiles, the thesis pointed out that a similarity of team profiles was presented in the middle of the regular season while a relative dissimilarity was discovered at the beginning and end of the season. A possible explanation would be that the tactical coordination and game styles of the team were constantly evolving during the season as a result of changing team cohesion, a well reported unstable phenomenon (Carron *et al.*, 2002; Muthiane *et al.*, 2015). Additionally, this evolution may be resulted from adaptation of adjusting their style of playing at the start of the season and coaches alterations in their playing rosters of teams at the end the season to

maximize player performance in the upcoming playoffs (Belk *et al.*, 2017). In individual team performance profile, each team performance profile in the NBA was built-up. The findings indicated that the Golden State Warriors showed the greatest similarity while the Denver Nuggets showed the greatest dissimilarity in the term of game-play characteristics throughout the in-season period. The results highlighted that it is beneficial for team development in a long term if the teams possess superstars and maintain the stable line-ups.

Figure 7.1 Overview of influencing factors considered in this thesis

When examining temporal change of game-related statistics throughout in-season period in the National Basketball Association, three point field-goals made and assists showed growth trend as the competition progressed. Therefore, it is paramount that coaches and sport scientists pay attention to this trend and develop techniques to team cohesion and long-range

shooting ability in order to achieve better team performance during game-play in the National Basketball Association.

In addition, section 1 summarised some of the findings from the first part of Chapter 6 to identify the key performance indicators (KPIs) taking into consideration team quality in the current NBA. The multiple studies have previously emphasised the importance of defensive rebounds during the game-play (Garcia *et al.*, 2013; Mikolajec *et al.*, 2013; Sampaio *et al.*, 2015; Teramoto & Cross, 2017). However, the results from these studies may not discuss in depth. The thesis not only found that defensive rebounds were the common KPIs that discriminated between winning and losing games for strong and weak teams in the current NBA also further highlighted that securing defensive rebounds more than 40.6 during the game-play, the winning percentage for strong and weak teams were 81.1% and 65.6%. In fact, highlighting defensive rebounds may be related to play styles such as fast-paced rhythms which generate more opportunities for fast-breaks in the offence whilst it is the reflection of effective team defensive communication in the defence in the NBA (Csataljay *et al.*, 2013; Paulauskas *et al.*, 2018b; Sampaio, Lago, & Drinkwater, 2010; Teramoto & Cross, 2010). Furthermore, performance profiles for strong teams indicated that blocked shots and assists discriminated between winning and losing game while performance profiles for weak teams showed that turnovers are the key performance indicators. Given the difference in the KPIs, coupled with the already know each team performance profile in the current NBA, there remains a detailed need on what type of players or position-specific players making contribution to winning the game between strong and weak teams. This justified Chapter 3, 4, 5, and 6 placing added emphasis on players' contribution.

7.1.2 Section 2 - Player performance profiles (Chapter 3 and 4)

From the player perspective, playing experience, anthropometric characteristics (height and weight), different levels of point production (lower-scoring and higher-scoring players), playing role (starters and non-starters), and playing position (guards, forwards and centres) were considered to explore and examine player performances in the National Basketball Association. The results of this section can be applied into designing technical and tactical strategies and the selection and recruitment of players in the National Basketball Association. A combination of cluster analysis and discriminate analysis was used in this section (Chapter 3 and 4) to group basketball players into similar clusters and then to identify the key performance indicators (KPIs) that best differentiate obtained clusters.

With much debate in the previous literature about the independent influence of playing experience or anthropometric characteristics on player performances (Black *et al.*, 2016; Diaz del Campo *et al.*, 2011; Taheri *et al.*, 2016), further analysis was conducted in Chapter 3 to explore player performances based on a combination of playing experience and anthropometric characteristics. In Chapter 3, playing experience, height and weight were selected as variables to group basketball players into different groups. The clustering process allowed identifying five different player profiles: Top height and weight (HW) with low experience, TopHW-LowE; Middle HW with middle experience, MiddleHW-MiddleE; Middle HW with top experience, MiddleHW-TopE; Low HW with low experience, LowHW-LowE; Low HW with middle experience, LowHW-MiddleE. The following discriminant analysis showed results as follows:

- TopHW-LowE presented highest association with discriminant variables (two-point field goals made and missed, offensive and defensive rebounds, blocks, personal fouls).

- LowHW-MiddleE presented highest association with explained variables (three-point field goals made and missed and passing-related variables).
- MiddleHW-MiddleE presented lowest links with explained variables (turnovers).
- LowHW-LowE presented lowest links with discriminant variables (passes made and touches).
- MiddleHW-TopE showed a similar profile as (TopHW-LowE) group.

In order to connect the results of the section 1, section 2 further visualized the distribution of all players (included starters and non-starters) from each team (included strong and weak teams) within five cluster groups. In general, players (included starters and non-starters) from weak teams were mostly distributed in LowHW-LowE group, whereas players (included starters and non-starters) from strong teams were mainly grouped in LowHW-MiddleE and MiddleHW-MiddleE groups. Given this, this section makes further explanation for why the assists were the key performance indicators for strong teams in the National Basketball Association possibly because LowHW-MiddleE players played a key role in the strong teams. Similarly, LowHW-LowE players contributed to weak teams leading to more turnovers.

In a basketball team, playing experience and anthropometric characteristics have some impact on game performance and the ability of point scoring often would be other key determinants of collective success. This thesis provided novel solution by classifying players based on different levels of point production. This way, lower-scoring players would improve their chances of having their performance evaluated and recognized and, later, coaching staffs can access objective data to provide suggestions for improvement. Following up this idea of analysing different levels of scoring production, there is a clear need to identify the subset of other game statistics that discriminate these levels of point production, taking into

consideration specific game positions (guards, forwards and centres). In Chapter 4, two cluster groups were acquired according to different levels of point production by the cluster analysis: one of the clusters was labelled as “lower-scoring players” and the other cluster was labelled as “higher-scoring players”. Discriminant analysis showed that there were variables achieving high discriminant status for all positions, such as the free-throws and turnovers, and more moderate variables, such as the assists and the defensive rebounds. In addition, the discriminant variables of the guards were related to field-goals (two and three-point), the forwards to defensive rebounds and free throws, and the centres to three-point field goals, touches and steals. In addition, visualising 30 team constitution profiles according to high-scoring and low-scoring player helps coaches and performance analysts to get the better understanding of the player strength of the team and opponent. From the results of visualisation, strong teams in the current NBA such as GSW, HOU, and PHI, were the teams with higher performance in guards from the high-scoring group, which highlighted that assists, defensive rebounds and three point field-goals played key role in winning the game. These main parameters identified would provide coaches and sport scientists a guide to recruit players and improve performances in the future.

Interestingly, coaches and performance analysts should note that physical variables such as distance covered and running speed were the only variables with no substantial discriminant status among different cluster groups in the first and second part of this section. It may be the reflection of the excellent athleticism of the players in the current NBA. Hence, coaches should note that deciding the final game outcome may be attributed to the difference on technical-tactical strategies to some extent.

In the section 1 and 2, team performance profiles and the distribution of different type of

players from each team in the National Basketball Association were visualised. However, the above performance profiles do not consider the influence of contextual factors such as home and away game, so establishing evidences in depth with situational variables in the following section 3 may provide new insights to analyse the game performances of the players and teams in the National Basketball Association.

7.1.3 Section 3 - Situational variables (Chapter 5 and 6)

Existing notational analysis has provided preliminary information on the effects of situational variables such as match location, match status, quality of the opponent and game period on basketball game performance at a team level (Gómez *et al.*, 2015; Gómez *et al.*, 2013; Sampaio *et al.*, 2013). However, little research considered the effect of situational variables on game performance at a player level in the National Basketball Association, which leads to exploring the influence of situational variables on position- specific players in Chapter 5. The results from Chapter 5 showed that guards and forwards from strong teams covered less distance at lower speed whilst forwards and centres from strong teams made more three point field-goals comparing with their peers from weak teams. It may be as the result of player recruitment because LowHW-LowE players were mostly comprised of weak teams and LowHW-MiddleE players were comprised of strong teams. Previously, more research identify that expert players may well make less mistakes when deciding when and where to run in both offense and defence, possibly taking shorter paths to reach their destinations (Diaz del Campo *et al.*, 2011; Sampaio *et al.*, 2015; Soltani *et al.*, 2016). In addition, by combining the findings of section 1, 2 and 3, three point field goals were found an clear growth trend throughout in-season period and LowHW-MiddleE players, high-scoring guards, forwards and centres from strong teams have better performance in three point field goals comparing to their peers from weak teams, but the findings from Chapter 5 pointed out that three point field

goals were the most unstable game actions showed substantial differences in variation when considering contextual variables (i.e. quality of the team and opponent, game outcome and game location). Consequently, coaches and sport scientists are supposed to train player's long-range shooting ability concurrently with simulating different scenarios to improve player and team performance.

The first part of this section has examined situational variables independently, not accounting for the possibility of higher-order interactions (e.g. playing against weak teams at home game). However, the examination of situational variables in isolation would appear to provide limited insight into the complex nature of basketball game performance (McGarry *et al.*, 2013). Hence, the interactive influences of situational variables on position-specific players were discussed as follows:

- ***Opposition interaction: strong teams Vs strong teams***

In home games, local players (guards, centres and forwards) from winning games presented greater auto-effectiveness and self-confidence in passing and assisting, which means that local players possibly covered shorter distances at lower average velocities during game-play. Conversely, in away games, due to the lack of home advantage, position-specific players from winning teams maintained fast tempo and positive running to suppress and break opposing tactics. Importantly, forwards played a key role on winning game when playing in away games, possibly because guards are subjected to increased pressure from opponents, which allows the guards to organise and assist forwards to participate more in the game (Sampaio *et al.*, 2008).

- ***Opposition interaction: strong teams Vs weak teams***

In home games, guard and centres made more steals and blocks with longer distance covered at higher average velocities than their peers from losing games, so the system of the aggressive defence has a positive impact on winning a game. In away games, centres from winning teams made more assists and steals which means that centres tend to take advantage of height and weight trying to competitively protect their basket and dominating the restricted area while guards and forwards move quickly the ball down the court (Drinkwater *et al.*, 2005). Importantly, the thesis highlighted the need to adjust for team ability when quantifying the magnitude of home advantage for individual teams in basketball because when a strong team plays against a weak team, their difference in ability is likely to outweigh the relatively small effect of home advantage when influencing the game outcome (Pollard & Gómez, 2007).

- ***Opposition interaction: weak teams Vs weak teams***

In home game, guards from winning teams made less fouls, centres made more steals, forwards allow opponents made less two point field goals at the rim in contrast to the corresponding position players from losing teams. These defensive variables further highlighted that effective defensive tactics may be the key to winning the game when weak teams played against weak teams. In away game, the thesis indicated that the defence of weak teams in away games should primarily prevent the offence's centre from receiving a pass in the low post because supplying the ball to the player near the basket correctly is a determinant for success.

By combining the Chapter 5 and 6, it is worth noting that game performance was influenced by the situational variables, either independently or interactively. Consequently, this thesis

emphasised the need for coaches and performance analysts to consider the potential interactive effects of situational variables during the assessment of tactical, technical and physical performances in the future research.

Based on the above analysis, a combination of player and team-based analysis is generally comprised of this thesis. Chapter 2 used a team-based analysis, while Chapter 3, 4, 5 and 6 conducted a player analysis. The previous studies used a team-based research and looked for significant statistical differences to answer research problems (Çene, 2018; Conte *et al.*, 2018; Csataljay *et al.*, 2009; Doğan *et al.*, 2016; Gómez *et al.*, 2008; García *et al.*, 2014; Mexas *et al.*, 2005; Paulauskas *et al.*, 2018a). However, particularly when evaluating player contribution, the team-based research may not properly deeper interpretation. Hence, in this thesis, a team-based analysis was used to identify key performance indicators before an individual-analysis was used to be refined the influence of player's contribution on team success. Specifically, team-based analysis in section 1 (Chapter 2) can mask significant performance factors, but the team-based performance analysis used did not account for each individual's strengths and weaknesses. Hence, more detailed player analysis was conducted in Sections 2 (Chapter 3 and 4) and 3 (Chapter 5 and 6) to underpin the findings in Section 1. Secondly, the player analysis used in Chapter 3 and 4 was useful to examine the contribution and distribution of different type of players for team success in the National Basketball Association. Finally, the isolated and interactive influences of contextual variables on position-specific player were discussed to uncover team tactic strategies and player movement pattern. Overall, a combination of team and individual-based analysis in this thesis was effective in extracting all information and assist in enhancing coaches and sport scientists' understanding of the practical issues in applied sport science.

7.2 Novel perspectives

The innovative opinions of the thesis were conducted in Chapter 3 and 4. This thesis was the first to directly group basketball players into similar cluster groups according to a combination of playing experience and anthropometric characteristics or different levels of scoring production. This thesis provides novel perspectives to assess the player's contribution to team success. Additionally, the results from section 2 (Chapter 3 and 4) made detailed explanation and underpin the key performance indicators (KPIs) identified from section 1.

In fact, the assessment of collective behaviour based-on game-related statistics is widely accepted since it offers useful qualitative and quantitative information to optimise training process and player preparation for the match (Nevill *et al.*, 2008). However, there is still an ongoing challenge to obtain accurate and complex descriptions of game behaviours to provide meaningful information in depth during game-play. With the development of sport technology, notational or match analysis constitutes a great tool for coaches and performance analysts, providing objective recording and examination of behavioural events among players during training or competition to detect performance indicators (McGarry *et al.*, 2002). These methods have gained interest due to the advantages of observing players' spontaneous and creative behaviours within their natural environment, which enrich considerably the quality and external validity of records (Liebermann *et al.*, 2002). However, player characteristics and playing experience or scoring ability may have a direct impact on decision-making behaviour and movement pattern (Williams & Ford, 2008). This information results in a heuristic process for this thesis in defining the game-play characteristic and evaluating game performance according to player characteristics and playing experience and scoring ability. As a result, this thesis has identified this opinion and further extended assessing method for the performance analysis in sport in the future.

7.3 Limitations

Throughout this thesis there were a number of limitations associated with the studies as follows:

The first limitation is that the criterion of evaluating team quality in this thesis is based on the final ranking in the NBA. It means that the team entered into play-offs as strong teams whereas team did not entered the next phase as weak teams. Currently, some studies have used different methods to evaluate and compare the quality of teams and their opponents, such as multi-criteria assessing methods like TOPSIS and AHP (Dadelo *et al.*, 2014; Kiani Mavi *et al.*, 2012) or cluster analysis (Marcelino *et al.*, 2011; Sampaio, Drinkwater, *et al.*, 2010). Besides, team quality has either been subjectively categorized as “successful” or “unsuccessful” according to their standings or winning percentage within a particular tournament (Gómez *et al.*, 2017; Ibáñez *et al.*, 2008; Pollard & Gómez, 2007; Sampaio *et al.*, 2006) or classified as “strong” or “weak” and “top half” or “bottom half” based on symmetric division of end-of-season classification (Doğan *et al.*, 2016; Sampaio, Lago, Casais, *et al.*, 2010). However, there are no uniform standards to define the team quality so far. In this thesis, the application of the criterion was that Ibáñez *et al.* (2008) pointed out that replacing game final outcome with the final-ranking classification would be a more suitable measure of team success. Similarly, this is supported by Gómez *et al.* (2015) reflecting the different approaches to evaluate the team quality and pointed out that the use of final-ranking is the optimal reflection of the overall team’s strength. Regardless of this limitation, it remains an advantage of evaluating game performance of the team and player as the results are more valid and generalizable.

Another limitation of this thesis is that playing experience used in this thesis was considered

as NBA playing experience, which was an issue caused by the available of the archive data from official website. Collected data may result in the bias of the results when examining technical-tactical performances. For example, the superstar player who entered into NBA in the first year was defined as “rookie”, even if this player has accumulated playing experience in the other basketball league.

Final limitation of this thesis is that balanced games (final score differences equal to or less than 10 points) were selected as the research sample in the Chapter 2, 4 and 5 because this filtering criterion can represent the highest level of competitiveness to the utmost extent in the National Basketball Association. Hence, the current research results fail to provide evidences to underpin previous studies in unbalanced game.

7.4 Future Directions

Future research is expected to set up the standard of evaluating team quality in order to objectively classify strong and weak teams in the National Basketball Association. In addition, grouping team strength based on team winning percentage using cluster analysis technique would be the current mainstream trend in the sports science which may provide the new results to underpin the current research.

Playing experience should take into consideration the whole basketball career that can be developed upon a longitudinal assessment. Building up a more detailed performance profiles and providing more evidence-based insights for player selection and preparation. In addition, replacing playing experience with age may be an objective method to evaluate player performance based on the novel perspectives of this thesis.

Although novel player classification can be available in the current research such as low-scoring and high-scoring players, future investigation would be encouraged to dig out decision-making behaviours and movement pattern of these players under specific game situations.

It is vital that future studies would be recommended to continue to further expand situational variables and to refine the interactive influences of these contextual variables on technical and physical performances according to playing position. This process is likely to be undertaken with the existence of massive sample integrating with machine learning and artificial intelligence.

Tesis Doctoral

D. Shaoliang Zhang

CHAPTER 8
Overall Conclusion

Chapter 8 Overall Conclusion

8.1 Overall conclusion

The general aim of the thesis is to model and simulate the game performances of basketball players and teams based on game-related statistics taking into consideration influencing factors in the National Basketball Association. To achieve this aim, the multivariate and individual team performance profiles were built and temporal change of game-related statistics was visualised. Besides, playing experience, anthropometric characteristics (height and weight), different levels of point production (lower-scoring and higher-scoring players), playing role (starters and non-starters), and playing position (guards, forwards and centres) were considered to explore and examine the contribution and distribution of different type of players from each team integrating with team quality. Finally, the isolated and interactive influences of contextual variables on position-specific players were considered. Combining the key findings from the entire thesis chapters, theoretical recommendations and overall conclusions were established as follows:

The beginning and ending of the season (October and April) showed relatively dissimilarity compared with the other analysed period in the current NBA. Refining to a specific team found that Golden State Warriors that were progressing along shortest paths (with exception of October) while the Denver Nuggets possess the most dynamic paths. Furthermore, defensive rebounds were the common KPIs that discriminated between winning and losing games for strong and weak teams in the current NBA. Securing defensive rebounds is more than 40.6 during the game-play, the winning percentage for strong and weak teams were 81.1% and 65.6%. Also, highlighting assists and blocked shots for strong teams and turnovers for weak teams were KPIs. Moreover, with the progress of the schedule, the tactical strategies

of the teams evolve into effective interactions in terms of offence and defence. Finally, although three point field goals were found a growth trend throughout in-season period, this performance indicator was the most unstable game action showed substantial differences in variation under different scenario.

Grouping basketball players into five clustering groups (e.g. TopHW-LowE, MiddleHW-MiddleE, MiddleHW-TopE, LowHW-LowE, and LowHW-MiddleE) based on a combination of anthropometric characteristics and playing experience or two clustering groups (e.g. lower-scoring and higher-scoring players) based on different levels of scoring production. All players (included starters and non-starters) from weak teams are mainly distributed in the LowHW-LowE group while all players (included starters and non-starters) from strong teams are mostly allocated in the LowHW-MiddleE and MiddleHW-MiddleE group. In addition, strong teams in the current NBA were the teams with higher performance in guards from the higher-scoring clustering group. This thesis emphasised and highlighted that the contribution and distribution of the above different types of players between strong and weak teams has a direct impact on the team performance. Hence, player selection and recruitment in the current NBA may play a key role in differentiating team quality and determining game outcome. Interestingly, there is no difference in physical variables among the above different types of players which may be the reflection of the excellent athleticism of the players in the current NBA. Hence, coaches should note that deciding the final game outcome may be attributed to the difference on technical-tactical strategies and player selection to some extent.

It is worth noting that game performance was influenced by the situational variables, either independently or interactively. Consequently, this thesis emphasised the need for coaches and performance analysts to consider the potential interactive effects of situational variables

during the assessment of tactical, technical and physical performances in the future research. When considering the isolated impact of situational variables on position-specific players this thesis found that guards and forwards from strong teams covered less distance at lower speed whilst forwards and centres from strong teams made more three point field-goals comparing to their peers from weak teams. In addition, when considering the interactive potential of situational variables on position-specific players this thesis found as follows: i) strong teams vs strong teams, local players (guards, centres and forwards) from winning games covered shorter distances at lower average velocities during game-play and presented greater auto-effectiveness and self-confidence in passing and assisting while in away games, position-specific players from winning teams tend to maintain fast tempo and positive running to suppress and break opposing tactics possibly due to the lack of home advantage; ii) strong teams vs weak teams, in home games, guard and centres made more steals and blocks with longer distance covered at higher average velocities than their peers from losing games while centres from winning teams made more assists and steals in away game; iii) weak teams vs weak teams, effective defensive tactics may be the key to winning the game in home and away games.

Tesis Doctoral

D. Shaoliang Zhang

Bibliography

Bibliography

- Abdelkrim, N. B., et al. (2010). Positional role and competitive-level differences in elite-level men's basketball players. *The Journal of Strength & Conditioning Research*, 24(5), 1346-1355.
- Aglioti, S. M., et al. (2008). Action anticipation and motor resonance in elite basketball players. *Nature Neuroscience*, 11(9), 1109-1116. doi:10.1038/nn.2182
- Alejandro, V., et al. (2015). Anthropometric Characteristics of Spanish Professional Basketball Players. *J Hum Kinet*, 46, 99-106. doi:10.1515/hukin-2015-0038
- Alemdaroğlu, U. (2012). The relationship between muscle strength, anaerobic performance, agility, sprint ability and vertical jump performance in professional basketball players. *Journal of human kinetics*, 31, 149-158.
- Arya, S., & Mount, D. (1993). *Algorithms for fast vector quantization.*: IEEE Press.
- Batterham, A. M., & Hopkins, W. G. (2006). Making meaningful inferences about magnitudes. *International Journal of Sports Physiology and Performance*, 1(1), 50-57.
- Belk, J. W., et al. (2017). The Effect of Regular-Season Rest on Playoff Performance Among Players in the National Basketball Association. *Orthopaedic journal of sports medicine*, 5(10), 2325967117729798.
- Ben Abdelkrim, N., et al. (2007). Time-motion analysis and physiological data of elite under-19-year-old basketball players during competition. *Br J Sports Med*, 41(2), 69-75; discussion 75. doi:10.1136/bjsm.2006.032318
- Black, G. M., et al. (2016). The effect of intense exercise periods on physical and technical performance during elite Australian Football match-play: A comparison of experienced and less experienced players. *J Sci Med Sport*, 19(7), 596-602. doi:10.1016/j.jsams.2015.07.007
- Bracewell, P. J. (2003). Monitoring meaningful rugby ratings. *Journal of sports sciences*,

21(8), 611-620. doi:10.1080/0264041031000102006

- Bruce, L., et al. (2018). Team and seasonal performance indicator evolution in the ANZ Championship netball league. *Journal of sports sciences*, 1-7.
- Butterworth, A., et al. (2013). Performance profiling in sports coaching: a review. *International Journal of Performance Analysis in Sport*, 13(3), 572-593.
- Calleja-Gonzalez, J., et al. (2016). The Spanish "Century XXI" academy for developing elite level basketballers: design, monitoring and training methodologies. *Physician and Sportsmedicine*, 44(2), 148-157.
- Caparrós, T., et al. (2017). The Use of External Workload to Quantify Injury Risk during Professional Male Basketball Games. *Journal of Sports Science and Medicine*, 16, 480-488.
- Carr, J. (2015). The Home-Court Advantage Effect in NBA Basketball.
- Carron, A. V., et al. (2002). Team cohesion and team success in sport. *Journal of sports sciences*, 20(2), 119-126. doi:10.1080/026404102317200828
- Carron, A. V., et al. (2005). The home advantage in sport competitions: Courneya and Carron's (1992) conceptual framework a decade later. *Journal of sports sciences*, 23(4), 395-407.
- Carter, J., et al. (2005). Somatotype and size of elite female basketball players. *Journal of sports sciences*, 23(10), 1057-1063.
- Çene, E. (2018). What is the difference between a winning and a losing team: insights from Euroleague basketball. *International Journal of Performance Analysis in Sport*, 1-14. doi:10.1080/24748668.2018.1446234
- Chiu, T., et al. (2001). A Robust and Scalable Clustering Algorithm for Mixed Type Attributes in Large Database Environment. . San Francisco, CA: ACM.

- Clark, J. E., & Phillips, S. J. (1993). A longitudinal study of intralimb coordination in the first year of independent walking: a dynamical systems analysis. *Child development*, 64(4), 1143-1157.
- Clay, D. C., & Clay, K. E. (2014). Player Rotation, On-court Performance and Game Outcomes in NCAA Men's Basketball. *International Journal of Performance Analysis in Sport*, 14(2), 606-619.
- Cleary, T. J., & Zimmerman, B. J. (2001). Self-Regulation Differences during Athletic Practice by Experts, Non-Experts, and Novices. *Journal of Applied Sport Psychology*, 13(2), 185-206. doi:10.1080/104132001753149883
- Cohen, J. (1988). *Statistical power analysis for the behavioural sciences*: Hillsdale, NJ: Erlbaum.
- Conte, D., et al. (2018). Monitoring training load and well-being during the in-season phase in NCAA Division I men's basketball. *International Journal of Sports Physiology and Performance*, 1-25.
- Conte, D., et al. (2018). Investigating the game-related statistics and tactical profile in NCAA division I men's basketball games. *Biology of Sport*, 35(2).
- Cooley, W., & Lohnes, P. (1971). *Multivariate data analysis*. . New York: John Wiley & Sons, Inc.
- Cormery, B., et al. (2008). Rule change incidence on physiological characteristics of elite basketball players: a 10-year-period investigation. *British journal of sports medicine*, 42(1), 25-30.
- Courel-Ibáñez, J., et al. (2016). Inside pass predicts ball possession effectiveness in NBA basketball. *International Journal of Performance Analysis in Sport*, 16(2), 711-725.
- Courel-Ibáñez, J., et al. (2017). Collective behaviour in basketball: a systematic review. *International Journal of Performance Analysis in Sport*, 17(1-2), 44-64.

- Csataljay, G., et al. (2013). Effects of defensive pressure on basketball shooting performance. *International Journal of Performance Analysis in Sport*, 13(3), 594-601.
- Csataljay, G., et al. (2009). Performance indicators that distinguish winning and losing teams in basketball. *International Journal of Performance Analysis in Sport*, 9(1), 60-66.
- Cunningham, P., & Delaney, S. (2007). *k-Nearest Neighbor Classifiers*. University College Dublin, Ireland.
- Dadelo, S., et al. (2014). Multi-criteria assessment and ranking system of sport team formation based on objective-measured values of criteria set. *Expert Systems with Applications*, 41(14), 6106-6113.
- Dežman, B., et al. (2001). Expert model of decision-making system for efficient orientation of basketball players to positions and roles in the game—Empirical verification. *Collegium Antropologicum*, 25(1), 141-152.
- Diaz del Campo, D. G., et al. (2011). Differences in decision-making development between expert and novice invasion game players. *Percept Mot Skills*, 112(3), 871-888. doi:10.2466/05.10.11.25.PMS.112.3.871-888
- Doğan, İ., et al. (2016). Examining the Turkish Men's Professional Basketball Team's Success According to Game-related Statistics with Discriminant Analysis. *International Journal of Performance Analysis in Sport*, 16(3), 829-836.
- Drinkwater, E. J., et al. (2005). Characterizing changes in fitness of basketball players within and between seasons. *International Journal of Performance Analysis in Sport*, 5(3), 107-125.
- Drinkwater, E. J., et al. (2008). Design and interpretation of anthropometric and fitness testing of basketball players. *Sports Medicine*, 38(7), 565-578.
- Erculj, F., & Strumbelj, E. (2015). Basketball shot types and shot success in different levels of competitive basketball. *PLoS One*, 10(6), e0128885.

- Ferreira, A. P., et al. (2014). Towards the game critical moments in basketball: a grounded theory approach. *International Journal of Performance Analysis in Sport*, 14(2), 428-442.
- Fewell, J. H., et al. (2012). Basketball teams as strategic networks. *PLoS One*, 7(11), e47445.
- FIBA. (2009). *Basketball Statisticians Manual*. Geneva: International Basketball Federation.
- Fotinakis, P., et al. (2002). Due pallacanestro a confronto. *SDS*, 21(55), 52-56.
- Fox, J. L., et al. (2017). A review of player monitoring approaches in basketball: Current trends and future directions. *The Journal of Strength & Conditioning Research*, 31(7), 2021-2029.
- Friedman, J. H., et al. (1977). An algorithm for finding best matches in logarithm expected time. *ACM Transactions on Mathematical Software*, 3, 209-226.
- Gómez, M.-Á., et al. (2006). Defensive systems in basketball ball possessions. *International Journal of Performance Analysis in Sport*, 6(1), 98-107.
- Gómez, M. á., et al. (2015). Examining choking in basketball: effects of game outcome and situational variables during last 5 minutes and overtimes. *Perceptual and Motor Skills*, 120(1), 111-124.
- Gómez, M. A., et al. (2016). Performance analysis of game dynamics during the 4th game quarter of NBA close games. *International Journal of Performance Analysis in Sport*, 16(1), 249-263.
- Gómez, M. A., et al. (2017). THE USE OF CLASSIFICATION AND REGRESSION TREE WHEN CLASSIFYING WINNING AND LOSING BASKETBALL TEAMS. *Kineziologija*, 49(1), 12-13.
- Gómez, M. A., et al. (2008). Differences in game-related statistics of basketball performance by game location for men's winning and losing teams. *Perceptual and Motor Skills*,

106(1), 43-50.

Gómez, M. A., et al. (2008). Differences in game-related statistics of basketball performance by game location for men's winning and losing teams. *Perceptual and Motor Skills*, 106(1), 43-50.

Gómez, M. A., et al. (2013). Ball possession effectiveness in men's and women's elite basketball according to situational variables in different game periods. *J Sports Sci*, 31(14), 1578-1587. doi:10.1080/02640414.2013.792942

Gómez, M. A., et al. (2009). Game related statistics discriminating between starters and nonstarters players in Women's National Basketball Association League (WNBA). *Journal of Sports Science and Medicine*, 8(2), 278-283.

Gómez, M. A., et al. (2008). Game-related statistics that discriminated winning and losing teams from the Spanish men's professional basketball teams. *Collegium Antropologicum*, 32(2), 451-456.

Gómez, M. A., & Pollard, R. (2011). Reduced home advantage for basketball teams from capital cities in Europe. *European Journal of Sport Science*, 11(2), 143-148.

Gómez, M. A., et al. (2013). Ball Possession Effectiveness in Men's Elite Floorball According to Quality of Opposition and Game Period. *Journal of human kinetics*, 38, 227-237. doi:10.2478/hukin-2013-0062

Gómez, M. A., et al. (2017). Exploring the effects of substituting basketball players in high-level teams. *Journal of sports sciences*, 35(3), 247-254.

Gómez, M. A., et al. (2013). Situational variables. In T. McGarry, P. O'Donoghue, & J. Sampaio (Eds.), *Routledge Handbook of Sports Performance Analysis* (pp. 259-269). London: Routledge, Taylor & Francis.

Gabbett, T., et al. (2009). Physiological and anthropometric characteristics of junior elite and sub-elite rugby league players, with special reference to starters and non-starters. *J Sci*

- Med Sport, 12(1), 215-222. doi:10.1016/j.jsams.2007.06.008
- Gabbett, T. J., & Abernethy, B. (2013). Expert–novice differences in the anticipatory skill of rugby league players. *Sport, Exercise, and Performance Psychology*, 2(2), 138-155. doi:10.1037/a0031221
- Galily, Y. (2018). Choking or Delivering Under Pressure? The Case of Elimination Games in NBA Playoffs. *Frontiers in Psychology*, 9, 979.
- García, J., et al. (2014). Basketball Game-related statistics discriminating ACB league teams according to game location, game outcome and final score differences. *International Journal of Performance Analysis in Sport*, 14(2), 443-452.
- García, J., et al. (2013). Identifying basketball performance indicators in regular season and playoff games. *Journal of human kinetics*, 36(1), 161-168.
- García, J., et al. (2010). Análisis de los campeonatos del mundo de baloncesto masculino (2002 y 2006). Diferencias entre jugadores con diferentes niveles de experiencia (Senior y Junior). *Motricidad. European Journal of Human Movement*, 24.
- Garcia, J., et al. (2013). Identifying basketball performance indicators in regular season and playoff games. *J Hum Kinet*, 36, 161-168. doi:10.2478/hukin-2013-0016
- George, M., et al. (2009). The inside game in World Basketball. Comparison between European and NBA teams. *International Journal of Performance Analysis in Sport*, 9(2), 157-164.
- Gonzalez, A. M., et al. (2013). Performance changes in NBA basketball players vary in starters vs. nonstarters over a competitive season. *The Journal of Strength & Conditioning Research*, 27(3), 611-615.
- Guerra, Y. d. S., et al. (2013). Basketball scoring in NBA games: an example of complexity. *Journal of Systems Science and Complexity*, 26(1), 94-103.
- Hamill, J., et al. (1999). A dynamical systems approach to lower extremity running injuries.

- Clinical biomechanics, 14(5), 297-308.
- Hoffman, J. R., et al. (1999). The Influence of Aerobic Capacity on Anaerobic Performance and Recovery Indices in Basketball Players. *The Journal of Strength & Conditioning Research*, 13(4), 407-411.
- Hopkins, W. G. (2007). A spreadsheet to compare means of two groups. *Sportscience*, 11, 22-24.
- Hopkins, W. G., et al. (2009). Progressive statistics for studies in sports medicine and exercise science. *Med Sci Sports Exerc*, 41(1), 3-13. doi:10.1249/MSS.0b013e31818cb278
- Huang, F., & Hong, F. (2015). Globalization and the Governance of Chinese Sports: The Case of Professional Basketball. *The International Journal of the History of Sport*, 32(8), 1030-1043.
- Hughes, M., & Franks, I. M. (2004). *Notational analysis of sport: Systems for better coaching and performance in sport*: Psychology Press.
- Ibáñez, S. J., et al. (2009). Shot differences between professional (ACB) and amateur (EBA) basketball teams. Multifactorial study. *Revista de Psicología del Deporte*, 18(3), 313-317.
- Ibáñez, S. J., et al. (2009). Effects of consecutive basketball games on the game-related statistics that discriminate winner and losing teams. *Journal of sports science & medicine*, 8(3), 458.
- Ibáñez, S. J., et al. (2008). Basketball game-related statistics that discriminate between teams' season-long success. *European Journal of Sport Science*, 8(6), 369-372. doi:10.1080/17461390802261470
- Ibáñez, S. J., et al. (2003). Game statistics discriminating the final outcome of junior world basketball championship matches (Portugal 1999). *Journal of Human Movement Studies*, 45(1), 1-20.

- Ibáñez, S. J., et al. (2015). Multifactorial analysis of free throw shooting in eliminatory basketball games. *International Journal of Performance Analysis in Sport*, 15(3), 897-912.
- Ibanez, S. J., et al. (2008). Basketball game-related statistics that discriminate between teams' season-long success. *European Journal of Sport Science*, 8(6), 369-372. doi:10.1080/17461390802261470
- Ittenbach, R. F., et al. (1992). Team Performance and National Polls - the 1990-91 Ncaa Division I Basketball Season. *Perceptual and Motor Skills*, 74(3), 707-710.
- Jones, M. B. (2007). Home Advantage in the NBA as a Game-Long Process. *Journal of Quantitative Analysis in Sports*, 3(4). doi:10.2202/1559-0410.1081
- Karipidis, A., et al. (2001). Factors characterizing a successful performance in basketball. *Journal of Human Movement Studies*, 41(5), 385-397.
- Kenkel, N. C., & Orlóci, L. (1986). Applying metric and nonmetric multidimensional scaling to ecological studies: some new results. *Ecology*, 67(4), 919-928.
- Kerlinger, F., & Pedhazur, E. (1973). *Multiple Regression in Behavioral Research*, Holt, Rinehart and Winston, New York, 1973.
- Kiani Mavi, R., et al. (2012). Ranking football teams with AHP and TOPSIS methods. *International Journal of Decision Sciences, Risk and Management*, 4(1-2), 108-126.
- Kitsantas, A., & Zimmerman, B. J. (2010). Comparing Self-Regulatory Processes Among Novice, Non-Expert, and Expert Volleyball Players: A Microanalytic Study. *Journal of Applied Sport Psychology*, 14(2), 91-105. doi:10.1080/10413200252907761
- Klusemann, M. J., et al. (2013). Activity Profiles and Demands of Seasonal and Tournament Basketball Competition. *International Journal of Sports Physiology and Performance*, 8(6), 623-629. doi:10.1123/ijsp.8.6.623
- Koh, K. T., et al. (2011). Discriminating Factors between Successful and Unsuccessful Teams:

- A Case Study in Elite Youth Olympic Basketball Games. *Journal of Quantitative Analysis in Sports*, 7(3). doi:10.2202/1559-0410.1346
- Kotecki, J. (2014). Estimating the Effect of Home Court Advantage on Wins in the NBA.
- Kozar, B., et al. (1994). Importance of Free-Throws at Various Stages of Basketball Games. *Perceptual and Motor Skills*, 78(1), 243-248.
- Kubatko, J., et al. (2007a). A Starting Point for Analyzing Basketball Statistics. *Journal of Quantitative Analysis in Sports*, 3(3), 1-22.
- Kubatko, J., et al. (2007b). A starting point for analyzing basketball statistics. *Journal of Quantitative Analysis in Sports*, 3(3), 1-22.
- Latin, R. W., et al. (1994). Physical and Performance Characteristics of NCAA Division I Male Basketball Players. *The Journal of Strength & Conditioning Research*, 8(4), 214-218.
- Leicht, A., et al. (2017a). Explaining match outcome during the men's basketball tournament at the Olympic Games. *Journal of Sports Science and Medicine*, 1-19.
- Leicht, A. S., et al. (2017b). Team Performance Indicators Explain Outcome during Women's Basketball Matches at the Olympic Games. *Sports*, 5(4), 96.
- Leite, N. M., et al. (2014). Effect of defensive pressure on movement behaviour during an under-18 basketball game. *Int J Sports Med*, 35(9), 743-748. doi:10.1055/s-0033-1363237
- Liebermann, D. G., et al. (2002). Advances in the application of information technology to sport performance. *Journal of sports sciences*, 20(10), 755-769.
- Liu, H., et al. (2016). Technical performance and match-to-match variation in elite football teams. *Journal of sports sciences*, 34(6), 509-518.
- Livingston, I. J., et al. (2011). Influencing experience: the effects of reading game reviews on player experience. Paper presented at the International Conference on Entertainment

Computing.

- Lorenzo, A., et al. (2010). Game related statistics which discriminate between winning and losing under-16 male basketball games. *Journal of Sports Science and Medicine*, 9(4), 664-668.
- Losada, A. G., et al. (2016). BKViz: A Basketball Visual Analysis Tool. *IEEE Computer Graphics and Applications*, 36(6), 58-68. doi:10.1109/MCG.2016.124
- Lyons, M., et al. (2006). The impact of moderate and high intensity total body fatigue on passing accuracy in expert and novice basketball players.
- Malarranha, J., et al. (2013). Dynamic Modeling of Performance in Basketball. *International Journal of Performance Analysis in Sport*, 13, 377-386.
- Mangine, G. T., et al. (2014). Visual tracking speed is related to basketball-specific measures of performance in NBA players. *The Journal of Strength & Conditioning Research*, 28(9), 2406-2414.
- Marcelino, R., et al. (2011). Effects of quality of opposition and match status on technical and tactical performances in elite volleyball. *Journal of sports sciences*, 29(7), 733-741. doi:10.1080/02640414.2011.552516
- Mateus, N., et al. (2015). Game-to-game variability of technical and physical performance in NBA players. *International Journal of Performance Analysis in Sport*, 15(3), 764-776.
- McGarry, T., et al. (2002). Sport competition as a dynamical self-organizing system. *Journal of sports sciences*, 20(10), 771-781.
- McGarry, T., et al. (2013). *Routledge handbook of sports performance analysis*: Routledge.
- McLean, B. D., et al. (2018). Quantifying Physical Demands in the National Basketball Association (NBA): Challenges in Developing Best-Practice Models for Athlete Care and Performance. *International Journal of Sports Physiology and Performance*, 1-22.
- Mertz, J., et al. (2016). Ranking the Greatest Nba Players: A Sport Metrics Analysis.

- International Journal of Performance Analysis in Sport, 16(3), 737-759.
- Mexas, K., et al. (2005). Comparison of effectiveness of organized offences between two different championships in high level basketball. *International Journal of Performance Analysis in Sport*, 5(1), 72-82.
- Mikolajec, K., et al. (2013). Game Indicators Determining Sports Performance in the NBA. *J Hum Kinet*, 37, 145-151. doi:10.2478/hukin-2013-0035
- Miller, S. (2002). Variability in basketball shooting: practical implications. *International research in sports biomechanics*, 27-34.
- Miller, S., & Bartlett, R. (1994). Notational analysis of the physical demands of basketball. *Journal of sports sciences*, 12(2), 181.
- Mori, S., et al. (2002). Reaction times and anticipatory skills of karate athletes. *Human movement science*, 21(2), 213-230.
- Moxley, J. H., & Towne, T. J. (2015). Predicting success in the National Basketball Association: Stability & potential. *Psychology of Sport and Exercise*, 16, 128-136.
- Muthiane, C. M., et al. (2015). The relationship between team cohesion and performance in Basketball League in Kenya. *International Journal of Applied Psychology*, 5(4), 90-95.
- Nevill, A., et al. (2008). Twenty-five years of sport performance research in the *Journal of Sports Sciences*. *Journal of sports sciences*, 26(4), 413-426.
- Newell, K. M., & Corcos, D. M. (1993). *Variability and motor control: Human Kinetics*.
- Norusis, M. J., & Inc, S. (2004). *SPSS 13.0 advanced statistical procedures companion*. Upper Saddle River, N.J.: Prentice Hall.
- O'Donoghue, P. (2005). Normative profiles of sports performance. *International Journal of Performance Analysis in Sport*, 5(1), 104-119.
- O'Donoghue, P. (2013). *Statistics for sport and exercise studies: an introduction*: Routledge.
- Oliver, D. (2004). *Basketball on Paper: Rules and Tools for Performance Analysis*: Brassey's,

Incorporated.

- Ostojic, S. M., et al. (2006). Profiling in basketball: physical and physiological characteristics of elite players. *The Journal of Strength & Conditioning Research*, 20(4), 740-744.
- Ozmen, M. U. (2012). Foreign Player Quota, Experience and Efficiency of Basketball Players. *Journal of Quantitative Analysis in Sports*, 8(1). doi:10.1515/1559-0410.1370
- Paul, M., & Garg, K. (2012). The effect of heart rate variability biofeedback on performance psychology of basketball players. *Applied Psychophysiology and Biofeedback*, 37(2), 131-144.
- Paulauskas, P., et al. (2018). Basketball game-related statistics that discriminate between European players competing in the NBA and in the Euroleague. *J. Hum. Kinet.*
- Pedhazur, E. J. (1982). *Multiple Regression in Behavioral Research*. . New York: Holt, Rinehart & Winston.
- Pinilla Arbex, J., et al. (2015). Performance variability in basketball players with intellectual impairment: Ankara World Championships 2013 analysis. *Revista de Psicología del Deporte*, 24(3), 77-83.
- Pojksic, H., et al. (2015). Positional Role Differences in the Aerobic and Anaerobic Power of Elite Basketball Players. *Journal of human kinetics*, 49(1), 219-227.
- Pollard, R., & Gómez, M. A. (2007). Home advantage analysis in different basketball leagues according to team ability. Paper presented at the Iberian congress on basketball research.
- Pollard, R., & Gómez, M. A. (2013). Variations in home advantage in the national basketball leagues of europe. *Revista de Psicología del Deporte*, 22(1), 263-266.
- Popovic, S., et al. (2013). Comparative study of anthropometric measurement and body composition between elite soccer and basketball players. *Int. J. Morphol*, 31(2), 461-467.

- R Core Team. (2015). R: A language and environment for statistical computing. Vienna, Australia: R Foundation for Statistical Computing.
- Robins, R., et al. (2006). The effect of shooting distance on movement variability in basketball. *Journal of Human Movement Studies*, 50(4), 217-238.
- Rowe, R., et al. (2009). The Effect of Disguise on Novice and Expert Tennis Players' Anticipation Ability. *Journal of Applied Sport Psychology*, 21(2), 178-185.
doi:10.1080/10413200902785811
- Ruiz, M., et al. (2014). The relationship between concentration of scoring and offensive efficiency in the NBA. *Journal of Quantitative Analysis in Sports*, 10(1).
doi:10.1515/jqas-2013-0060
- Sallet, P., et al. (2005). Physiological differences in professional basketball players as a function of playing position and level of play. *Journal of sports medicine and physical fitness*, 45(3), 291.
- Sampaio, J., et al. (2009). Análisis de las estadísticas discriminantes en jugadores de baloncesto según su puesto específico, en las finales de las competiciones europeas (1988-2006). Diferencias entre jugadores titulares y suplentes. *Apunts. Educación física y deportes*, 2(96), 53-58.
- Sampaio, J., et al. (2010). Effects of season period, team quality, and playing time on basketball players' game-related statistics. *European Journal of Sport Science*, 10(2), 141-149.
- Sampaio, J., et al. (2004). Discriminative power of basketball game-related statistics by level of competition and sex. *Perceptual and Motor Skills*, 99(3 suppl), 1231-1238.
- Sampaio, J., et al. (2014). Exploring how basketball players' tactical performances can be affected by activity workload. *Science & Sports*, 29(4), e23-e30.
doi:10.1016/j.scispo.2013.05.004

- Sampaio, J., et al. (2008). Game location influences basketball players performance across playing positions. *International Journal of Sport Psychology*, 39(3), 43-50.
- Sampaio, J., et al. (2006). Discriminative game-related statistics between basketball starters and nonstarters when related to team quality and game outcome. *Perceptual and Motor Skills*, 103(2), 486-494.
- Sampaio, J., et al. (2013). Basketball. In T. McGarry, P. O'Donoghue, & J. Sampaio (Eds.), *Routledge Handbook of Sports Performance Analysis* (pp. 357-366). London: Routledge, Taylor & Francis.
- Sampaio, J., & Janeira, M. (2003). Statistical analyses of basketball team performance: understanding teams' wins and losses according to a different index of ball possessions. *International Journal of Performance Analysis in Sport*, 3(1), 40-49.
- Sampaio, J., et al. (2006). Discriminant analysis of game-related statistics between basketball guards, forwards and centres in three professional leagues. *European Journal of Sport Science*, 6(3), 173-178. doi:10.1080/17461390600676200
- Sampaio, J., et al. (2013). Brief exploration of short and mid-term timeout effects on basketball scoring according to situational variables. *European Journal of Sport Science*, 13(1), 25-30. doi:10.1080/17461391.2011.582163
- Sampaio, J., et al. (2010). Effects of starting score-line, game location, and quality of opposition in basketball quarter score. *European Journal of Sport Science*, 10(6), 391-396. doi:10.1080/17461391003699104
- Sampaio, J., et al. (2010). Explanations for the United States of America's dominance in basketball at the Beijing Olympic Games (2008). *Journal of sports sciences*, 28(2), 147-152. doi:10.1080/02640410903380486
- Sampaio, J., et al. (2015). Defensive pressure affects basketball technical actions but not the time-motion variables. *Journal of Sport and Health Science*.

doi:10.1016/j.jshs.2015.01.011

Sampaio, J., et al. (2015). Exploring Game Performance in the National Basketball Association Using Player Tracking Data. PLoS One, 10(7), e0132894.

doi:10.1371/journal.pone.0132894

Sampaio, J., et al. (2015). Exploring Game Performance in the National Basketball Association Using Player Tracking Data. PLoS One, 10(7). doi:ARTN e0132894

10.1371/journal.pone.0132894

Santos, S., et al. (2016). Do previous sports experiences influence the effect of an enrichment programme in basketball skills? J Sports Sci, 1-9.

doi:10.1080/02640414.2016.1236206

Scanlan, A., et al. (2011). A comparison of the activity demands of elite and sub-elite Australian men's basketball competition. J Sports Sci, 29(11), 1153-1160.

doi:10.1080/02640414.2011.582509

Shaoliang, Z., et al. (2017). Players' technical and physical performance profiles and game-to-game variation in NBA. International Journal of Performance Analysis in Sport, DOI:10.1080/24748668.2017.1352432.

Shea, S. M., & Baker, C. E. (2013). Basketball Analytics: Objective and Efficient Strategies for Understanding How Teams Win.

Soebbing, B. P., & Mason, D. S. (2009). Managing legitimacy and uncertainty in professional team sport: the NBA's draft lottery. Team Performance Management: An International Journal, 15(3/4), 141-157.

Soltani, P., et al. (2016). Do player performance, real sport experience, and gender affect movement patterns during equivalent exergame? Computers in Human Behavior, 63, 1-8. doi:10.1016/j.chb.2016.05.009

Staunton, C., et al. (2018). The Effect of Match Schedule on Accelerometry-Derived Exercise

- Dose during Training Sessions throughout a Competitive Basketball Season. *Sports* (Basel, Switzerland), 6(3).
- Steenland, K., & Deddens, J. A. (1997). Effect of travel and rest on performance of professional basketball players. *Sleep*, 20(5), 366-369.
- Stergiou, N., & Decker, L. M. (2011). Human movement variability, nonlinear dynamics, and pathology: is there a connection? *Human movement science*, 30(5), 869-888.
- Stergiou, N., et al. (2006). Optimal movement variability: a new theoretical perspective for neurologic physical therapy. *Journal of Neurologic Physical Therapy*, 30(3), 120-129.
- Štirn, I., et al. (2016). Influence of different heights and widths of basic athletic stance on the response time in basketball. *International Journal of Performance Analysis in Sport*, 16(1), 53-63.
- Stojanović, E., et al. (2017). The Activity Demands and Physiological Responses Encountered During Basketball Match-Play: A Systematic Review. *Sports Medicine*, 1-25.
- Strumbelj, E., & Erculj, F. (2014). Analysis of experts' quantitative assessment of adolescent basketball players and the role of anthropometric and physiological attributes. *J Hum Kinet*, 42, 267-276. doi:10.2478/hukin-2014-0080
- Swann, C., et al. (2012). A systematic review of the experience, occurrence, and controllability of flow states in elite sport. *Psychology of Sport and Exercise*, 13(6), 807-819. doi:10.1016/j.psychsport.2012.05.006
- Taheri, H., et al. (2016). The Effect of Variability of Practice at Execution Redundancy Level in Skilled and Novice Basketball Players. *Perceptual and Motor Skills*, 124(2), 491-501. doi:10.1177/0031512516684078
- Tarlow, J. (2012). Experience and winning in the national basketball association. MIT Sloan Sports Analytics Conference 2012.
- Tatsuoka, M. (1971). *Multivariate analysis*. New York: John Wiley & Sons, Inc.

- Taylor, B. A., & Trogon, J. G. (2002). Losing to win: Tournament incentives in the National Basketball Association. *Journal of Labor Economics*, 20(1), 23-41.
- Teramoto, M., & Cross, C. L. (2010). Relative Importance of Performance Factors in Winning NBA Games in Regular Season versus Playoffs. *Journal of Quantitative Analysis in Sports*, 6(3). doi:10.2202/1559-0410.1260
- Teramoto, M., & Cross, C. L. (2017). Importance of team height to winning games in the National Basketball Association. *International Journal of Sports Science & Coaching*, 1747954117730953.
- Teramoto, M., et al. (2017). Game injuries in relation to game schedules in the National Basketball Association. *Journal of science and medicine in sport*, 20(3), 230-235.
- Thelen, E. (1995). Motor development: A new synthesis. *American psychologist*, 50(2), 79.
- Thomas, J. R., et al. (2015). *Research methods in physical activity*, 7E: Human kinetics.
- Tomovic, M., et al. (2016). P-91 Anthropometric features of elite male basketball players regarding their playing position. can a high bmi be a health risk for this group of athletes? *Br J Sports Med* 2016;50:A82
- Torres-Unda, J., et al. (2013). Anthropometric, physiological and maturational characteristics in selected elite and non-elite male adolescent basketball players. *Journal of sports sciences*, 31(2), 196-203.
- Travassos, B., et al. (2013). Expertise effects on decision-making in sport are constrained by requisite response behaviours – A meta-analysis. *Psychology of Sport and Exercise*, 14(2), 211-219. doi:10.1016/j.psychsport.2012.11.002
- Trewin, J., et al. (2017). The influence of situational and environmental factors on match-running in soccer: a systematic review. *Science and Medicine in Football*, 1-12.
- Trninić, S., et al. (2008). Player selection procedures in team sports games. *Acta Kinesiologica*, 2(1), 24-28.

- Trninic, S., et al. (1999). Set of criteria for the actual quality evaluation of the elite basketball players. *Collegium Antropologicum*, 23(2), 707-721.
- Tsitskaris, G., et al. (2003). Speed, speed dribble and agility of male basketball players playing in different positions. *Journal of Human Movement Studies*, 45(1), 21-30.
- van Beers, R. J., et al. (2004). The role of execution noise in movement variability. *Journal of neurophysiology*, 91(2), 1050-1063.
- Weston, M., et al. (2010). Ageing and physical match performance in English Premier League soccer referees. *Journal of science and medicine in sport*, 13(1), 96-100.
doi:10.1016/j.jsams.2008.07.009
- Williams, A. (1993). Advance cue utilization in soccer. *Science and football II*, 284-290.
- Williams, A. M., & Ford, P. R. (2008). Expertise and expert performance in sport. *International Review of Sport and Exercise Psychology*, 1(1), 4-18.
doi:10.1080/17509840701836867
- Willoughby, D. S., & Simpson, S. (1996). The Effects of Combined Electromyostimulation and Dynamic Muscular Contractions on the Strength of College Basketball Players. *The Journal of Strength & Conditioning Research*, 10(1), 40-44.
- Wood, S. N. (2003). Thin plate regression splines. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, 65(1), 95-114.
- Woods, C. T., et al. (2018). Game-play characteristics differ between the European Super League and the National Rugby League: Implications for coaching and talent recruitment. *International Journal of Sports Science & Coaching*, 1747954118788449.
- Woods, C. T., et al. (2017). Evolution of game-play in the Australian Football League from 2001 to 2015. *Journal of sports sciences*, 35(19), 1879-1887.
- Woods, C. T., et al. (2018). Transferring an analytical technique from ecology to the sport sciences. *Sports Medicine*, 48(3), 725-732.

- Woods, C. T., et al. (2017). Non-metric multidimensional performance indicator scaling reveals seasonal and team dissimilarity within the National Rugby League. *Journal of science and medicine in sport*.
- Zhang, S., et al. (2017). Players' technical and physical performance profiles and game-to-game variation in NBA. *International Journal of Performance Analysis in Sport*, 17(4), 466-483. doi:10.1080/24748668.2017.1352432
- Zhang, S., et al. (2017). Performance Profiles of Basketball Players in NBA According to Anthropometric Attributes and Playing Experience. Paper presented at the Complex Systems in Sport, International Congress Linking Theory and Practice.
- Zhang, S., et al. (2018). Clustering performances in the NBA according to players' anthropometric attributes and playing experience. *Journal of sports sciences*, 36(22), 2511-2520. doi:10.1080/02640414.2018.1466493
- Zhang, T., et al. (1996). BIRCH: An efficient data clustering method for very large databases. In: *Proceedings of the ACM SIGMOD Conference on Management of Data*. . Montreal, Canada: ACM.
- Zimmer, T., & Kuethe, T. H. (2009). Testing for Bias and Manipulation in the National Basketball Association Playoffs. *Journal of Quantitative Analysis in Sports*, 5(3). doi:10.2202/1559-0410.1149
- Zuccolotto, P., et al. (2017). Big data analytics for modeling scoring probability in basketball: The effect of shooting under high-pressure conditions. *International Journal of Sports Science & Coaching*, 1747954117737492.

Tesis Doctoral

D. Shaoliang Zhang

Appendix

Appendix– Publications and Conference Presentations

Publications in scientific journals

Zhang, S., Lorenzo, A., Gómez, M. A., Liu, H., Gonçalves, B., & Sampaio, J. (2017). Players' technical and physical performance profiles and game-to-game variation in NBA. *International Journal of Performance Analysis in Sport*, 17(4), 466-483. doi: 10.1080/24748668.2017.1352432.

Zhang, S., Lorenzo, A., Gómez, M. A., Mateus, N., Gonçalves, B., & Sampaio, J. (2018). Clustering performances in the NBA according to players' anthropometric attributes and playing experience. *Journal of Sports Sciences*, 36(22), 2511-2520. doi: 10.1080/02640414.2018.1466493.

Zhang, S., Lorenzo, A., Zhou, C., Cui, Y., Gonçalves, B., & Gómez, M. A. (2019). Performance profiles and opposition interaction during game-play in elite basketball: evidences from National Basketball Association. *International Journal of Performance Analysis in Sport*, 19(1), 28-48. doi:10.1080/24748668.2018.1555738

Zhang, S., Lorenzo, A., Woods, C. T., Leicht, A. S. & Gómez, M. A. (2019). Evolution of game-play characteristics with-in-season for the National Basketball Association. *International Journal of Sports Science & Coaching*.

Zhou, C., **Zhang, S.**, Lorenzo, A., & Cui, Y. (2018). Chinese soccer association super league, 2012–2017: key performance indicators in balance games. *International Journal of Performance Analysis in Sport*, 18(4), 645-656. doi: 10.1080/24748668.2018.1509254.

José Bonal, Sergio Jimenez, **Shaoliang Zhang**, Alberto Lorenzo (2019). Key factors on talent development of expertise basketball players in China. *Revista de Psicología del Deporte/Journal of Sport Psychology*

Juan Traperro, Carlos Sosa, **Shaoliang Zhang**, Rubén Portes, Miguel-Angel Gómez, José Bonal, Sergio Jiménez & Alberto Lorenzo (2019). Comparison of the movement

characteristics based on position-specific between semi-elite and elite basketball players. *Revista de Psicología del Deporte/Journal of Sport Psychology*

Ordóñez, A. F., Polo, B., Lorenzo, A., & **Shaoliang, Z.** (2019). Effects of a School Physical Activity Intervention in Pre-adolescents. *Apunts. Educación Física y Deportes*, 136, 49-61. doi:10.5672/apunts.2014-0983.es.(2019/2).136.04

Liu, H., Cui, Y., **Zhang, S.** (2016). Development and outlook of sports performance analysis (In Chinese, English abstract). *Journal of Physical Education*. 23(2):112-117. doi: 1006-7116(2016)02-0112-06

Wei, L., LU, Z., **Zhang, S.** (2015). Contemplation of the Chinese professional football league competition balancing mechanism——Based on the impact of “Evergrande Mode” on league competition balance (In Chinese, English abstract). *Journal of Physical Education*. 2015(1):23-27. doi: 1006-7116(2015)01-0023-05

Presentations in International Conferences

Zhang, S., Hongyou, L., Lorenzo, A. (2016). Evaluating the quality of opposition in basketball games based on TOPSIS method. *21st annual congress of the European college of sport science. (Mini-oral presentation)*

Zhang, S., Lorenzo, A., Gómez, M. A., Mateus, N., Gonçalves, B., & Sampaio, J. (2018). Performance Profiles of Basketball Players in NBA According to Anthropometric Attributes and Playing Experience. *Complex Systems in Sport, International Congress Linking Theory and Practice. (Oral presentation)*

Zhou, C., Lorenzo, A., Gómez, M. A., **Zhang, S.**, (2018). Physical Performance in Match of Teams in the Chinese Football Association Super League: Effects of Match Location, Period and Ball Possession Status. *Complex Systems in Sport, International Congress Linking Theory and Practice. (Oral presentation)*

Zhang, S., Lorenzo, A., Gómez, M. A. (2018). The interactive effects of situational variables on team performance in the NBA. *23st annual congress of the European college of sport science. (Mini-oral presentation)*

Zhou, C., Lorenzo, A., Gómez, M. A., **Zhang, S.** (2018). Match Performance profiles of strong teams and weak teams In Chinese Soccer Super League. *23st annual congress of the European college of sport science. (Mini-oral presentation)*

Juan Trapero, Carlos Sosa, **Shaoliang Zhang**, Rubén Portes, Miguel-Angel Gómez, José Bonal, Sergio Jiménez & Alberto Lorenzo (2018). Comparison of the movement characteristics based on position-specific between semi-elite and elite basketball players. *Iberian Congress on Basketball Research. (Oral presentation)*

José Bonal, Sergio Jimenez, **Shaoliang Zhang**, Alberto Lorenzo (2018). Key factors on talent development of expertise basketball players in China. *Iberian Congress on Basketball Research. (Oral presentation)*

Book published:

Book title: Modelling and Simulation in Sport and Exercise

Chapter: basketball

Series: Routledge Research in Sport and Exercise Science

Hardcover: 296 pages

Publisher: Routledge

Year: 1 edition (September 7, 2018)

Language: English

Location: New York and London

ISBN-13: 978-1138059931