Universidad Miguel Hernández de Elche

Programa de Doctorado en Deporte y Salud

Epidemiology and prediction models of injuries in elite futsal

Doctoral thesis

A dissertation presented by

Ignacio Ruiz Pérez

Directed by

Dr. Francisco Ayala Rodríguez and Dr. José Luis López Elvira

Elche, 2020

Esta tesis doctoral, titulada *Epidemiology and prediction models of injuries in elite futsal*, se presenta con los siguientes indicios de calidad:

- Artículo 2:

Published as: Ruiz-Pérez, I., López-Valenciano, A., Jiménez-Loaisa, A., Elvira, J. L. L. L., De Ste Croix, M., & Ayala, F. (2019). Injury incidence, characteristics and burden among female sub-elite futsal players: a prospective study with three-year follow-up. PeerJ, 7, e7989. https://doi.org/10.7717/peerj.7989

Revista indexada en *Journal Citation Reports* con un factor de impacto de 3,234 (Q2).

- Artículo 5:

Published as: Ruiz-Pérez, I., Ayala, F., Puerta, J. M., Elvira, J. L. L., De Ste Croix, M., Hernández-Sánchez, S., & Vera-García, F. J. (2019). A Bayesian Network approach to study the relationships between several neuromuscular performance measures and dynamic postural control in futsal players. PLOS ONE, 14(7), e0220065. https://doi.org/10.1371/journal.pone.0220065

Revista indexada en *Journal Citation Reports* con un factor de impacto de 2,353 (Q2).

El Dr. Francisco Ayala Rodríguez junto al Dr. José Luis López Elvira, Titular de la Universidad Miguel Hernández de Elche hacen constar que el trabajo de investigación titulado *Epidemiology and prediction models of injuries in elite futsal* realizado por el doctorando D. Ignacio Ruiz Pérez, ha sido supervisado bajo su dirección y autorizado para su defensa de Tesis Doctoral en esta Universidad ante el tribunal correspondiente.

Lo que firman para los efectos oportunos en:

Elche, a 19 de mayo de 2020

Firmado por AYALA RODRIGUEZ FRANCISCO - 48500355W el día 18/01/2021 con un certificado emitido por AC FNMT Usuarios

Fdo.: Francisco Ayala Rodríguez

JOSE LUIS| LOPEZ| ELVIRA

Firmado digitalmente por JOSE LUIS|LOPEZ| ELVIRA
Fecha: 2020.11.18 13:10:48 +01'00'

Fdo.: José Luis López Elvira

Universidad Miguel Hernández de Elche

UNIVERSITAS
Miguel Hernández

El Dr. Francisco Javier Moreno Hernández, coordinador del programa de doctorado Deporte y Salud de la Universidad Miguel Hernández de Elche.

AUTORIZA:

Que el trabajo de investigación titulado: *"Epidemiology and prediction models of injuries in elite futsal"* realizado por D. Ignacio Ruiz Pérez bajo la dirección del Dr. Francisco Ayala Rodríguez y el Dr. José Luis López Elvira, sea defendido como Tesis Doctoral en esta Universidad ante el tribunal correspondiente.

Lo que firma para los efectos oportunos en:

Elche, a 19 de mayo de 2020

FRANCISCO JAVIER|MORENO| HERNANDEZ

Firmado digitalmente por FRANCISCO JAVIER| MORENO|HERNANDEZ
Fecha: 2021.01.18 14:23:45 +01'00'

Fdo.: Francisco Javier Moreno Hernández

Coordinador del programa de doctorado

Universidad Miguel Hernández de Elche

UNIVERSITAS
Miguel Hernández

El doctorando contó con una beca de Formación del Personal Investigador financiada por el Ministerio de Economía y Competitividad (Ref: BES-2015-07200) para el desarrollo de la Tesis Doctoral.

UNIVERSIDAD MIGUEL HERNÁNDEZ DE ELCHE

Programa de Doctorado en Deporte y Salud

Título de la Tesis:

EPIDEMIOLOGY AND PREDICTION MODELS OF INJURIES IN ELITE FUTSAL

Tesis Doctoral presentada por:

D. Ignacio Ruiz Pérez

Dirigida por el Dr. Francisco Ayala Rodríguez y del Dr. José Luis López Elvira

El director	**El codirector**	**El doctorando**
	Firmado por AYALA RODRIGUEZ FRANCISCO - 48500355W el día	
Fdo.: José Luis López Elvira	Fdo.: Francisco Ayala Rodríguez	Fdo.: Ignacio Ruiz Pérez

Elche, mayo de 2020

UNIVERSIDAD MIGUEL HERNÁNDEZ DE ELCHE

Programa de Doctorado en Deporte y Salud

Epidemiology and Prediction Models of Injuries in Elite Futsal

Doctoral Thesis

A dissertation presented by Ignacio Ruiz Pérez

Directores: Dr. Francisco Ayala Rodríguez y Dr. José Luis López Elvira

A mi padre, Lucio.

AGRADECIMIENTOS

Antes de nada, decir, que esta tesis doctoral no es mía. Sí, es posible que el nombre que aparezca en la portada sea el mío, pero ni mucho menos me atrevería a decir que es mía en el más estricto sentido de la palabra.

Esta tesis es de Fran Ayala, gran Maestro *Jedi*. No es que sea solamente el genio cuyo ejemplo seguir en el mundo de la investigación, sino que es igualmente una gran persona a la que admirar. Firme en sus principios, honesto, bondadoso y siempre ayudando a todo aquel que puede. Tras comentarme que iba a empezar a realizar con él esta tesis, algo sobre deporte de alto rendimiento y que nada tenía que ver con el tema que llevaba yo ya investigando tres años, le dije que no me atraía para nada la idea del tema. Por supuesto ni se inmutó, "seguiremos siendo igual de amigos", frase que creo le ha oído decir todo aquel que haya sido su alumno. Tranquilamente me empezó a explicar cosas sobre inteligencia artificial, relaciones causales y de independencia condicionada entre variables, *machine learning* y redes bayesianas. Claramente, yo no entendí absolutamente nada. No se por qué, pero eso consiguió que me fascinara el tema y acabara desarrollando una pasión que me trae hoy a este momento. Honestamente, no me arrepiento de la decisión que tomé aquel día de seguir a este murciano por el camino que él me indicara como buen *padawan*.

Esta tesis es también de José Luis, mi otro director. Esa persona capaz de preguntarte con qué videojuego estrenar el nuevo ordenador que se ha comprado como de desarrollarte un software con el que obtener datos de manera "sencillísima" del querido Vicon. Ese maravilloso sistema que algún que otro día he querido ver arder en llamas y estoy seguro de que él también. Igualmente, esta tesis pertenece a Fran Vera, director del laboratorio de biomecánica, mi primer maestro en esto de la ciencia y el responsable de que quisiera empezar a investigar. Cierto que me costó convencerle de que me dejara entrar al laboratorio, y hasta que no me corté las rastas no hubo una respuesta afirmativa. Seguramente casualidad que coincidiera en el tiempo, seguramente.

Por supuesto, los mayores responsables de que esta tesis exista son mi Familia. Familia que me vio marchar en el 2007 de Bilbao porque en las pruebas físicas de acceso a la carrera en Vitoria el tema principal de estudio de esta tesis, las lesiones, tuvo que hacer su aparición. Gracias a mi madre, Nieves, a mi padre, Lucio, a mis hermanos, Jorge y Gustavo, a mis cuñadas Ainhoa y Saray, y por supuesto gracias a mis fantásticos sobrinos, Ibai, Maider, Beñat e Izane. Gracias por los sacrificios que han tenido que hacer para que yo estudiara aquí, los cumpleaños y fiestas importantes ausentes, las visitas cada tres o cuatro meses en el mejor de los casos, entre otras muchas cosas. Gracias a mis abuelos por acogerme en tierras alicantinas, a mis tíos y primos que me dieron su apoyo en todo momento, aunque a veces se quejen de que no hago mucho uso de él. Sobre todo, gracias a Carlos, que me dio el aire que me faltaba en muchos momentos, me unió a su grupo de amigos y me hizo el inicio de mi nueva vida mucho más sencilla.

Esta tesis también es de esa otra familia, la que descubrí en Elche. La vida hubiera sido mucho más difícil si no llega a ser por ellos. Gracias a Artur, Álvaro, Alejandro, Adri, Carla, María, Marta, Alicia, Alba, Chiki, Xoxe, Sarabia, Rafa… La posibilidad de ir los jueves, o cualquier día que se terciara, a tomar unas cervezas, a viajar, a conciertos, a jugar a lo que fuera y desconectar de ese centro de investigación estando con la misma gente, haciendo las mismas idioteces, pero siendo felices, no tiene precio.

Como decía, esta tesis no es mía, si no fuera por todas aquellas personas que me han regalado horas de su vida echándome una mano para las muy muchas y muy largas sesiones de mediciones. Fran, dispuesto a ser uno más del equipo, Sergio y su perenne sonrisa y buen humor. Qué decir de los compañeros que me han acompañado siempre, como Alejandro, Maripili, Casto, Carlos, Diego, Pedro, Amaya, Javi, Belén, los murcianos Fran y May… gracias. Os lo intentaba compensar con empanadillas para haceros más llevaderas las sesiones de mediciones, espero que sirvieran de algo. Ese gran grupo de

BIOMEC, sin el cual, el investigar estos años habría carecido completamente de sentido. Gracias a Alejandro, siempre con opiniones completamente opuestas a la mía en todo lo que discutiéramos. Lo mismo daba qué hablásemos, ya fuera de como enfocar la actividad física saludable, el cómo evaluar a los alumnos o lo que se terciara en ese momento. A pesar de ello, o tal vez por ello, podemos estar orgullosos del trabajo que hemos llevado a cabo. Esta tesis no es más que una extensión de la que él presentó en su día y sin ese trabajo previamente hecho, posiblemente ésta sería muy distinta la que ha acabado siendo. Él ha sido el otro *padawan* en nuestro entrenamiento *Jedi*, y estoy seguro de que, a pesar de que su *curriculum* sea ya envidiable y digno de enmarcar, mejorará y acabará siendo un referente en el campo que él se proponga. Gracias a Casto, que fue el que me enseñó a no perderme y orientarme en el mundo de la docencia universitaria. Salidas de rápel, escalada, vías ferratas o descenso de barrancos, son solo algunas de las experiencias que me regaló mientras solucionábamos el mundo de la investigación y del centro donde nos formábamos. Gracias a Maripili, echando una y mil horas trabajando y enseñando a todos lo que es la constancia y el esfuerzo. Gracias a Diego, con el que empecé este camino dentro del laboratorio y sé que tarde o temprano conseguirá lo que está buscando, aunque quién sabe en qué lugar. Gracias a Barbado, con el que poder hablar de libros y literatura, de vino, de qué pasa con ese artículo que le enviaste hace año y medio y de que te proponga miles de análisis estadísticos nuevos que acaba de descubrir y cree que serán perfectos para el mismo y por lo tanto habrá que volver a empezar. Gracias a Amaya, esa chica del sur, que se mudó más al sur para poder investigar con su referente y que está secretamente enamorada de Bilbao.

Dudo que ellos lo sepan, pero esta tesis también pertenece al Club Algar, especialmente a su personificación, Víctor Alberola, ese hombre que se deja la vida y la salud en su pasión y en todos aquellos que le rodean. Aunque mi presencia allí haya sido, cuanto menos inconsistente, siempre han estado cada vez que los he necesitado. Simplemente aparecer con el kimono y volver a sentirte en un sitio seguro, entre amigos y sabiendo que puedes confiar en ellos, acogido de nuevo.

Esta tesis también es de aquellos que siempre, sin importar las circunstancias han estado para lo que hiciese falta. Amigos con mayúsculas que desde que llegué a Elche han estado siempre presentes en mi vida, y siempre seguirán estándolo. Tanto con los que empecé la carrera como Aranda, Bolero, Solsona o Carles como las nuevas incorporaciones como Nacho. Aranda, ese hombre cuya pasión por la vida y el deporte le llevó a estudiar una carrera demostrando que pese a trabajar durante todas las tardes y gran parte de las noches, se esforzaba por acudir por las mañanas a la universidad. Lo que restaba de las noches, eso sí, se dedicaban a la infinitud de sesiones de chistes malos vaso en mano. Bolero que acabó realizando su sueño de tener un gimnasio y aunque solo sea medio hombre, es un gran medio hombre. Solsona que, aunque nos separen cientos de kilómetros, sigue siendo recogiendo setas o pescando como si la madre de nadie le hubiera impedido salir de la cama temprano. Nacho, el gran artífice de la sobrecubierta que ilustra esta tesis.

De la misma manera esta tesis también es de aquellos amigos que llevan acompañándome toda la vida en este camino. Aquello que cada vez que vuelvo al hogar están ahí, sin importar los años que pasen o el tiempo que llevemos sin vernos. Muchas gracias Viqueira, Morrondo, Lorenzo, Sierra, Negro, Haritza, Piolo, Gorka… *eskerrik asko*.

Pertenece igualmente a toda esa gente en el CID que no he mencionado aún, aquellos que crearon un ambiente en el que ir a trabajar se convertía en ir a “trabajar”, porque pese a las muchas veces incontables horas, era siempre disfrutando. Gracias a Juan Pedro, el hombre que, necesitaras lo que necesitases, con un velcro, un par de retales de lona, un par de clips y cualquier cosa que encontrara por ahí era capaz de construírtelo. Gracias a Dori, por sus sonrisas por la mañana y alegría constante. Gracias a Fito por todo lo aprendido de él en estos años, pocos profesores llegan a marcar en esta vida como él lo ha hecho en tantísimos de sus alumnos. Gracias a Jaime, por enseñarme tanto e incluirme en sus aventuras. Gracias a Tomás, gran experto en el arte de la nutrición de la media mañana.

Esta tesis habría sido imposible también sin todas aquellas personas que nos han ayudado en la investigación desinteresadamente y por ayudar a su deporte. Todos esos preparadores físicos, entrenadores y jugadores que nos dieron el tiempo y esfuerzo necesario para la recogida de datos. Gracias en especial a Alex y el Juventut que son los que más nos han sufrido.

Sin duda, esta tesis no sería lo mismo y por lo tanto también pertenece a toda esa gente que, estando en el extranjero, ha influido tantísimo en ella. *Thank you* Mark por, además de ser el co-tutor en la sombra, haberme enviado a la República Checa para hacer una, que finalmente fueron tres, estancias de investigación. *Děkuji* Michael, por acogerme en Olomouc y por hacerme partícipe de tus investigaciones y conversaciones, pero sobre todo por meterme en el despacho de relaciones internacionales. Lo que me permitió conocer a Tereza.

Esta tesis es también de Tereza, la pobre persona a la que invadí el despacho en la República Checa porque nadie quería tener que hablar en inglés con el extranjero que llegaba de vete tú a saber dónde. La pobre que se ha tenido que leer toda la tesis para corregir los errores en inglés y que ha hecho un sacrificio inmenso que pocas personas serían capaz de hacer. Dejarlo todo, su vida, su familia y su carrera por mudarse aquí conmigo. Y por lo tanto gracias también a toda la familia Kučera por haberla dejado escapar y aceptarme a mí. Espero que pronto sea capaz de entender estas palabras dedicadas a ella en castellano.

En definitiva, esta tesis llevará mi nombre escrito, pero no me pertenece como el lector habrá podido comprobar. Además, ha querido la vida que tenga que llegar una pandemia mundial para que la termine. Estamos ante momentos difíciles y no sabemos lo que se avecinará en el futuro cercano, pero como dijo J.R.R. Tolkien a través de Samsagaz Gamyi: "Sólo atravesando la noche se llega a la mañana". Y os digo yo, que la mañana llegará.

TABLE OF CONTENTS

Table of Contents 23
List of Figures 27
List of Tables 31
List of Appendixes 33
Abstract 37
Resumen 41
Abbreviations 45
Chapter 1. General Introduction 49
  1.1. Introduction 51
  1.2. Epidemiology of injuries in elite futsal 56
  1.3. Injury prediction in elite futsal 60
  1.4. Lines of action of the thesis 67
Chapter 2. Research Objectives and Hypotheses 69
  2.1. General objectives 71
  2.2. Specific objectives 72
  2.3. Research hypotheses 74
Chapter 3. Study 1 77
  3.1. Abstract 79
  3.2. Introduction 81
  3.3. Methods 82
  3.4. Results 87
  3.5. Discussion 95
  3.6. Limitations 98

3.7. Conclusions..99
3.8. Appendixes..100
Chapter 4. Study 2..113
4.1. Abstract..115
4.2. Introduction..117
4.3. Methods..119
4.4. Results..123
4.5. Discussion..134
4.6. Limitations..139
4.7. Conclusions..140
4.8. Appendixes..141
Chapter 5. Study 3..151
5.1. Abstract..153
5.2. Introduction..155
5.3. Methods..157
5.4. Results..165
5.5. Discussion..172
5.6. Limitations..175
5.7. Conclusions..176
Chapter 6. Study 4..177
6.1. Abstract..179
6.2. Introduction..181
6.3. Methods..183
6.4. Results..192
6.5. Discussion..200

6.6. Limitations 204

6.7. Conclusions 205

6.8. Appendixes 206

Chapter 7. Study 5 227

7.1. Abstract 229

7.2. Introduction 231

7.3. Methods 233

7.4. Results 239

7.5. Discussion 255

7.6. Limitations 257

7.7. Conclusions 258

7.8. Appendixes 259

Chapter 8. Epilogue 263

8.1. General conclusions 265

8.2. Study limitations and future research 268

Capítulo 9. Epílogo 271

9.1. Conclusiones generales 273

9.2 Limitaciones de la tesis y líneas futuras de investigación 277

Chapter 10. References 281

LIST OF FIGURES

Figure 1.1. The four-step "sequence of prevention" described by van Mechelen et al.[14]

Figure 1.2. Sequence of the injury prevention model described by van Mechelen et al.[14] and later expanded by Finch[15] and then by van Tiggelen et al.[16]

Figure 1.3. Graphical description of the complex model for sports injury prediction described by Bittencourt et al.[18]. The group of variables at the bottom makes up the web of determinants (i.e. previously known as risk factors [e.g. dynamic knee valgus, fatigue]), which is composed of contributing units with different weights. Variables circled by darker lines have more interactions than variables circled by lighter lines and exert a greater influence on the outcome (injury). Dotted lines represent a weak interaction and thick lines represent a strong interaction between variables. Arrows indicate the relationship between the observable regularities, which captures the risk/protective profile, and the emerging outcome (i.e. high or low risk of injury).

Figure 1.4. Quantitative risk matrix in UEFA Champions League football (based on data from the UEFA Elite Club Injury Study), illustrating the relationship between the severity (consequence) and incidence (likelihood). For each injury type, severity is shown as the average number of days lost from training and competition (log scale), while incidence is shown as the number of injuries per 1000 hours of total exposure (match and training combined) for each injury type. Figure adapted from Bahr, Clarsen and Ekstrand[25].

Figure 3.1. Flow chart of the selection of studies for the meta-analysis.

Figure 3.2. Overall (a) and match (b) injury incidence in male players with 95% confidence intervals.

Figure 3.3. Overall (a), match (b) and training (c) injury incidences in female players with 95% confidence intervals.

Figure 3.4. Match incidence during male international (a) and national (b) tournaments forest plot with 95% confidence intervals.

Figure 4.1. Quantitative risk matrix of injuries, illustrating the relationship between the severity (consequence) and incidence (likelihood) of the most common injuries.

Figure 4.2. Distribution of total injury incidence.

Figure 5.1. Frontal view 2D analysis.

Figure 5.2. Lateral view 2D analysis.

Figure 5.3. Validity measures of the frontal view variable FPPA.

Figure 5.4. Validity measures of the frontal view variable KASR.

Figure 5.5. Validity measures of the frontal view variable KMD.

Figure 5.6. Validity measures of lateral view variable: HF ROM.

Figure 5.7. Validity measures of lateral view variable KF ROM.

Figure 5.8. Bland and Altman plots showing individual differences between 2D and 3D system FPPA values plotted against the mean.

Figure 5.9. Bland and Altman plots showing individual differences between 2D and 3D system KASR values plotted against the mean.

Figure 5.10. Bland and Altman plots showing individual differences between 2D and 3D system KMD values plotted against the mean.

Figure 5.11. Bland and Altman plots showing individual differences between 2D and 3D system HF ROM values plotted against the mean.

Figure 5.12. Bland and Altman plots showing individual differences between 2D and 3D system KF ROM values plotted against the mean.

Figure 6.1. Graphical representation of the first classifier of the DS 6 (lower extremity joint ranges of motion). Prediction nodes are represented by ellipses and splitter nodes by rectangles. Each splitter node is associated with a real valued number indicating the rule condition, meaning: If the feature represented by the node satisfies the condition value, the prediction path will go through the left child node; otherwise, the path will go through the right child node. The numbers before the feature names in the prediction nodes indicate the order in which the different base rules were discovered. This ordering can to some extent indicate the relative importance of the base rules. The final classification score produced by the tree is found by summing the values from all the prediction nodes reached by the instance, with the root node being the precondition of the classifier. If the summed score is greater than zero, the instance is classified as true (low risk of LE-ST injury).

Figure 6.2. Graphical representation of the first classifier of the DS 8 (dynamic postural control). The arrows show the single pathway (transverse to the tree) through the classifier that should be followed according to participant´s scores in order to achieve a dichotomic output (high [Yes] or low [No] risk of LE-ST injury.

Figure 6.3. Description of the first classifier of the DS 10 (field-based tests).

Figure 6.4. Graphical representation of the first classifier of the DS 11 (global). The arrows show the single pathway (transverse to the tree) through the classifier that should be followed according to participant´s scores in order to achieve a dichotomic output (high [Yes] or low [No] risk of LE-ST injury.

Figure 7.1. Directed acyclic graphs corresponding to the dynamic postural control BNs built for the dominant leg (figure 7.1a) and non-dominant leg (figure 7.1b). The a priori probability distributions for each feature are given, where the likelihood for each feature's label is expressed in percentage.

Figure 7.2. A top-down reasoning for the dynamic postural control BNs of the dominant leg in which the class variable (Y-Balance composite scores) was instantiated in their two labels: a) low risk and b) moderate risk.

LIST OF TABLES

Table 1.1. Main characteristics of the prospective epidemiological studies that have investigated injuries sustained by elite futsal players.

Table 1.2. Injury risk factors.

Table 1.3. Criterion-related validity scores (correlations) of frontal plane knee alignment measures obtained using 2D video analysis procedures.

Table 3.1. Characteristics of the studies included in this systematic review and meta-analysis.

Table 4.1. Players and team characteristics and exposure time.

Table 4.2. Injury incidence.

Table 4.3. Injury characteristics and incidence according location and type of injury.

Table 5.1. Mean values for 3D and 2D variables during bilateral drop vertical jumps (DVJ).

Table 5.2. Kappa correlations.

Table 6.1: Features selected (displayed for order of importance) after having applied the classify subset evaluator filter to the data sets (DS) 10 and 11.

Table 6.2: Best-performing sub-set of algorithms for those data sets (DS) that allowed building prediction models with AUC scores ≥0.7. Highlighted in bold are the algorithms selected in each DS for the posterior inter-group comparative analysis.

Table 7.1. Comparisons among the accuracy scores obtained by all the BN-based feature selection methods for the dominant leg. In grey is highlighted the best performing BN.

Table 7.2. Comparisons among the accuracy scores obtained by all the BN-based feature selection methods for the non-dominant leg. In grey is highlighted the best performing BN.

Table 7.3. Individual contribution of each level of the final variables selected on the probability of having the class variable (Y-Balance composite score) of the non-dominant leg in its low and moderate risk states. In grey are highlighted the labels of the variables that present the highest individual contribution of having the class variable in its low and moderate risk scores.

Table 7.4. Step-by-step instantiations leading to maximization of the likelihood of having the class variable (Y-Balance) of the dominant leg in its low and moderate risk categories.

Table 7.5. Step-by-step instantiations leading to maximization of the likelihood of having the criterion variable (Y-Balance) of the non-dominant leg in its low and moderate risk states.

LIST OF APPENDIXES

Appendix 3.1. PRISMA checklist**.**

Appendix 3.2. Inclusion/exclusion criteria for futsal literature search.

Appendix 3.4. Moderator variables codded.

Appendix 3.5. Description of the 22 of STROBE Statement—checklist of items that should be included in reports of observational studies.

Appendix 3.6. Risk of bias assessment of the studies (Newcastle Ottawa scale).

Appendix 4.1. Definitions used to include studies.

Appendix 4.2. Description of the 22 of STROBE Statement—checklist of items that should be included in reports of observational studies.

Appendix 4.3: Description of the 8 criteria designed to assess risk of bias of external validity quality in the studiesT. This instrument is an adapted version of the Newcastle Ottawa Scale (NOS) for cohort studies.

Appendix 6.1. TRIPOD Checklist: Prediction Model Development and Validation.

Appendix 6.2. Description of the personal or individual injury risk factors recorded.

Appendix 6.3. Description of the psychological risk factors recorded.

Appendix 6.4. Description of the testing manoeuvre and measures obtained from the isometric hip abduction and adduction strength test.

Appendix 6.5. Description of the testing manoeuvre and measures obtained from the Y-Balance test.

Appendix 6.6. Description of the testing manoeuvre and measures obtained from the ROM-Sport battery.

Appendix 6.7. Descriptions of the resampling, ensemble and cost-sensitive algorithms applied to the base classifiers.

Appendix 6.8. AUC results (mean and standard deviation) of the personal or individual characteristics data set (DS 1) for the five base classifiers in isolation and after applying in them the resampling, ensemble (Classic, Boosting-based, Bagging-based and Class-balanced ensembles) and cost-sensitive learning techniques selected.

Appendix 6.9. AUC results (mean and standard deviation) of the sleep quality data set (DS 2) for the four base classifiers in isolation and after applying in them the resampling. ensemble (Classic, Boosting-based, Bagging-based and Class-balanced ensembles) and cost-sensitive learning techniques selected.

Appendix 6.10. AUC results (mean and standard deviation) of the Athlete Burnout data set (DS 3) for the four base classifiers in isolation and after applying in them the resampling. ensemble (Classic, Boosting-based, Bagging-based and Class-balanced ensembles) and cost-sensitive learning techniques selected.

Appendix 6.11. AUC results (mean and standard deviation) of the psychological characteristics related to sport performance data set (DS 4) for the four base classifiers in isolation and after applying in them the resampling. ensemble (Classic, Boosting-based, Bagging-based and Class-balanced ensembles) and cost-sensitive learning techniques selected.

Appendix 6.12. AUC results (mean and standard deviation) of the self-perceived chronic ankle instability data set (DS 5) for the four base classifiers in isolation and after applying in them the resampling. ensemble (Classic, Boosting-based, Bagging-based and Class-balanced ensembles) and cost-sensitive learning techniques selected.

Appendix 6.13. AUC results (mean and standard deviation) of the lower extremity joint ranges of motion data set (DS 6) for the five base classifiers in isolation and after applying in them the resampling, ensemble (Classic, Boosting-based, Bagging-based and Class-balanced ensembles) and cost-sensitive learning techniques selected.

Appendix 6.14. AUC results (mean and standard deviation) of the isometric hip abduction and adduction strength data set (DS 7) for the five base classifiers in isolation and after applying in them the resampling, ensemble (Classic, Boosting-based, Bagging-based and Class-balanced ensembles) and cost-sensitive learning techniques selected.

Appendix 6.15. AUC results (mean and standard deviation) of the dynamic postural control data set (DS 6) for the five base classifiers in isolation and after applying in them the resampling, ensemble (Classic, Boosting-based, Bagging-based and Class-balanced ensembles) and cost-sensitive learning techniques selected.

Appendix 6.16. AUC results (mean and standard deviation) of the measures obtained through questionnaires data set (DS 6) for the five base classifiers in isolation and after applying in them the resampling, ensemble (Classic, Boosting-based, Bagging-based and Class-balanced ensembles) and cost-sensitive learning techniques selected.

Appendix 6.17. AUC results (mean and standard deviation) of the field-based tests of neuromuscular performance data set (DS 6) for the five base classifiers in isolation and after applying in them the resampling, ensemble (Classic, Boosting-based, Bagging-based and Class-balanced ensembles) and cost-sensitive learning techniques selected.

Appendix 6.18. AUC results (mean and standard deviation) of the global data set (DS 11) for the five base classifiers in isolation and after applying in them the resampling, ensemble (Classic, Boosting-based, Bagging-based and Class-balanced ensembles) and cost-sensitive learning techniques selected.

Appendix 7.1. Description of the features recorded to build the Bayesian Networks.

ABSTRACT

Futsal (the five-a-side indoor version of associated football) requires players to perform on a reduced (usually indoor) pitch size (40 x 20 m) and during two x 20-minute periods (with time stopping at every dead ball and unlimited substitutions) a substantive number of repeated high intensity multiplanar movements such as sudden acceleration and deceleration, rapid changes of direction, tackling and kicking. At elite levels, the combination of these high physical demands alongside exposure to contacts and stress and anxiety caused by the congested match calendar might place futsal players at high risk of injury. In fact, futsal has been suggested as one of the top 10 most injury prone sports, all of this despite the substantive effort made by the scientific community and physical trainer practitioners to reduce their number and severity. The inefficacy of the preventive measures applied might be caused, in part, by the limitations present in the literature which hinder: a) the accurate estimation of the most frequent futsal-related injuries; b) the identification of team sport athletes at high risk of injury; and c) the identification of the factors and their interactions that play a main role on the adoption of altered movement patterns during dynamic actions.

Therefore, and based on these limitations, the main objectives of the current doctoral thesis were: 1) to describe injury incidence, characteristics and burden in futsal; 2) to examine the criterion-related validity of five kinematic measures of frontal plane knee alignment and hip and knee motion in the sagittal plane using a 2D video analysis and a 3D motion analysis system during bilateral drop landings through a contemporary statistical approach; 3) to analyze and compare the individual and combined ability of several measures obtained from different questionnaires and field-based tests to prospectively predict lower extremity soft-tissue injuries after having applied supervised Machine Learning techniques; and 4) to analyze the relationships between several parameters of neuromuscular performance with dynamic postural control using a Bayesian

Network Classifiers based analysis. To achieve these objectives, a systematic literature review and meta-analysis, a prospective epidemiological study, a validation study and two multivariable prediction model studies were conducted.

The main findings of the studies one and two report that male and female futsal players are exposed to a substantial risk of sustaining injuries, especially during matches. In particular, and in both sexes, lower extremity injuries are, by far, the most frequent. Although the most common injury mechanism reported was by non-contact, it should be highlighted that a remarkable number of injuries (around 30%) were caused by a contact mechanism. For females, the injuries with the highest injury burden were those that occurred at the knee (31.9 days loss per 1000 hours of futsal exposure), followed by quadriceps (15.3 days loss per 1000 hours of futsal exposure) and hamstring (14.4 days loss per 1000 hours of futsal exposure) strains. On the other hand, the results of study three confirm that the knee medial displacement (standardized TE_{EST} = 0.53 [small], r = 0.88 [moderate to high], kappa statistic = 0.72 [high]) and knee flexion range of motion (standardized TE_{EST} = 0.56 [small], r = 0.87 [moderate to high], kappa statistic = 0.74 [high]) measures calculated during a bilateral drop vertical landing and using a cost-effective, technically undemanding and portable 2D video analysis procedure might be considered as valid and feasible alternatives to their respective 3D criterion to quantify knee kinematics and to detect futsal players who demonstrated aberrant movement patterns in the frontal and sagittal planes, respectively. Study four demonstrated that lower extremity soft-tissue injuries can be predicted with moderate accuracy through a combination of easy to employ field-based tests in elite futsal players using machine learning techniques. The best performing model, which was built with just four ROM measures, reported an area under the curve score of 0.767 with true positive and negative rates of 85.1% and 62.1% respectively. Finally, the Bayesian network built in study five showed that dynamic postural control has strong relationship with the abilities to flex the hip, knee and ankle, and with the control of the core structures during static but mainly dynamic tasks.

Overall, both the results and methodology used in the present doctoral thesis might be used by coaches, physical trainers and clinicians to improve the decision-making process to reduce the number and impact of injuries in futsal.

Key words: futsal, injury, prevention, soft-tissue injury, learning algorithm, data mining, dynamic balance, core stability, neuromuscular performance, range of motion, field-based test.

RESUMEN

El fútbol sala (versión para cinco jugadores del fútbol) requiere que los jugadores realicen, en un campo de tamaño reducido (generalmente en interiores) (40 x 20 m) y durante dos períodos de 20 minutos (con tiempo detenido cada vez que se para el balón y con sustituciones ilimitadas), un gran número de movimientos repetidos de alta intensidad tales como aceleraciones y desaceleraciones repentinas, cambios rápidos de dirección, entradas y golpeos. A nivel de élite, la combinación de estas altas demandas físicas, junto con la exposición a los contactos, el estrés y la ansiedad causados por el calendario congestionado de partidos podría situar a los jugadores de fútbol sala en un alto riesgo de lesión. De hecho, el fútbol sala ha sido descrito como uno de los diez deportes con mayor riesgo lesivo para sus jugadores. Todo esto a pesar del gran esfuerzo realizado por la comunidad científica y los preparadores físicos para reducir el número y gravedad de estas lesiones. La ineficacia de las medidas preventivas aplicadas podría deberse, en parte, a las limitaciones presentes en la literatura científica que dificultan: a) la estimación precisa de las lesiones, más frecuente en el fútbol sala; b) la identificación de atletas de deportes de equipo con alto riesgo de lesiones; c) la identificación de los factores y sus interacciones que juegan un papel principal en la adopción de patrones de movimiento alterados durante las acciones dinámicas.

Por lo tanto, y en base a estas limitaciones, los objetivos principales de la presente tesis doctoral fueron: 1) describir la incidencia, las características y las consecuencias (entendidas en días perdidos sin entrenar y jugar por lesión por cada 1000 horas de exposición a la práctica deportiva) de las lesiones en el fútbol sala; 2) examinar la validez de criterio de cinco medidas cinemáticas de la alineación de la rodilla en el plano frontal y el movimiento de la cadera y la rodilla en el plano sagital utilizando un análisis de video 2D y un sistema de análisis de movimiento 3D durante los aterrizajes tras caída bilateral desde cajón a través de un enfoque estadístico contemporáneo; 3) analizar y comparar la

capacidad individual y combinada de varias medidas obtenidas de diferentes cuestionarios y pruebas de campo para predecir prospectivamente las lesiones de tejido blando de las extremidades inferiores después de haber aplicado técnicas supervisadas de Aprendizaje Automático; y 4) analizar las relaciones entre varios parámetros del rendimiento neuromuscular con el control postural dinámico utilizando un análisis basado en clasificadores de Redes Bayesianas. Para lograr estos objetivos, se realizó una revisión sistemática de la literatura y un meta-análisis, un estudio epidemiológico prospectivo, un estudio de validación y dos estudios de modelos de predicción multivariantes.

Los principales hallazgos de los estudios uno y dos informan que los jugadores de fútbol sala masculinos y femeninos están expuestos a un gran riesgo de sufrir lesiones, especialmente durante los partidos. En particular, y en ambos sexos, las lesiones de las extremidades inferiores son, con diferencia, las más frecuentes. Aunque el mecanismo de lesión más común fue por no contacto, debe destacarse que un número remarcable de lesiones (alrededor del 30%) fueron causadas por un mecanismo de contacto. Para las mujeres, las lesiones con las mayores consecuencias fueron las de rodilla (pérdida de 31.9 días por 1000 horas de exposición al fútbol sala), seguidas de cuádriceps (pérdida de 15.3 días por 1000 horas de exposición al fútbol sala) e isquiosurales (14.4 días de pérdida por 1000 horas de exposición al fútbol sala). Por otro lado, los resultados del estudio tres confirman que el desplazamiento medial de la rodilla (Error típico estimado estandarizado = 0.53 [pequeño], r = 0.88 [moderado a alto], estadística kappa = 0.72 [alto]) y rango de movimiento de flexión de rodilla (Error típico estimado estandarizado = 0.56 [pequeño], r = 0.87 [moderado a alto], estadística kappa = 0.74 [alto]) calculados durante un aterrizaje vertical tras caída bilateral desde cajón y el uso de un procedimiento de análisis de video 2D económico, técnicamente poco exigente y portátil podrían ser consideradas alternativas válidas y factibles a sus respectivos criterios 3D para cuantificar la cinemática de la rodilla y detectar jugadores de fútbol sala con patrones de movimiento alterados en los planos frontal y sagital, respectivamente. El estudio cuatro demostró que las lesiones de tejido blando de las extremidades inferiores se pueden predecir con una precisión moderada a través de una combinación de pruebas de campo fáciles de emplear en jugadores de fútbol sala de élite a través de técnicas de Aprendizaje Automático. El modelo que mejor resultado mostró, construido con solo cuatro medidas de Rango de Movilidad Articular, reportó un área bajo la curva de 0.767 con tasas de verdaderos positivos y negativos de 85.1% y 62.1% respectivamente. Finalmente, la red bayesiana construida en el estudio cinco mostró que el control postural dinámico tiene una fuerte relación con las habilidades para flexionar la cadera, la rodilla y el tobillo, y con el control de las estructuras del tronco durante tareas estáticas, pero sobre todo dinámicas.

En general, tanto los resultados como la metodología utilizada en la presente tesis doctoral pueden ser utilizados por entrenadores, preparadores físicos y médicos para mejorar el proceso de toma de decisiones, y así, reducir el número y el impacto de las lesiones en el fútbol sala.

Palabras Clave: fútbol sala, lesión, prevención, lesión del tejido blando, algoritmos de aprendizaje, minería de datos, equilibrio dinámico, estabilidad del tronco, rendimiento neuromuscular, rango de movimiento, test de campo.

ABBREVIATIONS

2D: Two-dimensional

3D: Three-dimensional

Abd: Abduction

ACL: Anterior Cruciate ligament

Add: Adduction

AKDF: Ankle dorsiflexion

AKDF$_{KE}$: Ankle dorsi-flexion with the knee extended

AKDF$_{KF}$: Ankle dorsi-flexion with the knee flexed

AP: Unstable sitting while performing anterior-posterior displacements with feedback

AUC: Area under the receiver operating characteristic curve

BF: Bayesian factor

BIL: Bilateral ratio

Bila: Bilateral

BN: Bayesian Network Classifiers

CAIT: Cumberland ankle instability tool

CD: Unstable sitting while performing circular displacements with feedback

CI: Confidence interval

CON: Concentric

CS: Core stability

CS-CD: Core stability circular

CS-ML: Core stability medial-lateral

DAGs: Directed acyclic graphs

DOM: Dominant leg

DS: Data set

DVJ: Bilateral drop vertical jump

ECC: Eccentric

FIFA: *Fédération Internationale de Football Association*

FFPA: Frontal plane projection angle of the knee

FP: False positive

h: Hours

H_0: Null hypothesis

H_1= Alternative hypothesis

HABD: Hip abduction at 90º of hip flexion

HE: Hip extension

HER: Hip external rotation

HF: Hip flexion

HF_{KE}: Hip flexion with the knee extended

HF_{KF}: Hip flexion with the knee flexed

HF_{KF}: Hip flexion with the knee flexed

HIR: Hip internal rotation

ICC: Intraclass correlation coefficient

ISOK: Isokinetic

ISOM: Isometric

K: Kappa

KASR: Knee-to-ankle separation ratio

KE: Knee extensors

KF: Knee flexion

KMD: Knee medial displacement

KNN: k-Nearest Neighbour

KSD: Knee separation distance

LE-ST: Lower extremity non-contact soft tissue

ML: Unstable sitting while performing medial-lateral displacements with feedback

NC: National cup

NF: No feedback.

NF: Unstable sitting without feedback

NL: National League

NONDOM: non-dominant leg

NOS: Newcastle Ottawa Scale

NT: National team

PT: Peak torque

R: Recall

r: Validity correlation

ROM: Range of motion

SD: Standard deviation

SMO: Support Vector Machines

STROBE: Strengthening the reporting of observational studies in epidemiology

TE_{EST}: Typical error of the estimate

TN: True negative

TP: True positive

U: Under

UEFA: Union of European football associations

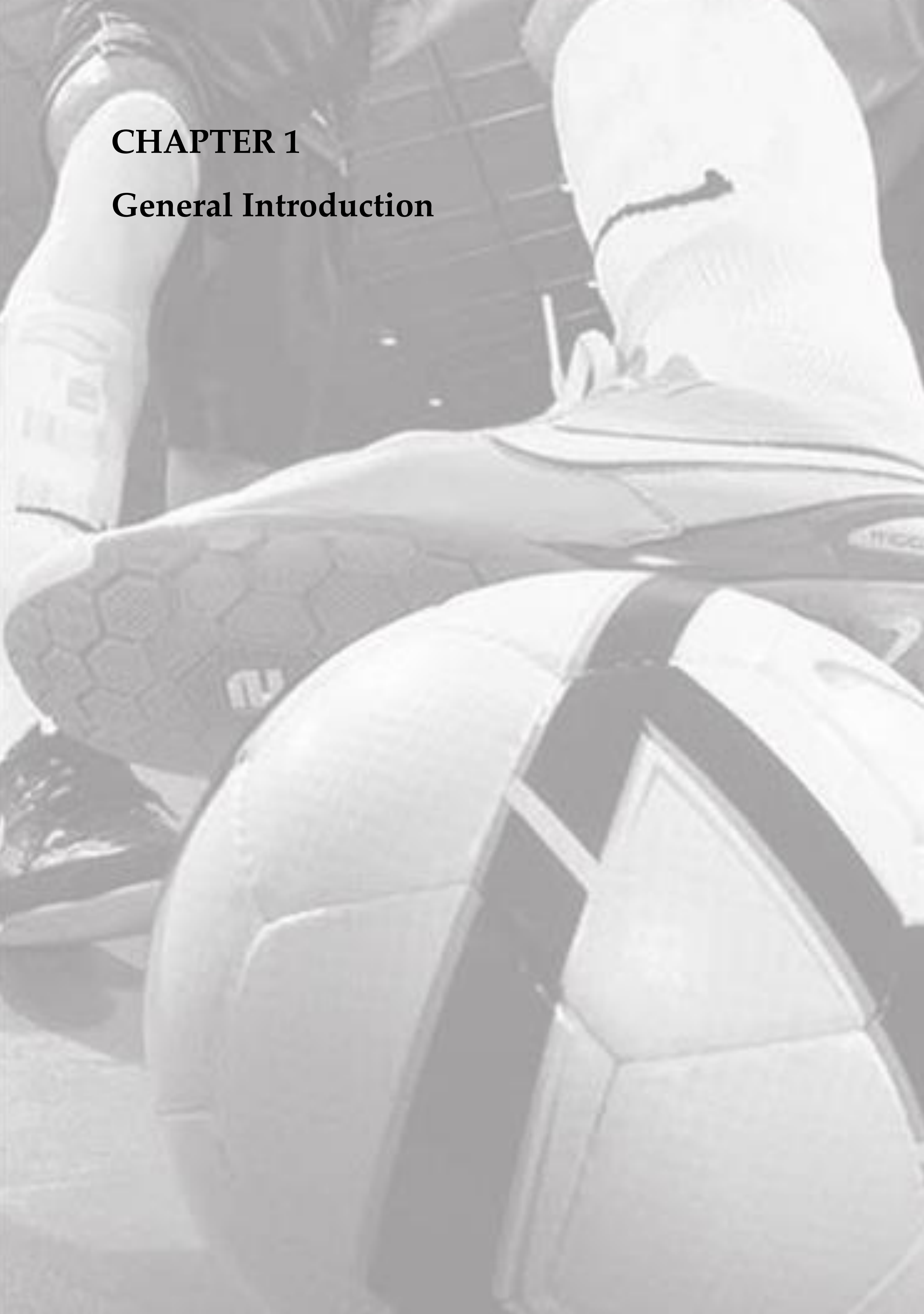
Uni: Unilateral

WC: World Cup

WF: Unstable sitting with feedback

CHAPTER 1

General Introduction



CHAPTER 1

General Introduction

1.1. Introduction

Futsal is the official name for the five-a-side indoor version of associated football (i.e. one goalkeeper and four outfield players) that is sanctioned by soccer's international governing body *Fédération Internationale de Football Association* (FIFA). It is played worldwide with more than 12 million players all over the world[1,2].

Futsal requires players to perform on a reduced (usually indoor) pitch size (40 x 20 m) and during two x 20-minute periods (with time stopping at every dead ball and unlimited substitutions) a substantive number of repeated high intensity multiplanar movements such as sudden acceleration and deceleration, rapid changes of direction, tackling and kicking[2–5]. At elite levels, the combination of these repeated high intensity movements that are performed during training and match play alongside current congested training and competitive calendars and exposure to contacts might place futsal players at high risk of injury. In fact, futsal has been suggested as one of the top 10 most injury prone sports[6].

These high injury rates might impact team and individual performances[7–10] and could have significant physical, psychological and financial short and long-term consequences for an individual player and their sport organizations[11–13]. Consequently, a fundamental task for futsal practitioners is the design, implementation and monitoring preventive and risk mitigation strategies that allow to reduce the number and severity of injuries.

In this sense, van Mechelen, Hlobil & Kemper[14] proposed a model for injury prevention in 1992 that involved four steps (figure 1.1). This classical injury prevention model was expanded by Finch in 2006[15] and later by van Tiggelen, Wickes, Stevens, Roosen & Witvrouw in 2008[16], resulting in a final model that comprises of seven steps (figure 1.2).

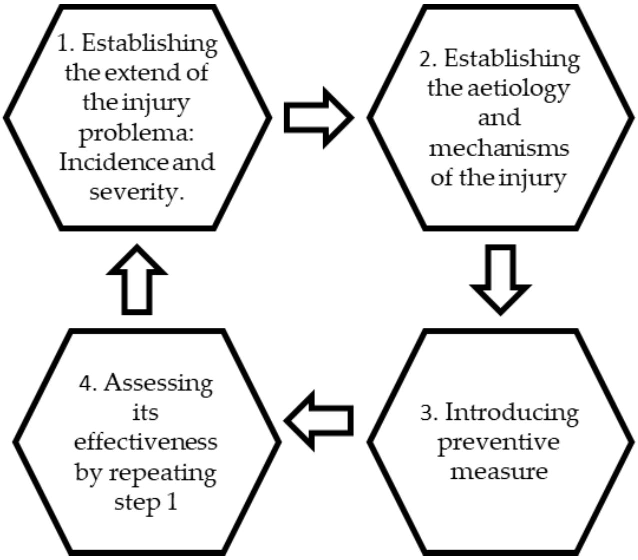


Figure 1.1. The four-step "sequence of prevention" described by van Mechelen et al.[14]

According to the seven-step injury prevention model, the fundamental first step must be establishing the extent of the injury problem, that is to say, the epidemiology for a determined sport population regarding what are the most common and burdensome injuries, as well as how (traumatic or overuse) and when (matches or training sessions) they usually occur. Recent studies have highlighted the importance of taking contextual determinants into account (as they play an important role in behaviour) when described this first step of the sequence of prevention because they may provide a more comprehensive view of the injury problem[17].

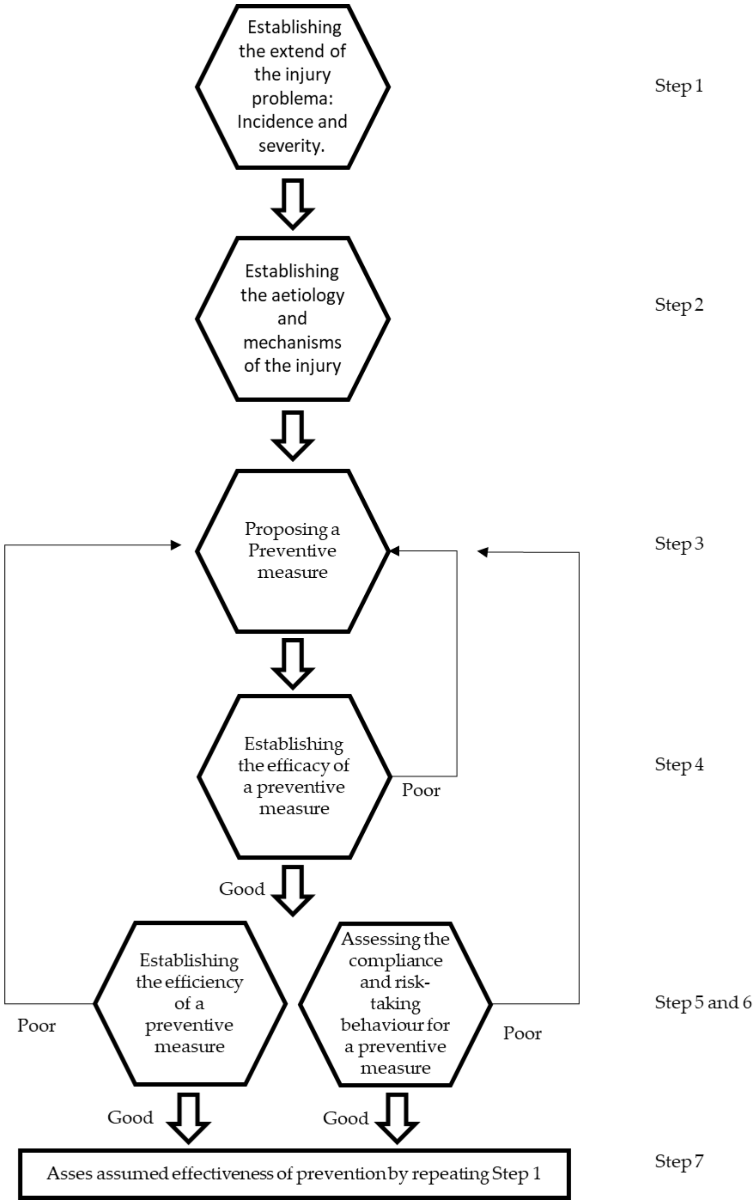


Figure 1.2. Sequence of the injury prevention model described by van Mechelen et al.[14] and later expanded by Finch[15] and then by van Tiggelen et al.[16]

Once the incidence and severity of injuries has been thoroughly analysed, the second step proposed in the model is to establish the aetiology and mechanisms of these injuries.

To better address this second step, the use of a complex system approach has been suggested which considers the multifactorial and complex nature of sport-related injuries[18]. This novel approach rests on analysing the injury mechanism (i.e. the acute or chronic [when repeated several times in a relatively short period of time] event or pattern that led to damage one or more body structures) and then identifying interactions (i.e. non-lineal relationships) within a web of determinants (i.e. potential predictors or risk factors) and clarifying how these interactions contribute to the emergence of specific injuries (e.g. soft tissue injuries) (figure 1.3). Likewise, it also may allow seeking regularities (repeated patterns) that enable the identification of risk profiles for an athlete or group. This knowledge forms the basis for developing screening models to prospectively identify athletes at high (or low) risk of injury.

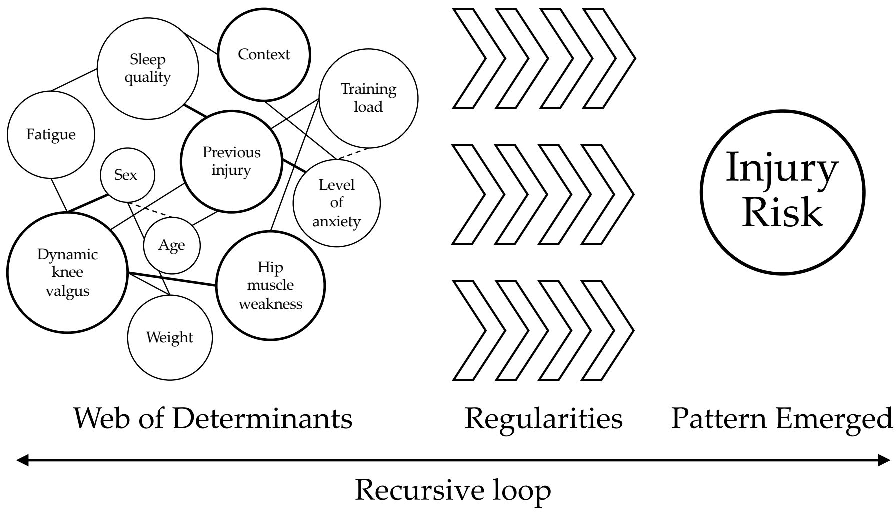


Figure 1.3. Graphical description of the complex model for sports injury prediction described by Bittencourt et al.[18]. The group of variables at the bottom makes up the web of determinants (i.e. previously known as risk factors [e.g. dynamic knee valgus, fatigue]), which is composed of contributing units with different weights. Variables circled by darker lines have more

interactions than variables circled by lighter lines and exert a greater influence on the outcome (injury). Dotted lines represent a weak interaction and thick lines represent a strong interaction between variables. Arrows indicate the relationship between the observable regularities, which captures the risk/protective profile, and the emerging outcome (i.e. high or low risk of injury).

The third step consists of designing and implementing tailored preventive measures (based on information identified in the second step) that allow to correct potentially hazardous movement patterns or regularities (e.g. excessive dynamic valgus at the knee joint during landing manoeuvres) in athletes and minimizing the impact of certain contextual factors (e.g. poor communication skills among teamwork members [doctors, physical trainers, coaches, managers], coach leadership style) that may be increasing the injury risk at individual and / or collective levels.

The fourth step of the model would consist of evaluating the effectiveness of the preventive measures implemented by repeating the first step. In this step, Finch[15] adds two additional actions to the sequence to assist in the translation of research into injury prevention practice: a) the need to include a description of the intervention context (personal, environmental, societal and sports delivery factors) to inform implementation strategies (step 5) and b) the evaluation of the implementation process of preventive measures via “real-world”, as opposed to solely scientific analytics (step 6). Later, van Tiggelen et al.[16] incorporated an additional step that enabled the inclusion of external factors with a significant effect on the outcome of a prevention intervention. This expansion of van Mechelen's model leads to a more global model in which the compliance level and risk-taking behaviour of the individual and the assessment of efficiency of the stakeholders have a key influence on the preventive measure.

1.2. Epidemiology of injuries in elite futsal

As outlined in the just mentioned seven-step injury prevention model (figure 1.2), before implementing any preventive measure, the first step is to describe the magnitude of the problem and its severity and characteristics[14–16]. The problem 'injury' has been typically measured by epidemiological measures and quantified in prospective epidemiological studies. In each sport, prevalence, incidence, severity, injury profiles, time loss and costs should all been well-described and stratified by age, sex, participation level, experience, etc. Such information will assist in identifying injury patterns and athletes at increased risk. Understanding the impact of injury on athlete availability, perceived performance and probability of sustaining a future injury before preventive and risk mitigation strategies are embedded into team programs will ensure that realistic expectations exist among stakeholders[19]. Accordingly, the objective of this section is to summarize the body of the knowledge available in the scientific literature regarding the epidemiology of injuries in elite futsal.

Despite being one of the most played sport in several countries, a limited number of prospective epidemiological studies have been published investigating injuries sustained by elite futsal players (mainly during match play)[6,20–23] (table 1.1). These studies have reported incidence rates for male players ranging from 1.6 to 208.6 injuries per 1000 hours of match play, most of them affecting the lower extremity with contusions of the lower leg and ankle sprains being the most frequently diagnosed types of injury[6,20–24]. For female players, only two studies[21,22] have reported incidence data, with values ranging from 6.7 to 86.6 injuries per 1000 hours of exposure and being ankle sprains and ligament ruptures the most observed injuries. However, the relatively small number of players included in most of these epidemiological studies alongside disparity in injury definitions and data collection procedures make inter-study comparisons difficult and may have clouded the current understanding of the incidence and characteristics of futsal-related injuries.

Table 1.1. Main characteristics of the prospective epidemiological studies that have investigated injuries sustained by elite futsal players

Reference / Country / Tournament	Study Duration	Nº Teams (Players)	Injury definition	Incidence (per 1000 hours of exposure) Overall	Training	Match
Hamid et al. Malaysia NL - 2010	1 season	32 (238 males and 230 females)	Injury was defined as any physical complaint sustained by a player that results from football match or football training, irrespective of the need for medical attention or time loss from football activities	-	-	91.5
Angoorani et al. Iran NL – 2011-12	1 season	3 (38 males and 17 females)	Injury was defined as any physical complaint sustained by a futsal player that results from a futsal match or career related training sessions, irrespective of the need for medical attention or time loss from futsal activities	2.2	1.6	6.3
Álvarez-Medina	2 seasons	1 (24 males)	Injury sustained by a player during a training session or competition	19.7	-	-

Spain NL – 2004-05 & 2011-12			which resulted in a player being unable to take a full part in future futsal training or match play			
Junge & Dvorak WC – 2004/2005/2008	1 tournament	16 (224 males)	An injury was defined as any physical complaint during a match which received medical attention from the team physician, regardless of the consequences with respect to absence from match or training	-	-	195.6
Ribeiro & Costa Brazil NC - 2004	1 tournament	10 (180 males)	An injury was defined as any commitment occurred during a game, regardless its consequences related to the subsequent removal from the games or training	-	-	208.6

WC: World Cup; NL: National League; NC: National Cup.

Furthermore, none of the studies that have provided epidemiological data of futsal-related injuries in male and female players have calculated the injury burden (the product of severity [consequences] and incidence [likelihood]) and/or built a risk matrix. A risk matrix is a graph of injury severity plotted against injury incidence with criteria incorporated into the graph for evaluating the level of risk, usually by dividing the graph into some risk areas using descriptive or quantified incidence, severity and risk evaluation categories[25] (figure1.4).

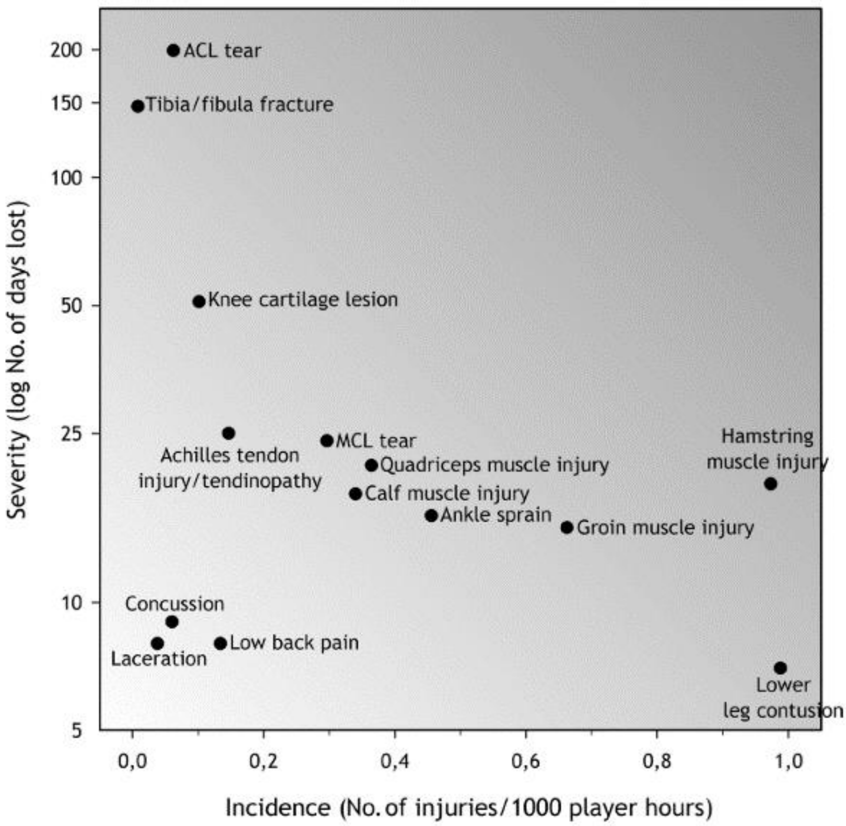


Figure 1.4. Quantitative risk matrix in UEFA Champions League football (based on data from the UEFA Elite Club Injury Study), illustrating the relationship between the severity (consequence) and incidence (likelihood). For each injury type, severity is shown

as the average number of days lost from training and competition (log scale), while incidence is shown as the number of injuries per 1000 hours of total exposure (match and training combined) for each injury type. Figure adapted from Bahr, Clarsen & Ekstrand[26].

Therefore, a study that reviews and employs a meta-analytical approach to the currently available epidemiological data to identify the incidence and severity of futsal injuries, separately by sex, as well as when (matches or training sessions) and where (anatomical location) they occur is warranted. Likewise, there is a clear need for more prospective epidemiological studies that inform about injury incidence, characteristics and burden in futsal players. This knowledge would lead coaches, physical trainers and physiotherapists to design and implement specific measures to prevent or reduce the risk of sustaining the most prevalent and burdensome futsal-related injuries.

1.3. Injury prediction in elite futsal

The effective design and posterior implementation of preventive and risk mitigation strategies in a sport context require firstly the successful assessment (in terms of validity and reliability) of potential factors or determinants that may alter the likelihood that an injury will be sustained, secondly the development of robust screening models to quantify injury risk and finally, the identification of risk profiles (regularities) that enable to understand why an athlete has been classified as having high or low risk of injury. These three actions have been suggested as the most challenging issues in modern sport[27].

Several biomechanical, neuromuscular, psychological and contextual factors have been suggested as potential determinants for the occurrence of injuries in intermittent team sports (table 1.2). Among them, the adoption of aberrant lower extremity movement patterns during the execution of high intensity weight-bearing dynamic tasks (e.g.: cutting and landing) such as an excessive dynamic valgus motion at the knee (a multi-joint and multiplane movement pattern comprised of varying degrees of hip adduction and internal rotation and knee abduction and external rotation joint kinematics) and limited hip and knee flexion ranges of motion (ROM) have been identified as primary and modifiable risk factors for knee injuries (mainly ligament injuries). These injuries are common among futsal players and therefore the pre-participation assessment of hip and knee joints kinematics during dynamic tasks might help categorize players at high risk.

Table 1.2. Potential injury risk factors

Context-related	Neuromuscular	Psychological	Biomechanical
Previous injury[28–33]	Flexibility[32,47,48]	Sleep quality[29,30]	Anthropometric factors[32,54]
Sex[34–39]	Deficit in muscle strength[33,47,49,50]	Physical/emotional exahaustion[52,53]	Misalignment[55,56]
Age[31,32,40]	Strength imbalances[33,47,49,50]	Sports devaluation[52,53]	Joint laxity or instabiltity[57,58]
Playing position[22,41–43]	Core stability[29,30,51]	Reduce sense of accomplishment[52,53]	
Fatigue[20,44–46]			

1.3.1. Assessment of hip and knee joints kinematics during bilateral drop-jump landings

Three-dimensional (3D) motion analysis systems have been considered as the criterion measurement (gold standard) to assess lower extremity joints kinematics during potentially high-risk tasks related to knee injuries (mainly ACL) due to their high levels of accuracy and reliability[59–63]. However, the use of 3D motion analysis systems is often restricted to research settings and not used in clinical environments or for pre-participation screening because of their high cost, lack of portability, time constraints and the need for sophisticated instruments and qualified technicians[61,64]. Consequently, cost-effective, technically undemanding and portable alternative measurements to 3D motion analysis are needed. A low-cost, portable and readily available alternative to screen lower extremity joints kinematics might be the two-dimensional (2D) video analysis procedures where standard cameras are used to capture performance of dynamic tasks which are then imported into user-friendly software packages (e.g.: Kinovea, Quintic, ImageJ and Dartfish™). Some studies have examined the criterion-related validity (mainly through correlation coefficients) of certain measures of frontal plane knee alignment (i.e.: frontal plane projection angle of the knee [FPPA][61,64–69], knee-to-ankle separation ratio [KASR][67,68] and knee medial displacement [KMD][70]) during dynamic tasks (mainly single leg squats and drop landings) that have been operationally designed to identify athletes with excessive dynamic knee valgus motion using two-dimensional (2D) video analysis procedures and 3D motion analysis systems simultaneously. In particular, these measures of frontal plane knee alignment obtained through the use of 2D video analysis procedures have reported correlations with their respective 3D criterion measures ranging from r = 0.20 to 0.96 (table 1.3).

Table 1.3. Criterion-related validity scores (correlations) of frontal plane knee alignment measures obtained using 2D video analysis procedures

Study	Task	Participants	FPPA	KASR	KMD
Gwynne & Curran[65]	Single leg squat	18	0.78	-	-
Herrington et al.[66]	Single leg squat	15	0.79	-	-
	Side jump		0.80	-	-
Mclean et al.[61]	Side step	10	0.76	-	-
	Shuttle run		0.20	-	-
Mizner et al.[67]	Drop vertical jump	36	0.38	0.50	-
Ortiz et al.[68]	Drop vertical jump	16	0.95*	0.96*	-
Sorenson et al.[69]	Single leg drop landing	31	0.87	-	-
Willson et al.[64]	Single leg squat	40	0.48	-	-
Myer et al.[70]	Drop vertical jump	100	-	-	0.87

FPPA: Frontal plane projection angle; KASR: Knee to ankle separation ratio; KMD: Knee medial displacement.

However, correlation coefficients do not indicate whether both measures or methods (e.g.: 3D motion analysis systems and 2D video analysis procedures) can be used interchangeably and thus whether the same cut-off scores can be used to detect the expected diagnosis (e.g.: the presence [or absence] of aberrant lower extremity movement patters during dynamic tasks). More contemporary statistical methods, such as the calculation of the estimation equation and typical error of the estimate (TE_{EST}) have not been taken into consideration when assessing criterion-related validity of the previously mentioned measures of frontal plane knee alignment. Likewise, the criterion-related validity of other ROM measures in the sagittal plane, such as hip and knee flexion ROM, has received very little attention.

Therefore, there is a clear need for studies that examine the criterion-related validity of the measures of frontal plane knee alignment and sagittal plane movement all recorded simultaneously using a 2D video analysis procedure and a 3D motion analysis system during dynamic tasks and applying a contemporary statistical approach.

1.3.3. Prediction models

Despite the substantive efforts made by the scientific community and sport practitioners, lower extremity non-contact soft tissue (muscle, tendon and ligament) (LE-ST) injuries are very common events in intermittent team sports such as soccer[71], futsal[72], rugby[73], bat (i.e. cricket and softball) and stick (i.e. field hockey and lacrosse) sports[74]. One of the main reasons that has been suggested to explain why LE-ST injury rates are still high is that none of the currently available screening models (based on potential risk factors), designed to identify athletes at high risk of suffering a LE-ST injury, have adequate predictive properties (i.e. accuracy, sensitivity and specificity)[27].

Perhaps the lack of available valid screening models to predict LE-ST injuries could be attributed to the use of statistical techniques (e.g.: traditional logistic regression) that have not been specifically designed to deal with class imbalance problems, such as the LE-ST injury phenomenon, in which the number of injured players (minority class) prospectively reported is always much lower than the non-injured players (majority class)[75–78]. Thus, in many scenarios including LE-ST injury, traditional screening models are often biased (for many reasons) towards the majority class (known as the "negative" class) and therefore there is a higher misclassification rate for the minority class instances (called the "positive" examples). Other issue with the current body of the literature is that the external validity of the screening models available may be limited because they are built and validated using the same date set (i.e. cohort of athletes). Apart from resulting in overly optimistic models´ performance scores, this evaluation approach does not indicate the true ability of the models to predict injuries in different data sets or cohort of athletes, which may be very low and consequently, not acceptable for injury prediction purposes. This appears to be supported by the fact that the injury predictors identified by some prospective studies have not been replicated by others using similar designs and assessment methodologies but with different samples of athletes[28,31,32,40,47,49,79–81]. These limitations have led some researchers to suggest that injury prediction may be a waste of time and resources[27].

In Machine Learning and Data Mining environments, some methodologies (e.g.: pre-processing, cost-sensitive learning and ensemble techniques) have been specially designed to deal with complex (i.e. non-lineal interactions among features or factors), multifactorial and class imbalanced scenarios[75–78]. These contemporary methodologies along with the use of resampling methods to assess models´ predictive power (i.e. cross-validation, bootstrap and leave-one-out) may overcome the limitations inherent to the current body of knowledge and enable the ability to build robust, interpretable and generalizable models to predict LE-ST injuries. In fact, recent studies have used these contemporary methodologies and resampling methods as alternatives to the traditional logistic regression techniques to predict injuries in elite team sport athletes[82]. Unlike previous studies that used traditional logistic regression techniques to build prediction models[47,81,83–88], most of these recent studies[29,30,89–93], although not all[50,94], have reported promising results (area under the receiver operator characteristics [AUC] scores > 0.700) to predict injuries.

However, one of the main limitations of most of these models built by the application of modern Machine Learning techniques lies in the fact that their use seems to be restricted to research settings (and not to applied environments) because sophisticated and expensive instruments (e.g.: isokinetic dynamometers, force platforms and GPS devices), qualified technicians and time-consuming testing procedures are required to collect such data. To the authors´ knowledge, there is only one study that has built a robust screening model using Machine Learning techniques (extreme gradient boosting algorithms) with data from field-based tests. Rommers et al.[95] built a model to predict injury in elite youth soccer players based on preseason anthropometric (stature, weight and sitting height) and motor coordination and physical fitness (strength, flexibility, speed, agility and endurance) measures obtained through field-based tests and reported an AUC score of 0.850.

If Machine Learning techniques could build "user friendly" models with adequate predictive properties and exclusively using data obtained from questionnaires and / or cost-effective, technically undemanding and time-efficient field-based tests, then injury prediction would not be a waste of time and resource in applied settings. In case these techniques provided a trustworthy positive response, coaches, physical trainers and medical practitioners may know whether any of the currently available questionnaires and field-based tests to predict injuries itself works and a hierarchical rank could be developed based on their individual predictive ability of those that showed reasonably high AUC, TP and TN scores. Furthermore, this knowledge might be used to analyze the cost-benefit (balance between the time required to assess a single player and the predictive ability of the measures recorded) of including measures in the screening sessions for injury prediction.

1.3.3. Identification of injury risk profiles

The identification of risk profiles (regularities) that enable to understand why an athlete has been classified as having high or low risk of injury is a vital previous step to develop tailored injury prevention and risk mitigation strategies.

The Y-Balance test is widely used to assess dynamic postural control[96] and it is usually included as part of an injury risk battery in both clinical and sporting contexts because poor performance and bilateral asymmetries may be considered as valid predictors for identifying athletes at high risk of non-contact lower extremity injuries (mainly knee and ankle injuries)[57,58,97–99].

The Y-Balance test involves maintaining single-legged balance whilst simultaneously reaching as far as possible with the contralateral leg in three directions (anterior, posterolateral and posteromedial). Potentially, the execution of this test might require, among others, adequate levels of hip and knee strength, power, trunk or core stability, coordination and lower extremity ranges of motion (ROM). With the aim of improving the design of training interventions, some studies have explored the individual contribution of certain measures of knee strength[100–102], hip strength[102–104], lower extremity power[105], core stability[102,105] and lower extremity ROMs[102–106] on Y-Balance test performance using linear regression models in different cohorts of athletes. However, these studies have reported conflicting results that might not permit clinicians, physiotherapists and physical trainers to make general training recommendations.

The use of contemporary statistical techniques, such as Bayesian Networks Classifiers (BNs) (also referred to as causal networks or belief networks) to provide evidence of relationships of dependency and conditional independence between different measures or variables[107] may overcome the current limitations of the scientific literature and shed light to better understand why an athlete has reached poor performance scores and / or showed bilateral asymmetries that place them in a prone situation to sustain an injury.

1.4. Lines of action of the thesis

Due to everything previously mentioned, it is needed to reduce the number of injuries in futsal. Several limitations are presented in the literature regarding the injury problem and they need to be resolved. Therefore, the aim of the present doctoral thesis focuses on establishing the extent of the injury problem (in terms of incidence, severity and burden) in futsal players (studies 1 and 2), improving the current understanding regarding the aetiology and mechanisms of injury through the development of robust screening models for injury prediction (studies 3 and 4) and the identification of hazardous movement patterns (risk profiles) (study 5) through the use of a range of contemporary Machine Learning techniques. The main findings of the current thesis will help coaches, physical trainers and medical practitioners in the decision-making process for injury prevention.

CHAPTER 2

Research Objectives and Hypothesis

CHAPTER 2

Research Objectives and Hypothesis

2.1. General Objectives

Based on the limitations of the scientific literature described in the previous chapter, the general objectives of the present doctoral thesis were: a) to establish the extent of the futsal injury problem, b) to develop novel "user friendly" prediction models to accurately identify professional futsal players at high or low risk of soft-tissue injury and c) to deepen the knowledge of the complex relationships among neuromuscular factors and to describe their contributions on the likelihood that futsal players adopt movement patterns during dynamic tasks that potentially might increase the risk of injury.

Five different studies were conducted to address these objectives. The first two studies focussed on the first step of the model for injury prevention, as both aimed at describing the magnitude, severity and characteristics of the injury problem in futsal through a meta-analysis and a three-year prospective epidemiology design, respectively. The third study examined the criterion-related validity of measures of knee and hip alignment (frontal plane) and motion (sagittal plane) recorded simultaneously using a field-based 2D video analysis and a laboratory-based 3D motion analysis system (gold standard) during bilateral drop landing applying a contemporary statistical approach. The fourth study used machine learning based techniques to develop screening models to identify futsal players at high or low risk of injury. The last study explored the complex (non-linear) interactions among several neuromuscular performance parameters and quantified their individual and combined contributions on players′ likelihood of having poor or good dynamic postural control values through Bayesian Networks Classifiers.

The titles of the five studies are the following:

- **Study 1:** Epidemiology of injuries in professional futsal injuries: a systematic review and meta-analysis.
- **Study 2:** Injury incidence, characteristics and burden among female sub-elite futsal players: A prospective study with three-year follow-up.
- **Study 3:** Criterion-related validity of 2-Dimensional kinematic of knee and hip measures during bilateral drop-jump landings.
- **Study 4:** A field-based approach to determine soft tissue injury risk in elite futsal using novel machine learning techniques.
- **Study 5:** A Bayesian Network approach to study the relationships between several neuromuscular performance measures and dynamic postural control in futsal players.

2.2. Specific objectives

The specific objectives have been organized depending on the five studies of this doctoral thesis.

Study 1:

1. To conduct a systematic review and meta-analysis quantifying the incidence of injuries in male and female futsal players.
2. To determine the overall effects regarding match and training injuries, injuries sustained during national leagues (clubs) and international tournaments (national teams), location, type and severity of injuries separately for males and females.

Study 2:

3. To analyse the injury incidence, characteristics and burden among sub-elite female futsal players during three consecutive seasons.

Study 3:

4. To examine the criterion-related validity of three measures of frontal plane knee alignment using a 2D video analysis and a 3D motion analysis system during bilateral drop landing and applying a contemporary statistical approach in elite futsal players.

5. To examine the criterion-related validity of two measures of sagittal plane hip and knee flexion ranges of motion using a 2D video analysis and a 3D motion analysis system during bilateral drop landing and applying a contemporary statistical approach in elite futsal players.

Study 4:

6. To analyze and compare the individual and combined ability of several personal, psychological, self-perceived chronic ankle instability and neuromuscular performance measures obtained from different questionnaires and field-based tests to prospectively predict LE-ST injuries after having applied supervised Machine Learning techniques in elite male and female futsal players.

Study 5:

7. To analyse the relationships between several parameters of neuromuscular performance with dynamic postural control using a Bayesian Network Classifiers based analysis.

2.3. Research hypotheses

The following hypothesis were established in the five studies of this doctoral thesis.

Study 1*:*

- Although no studies have been found comparing injury incidence between male and female futsal players, based on the results of prospective studies conducted in soccer players[41,108], the incidence of male futsal players will most likely be higher than the incidence of injuries in female futsal players.
- The well-documented sex-related anatomical[109], musculoskeletal[110] and hormonal[111] differences (among other factors) will generate that male and female futsal players show differences in injury characteristics.
- Based on previous epidemiological studies conducted in futsal[6,20–23] and recently published meta-analyses on injuries in other intermittent team sports such as soccer[71] and rugby[73], the incidence of match injuries will most likely be higher than the incidence of injuries in training, independently of the sex.
- According to the literature[6,20–23], the incidence during international tournaments will be most likely higher than the incidence during national tournament.

Study 2:

- Similar to what have been documented in males[6,23], injury incidence rates in female futsal players will be high in comparisons with other popular women´s sports such as bat (i.e. cricket and softball) and stick (i.e. field hockey and lacrosse) sports[74] and football[112].
- In line with the literature[21,22], lower extremity injuries and particularly ankle sprains and ligament ruptures will be the most frequently diagnosed injuries.

- The substantive number of high intensity collisions and contact situations that usually occur during futsal play[3,4] will contribute to that fact that most injuries happen in contact situations.

Study 3:

- Considering that previous studies have reported moderate correlation validity scores between certain measures of frontal plane knee alignment obtained through the use of 2D video analysis procedures with their respective 3D criterion measures[61,64–69], it was hypothesized that frontal plane projection angle of the knee, knee-to-ankle separation ratio and knee medial displacement will also show acceptable typical error of the estimate scores and Kappa statistic values, whereby both kinematic methodologies may be used interchangeably.
- Based on the results reported by the only one study has analysed the correlation validity of lower extremity kinematic measures obtained simultaneously through 2D video analysis procedures and 3D motion analysis systems in planes other than the frontal plane during dynamic tasks[70], the hypothesis of this study is that 2D sagittal plane hip and knee measures will show acceptable validity scores when compared with their respective gold-standard measures.

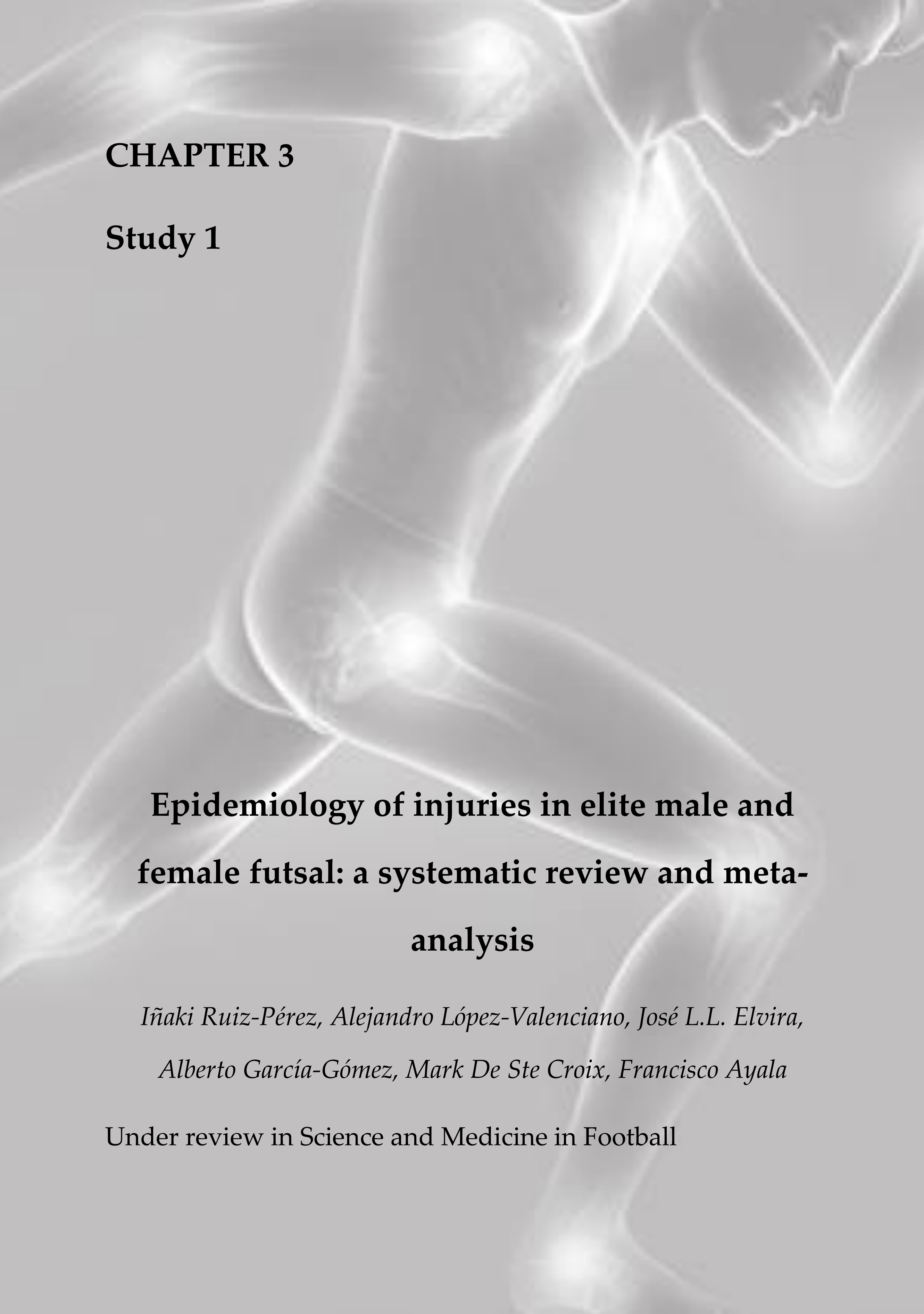
Study 4:

- Accepting that the sport-related injury may be defined as a multifactorial and complex phenomenon[18], no group of personal, psychological, self-perceived chronic ankle instability and neuromuscular performance measures itself will allow Machine Learning techniques to build models with an acceptable predictive ability from an injury risk standpoint.
- Contrarily to what has been just stated, the combination of all measures obtained from three different field-based tests and five questionnaires in the same database

will allow building robust models to prospectively identify elite futsal players at high risk of sustaining an injury.

Study 5:

- As it has been exhibited in other fields of knowledge (i.e. Computer Sciences and Environmental Sciences), the Bayesian Network classifiers will be robust techniques that allow to explain graphically and probabilistically the complex relationship between modifiable measures of neuromuscular performance and the dynamic postural control using the same variables for both, the dominant and the non-dominant lower extremities.



CHAPTER 3

Study 1

Epidemiology of injuries in elite male and female futsal: a systematic review and meta-analysis

Iñaki Ruiz-Pérez, Alejandro López-Valenciano, José L.L. Elvira, Alberto García-Gómez, Mark De Ste Croix, Francisco Ayala

Under review in Science and Medicine in Football

CHAPTER 3

Study 1

Epidemiology of injuries in elite male and female futsal: a systematic review and meta-analysis

Iñaki Ruiz-Pérez, Alejandro López-Valenciano, José L.L. Elvira, Alberto García-Gómez, Mark De Ste Croix, Francisco Ayala

3.1. Abstract

Objective: The main purpose of this study was to conduct a systematic review and meta-analysis quantifying the incidence of injuries in futsal players.

Method: A systematic search was conducted using various databases (MEDLINE, PubMed, Web of Science, Scopus and Google Scholar) and subsequently 6 studies (14 cohorts) were selected that prospectively reported the incidence of injuries in futsal. Two reviewers independently extracted data and assessed trial quality using the Strengthening the Reporting of Observational Studies in Epidemiology statement and Newcastle Ottawa Scale. Separate meta-analyses for male and female players were conducted using a Poisson random-effect regression model approach.

Results: The overall and match incidence rates in elite male futsal players were 6.8 (95% CI = 0.0 - 15.2) and 44.9 (95% CI = 17.2 - 72.6) injuries/1000 hours of exposure. For females, an overall, training and match incidence rates of 5.3 (95% CI = 3.5 - 7), 5.1 (95% CI = 2.7 - 7.6) and 10.3 (95% CI = 0.6 - 20.1) injuries/1000 hours of exposure were reported. In males, match incidence rate in International tournaments was 8.5 times higher than in national leagues (77.2 [95% CI = 60.0 - 94.5] vs 9.1 [95% CI = 0.0 - 19.3] for international tournaments and national leagues, respectively). Due to the lack of injury incidence data available for both sexes, it was not possible to conduct other sub-analyses (e.g.: location, type and severity of injuries).

Conclusions: Elite male and female futsal players are exposed to a substantial risk of sustaining injuries, especially during matches.

Keywords: Injury incidence, sports injury, injury prevention, five-a-side football, risk of injury

3.2. Introduction

Futsal is the official name for the 5-a-side indoor version of associated football (i.e. 1 goalkeeper and 4 outfield players) that is sanctioned by soccer's international governing body *Fédération Internationale de Football Association* (FIFA). Futsal is played worldwide with more than 12 million players all over the world[1,2]. During the game of futsal, players are exposed to regular collisions and repeated high-intensity physical demands such as sudden accelerations and decelerations, rapid changes of direction, tackling and kicking[3,4]. Similar to that which has been observed in other intermittent team sports (e.g. football [71], rugby [73] and basketball [113]), at top levels, the combination of these heavy physical demands, the frequent exposure to collisions and contacts along with the current congested calendars and the high levels of performance-related psychological stress may place futsal players at substantial risk of injury. In fact, it has been suggested that futsal is among the top ten injury-prone sports[6].

Therefore, and given the potential short and long-term negative effects that injuries may elicit on player´ well-being[114,115], team success[8,116] and club´ financial performance[117], the design and implementation of effective preventive measures in daily futsal training sessions should be considered a fundamental task for coaches and sport science specialists. However, before implementing any injury prevention measure it is essential to know the injury profile of futsal, in terms of incidence, severity and location of the most common injuries[14–16]. Furthermore, it is likely that the well-documented sex-related anatomical[109], musculoskeletal[110] and hormonal[111] differences, (among other factors) may contribute to sex-specific differences in injury incidences and characteristics. Consequently, the study of the injury profile in futsal should be conducted separately for male and female players.

Currently, the available prospective epidemiological studies that report injury incidence data have shown incidence rates that range from 0.9 to 195.6 and from 6.7 to 86.6 injuries per 1000 hours of male and female players exposure, respectively. However, the relatively small number of players included in most of these epidemiological studies alongside disparity in injury definitions and data collection procedures make inter-study comparisons difficult and may have clouded our understanding of the incidence, severity and location of futsal-related injuries. Therefore, a study that reviews and employs a meta-analytical approach to the currently available epidemiological data to identify the incidence and severity of futsal injuries, separately by sex, as well as when (matches or training sessions) and where (anatomical location) they occur is warranted. This knowledge could lead coaches and sport science specialists to priorities the application of sex-specific measures to prevent or reduce the risk of sustaining such injuries.

Therefore, the main purpose of this study was to conduct a systematic review and meta-analysis quantifying the incidence of injuries in male and female futsal players. When possible, sub-analyses separately by sex were carried out to determine the overall effects regarding match and training injuries, injuries sustained during national leagues (clubs) and international tournaments (national teams), location, type and severity of injuries.

3.3. Methods

To conduct this study (PROSPERO ID: 153544), guidelines for reporting meta-analysis of observational studies in epidemiology (Preferred Reporting Items for Systematic Reviews and Meta-Analyses [PRISMA] guidelines) were followed[118]. The PRISMA checklist is presented in appendix 3.1.

3.3.1. Study Selection

Eligibility criteria were established and agreed upon by all authors based on the concept of population, intervention/indicator, comparator/control and outcome (PICO)[119] (for more information please see appendix 3.2).

Thus, to be included in this systematic review and meta-analysis studies had to fulfil the following criteria:

(1) Injury must be defined in terms of time loss (i.e.: injury that results in a player being unable to take full part in future futsal training or match play)[120,121].

(2) Participants had to be elite or sub-elite futsal players (i.e.: players who belong to teams engaged in first or second national futsal leagues or play international senior competitions)[42,122–124].

(3) The study had to be a full-text article published in a peer-reviewed journal before November 2019.

(4) Eligible studies must report either incidence rate or prevalence among the surveyed players or provide sufficient data from which these figures could be calculated through standardized equations.

Studies using injury definitions other than time loss were excluded. Literature reviews, abstracts, editorial commentaries and letters to the editor were also excluded. Finally, some authors were contacted to provide missing data or to clarify if data were duplicated in other publications. Incomplete data, or data from an already included study, were excluded.

3.3.2. Search strategy

A systematic computerized search was conducted up to 31st October 2019 in the databases MEDLINE, PubMed, Web of Science and Scopus. In addition, a complementary search of the reference lists of included articles and a Google Scholar search were also performed. This was done using backward citation tracking (to manually search the reference list of a journal article), and forward citation tracking (scanning a list of articles that had cited a given paper since it was published)[125]. Citations were tracked using Google Scholar to make sure that studies were not missed inadvertently. When additional studies that met the inclusion criteria were identified, they were included in the final pool of studies. Relevant keywords were used to construct Boolean search strategies, including terms such as futsal, injury, injuries and epidemiology.

Two reviewers independently (IR-P and AL-V) selected studies for inclusion in a two-step process. First, studies were screened based on title and abstract. In a second stage, full-text studies were reviewed to identify those studies that met the eligibility criteria. A study was excluded immediately once it failed to meet a single inclusion criterion. Disagreements were resolved through consensus or by consulting a third reviewer (FA).

3.3.3. Data extraction

A codebook was produced to standardize the coding of each study in order to maximize the highest objectivity and each study was codified by two different reviewers. The moderator variables of the eligible studies were coded and grouped into three categories: 1) General study descriptors (authors, year of publication and study design); 2) Study population (sample size, sex and level of play); 3) epidemiological data (injury [including it mains characteristics according to Fuller et al.[120]] and exposure data). If applicable, the authors of included studies were contacted to provide clarifications or access to raw data. Operational definitions used in this study are shown in appendix 3.3. Appendix 3.4 also displays the moderator variables coded separately by category.

3.3.4. Quality assessment

As suggested by Von Elm et al.[126] the quality of each of the studies included was assessed using the full version of the "Strengthening the Reporting of Observational Studies in Epidemiology" (STROBE) scale. Three categories for quality assessment were established arbitrarily: high: the study fulfilled more than 80% criteria stated in STROBE; moderate: 50–80% of STROBE criteria were fulfilled; low: if less than 50% criteria could be achieved[127].

Furthermore, to assess risk of bias of external validity quality, an adapted version of the Newcastle Ottawa Scale (NOS) for cohort studies was used. The NOS was adapted to fit the purpose of this review, as undertaken in previous publications[71,128–130]. Thus, two of the eight items were deleted. Item 2 was excluded because a selection of the non-exposed cohort was irrelevant as long as the total study population was exposed to futsal play and item 5 (comparability of cohorts on the basis of the design or analysis) was excluded because it was linked to item 2. Two new items were added to the original scale (items 1 and 3). Therefore, the criteria adopted to assess risk of bias were: 1) description or type of futsal players, 2) definition of injury, 3) representativeness of the exposed cohort, 4) ascertainment of exposure, 5) demonstration that the outcome of interest was not present at the start of study, 6) assessment of outcome, 7) whether follow-up was long enough for outcomes to occur, 8) adequacy of follow-up of cohorts. An article could be awarded a maximum of one star for each item if appropriate methods had been clearly reported. Thus, a total of eight stars could be given to an article. The higher the number of stars given to an article the lower the risk of bias and studies scoring at least 6 stars were classified as high quality studies[131].

The data extraction and quality assessment (including risk of bias of external validity) were carried out by two reviewers (AL-V and IR-P). For the quantitative moderator variables intraclass correlation coefficients ($ICC_{3,1}$) were calculated, while for the qualitative moderator variables Cohen's k coefficients were applied. On average, the ICC was 0.95 (range: 0.9–1.0) and the k coefficient was 0.97 (range: 0.94–1.0), Inconsistencies between the two coders were resolved by consensus, and when these were due to ambiguity in the coding book, this was corrected. As before, any disagreement was resolved by mutual consent in consultation with a third reviewer (FA).

3.3.5. Statistical analysis

Injury incidence rates per 1000 hours of player exposures were extracted from the included studies. If injury incidence rates were not specifically reported, they were, if possible, calculated from the available raw data using the following formulas:

Incidence = 1000 × (∑injuries/∑exposure hours)

Incidence = n° of injuries / (n° of matches × 5 players × match duration*) × 1000

* Match duration, using the factor 0.67, based on standard 40 min match play

Separate injury incidence meta-analyses were performed for male and female futsal players. Similar to previous meta-analysis on epidemiology of injuries in sports[71,132], data were modelled by a random effects Poisson regression model, as previously described[133]. The response variable in each meta-analysis was the number of observed injuries, offset by the log of the number of exposure hours. A random effects term was included to account for the correlation arising from using multiple rows of data from the same study. Factors of interest were included as random effects. A weighting factor used was: study exposure time (hours) / mean study exposure time (hours). For injury incidence data, the overall estimated means for each random effect factor were obtained from the model and then back-transformed to give incidence rates, along with 95% CIs (CIs that showed negative values were adjusted to 0 for better interpretability). A forest plot was also constructed for each meta-analysis. Heterogeneity was evaluated using the I^2 statistic, which represents the percentage of total variation across all studies due to between-study heterogeneity[134].

Sub-analyses separately by sex were carried out when there were at least three incidence rates (cohorts) coming from a minimum of two different studies and the sum of the number of players involved was higher than 30 players to determine the pooled effects regarding overall, match and training injuries, injuries sustained during national leagues (clubs) and international tournaments (national teams), location (lower extremity, trunk, upper extremity, head and neck), type (fractures and bone stress, joint [non-bone] and ligament, muscle and tendon, contusions, laceration and skin lesion, central/peripheral nervous system and undefined/other) and severity (slight/minimal [1–3 days], minor/mild [4–7 days], moderate [8–28 days], major/severe [>28 days]) of injuries. All statistical analyses were performed using the statistical software package R V.2.4.1 (The R Foundation for Statistical Computing) and the 'metafor' package[135].

Comparisons between factors were then made using a spreadsheet for combining effect statistics[136], whereby the incidence rate ratio (and its associated confidence limits) were assessed against predetermined thresholds. An incidence rate ratio of 0.91 represented a substantially lower injury risk, while an incidence rate ratio of 1.10 indicated a substantially higher injury risk[137]. An effect was deemed unclear if its confidence interval overlapped the thresholds for substantiveness; that is, if the effect could be substantial in both a positive and negative sense. Otherwise the effect was clear and deemed to have the magnitude of the largest observed likelihood value. This was qualified with a probabilistic term using the following scale: <0.5%, most unlikely; 0.5–5 %, very unlikely; 5–25%, unlikely; 25–75%, possible; 75–95%, likely; 95–99.5%, very likely; >99.5%, most likely[136,138].

3.4. Results

3.4.1. Study selection

Of the 479 studies found via our electronic and manual searching of the databases, finally six[6,20–23,128] were included in this systematic review and meta-analysis (11 cohorts). Details of exclusion and reason for exclusion are provided in figure 3.1.

The studies were carried out between 2010 and 2019 and comprised male[6,20–23] and female[21,22,128] futsal players from both International tournaments[6,23] and national futsal leagues in different countries (Spain[20,128], Iran[21] and Malaysia[22]). A summary of included studies is presented in table 3.1.

3.4.2. Quality assessment of the studies selected

With regard to the reporting quality of the studies selected in this systematic review and meta-analysis, five out of the six studies achieved STROBE scores that were categorized as high (18[23], 19[6,21,22] and 20[128] points out of the 22-maximum achievable) while only one study[20] demonstrated a STROBE score that was categorized as low (13 points). Regarding the assessment of the risk of bias of external validity quality, all the studies selected obtained seven out of eight stars in the NOS scale, with the exception of the study conducted by Álvarez-Medina et al.[20] which was awarded only 5 stars. A detailed description of the results obtained in each study from the STROBE and NOS scales is presented in appendixes 3.5 and 3.6, respectively.

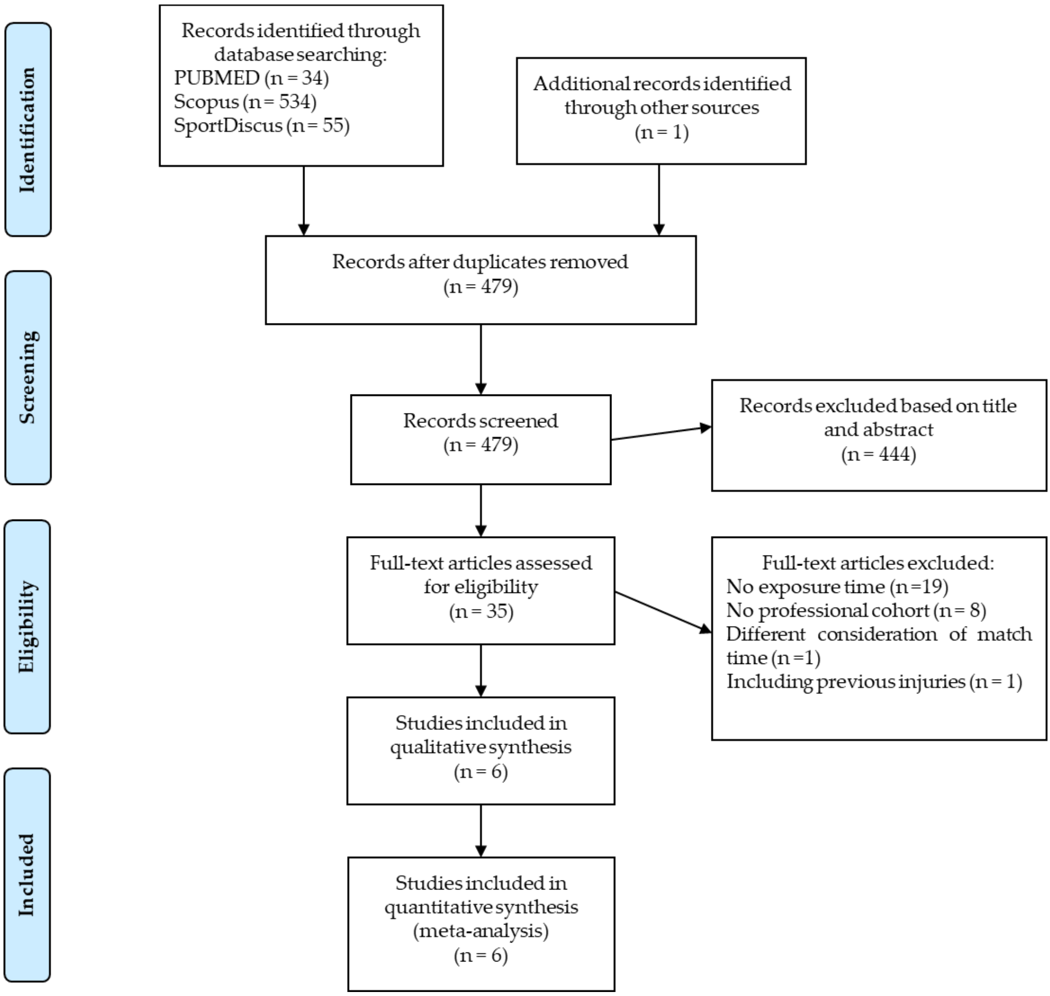


Figure 3.1. Flow chart of the selection of studies for the meta-analysis.

Table 3.1. Characteristics of the studies included in this systematic review and meta-analysis

Reference Country / Tournament	Study Duration (weeks)	Nº Teams (Players)	Exposure (hours) Overall	Exposure (hours) Training	Exposure (hours) Match	Injuries Overall	Injuries Training	Injuries Match	Incidence Overall	Incidence Training	Incidence Match	STROBE reporting quality	NOS External validity
Ruiz-Pérez et al.[128] +[a] ♀ Spain NL – 2015-16	36	1 (14)	1506.7	1413.3	93.3	8	0	8	5.3 (1.6 - 9.0)	5.7 (1.7 - 9.6)	0.0 (0.0 - 0.0)	19 (High)	7 (High)
Ruiz-Pérez et al.[128] +[b] ♀ Spain NL – 2016-17	36	1 (14)	1328.8	1222.1	106.7	12	11	1	9.0 (3.9 - 14.1)	9.0 (3.7 - 14.3)	9.4 (0.0 - 27.7)	19 (High)	7 (High)
Ruiz-Pérez et al. [128] +[c] ♀ Spain NL – 2017-18	36	1 (13)	1610.7	1500.7	110	10	9	1	6.2 (2.4 - 10.0)	6.0 (2.1 - 9.9)	9.1 (0.0 - 26.9)	19 (High)	7 (High)
Hamid et al.[22] +[a] ♂ Malaysia NL – 2010	24	16 (238)	-	-	466.7	-	-	11	-	-	23.6 (9.6 - 37.5)	19 (High)	7 (High)
Hamid et al.[22] +[b] ♀ Malaysia NL – 2010	24	16 (230)	-	-	473.3	-	-	14	-	-	29.6 (14.1 - 45.0)	19 (High)	7 (High)
Angoorani et al.[21] +[a] ♀ Iran NT – 2011-12	76	1 (17)	6714.6	5787.8	930.2	28	18	10	4.2 (2.6 - 5.7)	3.1 (1.7 - 4.6)	10.7 (4.1 - 14.4)	19 (High)	7 (High)
Angoorani et al.[21] +[b] ♂ Iran NT – 2011-12	76	1 (15)	8888.9	8108.1	819.7	8	3	5	0.9 (0.3 - 1.5)	0.4 (0.0 - 0.8)	6.1 (0.7 - 11.4)	19 (High)	7 (High)
Angoorani et al.[21] +[c] ♂ Iran NT – 2011-12	76	1 (23)	8695.6	7262.6	1436.8	18	13	5	2.1 (1.1 - 3.0)	1.8 (0.8 - 2.8)	3.5 (0.4 - 6.5)	19 (High)	7 (High)
Álvarez-Medina et al.[20] +[a] ♂ Spain NL – 2004-05	40	1 (12)	5477	-	-	108	-	-	19.7 (16.0 - 23.4)	-	-	13 (Moderate)	5 (Low)

Álvarez-Medina et al.[20]+ b ♂ Spain NL – 2011-12	40	1 (12)	4931	-	-	26	-	-	5.3 (3.2 - 7.3)	-	-	13 (Moderate)	5 (Low)
Junge & Dvorak[6] a ♀ Guatemala / WC – 2000	2	16 (224)	-	-	220	-	-	17	-	-	77.2 (40.4 - 113.9)	19 (High)	7 (High)
Junge & Dvorak[6] b ♀ Chinese Taipei / WC – 2004	2	16 (224)	-	-	266.7	-	-	18	-	-	67.5 (36.3 - 98.7)	19 (High)	7 (High)
Junge & Dvorak[6] c ♀ Brazil / WC – 2008	3	20 (280)	-	-	356.7	-	-	32	-	-	89.9 (58.8 - 121.0)	19 (High)	7 (High)
Ribeiro & Costa[23] ♀ Brazil U20 NC - 2004	1	10 (180)	-	-	153.4	-	-	11	-	-	71.7 (29.3 - 114.1)	18 (High)	7 (High)

+Study was implemented according to the 2006 consensus statement for epidemiological studies in soccer

(a);(b);(c): indicate different cohorts in the same study

♀: indicates that it is female cohort

*: study duration expressed in number of weeks

NT: national team; WC: world cup; NC: national cup; NL: national league

U: under

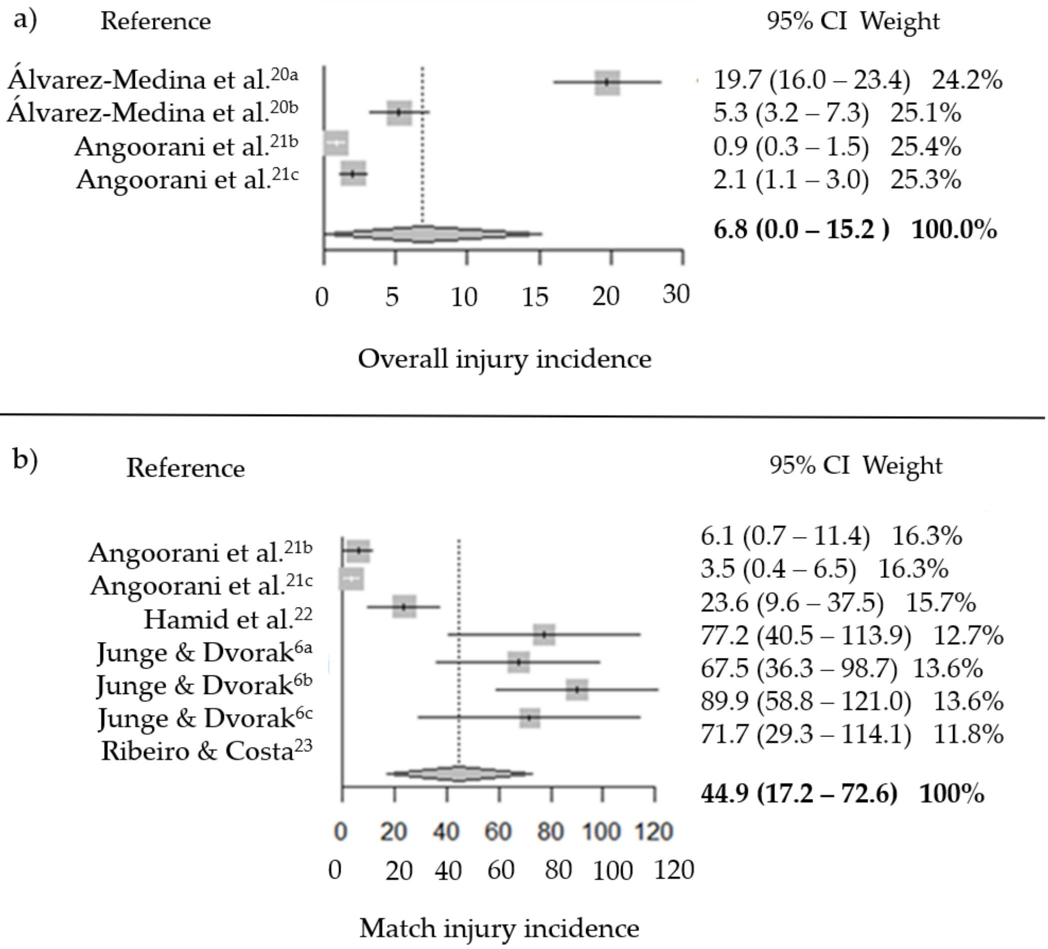


Figure 3.2. Overall (a) and match (b) injury incidence in male players with 95% confidence intervals.

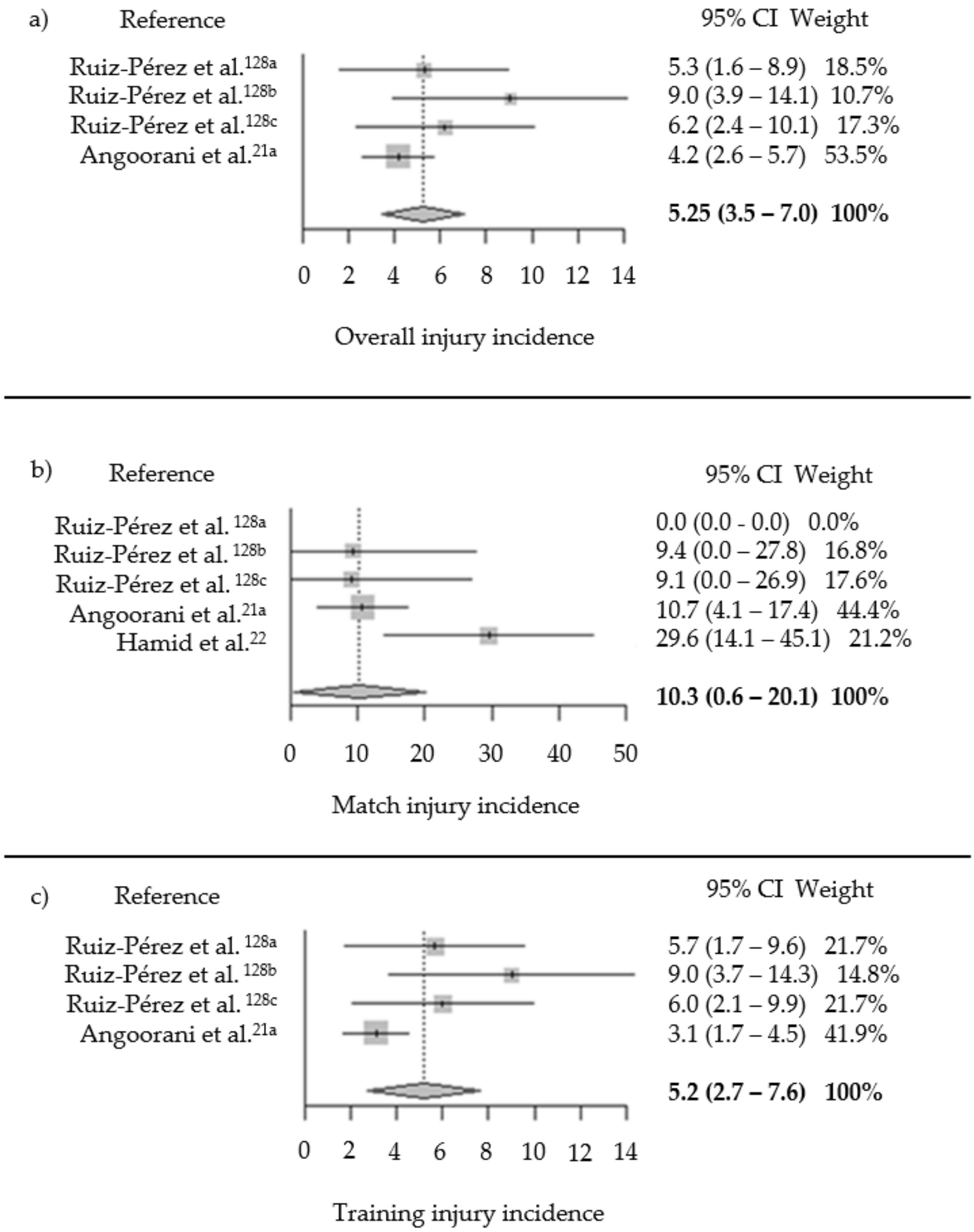


Figure 3.3. Overall (a), match (b) and training (c) injury incidences in female players with 95% confidence intervals.

There were non-significant sex-related differences in the overall incidence rates (with a probability of 44.8%). However, males showed a statistically significant 4.3 times higher match injury incidence rate than females futsal players (with a probability of 92.3%).

3.4.3.2. Injury characteristics

3.4.3.2.1. National leagues vs. international tournaments

For males, two studies[6,23] provided match injury incidence data during futsal international tournaments (three World Cups [Guatemala 2000, China Taipei 2004 and Brazil 2008] and one national cup [Brazil 2004]) and other two studies[20,21] reported epidemiological information regarding injuries sustained during futsal match play in different national leagues. Consequently, the seven cohorts that showed match injury incidence rates in male futsal players were grouped into two categories: a) national leagues (three cohorts) and b) international tournaments (four cohorts). Match incidence rates in international tournaments were 8.5 times likely higher (statistically significant with a probability of 93.5%) than in national leagues (77.2 [95% CI = 60.0 - 94.5] vs 9.1 [95% CI = 0.0 – 2.39] for international tournaments and national leagues, respectively) (figure 3.4).

Unlike males, no studies were found that reported injury incidence rates for females in international futsal tournaments and hence, this sub-analysis could not be carried out.

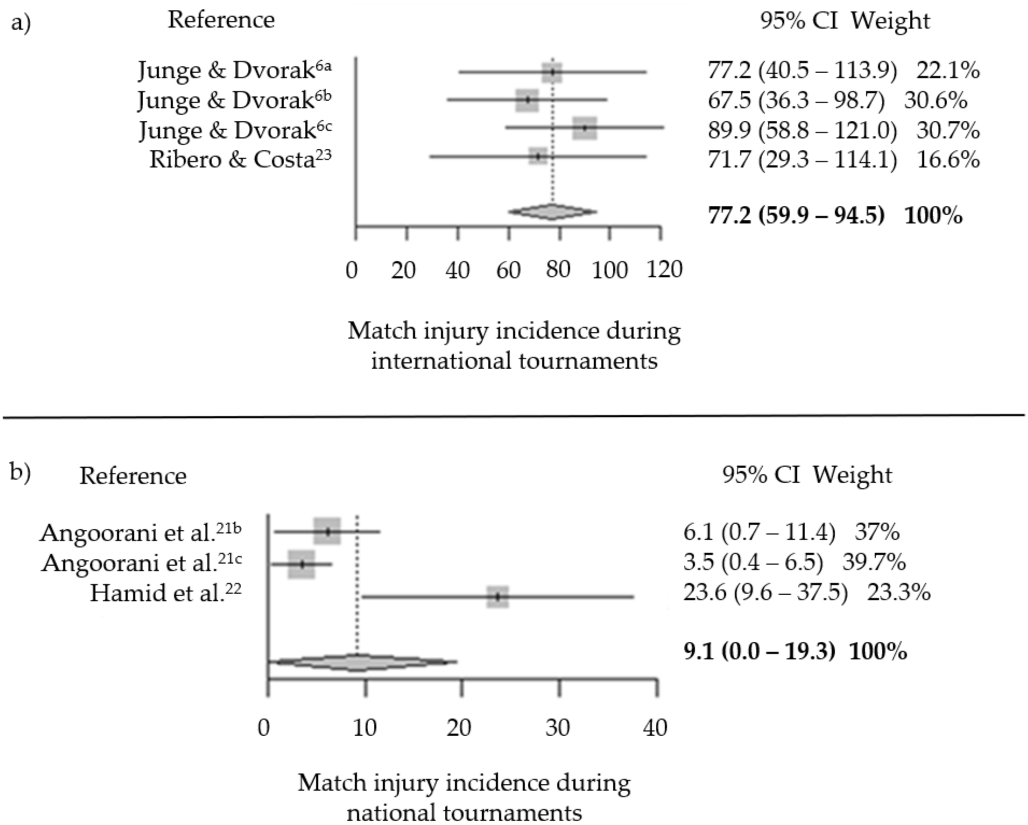


Figure 3.4. Match incidence during male international (a) and national (b) tournaments forest plot with 95% confidence intervals.

3.4.3.2.2. Location, type and severity of injury

Although some studies provided epidemiological data regarding the location, type and severity of the injuries occurred during futsal[6,22,23], only Ruiz-Pérez et al.[128] and Angoorani et al.[21] reported incidence rates for these three time loss injury characteristics separately for each of the four cohorts of female futsal players and two cohorts of male futsal players, respectively. As a consequence, sub-analysis for these moderator variables could not be carried out.

3.5. Discussion

The main findings of this systematic review and meta-analysis suggest that both male and female elite futsal players have a substantial risk of sustaining an injury. In particular, and for males, the results show pooled overall and match incidence rates of 6.8 and 44.9 injuries per 1000 hours of exposure. These overall and match injury incidence rates are in line with the injury incidences reported in other elite team sports such as football (8.1 [overall] and 36 [match] injuries per 1000 hours of exposure)[71], rugby (from 68 to 81 injuries per 1000 hours of match play exposure)[73,139] and handball (6.5 [overall] and 22.2 [match] injuries per 1000 hours of exposure to match play)[140]. The current study also demonstrated that female players pooled overall, match and training incidence rates were 5.3, 5.1 and 10.3 injuries per 1000 hours of exposure, respectively. These results are also similar to the incidence rates documented for elite female football (from 5.5 to 9.4, from 3.1 to 4.6 and from 16.1 to 22.7 injuries per 1000 hours of exposure to overall, training and match play)[24,41,141–144], hockey (3.8 [overall], 2.7 [training] and 9.8 [match] injuries per 1000 hours of exposure]) and basketball players (4.7 injuries per 1000 hours of overall exposure to basketball play)[145].

Although the results of the current meta-analysis indicate that male futsal players exhibit a higher match injury incidence rate than their counterpart female players (44.9 [males] vs. 10.3 [females] per 1000 hours of exposure), when the incidence rates reported by the two prospective epidemiological studies carried out in men´s international tournaments (national teams)[6,23] were removed from the random model (as the pooled match injury incidence rate obtained for females did not included data from individual epidemiological studies conducted during international tournaments), these documented sex-related differences became non-significant from a sport injury risk standpoint (see method) (9.1 vs. 10.3 injuries per 1000 hours of male and female players exposure to futsal match play, respectively). These findings are not in agreement with the results reported by previous studies comparing injury incidence rates between male and female professional football players[24,41]. These studies have attributed the presence of sex-related differences in injury risk to the higher number of contact injuries sustained by male football players and that may be due to the higher intensity and number of contact situations that have been observed in male football[24,41]. Perhaps, and unlike football, the reduced (usually indoor) pitch size (40 x 20 m) and the unlimited possibility to substitute the players during the game may guarantee that most of the physical actions are performed at a very high intensity, making collisions with other players and tackling to keep possession of or to win the ball situations that are very repeatedly observed during matches, independently of the sex of the players. In fact, futsal has been considered one of the most demanding team sports (higher than football, basketball and handball) due to its average heart rate (around 90% of maximum heart rate) and work to rest ratio of 1:1, with a locomotor activities changing every 3.3 seconds with short recovery time intervals (20-30 s) between the high intensity bout sequences (3-4 bouts)[3,146,147].

Other relevant findings of the present study are related with the fact that, for females, and similar to what has been found in other team sports (e.g. football and handball), match injury incidence (10.3 injuries per 1000 hours of exposure) was significantly higher (almost twice) than the injury rate obtained for training sessions (5.3 injuries per 1000 hours of exposure). Although for males, the epidemiological data available regarding injury incidence during futsal training was insufficient to conduct a meta-analysis, the results of the sole study that provided both match and training incidences in elite male futsal suggest that, and similar to females, most of the injuries occur during matches[21]. Previous studies have attributed these differences in injury incidence rates between match and training to several factors, including the higher physical demands on players during matches in comparison with training sessions, the number of contacts and collisions during matches, and fatigue generated during the course of the match[46,148]. Therefore, coaches and sports science specialists, when possible, should include in the training session tasks that reproduce the worst-case scenarios (in terms of physical demands) of futsal match play so that players can be better prepared for competitive match play, which potentially may reduce the risk of injury.

The results of this study also highlight that for male futsal players, the incidence rate during international tournament matches (77.2 [95% IC = 59.9 - 94.5] injuries per 1000 hours of exposure) was 8.5 times higher than during national league matches (9.1 injuries per 1000 hours of exposure). Similar findings were found by López-Valenciano et al.[71] in professional football players, so that during International tournaments, the match injury incidence rate was significantly higher than its counterpart calculated during national leagues (41.1 vs. 32.3 injuries per 1000 hours of match exposure). The higher density of matches played, fatigue levels and the mental stress and anxiety generated in the players have been suggested as contributing factors for this increase in the number of injuries sustained during international tournament matches[149–152]. Consequently, during international tournaments the application of effective post-match recovery strategies might help players to alleviate some of the major fatigue-related physical and psychological impairments and this may lead them to a better state to re-perform and to reduce the risk of injury.

Although the epidemiological data available up to date do not allow us to conduct sub-analyses regarding the location, type and severity of the injuries that occur as a consequence of futsal play, the few studies that have provided data in this regard[6,21,23,128] demonstrate that, in both sexes, lower extremity injuries are, by far, the most frequent. Although the most common injury mechanism reported was by non-contact, it should be highlighted that a remarkable number of injuries (around 30%) were caused by a contact mechanism. As mentioned before, the substantive number of high intensity phases observed in elite players during the course of futsal play[5,153] might contribute to generate several contusions and tackling situations and partially explain the fact that contact injuries are more frequent than in other team sports such as football[41,71] and basketball[154] in which the number of high intensity phases may be lower[5,155–157]. However, more studies examining physical demands (number of accelerations and decelerations, changes of direction, distance covered at high speed running, etc.) of futsal play are needed to look at potential injury mechanisms. Likewise, epidemiological studies also show that the thigh, knee and ankle seem to be the anatomical region of the lower extremity where injuries occurred significantly more in male and female players. In addition, the most common types of injury grouping were ligament (ankle and knee sprains) and muscle/tendon (hamstring, adductors and quadriceps muscle strains) injuries. Fortunately, most of the futsal-related injuries usually have a slight/minimal (1-3 day) or minor/mild severity (4-7 days) and hence, the injury burden seems generally low, but more studies are needed to explore injury burden in futsal-related injuries. Therefore, and for both male and female futsal players, medical and fitness team staff should focus their attention on designing, implementing and then evaluating preventative measures that target the most common knee and ankle ligament and thigh muscle and tendon injuries.

3.6. Limitations

Although this novel study was conducted following the international guidelines for systematic reviews and meta-analyses, some limitations should be acknowledged. One of the main limitations of this study was the reduced number of studies that were finally included (n = 6) and that together with the limited sample sizes (< 30 players) present in some of their cohorts may have resulted in a high degree of inconsistency in the injury estimates. However, it should be highlighted that the number of studies and cohorts included in this study was similar than the ones included in previous meta-analyses on sport-related injury incidence[73,158,159]. Another source of inconsistency may have also been the variations in injury definitions and lack of uniform data collection methods found among studies. Other factor that may have also contributed to the high degree of inconsistency could be the differences existing among the national leagues in terms of numbers of matches and in-season breaks, periods of fixed match congestion and level of professionalism. Due to lack of suitable data, sub-analyses regarding location, type and severity of the injuries sustained during futsal play could not be conducted. Therefore, more studies are needed reporting the number of injuries sustained in futsal training sessions and matches separately for males and females, and also the location, type and severity of such injuries per 1000 hours of exposure following standardized injury definitions and data collection procedures. Injury burden (the product of severity and incidence[26]) should also be reported in future epidemiological studies to help interpret injury data from a novel risk management standpoint.

3.7. Conclusions

Elite male and female futsal players are exposed to a substantial risk of sustaining injuries, especially during matches. No sex-related differences were found in the overall futsal injury incidence. For males, this risk of injury during futsal match play is eight times higher during international tournaments than in national leagues. Due to the lack of injury incidence data available for both sexes, future studies are warranted reporting the number of injuries sustained in futsal training sessions and matches separately, and also the location, type and severity of such injuries per 1000 hours of exposure using standardized injury definitions and data collection procedures.

3.8. Appendixes

Appendix 3.1. PRISMA checklist

Section/topic	#	Checklist item	Reported on page #
TITLE			
Title	1	Identify the report as a systematic review, meta-analysis, or both	79
ABSTRACT			
Structured summary	2	Provide a structured summary including, as applicable: background; objectives; data sources; study eligibility criteria, participants, and interventions; study appraisal and synthesis methods; results; limitations; conclusions and implications of key findings; systematic review registration number	79
INTRODUCTION			
Rationale	3	Describe the rationale for the review in the context of what is already known	81
Objectives	4	Provide an explicit statement of questions being addressed with reference to participants, interventions, comparisons, outcomes, and study design (PICOS)	82
METHODS			
Protocol and registration	5	Indicate if a review protocol exists, if and where it can be accessed (e.g., Web address), and, if available, provide registration information including registration number	83

Eligibility criteria	6	Specify study characteristics (e.g., PICOS, length of follow-up) and report characteristics (e.g., years considered, language, publication status) used as criteria for eligibility, giving rationale	83
Information sources	7	Describe all information sources (e.g., databases with dates of coverage, contact with study authors to identify additional studies) in the search and date last searched	83
Search	8	Present full electronic search strategy for at least one database, including any limits used, such that it could be repeated	83
Study selection	9	State the process for selecting studies (i.e., screening, eligibility, included in systematic review, and, if applicable, included in the meta-analysis)	82
Data collection process	10	Describe method of data extraction from reports (e.g., piloted forms, independently, in duplicate) and any processes for obtaining and confirming data from investigators	84
Data items	11	List and define all variables for which data were sought (e.g., PICOS, funding sources) and any assumptions and simplifications made	84
Risk of bias in individual studies	12	Describe methods used for assessing risk of bias of individual studies (including specification of whether this was done at the study or outcome level), and how this information is to be used in any data synthesis	84
Summary measures	13	State the principal summary measures (e.g., risk ratio, difference in means)	85

Synthesis of results	14	Describe the methods of handling data and combining results of studies, if done, including measures of consistency (e.g., I^2) for each meta-analysis	86
Risk of bias across studies	15	Specify any assessment of risk of bias that may affect the cumulative evidence (e.g., publication bias, selective reporting within studies)	84
Additional analyses	16	Describe methods of additional analyses (e.g., sensitivity or subgroup analyses, meta-regression), if done, indicating which were pre-specified	86
RESULTS			
Study selection	17	Give numbers of studies screened, assessed for eligibility, and included in the review, with reasons for exclusions at each stage, ideally with a flow diagram	87
Study characteristics	18	For each study, present characteristics for which data were extracted (e.g., study size, PICOS, follow-up period) and provide the citations	89
Risk of bias within studies	19	Present data on risk of bias of each study and, if available, any outcome level assessment (see item 12)	87
Results of individual studies	20	For all outcomes considered (benefits or harms), present, for each study: (a) simple summary data for each intervention group (b) effect estimates and confidence intervals, ideally with a forest plot	91
Synthesis of results	21	Present results of each meta-analysis done, including confidence intervals and	91

		measures of consistency	
Risk of bias across studies	22	Present results of any assessment of risk of bias across studies (see Item 15)	89
Additional analysis	23	Give results of additional analyses, if done (e.g., sensitivity or subgroup analyses, meta-regression [see Item 16])	93
DISCUSSION			
Summary of evidence	24	Summarize the main findings including the strength of evidence for each main outcome; consider their relevance to key groups (e.g., healthcare providers, users, and policy makers)	95
Limitations	25	Discuss limitations at study and outcome level (e.g., risk of bias), and at review-level (e.g., incomplete retrieval of identified research, reporting bias)	98
Conclusions	26	Provide a general interpretation of the results in the context of other evidence, and implications for future research	99
FUNDING			
Funding	27	Describe sources of funding for the systematic review and other support (e.g., supply of data); role of funders for the systematic review	-

Appendix 3.2. Inclusion/exclusion criteria for futsal literature search

	Inclusion criterion	Exclusion criterion	Rationale for this criterion
Publication type	Peer-reviewed original research articles only	Non-peer-reviewed articles, newspapers, opinion pieces, systematic reviews and meta-analysis, editorials, commentaries and letters to the editor Conference proceedings/abstracts	For reasons of practicality, it was deemed acceptable to include only studies published in peer-reviewed journals
Language	English, Spanish and Portuguese language	Non-English, Spanish or Portuguese	For reasons of practicality, it was deemed acceptable to include only studies published in English, Spanish or Portuguese
Study design	Descriptive epidemiological studies	Anecdotal studies. Case studies or expert opinion	Based on the evidence hierarchy as a guide, ONLY study designs ranked at least as 'good' were included in this systematic review and meta-analysis. This was to ensure high methodological rigour and offer reasonable empirical support for the incidence and aetiology of injuries

			among males and females who play elite futsal
Age	Male and female futsal players > 16 years participating in a competitive league (matches or training) OR international tournament	Ages <18 years, age unspecified studies	Players aged >18 years were considered as appropriate. The injury profile of players aged >18 years is important given that they participate in elite competition. Studies that reported injuries for players <18 years and >18 years and have data for age groups, but presented separately, were included
Playing level	Elite and sub-elite players	Amateur	The physical demands of futsal game may vary across different playing levels and this may led develop different injury patters
Sport	Futsal	Any sport other than futsal	Inclusion of sports with different regulations and physical demands can results in different injury incidence and characteristic

Injury definition	Time loss injuries (injury that results in a player being unable to take full part in future football training or match play)	Other definitions different than time loss injuries	Different injury definitions (i.e. decrease in the performance due physical complaints, needed of going to the hospital to be considered an injury) may result in different incidence rates
Main outcomes	Injury incidence rates per 1000 hours of player exposures	Descriptive epidemiological studies that do not include exposure time	For reasons of practicality, it was deemed acceptable to include only studies that included exposure time in order to make inter-studies comparisons

Appendix 3.3. Operational definitions used to include studies in the meta-analysis.

Term	Definition
Injury	Any physical complaint sustained by a player that results from a futsal match or futsal training, irrespective of the need for medical attention or time loss from futsal activities
Time loss injury	Injury that results in a player being unable to take a full part in future futsal training or match play
Recurrent injury	An injury of the same type and at the same site as an index injury and which occurs after a player's return to full participation from the index injury
Injury severity	The number of days that have elapsed from the date of injury to the date of the player's return to full participation in team training and availability for match selection. Injuries are grouped as: ▪ Slight / Minimal Absence (1-3 days) ▪ Minor / Mild Absence (4-7 days) ▪ Moderate Absence (8-28 days) ▪ Major / Severe Absence (>28 days)
Match exposure	Play between teams from different clubs
Training exposure	Team-based and individual physical activities under the control or guidance of the team's coaching or fitness staff that are aimed at maintaining or improving players' futsal skills or physical condition
Overuse injury	An injury caused by repeated microtrauma without a single, identifiable event responsible for the injury
Traumatic injury	Injury with sudden onset and known cause
Injury location	▪ Head and neck (Head/face; Neck/cervical spine)

	▪ Upper limbs (Shoulder/clavicula; Upper arm; Elbow; Forearm; Wrist; Hand/finger/thumb) ▪ Trunk (Sternum/ribs/upper back; Abdomen; Lower back/pelvis/sacrum) ▪ Lower limbs (Hip/groin; Thigh; Knee; Lower leg/Achilles tendon; Ankle; Foot/toe)
Type of injury	• Fractures and bone stress • Joint (non-bone) and ligament (Dislocation/subluxation; Sprain/ligament injury; Lesion of meniscus or cartilage) • Muscle and tendon (Muscle rupture/tear/strain/cramps; Tendon injury/rupture/tendinosis/bursitis) • Contusions (Haematoma/contusion/bruise) • Laceration and skin lesion (Abrasion; Laceration) • Central/peripheral nervous system (Concussion [with or without loss of consciousness]; Nerve injury) • Other (Dental injuries; Other injuries)
Injury incidence	Number of injuries per 1000 player hours ([Σ injuries/Σ exposure hours] ×1000)

Appendix 3.4. Moderator variables codded

General study descriptors
▪ Authors
▪ Year of the study
▪ Country / Tournament
▪ Sampling time (number of seasons)
Description of the study population
▪ Sample size
▪ Number of teams
▪ Age
▪ Level of play (club or national team)
Epidemiological descriptors
▪ Injury definition
▪ Number of injuries (total, match and training)
▪ Exposure time (total, match and training)
▪ Incidence (total, match and training)
▪ Injury burden or days lost per injury
▪ Injury location
▪ Type of injury
▪ Severity of injury
▪ Recurrence
▪ Injury mechanism (traumatic or overuse)
▪ Quality of the study (abbreviated STROBE scale)
▪ Risk of bias (adapted NOS scale)

Appendix 3.5. Description of the 22 of STROBE Statement—checklist of items that should be included in reports of observational studies

Item	Item number	Ruiz-Pérez et al.[128]	Ribeiro & Costa[23]	Hamid et al.[22]	Junge & Dvorak[6]	Angoorani et al.[21]	Álvarez-Medina et al.[20]
Title and abstract	1	Yes	Yes	No	Yes	Yes	No
Introduction							
▪ Background / rationale	2	Yes	Yes	Yes	Yes	Yes	Yes
▪ Objectives	3	Yes	Yes	Yes	Yes	Yes	Yes
Methods							
▪ Study design	4	Yes	Yes	Yes	Yes	Yes	Yes
▪ Setting	5	Yes	Yes	Yes	Yes	Yes	Yes
▪ Participants	6	Yes	Yes	Yes	Yes	Yes	Yes
▪ Variables	7	Yes	Yes	Yes	Yes	Yes	Yes
▪ Data sources / measurement	8	Yes	Yes	Yes	Yes	Yes	Yes
▪ Bias	9	No	No	No	No	No	No
▪ Study size	10	No	No	No	No	No	No
▪ Quantitative variables	11	Yes	Yes	Yes	Yes	Yes	Yes
▪ Statistical methods	12	Yes	Yes	Yes	Yes	Yes	Yes
Results							
▪ Participants	13	Yes	Yes	Yes	Yes	Yes	Yes

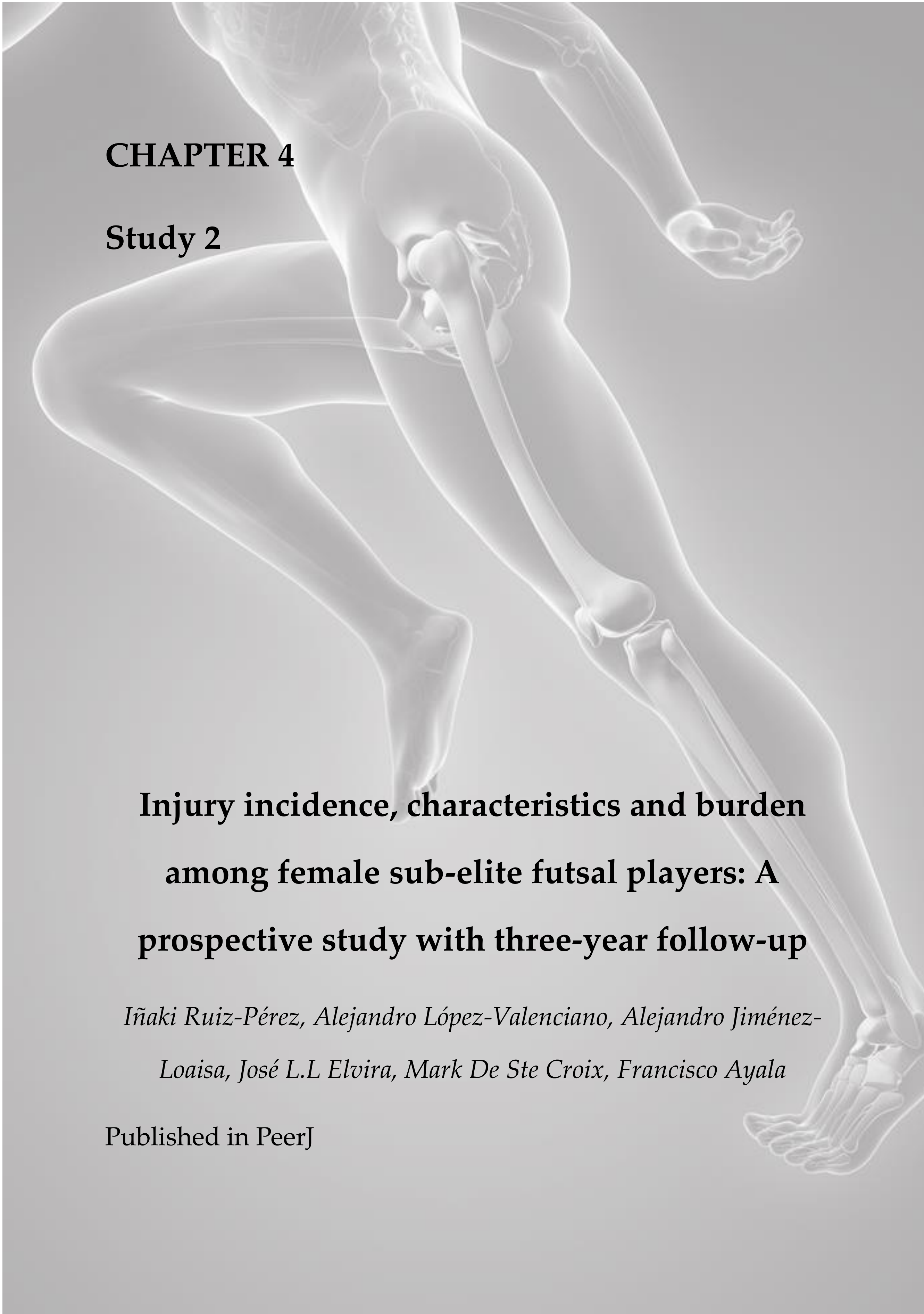
▪ Descriptive data	14	Yes	Yes	Yes	Yes	Yes	Yes
▪ Outcome data	15	Yes	Yes	Yes	Yes	Yes	Yes
▪ Main results	16	Yes	No	Yes	Yes	No	No
▪ Other analyses	17	Yes	Yes	Yes	Yes	Yes	No
Discussion							
▪ Key results	18	Yes	Yes	Yes	Yes	Yes	Yes
▪ Limitations	19	Yes	No	Yes	No	Yes	No
▪ Interpretation	20	Yes	Yes	Yes	Yes	Yes	No
▪ Generalizability	21	Yes	Yes	Yes	Yes	Yes	No
Other information							
▪ Funding	22	Yes	Yes	Yes	Yes	Yes	No
TOTAL SCORE		20	18	19	19	19	13
Qualitative interpretation		High	High	High	High	High	Moderate

Appendix 3.6. Risk of bias assessment of the studies (Newcastle Ottawa scale)

Study	Criteria for assessing risk of bias								Total
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	
Ruiz-Pérez et al.[128]	*	*	*	*	*		*	*	7
Ribeiro & Costa[23]	*	*	*	*	*		*	*	7
Hamid et al.[22]	*	*	*	*	*		*	*	7
Junge & Dvorak[6]	*	*	*	*	*		*	*	7
Angoorani et al.[21]	*	*	*	*	*		*	*	7
Álvarez-Medina et al.[20]	*		*	*			*	*	5

Criteria for assessing risk of bias: 1) description or type of futsal players, 2) definition of injury, 3) representativeness of the exposed cohort, 4) ascertainment of exposure, 5) demonstration that outcome of interest was not present at start of study, 6) assessment of outcome, 7) was follow-up long enough for outcomes to occur and 8) adequacy of follow-up of cohorts.

*Star(s) awarded for each criterion



CHAPTER 4

Study 2

Injury incidence, characteristics and burden among female sub-elite futsal players: A prospective study with three-year follow-up

Iñaki Ruiz-Pérez, Alejandro López-Valenciano, Alejandro Jiménez-Loaisa, José L.L Elvira, Mark De Ste Croix, Francisco Ayala

Published in PeerJ

CHAPTER 4

Study 2

Injury incidence, characteristics and burden among female sub-elite futsal players: A prospective study with three-year follow-up

Iñaki Ruiz-Pérez, Alejandro López-Valenciano, Alejandro Jiménez-Loaisa, José L.L. Elvira, Mark De Ste Croix, Francisco Ayala

4.1. Abstract

Objective: The main purpose of the current study was to analyze the injury incidence, characteristics and burden among sub-elite female futsal players.

Method: Individual exposure to match play and training, injury incidence and characteristics (player position, injury mechanism, type of injuries, severity of injuries, recurrent versus new injuries, season variation of injury pattern) in a female futsal team were prospectively recorded for three consecutive seasons (2015-2018). Incidences were calculated per 1000 hours of exposure.

Results: A total of 30 injuries were reported during the three seasons within a total exposure of 4446.1 hours. The overall, match and training incidence of injuries were 6.7, 6.4 and 6.8 injuries/1000 hours of exposure, respectively. Most injuries had a non-contact mechanism (93%), with the lower extremity being the most frequently injured anatomical region (5.62 injuries/1000 hours of exposure). The most common type of injury was muscle/tendon (4.9 injuries/1000 hours of exposure) followed by joint (non-bone) and ligament (1.3 injuries/1000 hours of exposure). The injuries with the highest injury burden were those that occurred at the knee (31.9 days loss/1000 hours exposure), followed by quadriceps (15.3 day loss/1000 hours) and hamstring (14.4 day loss/1000 hours) strains. The first few weeks of competition after pre-season and soon after the Christmas break were the time points when most injuries occurred. These data indicate that sub-elite female futsal players are exposed to a substantial risk of sustaining an injury.

Conclusions: To reduce overall injury burden, efforts should be directed toward the design, implementation and assessment of preventative measures that target the most common diagnoses, namely, muscle/tendon and ligament injuries.

Key words: Epidemiology, injury surveillance, muscle/tendon injuries, injury patterns, prevention.

4.2. Introduction

Futsal, the five-a-side version of associated football, is played worldwide with more than one million registered players all over the world[160–162]. Futsal requires players to perform on a reduced (usually indoor) pitch size (40 x 20 m) and during two x 20 min periods (with time stopping at every dead ball and unlimited substitutions) a high number of repeated high intensity multiplanar movements such as sudden acceleration and deceleration, rapid changes of direction, tackling and kicking[2,3,5]. At top levels, the combination of these repeated high intensity movements that are performed during training and match play alongside current congested training and competitive calendars and exposure to contacts might place futsal players at high risk of injury. However, prior to implementing injury prevention programmes into everyday futsal training routines, it is essential to establish the extent of the problem in terms of the incidence and characteristics of injuries[16,163].

Despite being one of the most played sport in several countries, a limited number of prospective epidemiological studies have been published investigating injuries sustained by elite futsal players (mainly during match play)[6,20–23]. These studies have reported incidence rates for male players ranging from 3.5 to 89.9 injuries per 1000 h of match play, most of them affecting the lower extremity with contusions of the lower leg and ankle sprains the most frequently diagnosed types of injury[6,20–24]. However, it should be noted that among these epidemiological studies, only two[21,22] have reported incidence data of female futsal players. Angoorani et al.[21] showed an incidence rate in female players of 10.7 injuries per 1000 h of match play during camps with the Iran national team (18 months of follow-up), whereas Hamid et al.[22] found an incidence rate of 19.7 injuries per 1000 h of match play during the Malaysian national futsal league. In both studies, ankle sprains and ligament ruptures were the most observed injuries, similar to what has been observed in other team sports such as football[41], handball[164] and rugby[165]. It is likely that the anatomical, hormonal and neuromuscular sex-related differences (among other factors) may contribute to sex-specific differences in injury incidence. Furthermore, only Angoorani et al.[21] provided injury incidence rates during training in male and female futsal players, reporting an incidence of 1.8 and 3.1 injuries per 1000 h of exposure, respectively. As the training volume[166] and the number of hours of high intensity training[167] have been significantly correlated with an increased risk of sustaining non-contact injuries in team sports (mainly attributed to an acute and/or cumulative fatigue state), knowing the injury incidence rates during futsal training may help coaches and physical trainers to identify if the training load and content allows players to recover fully from match demands. None of the studies that have provided epidemiological data of futsal-related injuries in male and female players have calculated the injury burden (the product of severity [consequences] and incidence [likelihood]) and/or built a risk matrix. A risk matrix is a graph of injury severity plotted against injury incidence with criteria incorporated into the graph for evaluating the level of risk, usually by dividing the graph into some risk areas using descriptive or quantified incidence, severity and risk evaluation categories[25].

Consequently, there is a clear need for more prospective epidemiological studies that inform about injury incidence and burden in female futsal players. Identifying the most common and burdensome futsal-related injuries, as well as how (traumatic or overuse) and when (matches or training sessions) they usually occur would lead coaches, physical trainers and physiotherapists to prioritize the application of specific measures to prevent or reduce the risk of sustaining such injuries. Therefore, the main purpose of the current study was to analyze the injury incidence, characteristics and burden among sub-elite female futsal players during three consecutive seasons.

4.3. Methods

4.3.1. Participants

All female sub-elite futsal players from the same team that were playing in the Spanish second division were prospectively followed during three consecutive seasons (2015/16, 2016/17 and 2017/18) which covered the period between September and May. Twenty-two different female futsal players participated in this study. However, as some players remained in the team for more than one season, the total number of player seasons was 39 (2015/16: 14 players followed, 2017/17: 13 players followed, 2017/18: 12 players followed). All players had more than 5 years of futsal experience. The team finished all three seasons in the top 10 of the league (4st, 6st and 9st). All players were verbally informed about the study procedures and provided written informed consent. For players younger than 18 years old (n = 3), written informed consent was also obtained from their parent or legal guardian. Players who left the team during the season (e.g. due to transfer) were included in the analysis according to their time on the team. The experimental procedures used in this study were in accordance with the Declaration of Helsinki and were approved by the University Office for Research Ethics (Órgano evaluador de proyectos, Universidad Miguel Hernández de Elche) (DPS.FAR.02.14).

4.3.2. Data collection

The study design and data collection followed both the consensus on definitions and data collection procedures for studies of football injuries outlined by the Union of European Football Associations (UEFA)[121] and the consensus document for football injury surveillance studies[120]. An injury was defined as any physical complaint sustained by a player that resulted from a futsal match or futsal training and where the player was unable to participate in a match or training sessions on the day after the injury (time-loss injury)[120]. The day on which an injury occurred was day 0 and was not counted when determining the severity of an injury. If a player had to stop training or participating in a match because of injury on 1 day but could participate the next day, the time loss was recorded as zero days.

The club's medical staff (which remained the same for all three seasons), diagnosed, treated and recorded all time-loss injuries on a standardised injury report form that was sent to the study group each month. Specifically, the team was supported by one certified medical doctor, one physical trainer and one physiotherapist. The doctor was the member of the medical staff who assessed and diagnosed injured players through the use of clinical judgements (e.g.: physical examination, posture and gait inspection, inspection and palpation of muscle bellies, etc.). Diagnostic imaging techniques (e.g.: echography, magnetic resonance imaging and ultrasound imaging) were also applied when it was needed. Although early treatment actions were delivered as soon as possible when a player sustained an injury during training or competition, the initial assessment and diagnosis were often carried out within 12 hours to 4 days post-injury as some signs of injury may arise a few hours or days later[168]. The physiotherapist administered the therapeutic exercises during the first stages of the rehabilitation process. The physical trainer was responsible for introducing injured players to the drills and skills that would be required to return to full participation in training and to be available for match selection. A futsal player was considered injured until the medical staff (upon agreement) allowed full participation in training and they were eligible for match play.

For all injuries that satisfied the inclusion criteria (time-loss injury), team medical staff provided the following details to investigators: date of injury, moment (training or competition), player position (goalkeeper or field player [lastwoman, wing or pivot]), injury mechanism (traumatic [contact or non-contact] or overuse), injury location, type of injury (the specific injury diagnosis was also recorded), extremity of the injury (dominant/non dominant), injury severity based on lay off time (0 days [when a player could not participate fully on the day of an injury but was available for full participation the next day], minimal [1-3 days], mild [4-7 days], moderate [8-28 days], severe [>28 days] and career ending injury), whether it was a recurrence or new injury and total time taken to resume full training and competition. Illnesses and any physical or mental complaint that did not result from a futsal match or training were excluded. Individual player exposure time in training and matches (friendly and competitive) were recorded daily in minutes by the physical trainer.

The operational definitions adopted by this study have been widely followed by both football and futsal epidemiological studies[6,22,24,41,169] and they are displayed in Appendix 4.1.

Those players who were already injured when the follow up process started (September 2015) were included in this study once medical staff agreed return to training and availability for match selection. Those individuals who were still injured at the end of the study period were included in the statistical analyses, and the estimated duration of the recovery period was established after discussion with the respective medical staff. As a medical history based on information from the player may be confounded by recall bias, previous injuries of those players who were recruited to the team after the study started were not included unless an accurate and detailed description of them were provided in the form of a report or standard form and signed by either a certified medical doctor or a former physiotherapist.

Demographic information such as stature, body mass, and age were collected during the last week of the preseason period (which was before the start of the season).

4.3.3. Data analysis

Descriptive data are presented as a mean with the corresponding standard deviation (SD), proportions (%), incidence rates and 95% confidence intervals (CI). The overall injury incidence, match injury incidence, and training injury incidence were the number of injuries divided by 1000 player-hours in total, match, and training, respectively. For incidence rates, 95% CIs were calculated as the incidence ±1.96 times the square root of the number of injuries divided by the number of participants. The injury burden was calculated as the number of lay-off days/1000 h[26]. Player overall hours were calculated by adding match and training hours. Player match hours were calculated by multiplying total number of matches in the season per five players per match duration (40 minutes with stopped clock)/60, and player training hours were calculated by adding individual training hours (warm up of the matches was not included). All of the analyses were performed using the PASW statistical package, version 18.0 (SPSS Inc., Chicago, IL, USA), with $p < 0.05$ considered statistically significant. A post-hoc power analysis was conducted using the software package, G* Power 3.1.2[170,171]. The sample size of 39 was used for the statistical power analyses. The alpha level used for this analysis was $p < 0.05$. The post-hoc analyses revealed the statistical power for this study was 0.74. It could be concluded that the given sample size was large enough to detect significant effects.

The spreadsheet designed by Hopkins[136] for combining effect statistics was used to make clinically (qualitative) inference for paired-comparisons between incidence rates. In particular, the incidence rate ratio (and its associated confidence limits) was assessed against predetermined thresholds. Thus, an incidence rate ratio of 0.91 represented a substantially lower injury risk, while an incidence rate ratio of 1.10 indicated a substantially higher injury risk[137]. An effect was considered unclear if its confidence interval overlapped the thresholds just mentioned; in other words, if the effect could be substantial in both a positive and negative sense. Otherwise the effect was clear and deemed to have the magnitude of the largest observed likelihood value. The following scale was used to qualify with a probabilistic term the magnitude of the observed effect: <0.5 %, most unlikely; 0.5–5 %, very unlikely; 5–25%, unlikely; 25–75 %, possible; 75–95 %, likely; 95–99.5 %, very likely; >99.5 %, most likely[136].

4.3.4. Study quality assessment

The quality of the study was assessed using the "Strengthening the Reporting of Observational Studies in Epidemiology" (STROBE)[126] and the risk of bias of external validity quality, using an adapted version of the Newcastle Ottawa Scale (NOS)[130,172]. The study fulfils all the criteria of the STROBE scale except the items 9, 10 and 22 (Appendix 4.2). Regarding the NOS adapted scale just item 6 was not fulfilled (Appendix 4.3). Thus, the reporting and external validity quality of the present study could be considered as high according to the qualitative descriptors proposed by von Elm et al.[126] and Wells et al.[173] respectively.

4.4. Results

During the three seasons, four players dropped out due to transfers to another club or they were released by the club but their injury data were included based on their time at the club. The average duration of each season was 34.3 ± 2.1 weeks with 31 ± 2.7 matches per season and 3.3 ± 1.3 trainings sessions per week. Player and team characteristics are presented in table 4.1.

4.4.1. Overall, match and training incidence

A total of 30 injuries were reported in 15 different players during the three seasons (2 match injuries and 28 training injuries) within a total exposure time of 4446.1 h (310 h of match exposure and 4136.1 h of training exposure), which is equivalent to an overall incidence rate of 6.75 injuries per 1000 hours of exposure (95% CI = 6.47 to 7.02). One of the injuries was not taken into account due to the player having to retire from sport because of the injury. The match injury rate was similar (no statistically [$p > 0.05$] and clinically irrelevant [very likely trivial] differences) to the training injury rate (6.45, 95% CI = 6.38 to 6.52 vs 6.77, 95% CI = 6.50 to 7.04 /1000 h) and 38% (15/39) of players sustained at least one injury during the three seasons. Players sustained 0.77 injuries per season on average, which is equivalent to 10 injuries per season for a squad of 13 players.

The injury incidence and characteristics of the injuries during the three seasons are shown in table 4.2.

Table 4.1. Players and team characteristics and exposure time

	Season			Total	Mean
	15/16	**16/17**	**17/18**		
Team size	14 (14)	13 (12)	12 (9)	39 (35)	13 ± 1
Players characteristics					
- Age (years)	23.8 ± 2.9	24.2 ± 4.1	24.2 ± 4.8	-	24.1 ± 3.9
- Height (cm)	165 ± 5.0	165 ± 4.0	165 ± 4.0	-	165 ± 4.0
- Body mass (kg)	60.4 ± 5.1	62.3 ± 7.4	61.9 ± 7.4	-	61.5 ± 6.6
- Weeks of follow-up	32	35	36	103	34.3 ± 2.1
Exposure					
- Total (h)	1506.7	1328.78	1610.7	4446.1	1482.1 ± 142.6
- Training (h)	1413.3	1222.1	1500.7	4136.1	1378.8 ± 142.5
- Match (h)	93.3	106.7	110	310	103.3 ± 8.8
- Matches/week	0.88	0.91	0.92	-	0.90
- Match exposure ratio	0.06	0.08	0.07	-	0.07
- Days of absence due to the injury	234	144	51	429	143 ± 91.5

h: hours; Values are mean ± SD.

Table 4.2. Injury incidence

Injuries	Season 15/16			Season 16/17			Season 17/18			Total		
	Number (%)	Incidence (95%CI)	Injury Burden	Number (%)	Incidence (95%CI)	Injury Burden	Number (%)	Incidence (95%CI)	Injury Burden	Number (%)	Incidence (95%CI)	Injury Burden
- Overall	8	5.3 (4.9-5.7)	155.3	12	9.03 (8.5-9.5)	108.4	10	9.1 (8.9-9.2)	31.7	30	6.7 (6.5-7.0)	96.5
- Training	8 (100)	5.7 (5.3-6.1)	165.6	11 (91.7)	9.0 (8.5-9.5)	108.0	9 (90)	6.00 (5.5-6.5)	30.0	28 (93.3)	6.8 (6.5-7.0)	99.4
- Match	0 (0)	0	0	1 (8.3)	9.4 (9.2-.5)	112.5	1 (10)	6.2 (5.7-6.7)	54.5	2 (6.7)	6.4 (6.4-6.5)	58.1
Mechanism												
- Traumatic training	5 (62.5)	3.32 (3.0-3.6)	145.4	8 (66.7)	6.0 (5.6-6.4)	87.3	7 (70)	4.3 (3.9-4.8)	16.1	20 (66.7)	4.50 (4.3-4.7)	82.1
- Traumatic match	0 (0)	0	0	1 (8.3)			1 (10)			2 (6.7)		
- Overuse training	3 (37.5)	1.99 (1.7-2.2)	10	4 (33.3)	3.0 (2.7-3.3)	21.1	3 (30)	1.9 (1.6-2.1)	15.5	10 (33.3)	2.2 (2.1-2.4)	14.4
Circumstance												
- Contact	0 (0)	0	0	0	0	0	2 (20)	1.24 (1.0-1.5)	5.6	2 (6.7)	0.45 (0.4-0.5)	2
- Non-Contact	8 (100)	5.31 (4.9-5.7)	155.3	12 (100)	9.03 (8.5-9.5)	108.4	8 (80)	4.97 (4.5-5.4)	26.1	28 (93.3)	6.30 (6.0-6.6)	94.5

Recurrence												
- No	8 (100)	5.3 (4.9-5.7)	155.3	9 (75)	6.0 (5.6-6.4)	82.0	8 (80)	5.0 (4.5-5.4)	25.5	25 (83.3)	5.6 (5.4-5.9)	86.4
- Yes	0 (0)	0	0	3 (25)	2.3 (2.0-2.5)	26.3	2 (20)	1.24 (1.0-1.5)	6.2	5 (16.7)	1.1 (1.0-1.2)	10.1
- Early	0 (0)	0	0	1 (33.3)	0.7 (0.6-0.9)	12.0	0 (0)	0	0.0	1 (20)	0.2 (0.2-0.3)	3.6
- Late	0 (0)	0	0	2 (66.7)	1.5 (1.3-1.7)	14.3	1 (50)	0.6 (0.5-0.8)	1.9	3 (60)	0.7 (0.6-0.8)	4.9
- Delayed	0 (0)	0	0	0	0	0	1 (50)	0.6 (0.5-0.8)	4.3	1 (20)	0.2 (0.2-0.3)	1.6
Severity												
- 0 days	0 (0)	0	0	0 (0)	0	0	0 (0)	0	0	0 (0)	0	0
- Minimal (1-3 days)	1 (12.5)	0.7 (0.5-0.8)	2.0	2 (16.7)	1.5 (1.3-1.7)	4.5	5 (50)	3.1 (2.7-3.5)	6.8	8 (26.7)	1.8 (1.7-2.0)	4.5
- Mild (4-7 days)	2 (25)	1.3 (1.1-1.5)	8.0	2 (16.7)	1.5 (1.3-1.7)	9.0	4 (40)	2.5 (2.2-2.8)	13.0	8 (26.7)	1.8 (1.7-1.9)	10.1
- Moderate (8-28 days)	4 (50)	2.6 (2.4-2.9)	51.1	7 (58.3)	5.3 (4.9-5.7)	94.8	6 (60)	0.6 (0.5-0.8)	11.8	12 (40)	2.7 (2.5-2.9)	49.9
- Severe (>28 days)	1 (12.5)	0.7 (0.5-0.8)	94.2	0 (0)	0	0	0 (0)	0	0	1 (3.3)	0.2 (0.2-0.3)	31.9
- Career ending	0 (0)	0	0	1 (8.3)	0.7 (0.6-0.9)	-	0 (0)	0	0	1 (3.3)	0.2 (0.2-0.3)	-
Position												
- Goalkeeper	2 (25)	1.3 (0.4-2.2)	16.6	2 (16.7)	1.5 (0.1-2.9)	7.5	0 (0)	0	0	4 (13.3)	0.9 (0.3-1.5)	7.9
- Lastwoman	4 (50)	2.6 (1.7-3.6)	40.5	7 (58.3)	5.3 (4.0-6.6)	77.5	4 (40)	2.5 (1.5-3.5)	11.2	15 (50)	3.4 (2.7-4.0)	40.9
- Wing	0	0	0	3	2.3	23.3	6	3.73	20.5	9	2.02	14.4

	(0)			(25)	(1.6-2.9)		(60)	(2.52-4.93)		(30)	(1.57-2.48)	
- Pivot	2	1.3	98.2	0	0	0	0	0	0	2	0.4	33.3
	(25)	(0.4-2.0)		(0)			(0)			(6.7)	(0.0-0.8)	

4.4.2. Injury characteristics

4.4.2.1. Player position

Lastwomen (3.37, 95% CI = 2.74 to 4.01 /1000 h) incidence rate was most likely higher (100% likelihood) than wings (2.02, 95% CI = 1.57 to 2.48 /1000 h), goalkeepers (0.90, 95% CI = 0.34 to 1.46 /1000 h) and pivots (0.45, 95% CI = 0.05 to 0.85 /1000 h). Wings had a very likely higher incidence rate (96.6% likelihood) than goalkeepers and most likely higher (100% likelihood) than pivots. Finally, goalkeepers had a likely higher incidence rate (76.6% likelihood) than pivots.

4.4.2.2. Injury mechanism

Two out of three injuries were due to trauma and one out of three injuries was due to overuse. The incidence rate of traumatic injuries was most likely higher (100% likelihood) than overuse injuries (4.5, 95% CI = 4.27 to 4.72 vs 2.25, 95% CI = 2.09 to 2.41 /1000 h). Most injuries were caused by non-contact situations (93%), with only 7% of injuries occurring during contact situations.

4.4.2.3. Injury location

Table 4.3 shows the injury location and type of injury per season. Lower extremity injuries (5.62 per 1000 hours of exposure, 95% CI = 5.37 to 5.87) were the most frequently injured location, followed by upper limb injuries (0.67 per 1000 hours of exposure, 95% CI = 0.59 to 0.76), and then trunk injuries (0.45 per 1000 hours of exposure, 95% CI = 0.38 to 0.52). No head and neck injuries were reported. The lower extremity region predominantly injured was the thigh (3.37 per 1000 hours of exposure, 95% CI = 3.18 to 3.57), followed by the ankle (0.90 per 1000 hours of exposure, 95% CI = 0.8 to 1.0), with the knee, hip/groin and lower leg/Achilles tendon regions demonstrating the same incidence rate (0.45 per 1000 hours of exposure, 95% CI = 0.38 to 0.52). No foot/toe injuries were reported. In terms of paired-comparisons, thigh injuries occurred more frequently (100% likelihood) than injuries in other lower extremity regions. Ankle injury rates were most likely higher (100%

likelihood) than knee, hip/groin and lower leg/Achilles tendon injuries. There were no meaningful differences between the remaining paired combinations.

4.4.2.4. Type of injures

The mean incidence of injury type grouping is presented per 1000 hours of exposure with 95% CIs. Most injuries were diagnosed as muscle/tendon injuries (4.95, 4.71 to 5.18), followed by joint (non-bone) and ligament (1.35, 1.23 to 1.47), and fractures and bone stress and contusions with the same injury incidence (0.22, 0.17 to 0.28). No central/peripheral nervous system injuries and skin lesions were recorded. The most common injury types were hamstring muscle injuries (1.80 per 1000 hours of exposure, 95% CI = 0.66 to 1.94), followed by quadriceps muscle injuries (1.57 per 1000 hours of exposure, 95% CI = 1.44 to 1.71), ankle sprains (0.90 per 1000 hours of exposure, 95% CI = 0.8 to 1.0) and anterior cruciate ligament tears (0.45 per 1000 hours of exposure, 95% CI = 0.38 to 0.52). Muscle/tendon injury incidence rates were most likely higher than other types of injury rates (100% likelihood). Likewise, joint (non-bone) and ligament incidence rate were most likely higher (100% likelihood) than fractures, bone stress and contusions.

Table 4.3. Injury characteristics and incidence according location and type of injury

	Season 15/16			Season 16/17			Season 17/18			Total		
	Number (%)	Incidence (95%CI)	Injury Burden	Number (%)	Incidence (95%CI)	Injury Burden	Number (%)	Incidence (95%CI)	Injury Burden	Number (%)	Incidence (95%CI)	Injury Burden
Injury location												
Upper limbs												
- Overall	1 (12.5)	0.7 (0.5-0.8)	14.6	0 (0)	0	0	2 (20)	1.2 (1.0-1.5)	2.5	3 (10)	0.7 (0.6-0.8)	5.8
- Shoulder/clavicula	0 (0)	0	0	0 (0)	0	0	1 (10)	0.6 (0.5-0.8)	0.6	1 (3.3)	0.2 (0.2-0.3)	0.2
- Hand/finger/thumb	1 (12.5)	0.66 (0.5-0.8)	14.6	0 (0)	0	0	1 (10)	0.6 (0.5-0.8)	1.9	2 (6.7)	0.4 (0.4-0.5)	5.6
Trunk												
- Overall	1 (12.5)	0.7 (0.5-0.8)	2.0	0 (0)	0	0	1 (10)	0.6 (0.5-0.8)	2.5	2 (6.7)	0.4 (0.4-0.5)	0.7
- Lower back/pelvis/sacrum	1 (12.5)	0.7 (0.5-0.8)	2.0	0 (0)	0	0	1 (10)	0.6 (0.5-0.8)	2.5	2 (6.7)	0.4 (0.4-0.5)	0.7
Lower limbs												
- Overall	6 (75)	4.0 (3.6-4.3)	138.7	12 (100)	9.0 (8.5-9.5)	108.4	7 (70)	4.3 (3.9-4.8)	26.7	25 (83.3)	5.6 (5.4-5.9)	90.0
- Hip/groin/adductor	0 (0)	0	0	1 (8.3)	0.75 (0.60-0.90)	16.6	1 (10)	0.6 (0.5-0.8)	2.5	2 (6.7)	0.4 (0.4-0.5)	5.8
- Thigh	3 (37.5)	1.99 (1.7-2.2)	22.6	7 (58.3)	5.27 (4.9-5.7)	48.9	5 (50)	3.1 (2.7-3.5)	20.5	15 (50)	3.4 (3.2-3.6)	29.7
- Hamstrings	1 (12.5)	0.7 (0.5-0.8)	10.0	5 (41.7)	3.8 (3.4-4.1)	33.1	2 (20)	1.2 (1.0-1.5)	3.1	8 (26.7)	1.8 (1.7-1.9)	14.4
- Quadriceps	2 (25)	1.3 (1.1-1.5)	12.6	2 (16.7)	1.5 (1.3-1.7)	15.8	3 (30)	1.9 (1.6-2.1)	17.4	7 (23.3)	1.6 (1.4-1.7)	15.3
- Knee	1 (12.5)	0.66 (0.52-0.80)	94.2	1 (8.3)	0.75 (0.60-0.90)	0	0 (0)	0.0	0	2 (6.7)	0.45 (0.38-0.52)	31.9

- Lower leg/Achilles tendon	1 (12.5)	0.7 (0.5-0.8)	4.0	1 (8.3)	0.7 (0.6-0.9)	9.0	0 (0)	0.0	0	2 (6.7)	0.45 (0.4-0.5)	4.0
- Ankle	1 (12.5)	0.7 (0.5-0.8)	17.9	2 (16.7)	1.5 (1.3-1.7)	33.9	1 (10)	0.6 (0.5-0.8)	3.7	4 (13.3)	0.9 (0.8-1.0)	17.5
Injury type												
Fracture and bone stress												
- Overall	0	0	0	0	0	0	1 (10)	0.6 (0.5-0.8)	1.9	1 (3.3)	0.2 (0.2-0.3)	0.7
- Fracture	0	0	0	0	0	0	1 (10)	0.6 (0.5-0.8)	1.9	1 (3.3)	0.2 (0.2-0.3)	0.7
Joint (non-bone) and ligament												
- Overall	3 (37.5)	1.99 (1.7-2.2)	126.8	2 (16.7)	1.51 (1.3-1.7)	21.1	1 (10)	0.6 (0.5-0.8)	0.6	6 (20)	1.3 (1.2-1.5)	49.5
- Sprain/Ligament injury	3 (37.5)	2.0 (1.7-2.2)	126.8	2 (16.7)	1.51 (1.3-1.7)	21.1	1 (10)	0.6 (0.5-0.8)	0.6	6 (20)	1.3 (1.2-1.5)	49.5
Muscle and tendon												
- Overall	5 (62.5)	3.3 (3.0-3.6)	28.5	10 (83.3)	7.5 (7.0-8.0)	87.3	7 (70)	4.35 (3.9-4.8)	25.5	22 (73.4)	4.9 (4.7-5.2)	45.0
- Muscle rupture / tear / strain /cramps	4 (50)	2.6 (2.4-2.9)	24.6	9 (75)	6.8 (6.3-7.2)	74.5	7 (70)	4.3 (3.9-4.8)	25.5	20 (66.7)	4.5 (4.3-4.7)	39.8
- Tendon injury /rupture / tendinosis / bursitis	1 (12.5)	0.7 (0.5-0.8)	4	1 (8.3)	0.7 (0.6-0.9)	12.8	0	0	0	2 (6.7)	0.4 (0.4-0.5)	5.2

CI: Confidence interval.

4.4.2.5. Severity of injuries

Concerning the severity of injuries, moderate injuries (2.70 per 1000 hours of exposure, 95% CI = 2.52 to 2.87) were the most usual injuries, followed by minimal and mild injuries (1.80 per 1000 hours of exposure, 95% CI = 1.66 to 1.94), and finally severe and career ending injuries (0.22 per 1000 hours of exposure, 95% CI = 0.17 to 0.28). No 0 days injuries were recorded.

Comparisons between each severity level showed that the moderate injury incidence rates were most likely higher (100% likelihood) than other severities. Minimal and mild injury incidence rates were most likely higher (100% likelihood) than severe and career ending injuries.

The recorded overall time-loss injuries was 429 days, so overall injury burden during the three seasons was 96.5 days loss/1000 hours exposure (58.1 in matches and 99.4 in trainings). Figure 4.1 shows a quantitative risk matrix illustrating the relationship between the severity and incidence of the most common reported injuries For each injury type, severity is shown as the average number of days lost (log scale), while incidence is shown as the number of injuries per 1000 hours of total exposure for each injury type. The shading illustrates relative importance of each of the injury types; the darker the colour, the greater the injury burden, and the greater the priority should be given to prevention. Furthermore, lastwomen and pivots showed the highest injury burden (40.9 and 33.3 days loss/1000 hours exposure) compared to goalkeepers and wings (7.9 and 14.4 days loss/1000 hours exposure). On the other hand, muscle/tendon injuries and joint (non-bone) and ligament injuries showed similar injury burden (44.98 and 49.48 days loss/1000 hours exposure) although their overall incidence was significantly different. Regarding injury location, the knee showed a significantly higher injury burden (31.9 days loss/1000 hours exposure) compared to the rest of the lower extremity muscle groups (ankle: 17.5; quadriceps: 15.3; hamstring: 14.4; hip/groin: 5.8 and lower leg/Achilles tendon: 4.0).

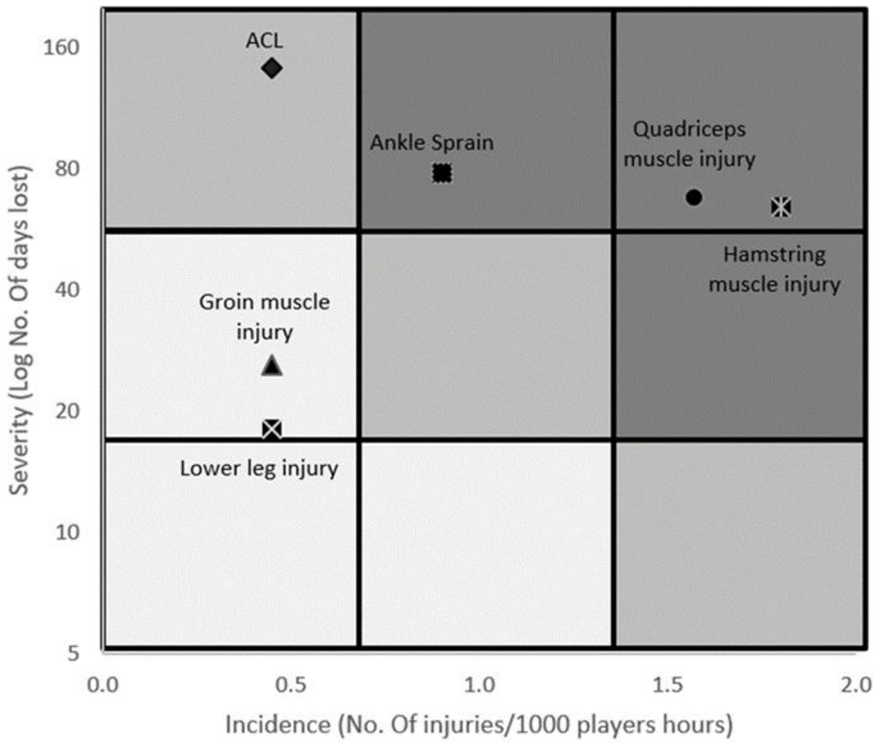


Figure 4.1. Quantitative risk matrix of injuries, illustrating the relationship between the severity (consequence) and incidence (likelihood) of the most common injuries.

4.4.2.6. Recurrent injuries

The incidence rate of new injuries (5.62 per 1000 hours of exposure, 95% CI = 5.37 to 5.87) was most likely higher (100% likelihood) than recurrent injuries incidence rate (1.12 per 1000 hours of exposure, 95% CI = 1.01 to 1.24). One-fifth of the overall injuries were recurrent injuries; of these, 20% of injuries were classified as "early recurrence" (within 0-2 months); 60% of injuries were classified as "late recurrence" (2-12 months); and 20% of injuries were classified as "delayed recurrence" (>12 months)[120]. The most common recurrent injury was quadriceps and hamstring strains. Regarding injury burden, new injuries had a significantly higher injury burden compared to recurrent injuries (86.4 vs 1.1 days lost/1000 hours exposure).

4.4.2.7. Season variation of injury pattern

Figure 4.2 illustrates monthly distribution of injuries, both overall, during training and match over the three seasons. The highest incidence of injuries was observed in October (1.35 per 1000 hours of exposure, 95% CI = 1.23 to 1.47). Training and match number of injuries follow a similar trend, in which the risk of injuries was higher in the early stages of the season and post winter/Christmas break.

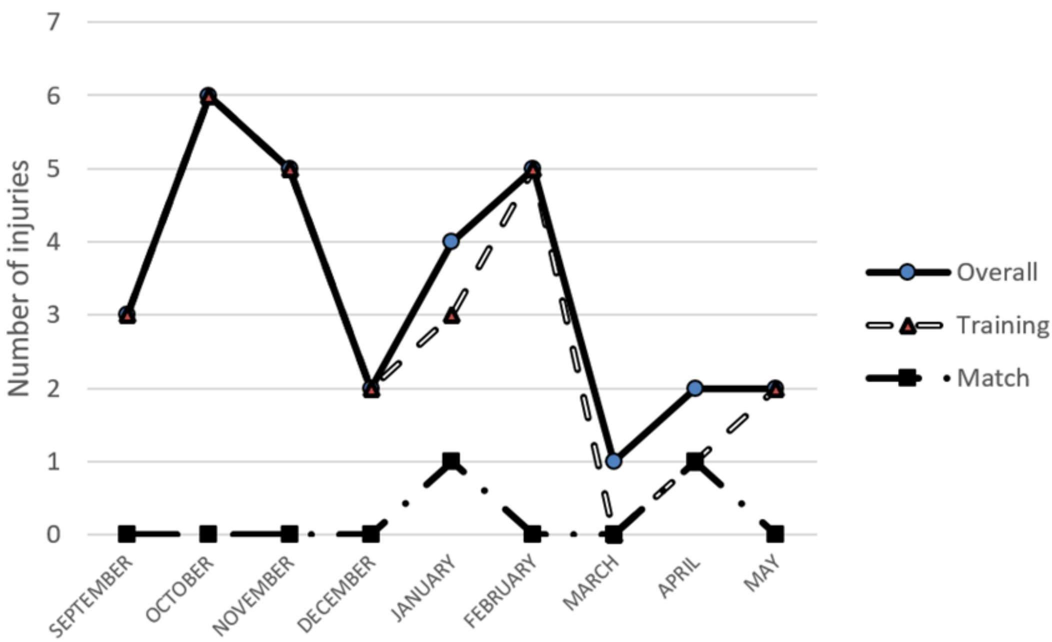


Figure 4.2. Distribution of total injury incidence.

4.5. Discussion

The overall, training and match incidence rates reported in the current study were comparable to those found in the only study (to the authors´ knowledge) that has provided three incidence rates separately in a cohort of 17 female futsal players[21] (4.7, 3.1 and 10.7 injuries per 1000 h of exposure to overall, training and match play, respectively). Conversely, the match injury incidence reported in the current study (6.4 injuries per 1000 h of match play) is lower than that reported by Hamid et al.[22] in the Malaysian female futsal league (29.6 injuries per 1000 h of exposure to match play). An explanation of this discrepancy may be attributed to the more congested competitive calendar in the study carried out by Hamid et al.[22] compared to our study. Thus, while in their study the Malaysian league had a duration of approximately 22 weeks (1st July until 28th November) with a break in August (because of fasting during Ramadan) and one or two matches per week, the three seasons (2015-2018) of the Spanish second division analyzed in the current study lasted eight months (average of 34.3 ± 2.1 weeks) with two breaks periods of 2-3 weeks (at Christmas and Easter) with one match played per week (usually at the weekend days). This hypothesis may be supported by evidence from prospective epidemiological studies carried out in elite male futsal players[6,23] and football players[174,175] during international tournaments (i.e. World cups) which have shown higher incidence rates in comparison with those conducted during national league futsal[20,22] and football[176,177]. This is likely due to the higher match demands during international tournaments with relatively shorter recovery times between matches. These tournaments also tend to occur at the end of long competitive league seasons where accumulated fatigue may also be a factor in the higher incidence rates.

Unlike data from other team sports (regardless of the sex of the players) [i.e. football[37,178], basketball[38], netball[39]] where match injury incidence is always notably higher (almost ten times) than the injury rate obtained for training sessions, in our study both incidence rates were similar. The latest trends in strength and conditioning for team sports have suggested that training session design (i.e. work-load, intensity, duration), when possible, should mimic match demands so that players are better prepared for what they face during matches[179]. Perhaps, the training sessions designed by the team staff might have included a large number of repeated high-intensity actions (e.g. accelerations and decelerations, changes of direction) in order to replicate the evolving nature of the futsal game. However, an excessive training load and/or an insufficient recovery of previous efforts might have forced players to perform some of these highly demanding training sessions under suboptimal states of readiness and this could have potentially increased the risk of injuries (mainly muscle-tendon and ligament injuries)[180]. To determine whether or not futsal players are in an optimal state of readiness for the stress that will be a priori elicited by training, it is advisable to monitor daily training load (internal and external) and strain, wellbeing and recovery status from previous efforts and also include regular physical performance tests as a component of the training program[181,182]. This information might help coaches and physical trainers to constantly re-adjust the design of the training sessions throughout the season so that the physical and psychological demands that will be imposed on the players do not negatively affect their optimal readiness to re-perform.

When exploring differences in playing position on incidence rates our data from the goalkeepers and outfield player's differed from the findings previously reported by Hamid et al.[22] Their study, also in female futsal players, showed a higher incidence rate in goalkeepers but we found outfield players showed higher incidence and higher amount of days off per injury than goalkeepers. Our findings are similar to that which has been reported in other team sports such as handball[183] and football[42,43]. It is difficult to prescribe a reason for the discrepancy between the findings of Hamid et al.[22] and our current study. However, it might be due to the fact that outfield players need to perform a larger number of repeated high intensity multiplanar movements that occur every few seconds[4], which may place outfield players at a higher risk of injury than goalkeepers.

Previous studies have indicated that a large percentage of injuries in male futsal players[6,23] are caused by contact trauma, however the current study demonstrates that most injuries sustained by female players are due to non-contact trauma (>90%). Our results are in agreement with the study of Angoorani's et al.[21] and might be partly attributed to the fact that both studies included training injury incidence data, something that other studies have failed to do. Furthermore, the higher number of high intensity phases observed in elite male players during the course of futsal play[5,153] might contribute to generate more tackling situations and partially explain the fact that males suffer more contact injuries than females.

With respect to the location of futsal-related injuries, and similar to previous studies in male[6,20,23] and female futsal players[21,22], lower extremity injuries were, by far, the most frequent injuries (83.3% of all the injuries recorded). The thigh (50% of all the injuries recorded) was the anatomical region of the lower extremity where injuries occurred significantly more followed by the knee (6.7% of all the injuries recorded) and ankle (6.7% of all the injuries recorded). Furthermore, the most common type of injury grouping was muscle/tendon injuries followed by joint (non-bone) and ligament injuries. As futsal is a fast-paced game relying mostly on the lower extremity for ball control, involving sprinting and frequent changes in direction such observations were anticipated. In football, it has been demonstrated that player match availability has a strong correlation ($r > 0.85$) with team success (i.e. ranking position, games won, goals scored, total points)[8,116,153]. If this statement also holds for futsal, then injury prevention measures should focus not just on reduction of the incidence of the most frequent injuries but also on reduction of the injuries with the highest burden (e.g. those injuries that keep players out of training and match play the longest)[26]. According to the results found in this study, knee and thigh injuries are those with the highest injury burden with 31.9 and 29.7 days of absence per 1000 player hours, respectively. In particular, medical and fitness staff should implement measures mainly aimed (but not solely) at reducing the number and severity of anterior cruciate ligament (ACL) and hamstring and quadriceps muscle injuries. It should be noted that one player from the team had to retire from futsal due to an ACL rupture, which was not included in the injury burden calculation as the number of days lost were not defined. This reinforces the need to deliver targeted interventions aimed at reducing this devasting and relatively frequent (two cases in the three seasons recorded in our study for a single team) type of injury in female athletes. It should be also highlighted that the overall (31.7 days) and training (30 days) injury burdens of the last season analyzed (2017/18) were significantly lower than those obtained for the two previous seasons (overall = 155.3 [2015/16] and 108.4 [2016/17] days; training = 165.6 [2015/16] and 108.0 [2016/17] days). Perhaps, the fact that during the three seasons that were object of study the club kept the same medical staff and head coach may have been a factor that may explain in part this circumstance. In this sense, and similar to what was found in previous studies[184,185], the potential and gradual improvement in the quality of the internal communication not only within the members of the medical staff but also between the medical staff and the coach that might have occurred throughout the three consecutive seasons may have had a positive impact on the players′ availability for futsal play in the last season. In fact, according to Ekstrand, et al.[184], the measures designed to reduce the injury burden in elite teams should not only address the traditionally proposed modifiable injury risk factors [e.g. eccentric strength deficits[49,81,186], poor neuromuscular control[187,188], altered muscle architecture[32,80,187], player load and match frequency[189,190] but also some new external factors such as job security and club stability and players adherence and coach's compliance to the injury prevention programs applied. The inclusion of updated and evidence-based advancements in factors related to injury management (including diagnosis techniques, treatment approaches and monitoring tools) might also have a positive impact on the injury burden.

As expected, new injury rates were higher than recurrent injury incidence rates (5.6 vs. 1.1 injuries per 1000 h). However, the recurrent rate identified in the present study may be considered high. It was found that 20% of recurrent injuries (mainly lower extremity muscle and tendon injuries) occurred within 2 months after return to play. This may be regarded as a sign of premature return to train/play and incomplete or inadequate rehabilitation. The lack of and evidence-based criteria for a safe return to train/play may have resulted in letting injured players return to play sooner than recommended. This may have been due to the desire to let them play in important matches or to let them play with ongoing minor symptoms, and this might be two primary reasons behind the high recurrent injury incidence rate. Future studies should extend our current knowledge further in relation to the improvement of the decision-making process for a safe return to train/play by developing learning algorithms or artificial intelligence-based models that allow the identification of when a player is successfully rehabilitated before returning to train/play.

Furthermore, medical and fitness team staff should allow players enough time for rehabilitation before return to train/play.

Regarding the moment when most injuries took place, the findings indicates that there are two periods when they are more likely to occur, October and January-February. The higher amount of injuries during October may be explained by the fact that within the pre-season period the training loads are much higher than during the competitive period[190] and accumulating fatigue may increase the injury risk during the first weeks of competition. Petersen et al.[191] reported a higher incidence in the two months after the winter break (January-February) which is consistent with the results of the present study.

4.6. Limitations

Despite being one of the first prospective studies that has analyzed the incidence rates and characteristics of futsal related injuries in female players, some limitations must be considered. The sample size of players and injuries is small, and results should be cautiously interpreted (especially the incidence rates reported for specific and less frequent injuries). The analysis of only one team limits the external validity of the results. Consequently, it is unknown if female players from other teams in which there could be a higher (or lower) medical staff-to-player ratio or access to other staff (such as strength and conditioning coaches, psychologists and nutritionists) may show similar injury incidence rates and characteristics than those reported in the current study. Even though all female players had sub-elite status, most of them had jobs besides futsal that could alter their risk of injury and recovery time, for example, by preventing them from training or taking full advantage of medical treatment. Therefore, future studies are needed in order to analyze if elite female futsal players on full-time (professional) contracts may show different injury incidence rates, characteristics and burden.

4.7. Conclusions

Sub-elite female futsal players (particularly outfield players) are exposed to a substantial risk of sustaining injuries. Most injuries had a non-contact mechanism, with the lower extremity the most frequently injured anatomical region. Knee (anterior cruciate ligament tears) and thigh (hamstring and quadriceps muscle strains) injuries are those with the highest injury burden. Special attention should be given to the first weeks of competition after pre-season and soon after the Christmas break as incidence rates peak during this period in female futsal players. Medical and fitness team staff should focus their attention on designing, implementing and then evaluating preventative measures that target the most common diagnoses, namely, ligament and muscle/tendon injuries highlighted in this study, as well as making sure that return to train/play criteria are in place in order to reduce the injury burden within female sub-elite futsal players.

4.7. Appendixes

Appendix 4.1. Definitions used to include studies

Term	Definition
Injury	Any physical complaint sustained by a player that results from a futsal match or futsal training, irrespective of the need for medical attention or time loss from futsal activities
Time loss injury	Injury that results in a player being unable to take a full part in future futsal training or match play
Recurrent injury	An injury of the same type and at the same site as an index injury and which occurs after a player's return to full participation from the index injury
Injury severity	The number of days that have elapsed from the date of injury to the date of the player's return to full participation in team training and availability for match selection. Injuries are grouped as: *Slight / Minimal* Absence (1-3 days) *Minor / Mild* Absence (4-7 days) *Moderate* Absence (8-28 days) *Major / Severe* Absence (>28 days)
Match exposure	Play between teams from different clubs.
Training exposure	Team-based and individual physical activities under the control or guidance of the team's coaching or fitness staff that are aimed at maintaining or improving players' futsal skills or physical condition
Overuse injury	An injury caused by repeated microtrauma without a single, identifiable event responsible for the injury.
Traumatic injury	Injury with sudden onset and known cause
Injury location	▪ Head and neck (Head/face; Neck/cervical spine)

	▪ Upper limbs (Shoulder/clavicula; Upper arm; Elbow; Forearm; Wrist; Hand/finger/thumb) ▪ Trunk (Sternum/ribs/upper back; Abdomen; Lower back/pelvis/sacrum) ▪ Lower limbs (Hip/groin; Thigh; Knee; Lower leg/Achilles tendon; Ankle; Foot/toe)
Type of injury grouping	• Fractures and bone stress • Joint (non-bone) and ligament [Dislocation/subluxation; Sprain/ligament injury; Lesion of meniscus or cartilage] • Muscle and tendon [Muscle rupture/tear/strain/cramps; Tendon injury/rupture/tendinosis/bursitis] • Contusions [Haematoma/contusion/bruise] • Laceration and skin lesion [Abrasion; Laceration] • Central/peripheral nervous system [Concussion (with or without loss of consciousness); Nerve injury] • Other [Dental injuries; Other injuries]
Injury incidence	Number of injuries per 1000 player hours ((Σ injuries/Σ exposure hours) ×1000)

Appendix 4.2. Description of the 22 of STROBE Statement—checklist of items that should be included in reports of observational studies

Section/topic	Item No	Checklist item	
Title and abstract	1	(*a*) Indicate the study's design with **Title and abstract** 1 a commonly used term in the title or the abstract	✓
		(*b*) Provide in the abstract an informative and balanced summary of what was done and what was found	
Introduction			
Background / rationale	2	Explain the scientific background and rationale for the investigation being reported	✓
Objectives	3	State specific objectives, including any prespecified hypotheses	✓
Methods			
Study design	4	Present key elements of study design early in the paper	✓
Setting	5	Describe the setting, locations, and relevant dates, including periods of recruitment, exposure, follow-up, and data collection	✓
Participants	6	(*a*) *Cohort study*—Give the eligibility criteria, and the sources and methods of selection of participants. Describe methods of follow-up *Case-control study*—Give the eligibility criteria, and the sources and methods of case ascertainment and control selection. Give the rationale for the choice of cases and controls	✓

		Cross-sectional study—Give the eligibility criteria, and the sources and methods of selection of participants	
		(b) Cohort study—For matched studies, give matching criteria and number of exposed and unexposed Case-control study—For matched studies, give matching criteria and the number of controls per case	
Variables	7	Clearly define all outcomes, exposures, predictors, potential confounders, and effect modifiers. Give diagnostic criteria, if applicable	✓
Data sources/ measurement	8	For each variable of interest, give sources of data and details of methods of assessment (measurement) Describe comparability of assessment methods if there is more than one group	✓
Bias	9	Describe any efforts to address potential sources of bias	✗
Study size	10	Explain how the study size was arrived at	✗
Quantitative variables	11	Explain how quantitative variables were handled in the analyses. If applicable, describe which groupings were chosen and why	✓
Statistical methods	12	(*a*) Describe all statistical methods, including those used to control for confounding	✓
		(*b*) Describe any methods used to examine subgroups and interactions	
		(*c*) Explain how missing data were addressed	
		(*d*) *Cohort study*—If applicable, explain how loss to follow-up was addressed	

		Case-control study—If applicable, explain how matching of cases and controls was addressed	
		Cross-sectional study—If applicable, describe analytical methods taking account of sampling strategy	
		(*e*) Describe any sensitivity analyses	
Results			
Participants	13	(a) Report numbers of individuals at each stage of study—eg numbers potentially eligible, examined for eligibility, confirmed eligible, included in the study, completing follow-up, and analysed	✓
		(b) Give reasons for non-participation at each stage	
		(c) Consider use of a flow diagram	
Descriptive data	14	(a) Give characteristics of study participants (e.g. demographic, clinical, social) and information on exposures and potential confounders	✓
		(b) Indicate number of participants with missing data for each variable of interest	
		(c) *Cohort study*—Summarise follow-up time (e.g., average and total amount)	
Outcome data	15	*Cohort study*—Report numbers of outcome events or summary measures over time	✓
		Case-control study—Report numbers in each exposure category, or summary measures of exposure	
		Cross-sectional study—Report numbers of outcome events or summary measures	
Main results	16	(*a*) Give unadjusted estimates and, if applicable, confounder-adjusted estimates and their precision	✓

		(e.g, 95% confidence interval). Make clear which confounders were adjusted for and why they were included	
		(*b*) Report category boundaries when continuous variables were categorized	
		(*c*) If relevant, consider translating estimates of relative risk into absolute risk for a meaningful time period	
Other analyses	17	Report other analyses done—e.g. analyses of subgroups and interactions, and sensitivity analyses	✓
Discussion			
Key results	18	Summarize key results with reference to study objectives	✓
Limitations	19	Discuss limitations of the study, taking into account sources of potential bias or imprecision Discuss both direction and magnitude of any potential bias	✓
Interpretation	20	Give a cautious overall interpretation of results considering objectives, limitations, multiplicity of analyses, results from similar studies, and other relevant evidence	✓
Generalisability	21	Discuss the generalizability (external validity) of the study results	✓

Other information			

Funding	22	Give the source of funding and the role of the funders for the present study and, if applicable, for the original study on which the present article is based	×

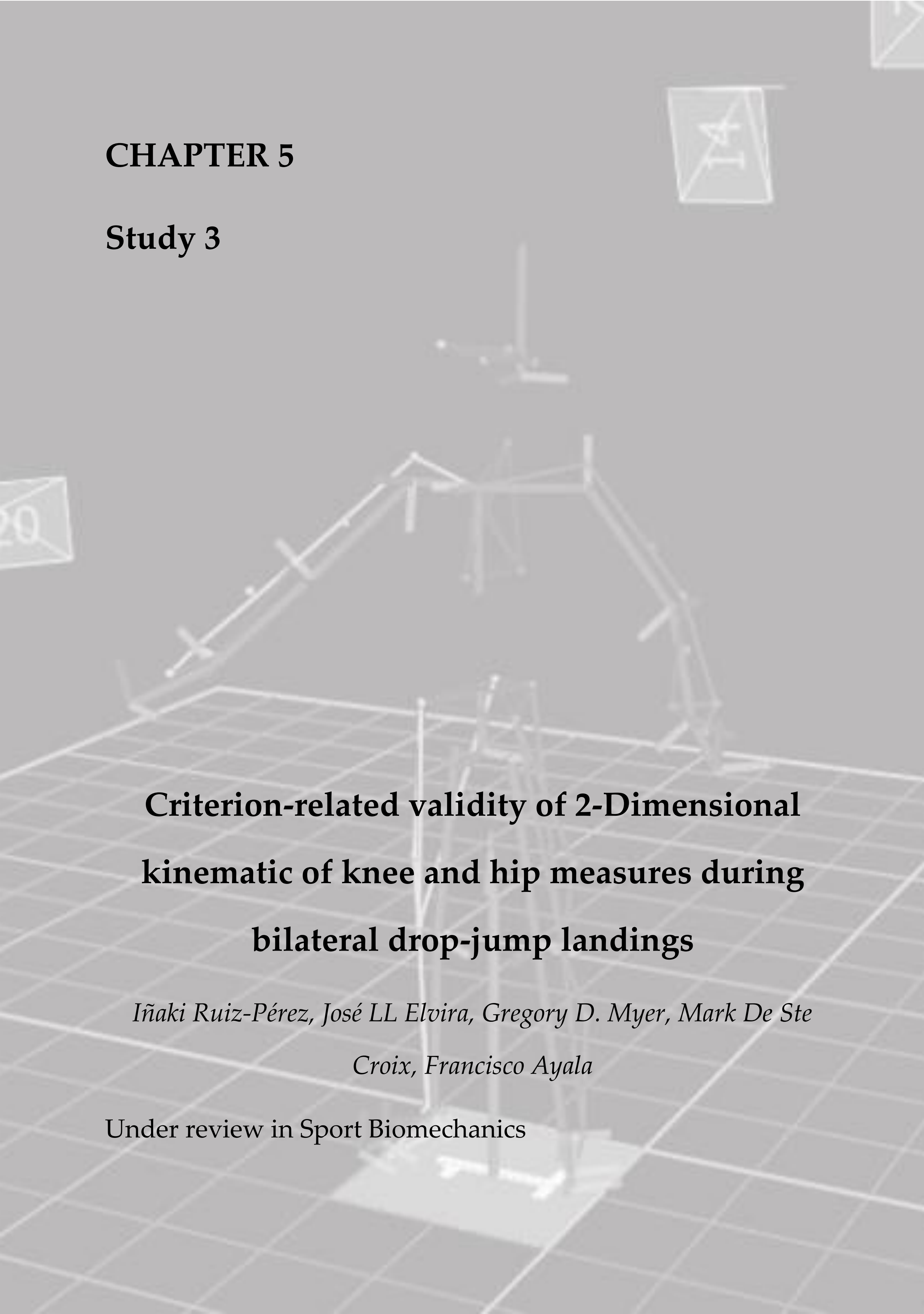
Appendix 4.3. Description of the 8 criteria designed to assess risk of bias of external validity quality in the studies. This instrument is an adapted version of the Newcastle Ottawa Scale (NOS) for cohort studies.

Criterion	Description of criteria
1. Description or type of football players.	There are several types of football players (amateur vs. professional, males vs. females). Without the description regarding to the type of football players it is impossible to conclude which population the incidence rates refer to. Studies that reported a description of the football players or informed the type of football players receive a star for this criterion. Studies conducted in football tournaments (which may determine the type of football players; e.g., World cup tournaments) and which describe the race characteristics receive a star for this criterion as well. Studies that did not describe the characteristics or the type of football players, and studies conducted in football tournaments that did not describe the characteristics of the tournament did not receive a star for this criterion.
2. Definition of football-related injury.	Studies that aimed to investigate football-related injuries should present a definition of an injury informing what was considered as an injury in the study. Studies that present a definition of time-loss injury received a star for this criterion.
3. Representativeness of the exposed cohort.	(a) Truly representative of the average football players in the community*; (b) somewhat representative of the average football players in the community*; (c) selected

		group of users; (d) no description of the derivation of the cohort.	
4.	Ascertainment of exposure.	(a) Secure record*; (b) structured interview*; (c) written self-report; (d) no description	✓
5.	Demonstration that outcome of interest was not present at start of study.	(a) Yes*; (b) no. Studies that described that all football players included were injury-free at baseline received a star for this criterion.	✓
6.	Assessment of outcome.	(a) Independent blind assessment*; (b) record linkage*; (c) self-report; (d) no description.	✓
7.	Was follow-up long enough for outcomes to occur risk factors.	(a) Yes*; (b) no. Studies that carried out a follow-up period of at least 12 weeks received a star for this criterion.	✓
8.	Adequacy of follow-up of cohorts	(a) Complete follow-up of all subjects accounted for*; (b) subjects lost to follow-up unlikely to introduce bias (up to 20 % loss) or description provided of those lost*; (c) follow-up rate <80% and no description of those lost; (d) no statement. A loss to follow-up greater than 20 % may increase the risk of bias in prospective studies (Fewtrell et al., 2008).	✓

T: The articles could be awarded a maximum of one star for each item. A total of 8 stars could be given for the articles.

* Articles with this alternative received a star for this criterion.



CHAPTER 5

Study 3

Criterion-related validity of 2-Dimensional kinematic of knee and hip measures during bilateral drop-jump landings

Iñaki Ruiz-Pérez, José LL Elvira, Gregory D. Myer, Mark De Ste Croix, Francisco Ayala

Under review in Sport Biomechanics

CHAPTER 5

Study 3

Criterion-related validity of 2-Dimensional kinematic of knee and hip measures during bilateral drop-jump landings

Iñaki Ruiz-Pérez, José LL Elvira, Gregory D. Myer, Mark De Ste Croix, Francisco Ayala

5.1. Abstract

Objective: Three-dimensional (3D) motion capture systems have been used to identify athletes in high risk of injury, but due to their cost, lack of portability and qualified technicians, an alternative is needed, such as two-dimensional (2D) systems. The purpose of this study was to examine the criterion-related validity of three measures of frontal plane knee alignment (Frontal plane projection angle [FPPA], knee-to-ankle separation ratio [KASR] and knee medial displacement [KMD]) and two sagittal plane measures (hip and knee flexion ranges of motion [ROMs]), recorded simultaneously using a 2D video analysis procedure and a 3D motion analysis system.

Method: Twenty-nine male futsal players had frontal and sagittal plane kinematics assessed while performing bilateral drop vertical jumps (DVJ). The criterion-related validity of the frontal and sagittal plane kinematic measures obtained using the 2D video analysis procedure and 3D motion system was determined through the estimation equation, typical error of the estimate (TE_{EST}) and validity correlation (r). Kappa correlations were also calculated to determine the agreement between the 2D and 3D kinematic approaches.

Results: The results showed poor validity for the FPPA measure (standardized TE_{EST} = 1.34 [large], r = 0.60) and moderate validity for KASR (standardized TE_{EST} = 0.88 [moderate], r = 0.77), KMD (standardized TE_{EST} = 0.53 [small], r = 0.88), hip flexion ROM (standardized

TE_{EST} = 0.62 [moderate], r = 0.85) and knee flexion ROM (standardized TE_{EST} = 0.56 [small], r = 0.87) measures. However, only the KMD and knee flexion ROM measures showed high levels of agreement (kappa > 0.7).

Results: Therefore, the KMD and knee flexion ROM measures calculated during a bilateral DVJ and using a 2D video analysis procedure might be considered as valid and feasible alternatives to their respective 3D criterion to quantify knee kinematics and to detect futsal players who demonstrated aberrant movement patterns in the frontal and sagittal planes, respectively.

Keywords: Dynamic knee valgus, injury, screening, motion analysis

5.2. Introduction

Knee injuries are common among individuals participating in team sports (e.g.: football[192], futsal[6], basketball[193] and rugby[194]). In most cases, knee injuries (including anterior cruciate ligament [ACL] tears) occur in athletes by non-contact mechanisms[195–198]. Although non-contact knee injuries are considered multifactorial in nature[18], aberrant lower extremity movement patterns during the execution of high intensity weight-bearing dynamic tasks (e.g.: cutting and landing) such as an excessive dynamic valgus motion at the knee (a multi-joint and multiplane movement pattern comprised of varying degrees of hip adduction and internal rotation and knee abduction and external rotation joint kinematics[199]) and limited hip and knee flexion ranges of motion (ROM) have been identified as primary and modifiable risk factors[62,200–206]. Therefore, pre-participation assessment of hip and knee joints kinematics during dynamic tasks might aid in the identification of athletes who adopt aberrant movement patterns associated with an increased risk of knee injuries[207].

Three-dimensional (3D) motion analysis systems have been considered as the criterion measurement (gold standard) to assess lower extremity joints kinematics during potentially high-risk tasks related to knee injuries (mainly ACL) due to their high levels of accuracy and reliability[59–64]. However, the use of 3D motion analysis systems is often restricted to research settings and not used in clinical environments or for pre-participation screening because of their high cost, lack of portability, time constraints and the need for sophisticated instruments and qualified technicians[61,64]. Consequently, cost-effective, technically undemanding and portable alternative measurements to 3D motion analysis are needed. A low-cost, portable and readily available alternative to screen lower extremity joints kinematics might be the two-dimensional (2D) video analysis procedures where standard cameras are used to capture performance of dynamic tasks which are then imported into user-friendly software packages (e.g.: Kinovea, Quintic, ImageJ and Dartfish™) that perform kinematic analysis in a plane perpendicular to the camera lens[208]. However, the criterion-related validity of their measures must be determined before these

2D video analysis procedures can be used as an objective and feasible alternative to the 3D motion analysis systems to quantify lower extremity joints kinematics and to identify athletes who adopt potentially hazardous movement patterns during dynamic tasks[209].

Some studies have examined the criterion-related validity (mainly through correlation coefficients) of certain measures of frontal plane knee alignment (i.e.: frontal plane projection angle of the knee [FPPA][61,64–69], knee-to-ankle separation ratio [KASR][67,68] and knee medial displacement [KMD][70]) during dynamic tasks (mainly single leg squats and drop landings) that have been operationally designed to identify athletes with excessive dynamic knee valgus motion using 2D video analysis procedures and 3D motion analysis systems simultaneously. In particular, these measures of frontal plane knee alignment obtained through the use of 2D video analysis procedures have reported correlations with their respective 3D criterion measures ranging from $r = 0.24$ to 0.96.

However, Hopkins[209] stated that the use of the correlation coefficients as the unique statistical outcome of validity only provides information regarding how well the observed value retains the true rank order of subjects and hence it does not indicate whether both measures or methods (e.g.: 3D motion analysis systems and 2D video analysis procedures) can be used interchangeably and thus whether the same cut-off scores can be used to detect the expected diagnosis (e.g.: the presence [or absence] of aberrant lower extremity movement patters during dynamic tasks). More contemporary statistical methods, such as the calculation of the estimation equation and typical error of the estimate (TE_{EST}) have not been taken into consideration. Determination of criterion-related validity of the previously mentioned measures of frontal plane knee alignment (FFPA, KASR and KMD) using contemporary statistical measures may be important for clinicians and strength and conditioning specialists because it can be used a) to assess an athlete and to predict his/her criterion value to get an accurate diagnosis (normal or aberrant frontal plane knee alignment) using the cut-off scores established for the criterion test (3D motion analysis system), b) to compare the validity of different measures or assessment methodologies and c) to determine the sample size for validity and cross-sectional studies[209].

On the other hand, only Myer et al.[70] have analyzed the criterion-related validity of lower extremity kinematic measures obtained simultaneously through 2D video analysis procedures and 3D motion analysis systems in planes other than the frontal plane and that had been previously associated with an increase in knee injury risk. In particular, Myer et al.[70] examined the criterion-related validity of knee flexion ROM in the sagittal plane during a bilateral drop jump showing an r score of 0.95. To the authors´ knowledge, the criterion-related validity of other ROM measures in the sagittal plane, such as hip flexion ROM, has not been explored.

Therefore, the purpose of this study was to examine the criterion-related validity of three measures of frontal plane knee alignment (FPPA, KASR and KMD) and two measures of sagittal plane movement (hip and knee flexion ROMs) recorded simultaneously using a 2D video analysis procedure and a 3D motion analysis system during a bilateral drop landing and applying a contemporary statistical approach in elite futsal players.

5.3. Methods

5.3.1. Participants

A total of 29 elite male futsal players (years = 23.2 ± 4.2 y, body mass = 73.8 ± 6.9 kg and stature = 1.76 ± 0.7 m) from four different teams (13 players belonging to two clubs engaged in the First [top] National Spanish Futsal division and 16 players from two clubs engaged in the Second National Spanish Futsal division) completed this study. Futsal is a variant of football (soccer) played on a hard court, smaller than a football pitch and mainly indoors. To be included, all players had to be free of pain and injury at the time of testing (self-reported). Before any participation, experimental procedures and potential risks were fully explained to the players in verbal and written form, and written informed consent was obtained from all of them. An Institutional Research Ethics committee approved the study protocol prior to data collection (DPS.FAR.02.14) conforming to the recommendations of the Declaration of Helsinki.

5.3.2. Procedure

Prior to testing, each athlete performed the standardized dynamic warm-up designed by Taylor, Sheppard, Lee, & Plummer.[210] The overall duration of the entire warm-up was approximately 20 min. After the warm-up, a 3-5 min rest was given for rehydrating and drying their sweat. Then, each player practiced the experimental task (bilateral drop vertical jump [DVJ]) three to five times. After the practice trials, players were prepared for data collection. Thus, the anthropometric measures required by the Vicon™ (Vicon Motion Systems Inc., Denver, CO, USA) Plug in Gait Full Body model were first taken then 35 reflective markers were placed on the skin with double-sided adhesive tape on each player´s anatomic landmarks according to the model´s instructions[211]. 2D and 3D data were captured simultaneously while players completed each trial of the experimental task in a laboratory setting. The same two experienced sport scientists were always responsible for placing reflective markers uniformly. Futsal players were examined wearing sports shorts and low ankle socks. Players were allowed their preferred futsal shoes to prevent any pain at landing that could alter their landing mechanics.

5.3.3. Bilateral drop vertical jump

A DVJ was performed according to Onate et al.[212] Briefly, players stood with feet shoulder-width apart on a 40 cm high box. They were instructed to lean forward and drop from the box as vertically as possible. Players were required to land with both feet simultaneously on a force platform (90x60 cm) that was located 20 cm in front of the box (with the purpose of serving as a reference object for the 2D video analysis system and to defined the landing phase of each DVJ for the 3D motion analysis system), then immediately perform a maximal vertical jump, finally landing back on the force platform. Each player performed three successful maximal DVJs, starting from a standing position with at least 30 s of recovery between jumps. Players were asked to jump as high as possible. Players were allowed to use the arms and were able to choose the amplitude and speed of the countermovement needed to achieve the maximum high during the jump. A failed trial was defined when the players (1) could not maintain a bilateral landing position, (2) landed farther than the platform, or (3) jumped up from the platform. Players took a sufficient rest period between the trials to avoid the effects of fatigue. Each successful maximal DVJ trial was considered as a unit of analysis.

5.3.4. Instrumentation

A motion capture system with seven T10 cameras (Vicon MX; Oxford Metrics Group, Oxford UK) sampling at 200 Hz and a Kistler 9287 force platform embedded into the floor (Kistler, Winterthur, Switzerland), sampling at 1000 Hz, were used to simultaneously collect 3D kinematic and kinetic variables during the first landing of the three DVJs.

Two commercially available HD cameras (DMC-FZ 200 Lumix) sampling at a frequency of 200 Hz were also used to capture players´ performance during the DVJs. The cameras were placed at a distance of 4 m from the player and at the height of 1 m, one perpendicular to the frontal plane and the other perpendicular to the sagittal plane.

5.3.5. Data reduction

5.3.5.1. 3D data

A static calibration trial was completed before each data collection session started in order to determine the anatomic segment coordinate systems. Marker trajectories were identified with Vicon Nexus v1.8 software and kinematic data (i.e. hip, knee and ankle joint angles in the sagittal, frontal and transverse planes) were obtained using Plug in Gait Full Body model. A double 2nd order Butterworth filter with a cutoff frequency of 6 Hz was used to filter marker coordinates.

The measures of frontal plane knee alignment FPPA and KASR were calculated relative to the laboratory or global coordinate system at the time of maximum knee flexion during the first landing immediately after stepping off from the box and following the methodology described by Minzer et al.[67] The frontal plane KMD measure and the sagittal plane hip and knee flexion ROMs were also calculated relative to the global coordinate system and from the hip and knee flexion at initial contact with the ground to the maximum knee flexion angle during the landing phase in their respective planes. Similar to previous studies, the landing phase of each DVJ was defined as the period when the unfiltered ground-reaction force exceeded 20 N[213]. Maximum knee flexion angle was defined as the maximum angle between the thigh and shank segments during the ground contact phase.

5.4.5.2. 2D data

The digital videos recorded by the HD cameras from each DVJ trial were uploaded into Kinovea 0.8.25 software for conversion to still images. Kinovea software allows to calculate all measures of frontal plane knee alignment and sagittal plane hip and knee flexion ROMs. The same investigator with extensive experience of using the software calculated all measures. Intra-rater reliability of the 2D kinematic measures calculated by this investigator was analyzed in a previous pilot study and all of them showed high ICC scores (>0.85). For the 2D video analysis, initial contact of the first landing phase was defined as the first frame in which ground contact was observed while maximum knee flexion angle was defined as the frame before the player started to knee extension in order to perform the maximum vertical jump. For the variables measured in distance in the frontal plane, the images were calibrated using the width of the platform (90 cm). Previous studies used reflective markers on bony landmarks (including joints center) to guide the calculation of the 2D measures of frontal plane knee alignment[64–66,68,69]. However, markers can often slide on the skin during the execution of high intensity weight-bearing dynamic tasks. On the contrary, 3D systems calculate the center of the joints and the error in the motion analysis associated with movement of the markers is lower. Consequently, and with the aim of improving the agreement of the 2D kinematic measures with their respective 3D criterion, no markers were used over bony landmarks to guide the calculation of the 2D frontal plane measurements.

FPPA was calculated for the left leg with the videos of the frontal camera. To measure the FPPA, the investigator first created a femoral segment by placing a straight line that bisected the thigh outline, terminating at the investigator’s estimation of the bisection of the femoral epicondyles. Similar to Mizner et al.[67], the epicondyle estimation was made from available visual landmarks such as the outline of shadowing of the patella, muscular shape outline of the quadriceps and the thickness of the leg’s outline in the area of the knee joint. The shank segment began at the termination of the thigh segment and bisected the borders of the lower leg terminating at the estimated position of the ankle's lateral malleolus. The ankle malleolus position was made from available visual landmarks such as shoe position, bony outlines or shadows of the bones of the leg and the thickness of the leg outline in the area of the ankle joint. The angle formed by these two segments was then measured and used for analysis (figure 5.1.a). A measurement of 0° represents a neutral position of the knee in the frontal plane; whereas negative values represent a 2D knee valgus angle, and positive values represent a 2D knee varus angle.

KASR was calculated following the procedure described by Mizner et al.[67]. Thus, this measure was determined from the frontal view, by drawing a horizontal line between the visual estimation of the centres of the knee (knee separation distance) and another horizontal line between the estimation of the centres of the ankles. The length of each line was measured and the ratio between the length of the knee line and the length of the ankle line was finally recorded (figure 5.1.b). A value of 1 represents an alignment of the knees directly on the ankles. A value less than 1 will occur when the centres of the knees are closer than the centres of the ankles, which have been suggested that represent 2D knee valgus. A value greater than 1.0 represented that knees were lateral to ankles, which have been suggested that represent 2D knee varus.

KMD was quantified as the displacement (in centimeters) of the visually estimated centre of the left knee during two different times of the landing phase[214]. First measurement was during the initial contact phase (d1) and the second when the player reached maximal peak knee flexion during the ground contact phase (d2) (figure 5.1.c). Thus, the KMD was expressed as the displacement measure between the 2 marked knee alignments (d2 – d1). Negative and positive values denoted 2D valgus and varus alignments, respectively.

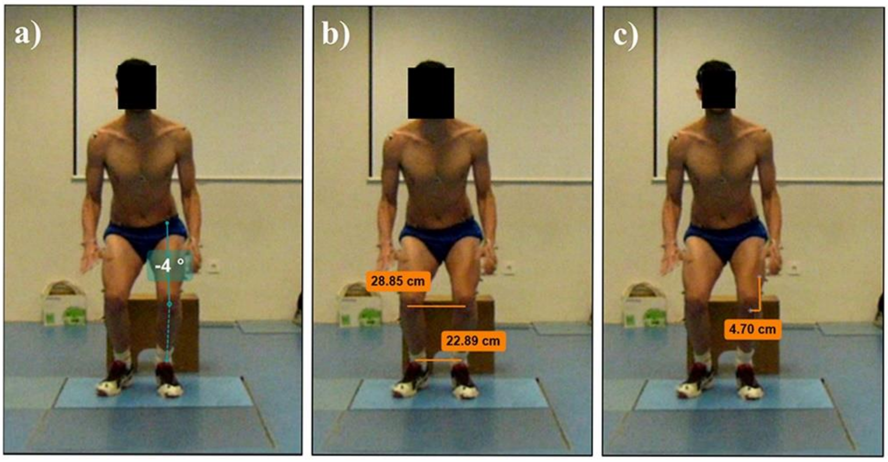


Figure 5.1. Frontal view 2D analysis.

The sagittal plane camera was used to capture and quantify hip and knee flexion ROMs of the left leg, which were calculated in the first video frame in which ground contact was observed and maximum knee flexion. Hip flexion angle was defined as the angle formed by a straight line joining the medial part of the thigh originating in the lateral femoral epicondyle marker and the straight line joining the estimated hip rotation axis with the projection of the spine in neutral position (figure 5.2). Knee flexion angle was considered the angle formed by the straight lines of the thigh, as previously described, and leg segments, joining the lateral femoral epicondyle and the lateral malleolus marker (figure 5.2).

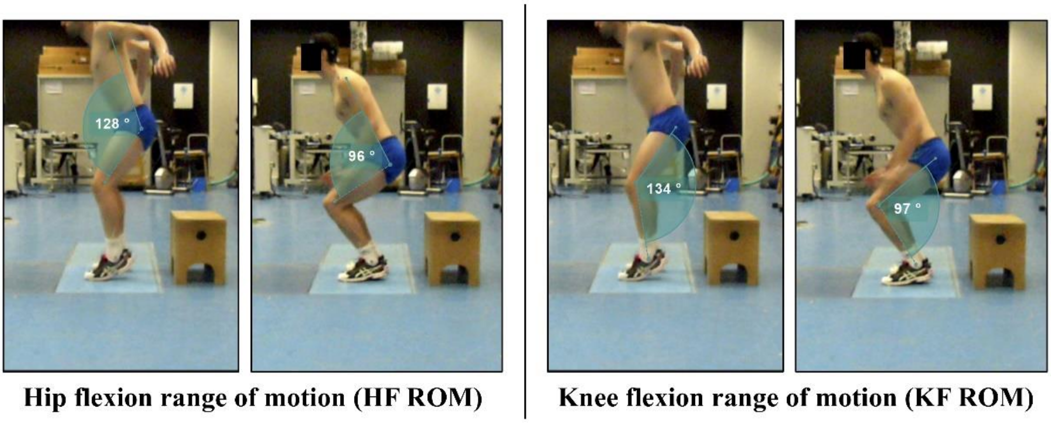


Figure 5.2. Lateral view 2D analysis.

5.3.6. Statistical analysis

The distribution of raw data sets was checked using the Kolmogorov–Smirnov test and demonstrated that all data had a normal distribution ($p > 0.05$). Descriptive statistics including means and standard deviations (SDs) were calculated for each measure.

The criterion-related validity of each measure was determined through an estimation equation, TE_{EST} and validity correlation (Pearson coefficient) using the method previously descried by Hopkins[209]. The estimation equation was calculated as the equation generated by plotting and after fitting a straight line to 3D data against 2D data ($y = slope \cdot X + intercept$). The TE_{EST} was calculated as the mean typical error of the difference between the 3D and 2D data reported by the players. To interpret the TE_{EST} values, Hopkins[209] suggests calculating the standardized TE_{EST} (TE_{EST}/SD of the criterion test [3D motion analysis]) and then using the following arbitrary values: <0.2 trivial, 0.2 to 0.6 small, >0.6 to 1.2 moderate, >1.2 to 2.0 large, and >2.0 very large. Validity correlation was expressed through Pearson correlation coefficients (r) between the 3D data and the 2D data. Magnitudes of correlations were assessed using the following scale of thresholds: <0.80 low, 0.80 to 0.90 moderate, and >0.90 high[209].

The assessing agreement (systematic bias and random error) between the 3D and 2D measures was calculated using the statistical methods described by Bland and Altman[215]. Heteroscedasticity was checked by analyzing the degree of correlation between the residuals and predictive values[209].

Additionally, the measures of frontal plane knee alignment were dichotomized to indicate a positive or negative score for each player based on the presence of dynamic knee valgus or varus using the cut-off scores previously described. Although limited hip and knee flexion ROMs in the sagittal plane have been associated with an increased risk of knee injury[204,216] no specific cutoff scores have been defined yet (from the authors´ knowledge). Consequently, in the absence of robust cut-off scores for identifying athletes at high risk of knee injury, the average hip flexion and knee flexion ROM scores reported for injured players by prospective studies aimed at investigating the relationship between selected sagittal plane hip and knee kinematic and the risk of ACL injury[70,204], alongside the authors´ extensive experience in screening athletes, were used to finally define the following cutoff score to indicate a high or low risk of loading the knee joint: <50 (high risk) and >50º (low risk) for both hip and knee flexion ROM measures. After reducing the data to a nominal variable (positive = dynamic knee valgus or high risk of loading the knee; negative = dynamic knee varus or low risk of loading the knee), Kappa (k) correlations were calculated to determine the agreement between the two techniques (3D motion analysis and 2D video analysis) of kinematic analysis. Magnitudes of k correlations were assessed using the following scale of thresholds: <0.20 poor; 0.20-0,40 fair, 0,41-0,60 moderate, 0.61- 0.80 high and 0.81-1.00 very high[217].

Data were analyzed using SPSS for Windows, Version 20.0 (SPSS Inc., Chicago, IL, USA) and Microsoft Excel spreadsheet.

5.4. Results

Mean values for each of the 2D and 3D outcome measures are presented in Table 5.1. Validity measures are presented in figures 5.3 to 5.7 for frontal plane knee and sagittal plane lower extremity joints alignment variables. Whereas poor validity scores were found for the measure of frontal plane knee alignment FPPA (standardized TE_{EST} = 1.34 [large] and r = 0.60 [low]), moderate validity scores were found for KASR (standardized TE_{EST} = 0.84 [moderate] and r = 0.77 [low]) and KMD (standardized TE_{EST} = 0.53 [small] and r = 0.88 [moderate]) measures. Likewise, moderate validity scores were obtained for the measures of hip flexion (standardized TE_{EST} = 0.62 [moderate] and r = 0.85 [moderate]) and knee flexion (standardized TE_{EST} = 0.56 [small] and r = 0.87 [moderate]) ROMs.

Table 5.1. Mean values for 3D and 2D variables during bilateral drop vertical jumps (DVJ)

Measures	3D (mean ± SD)	2D (mean ± SD)
Frontal plane knee alignment		
FPPA (º)	1.1 ± 16.6	10.1 ± 16.7
KASR	1.42 ± 0.35	1.24 ± 0.31
KMD (cm)	-6.7 ± 3.4	1.1 ± 4.5
Sagittal plane lower extremity joints alignment		
HF ROM (º)	54.1 ± 16.1	63.6 ± 18.7
KF ROM (º)	72.3 ± 13.9	67.1 ± 11.9

2D: two-dimensional; 3D: three-dimensional; SD: standard deviation; FPPA: frontal plane projection angle; KASR: knee-to-ankle separation ratio; KMD: knee medial displacement; HF: hip flexion; KF: knee flexion; ROM: range of motion.

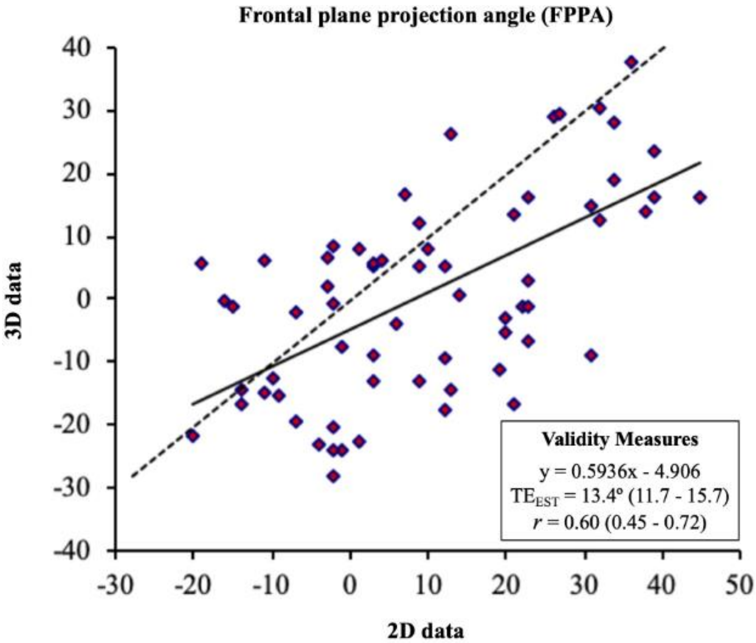


Figure 5.3. Validity measures of the frontal view variable FPPA.

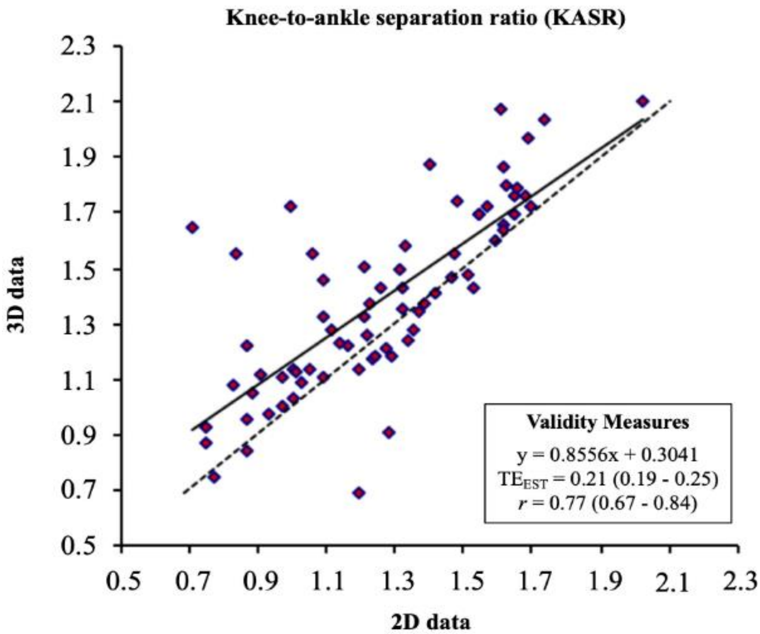


Figure 5.4. Validity measures of the frontal view variable KASR.

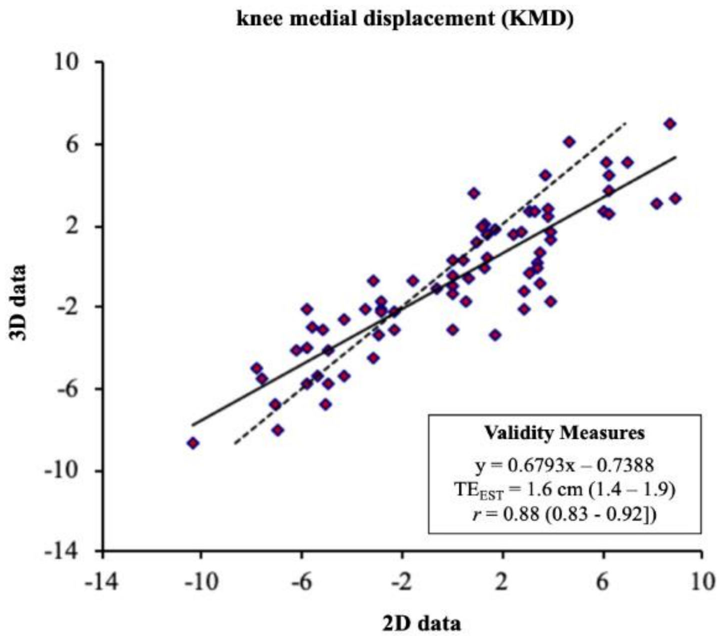


Figure 5.5. Validity measures of the frontal view variable KMD.

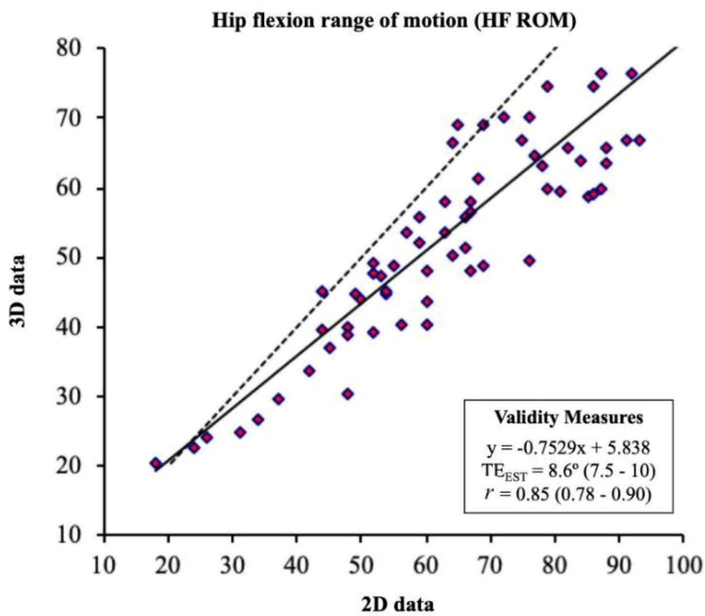


Figure 5.6. Validity measures of lateral view variable: HF ROM.

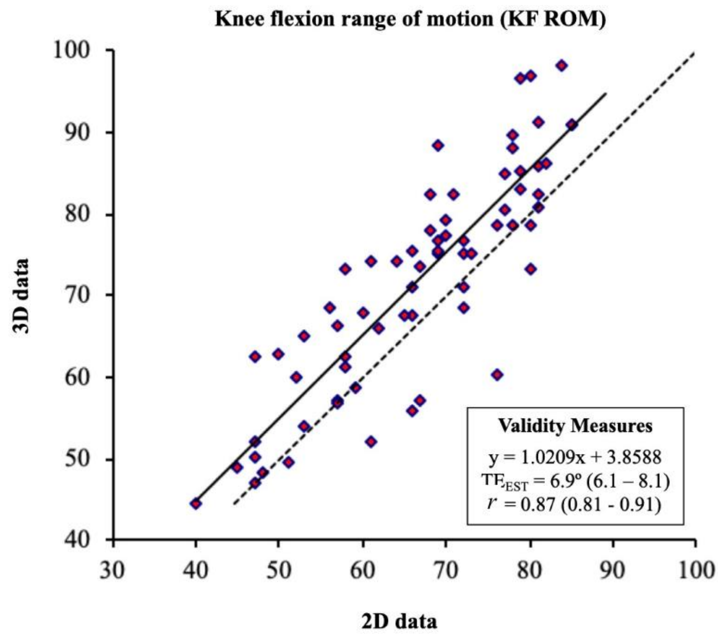


Figure 5.7. Validity measures of lateral view variable KF ROM.

Bland-Altman plots (figures 5.8 to 5.13) confirmed that all measures of frontal plane knee alignment (FPPA = 9.0 ± 14.9º, KASR = -0.12 ± 0.22, KMD = -0.7 ± 2.71 cm) and sagittal plane hip and knee flexion ROMs (hip flexion ROM = 9.4 ± 10.5º, knee flexion ROM = -5.3 ± 6.9º) showed systematic bias ($p < 0.05$) between 3D motion analysis and 2D video analysis. Furthermore, no statistically significant associations between predictive and residual scores were found for all paired kinematic measures.

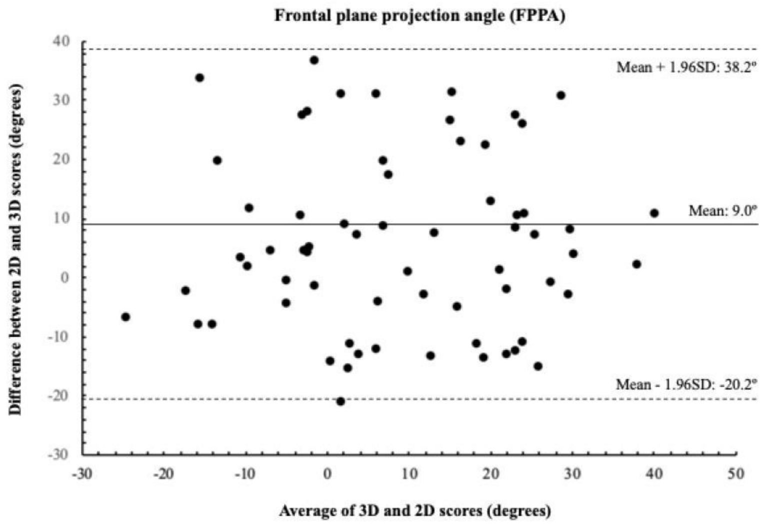


Figure 5.8. Bland and Altman plots showing individual differences between 2D and 3D system FPPA values plotted against the mean.

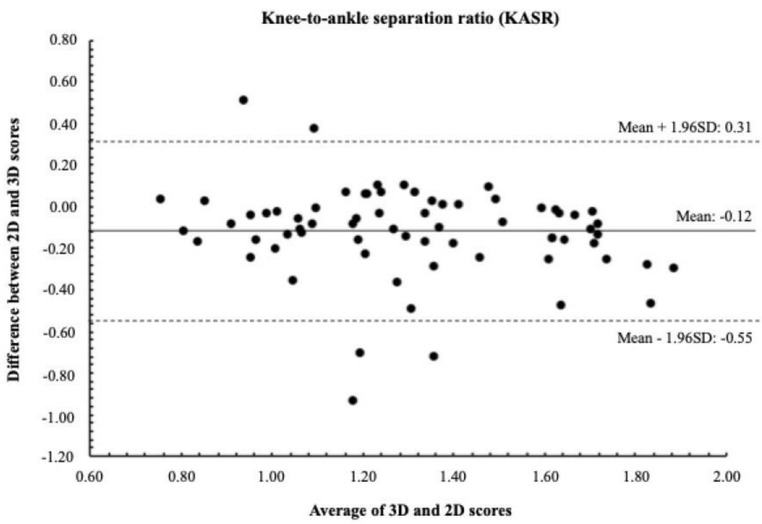


Figure 5.9. Bland and Altman plots showing individual differences between 2D and 3D system KASR values plotted against the mean.

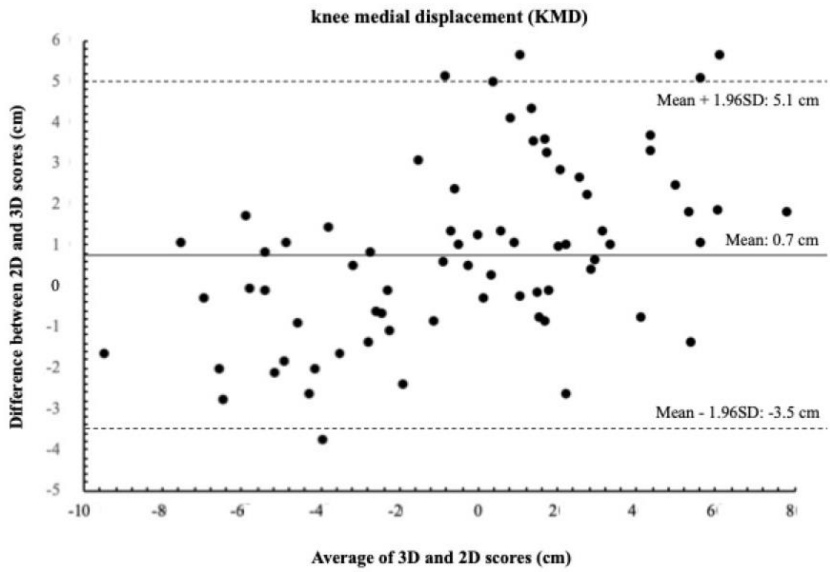


Figure 5.10. Bland and Altman plots showing individual differences between 2D and 3D system KMD values plotted against the mean.

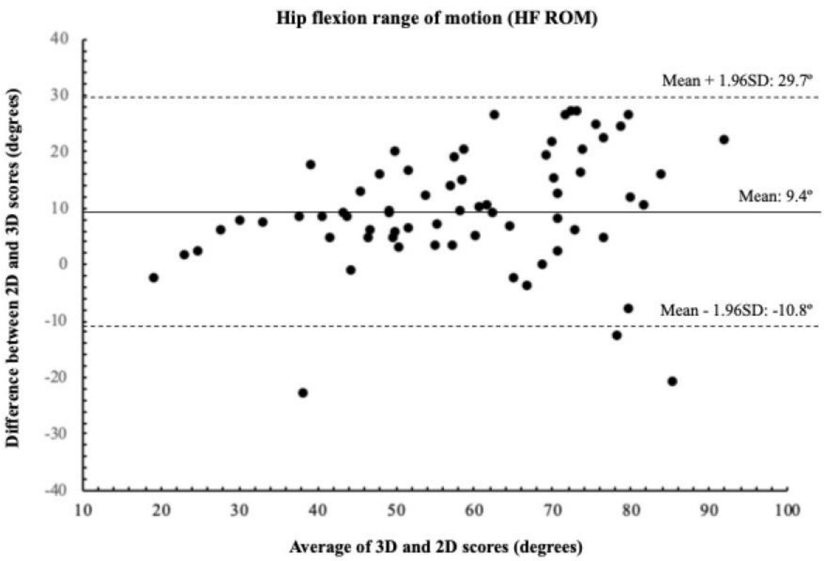


Figure 5.11. Bland and Altman plots showing 1individual differences between 2D and 3D system HF ROM values plotted against the mean.

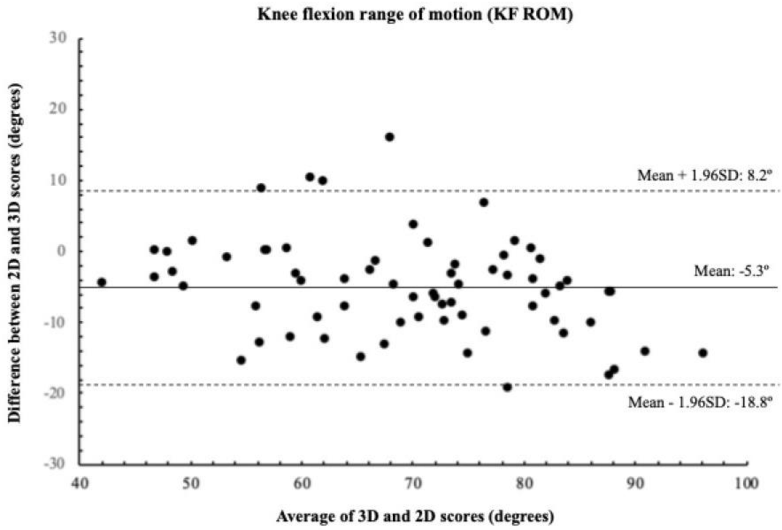


Figure 5.12. Bland and Altman plots showing 1individual differences between 2D and 3D system KF ROM values plotted against the mean.

Table 5.2 demonstrates the Kappa agreement among measures. Only the KMD and knee flexion ROM measures showed high levels of agreement (k > 0.7, p < 0.05).

Table 5.2. Kappa correlations

	FPPA	KASR	KMD	HF ROM	KF ROM
FPPA	0.327*				
KASR		0.424*			
KMD			0.719*		
HF ROM				0.528*	
KF ROM					0.742*

FPPA: frontal plane projection angle; KASR: knee-to-ankle separation ratio; KMD: knee medial displacement; HF: hip flexion; KF: knee flexion; ROM: range of motion. *: p < 0.05.

5.5. Discussion

The main findings of the current study report that the measure of frontal plane knee alignment FPPA calculated during a bilateral DVJ and using a 2D video analysis procedure presented poor criterion-related validity (standardized TE_{EST} = 1.34 [large], r = 0.60 [low] and k = 0.327 [poor]) with respect to its counterpart criterion measure, which was registered simultaneously through a 3D motion analysis system. These findings were similar to those reported in previous studies[68,69], although not all[67], using only the Pearson coefficient (validity correlation) as an indicator of validity and a DVJ as the experimental task. For example, Ortiz et al.[68] found Pearson correlation values of r = 0.39 and 0.57 between the FPPA scores obtained concurrently through a 2D video analysis procedure and a 3D motion analysis system, for the dominant and non-dominant legs respectively. A plausible explanation for the poor validity scores found for the FPPA obtained using 2D video analysis procedures might be based on the fact that this measure is a combination of frontal and transverse plane motions of the hip and knee and this may lead to a perspective error as standard cameras have the limitation (among others) of only recording uniplanar imagines placed transversally to their lens. Furthermore, the hip and knee multiplanar movements executed during the DVJ may have made the visual identification of the anatomical landmarks and the subsequent process of drawing lines (bisectors) that are needed to determine the angulation of both segments difficult, which may have also led to an increase in the measurement error. The results of the present study also reported that the 2D video analysis system showed statistically significant overestimations of the FPPA scores when they were compared with their 3D criterion measures (mean systematic bias = 9 ± 14.9º; effect size = 0.54 [small]). Ortiz et al.[68] also found that the 2D video analysis techniques overestimate the true values (defined by the 3D motion analysis system) of the FPPA kinematic measure by approximately 7º, which is comparable to the 9º reported in the current study.

In the scientific literature, some studies have examined the criterion-related validity of the FPPA measure obtained simultaneously using 2D and 3D systems during functional tasks (such as running[218], single leg squat[64–66,69] and lateral side step[61] that are less complex than DVJs. These studies demonstrate slightly higher Pearson correlation scores between the 3D and 2D analysis for the FPPA than those found when DVJ tasks were used. Gwynne & Curran[65] and Herrington et al.[66] reported correlation values of r = 0.78 and 0.79 between the 3D and 2D systems and for the FPPA measure recorded at 60º and 45º of knee flexion while participants adopted a single leg squat testing position. However, the clinical relevance of these 2D FPPA measures obtained during simple and slow functional tasks might be lower than the FPPA measures obtained during explosive dynamic tasks, such as landings and cutting maneuvers, in which the mechanism of knee overload (high knee abduction moment) might be more accurately reflected[219,220].

Regarding the two other measures of frontal plane knee alignment (KASR and KMD), the results of this study showed that there were moderate criterion-related validity scores between the 2D and 3D systems for both kinematic measures. In particular, the KMD was the measure of frontal plane knee alignment that exhibited the highest criterion-related validity scores (standardized TE_{EST} = 0.53 [small], r = 0.88 [moderate] and k = 0.72 [high]). A reason that might partially explain why the KMD showed the highest validity scores in comparison with the other two measures of frontal plane knee alignment could be based on the fact that the calculation process using 2D video analysis is easier. Thus, and in order to calculate the KMD, clinicians and strength and conditioning specialists only need to visually identify an anatomic landmark (centre of the knee) and quantified the displacement (in centimeters and through the use of the tool facilitated for the software for such aim) during two different times of the landing phase. Contrarily, the quantification of the KASR requires the identification of more anatomic landmarks (centres of the knee and ankle) while the FPPA measure needs not only the identification of anatomic landmarks but to visually create a femoral and shank segments by placing straight lines that bisected the thigh and the borders of the lower leg, respectively. Similar Pearson correlation values between the 2D and 3D systems were found by Myer et al. (2010) for the KMD measure ($r = 0.87$). However, Ortiz et al. (2016) showed slightly higher validity scores than the ones found in the current study for the KASR ($r = 0.96$) and KMD ($r = 0.94$) measures. A factor that may be behind this difference could be that Ortiz et al. (2016) analyzed the correlation validity between 2D and 3D systems using the average of the four DVJ trials carried out per participant, while in the current study each DVJ trial was considered a unit of analysis (instance) and this may have potentially increased the variability of the results acquired. In the present study, each DVJ was considered as an independent unit of analysis in an attempt to accurately reflect the common practices that occur in most clinical and sports settings. In these settings, both clinicians and strength and condition specialists are often forced to assess a large number of patients and athletes from different biomechanical and neuromuscular parameters in a short period of time. Consequently, employing more than 30 minutes in analyzing only the frontal plane knee alignment of each athlete in 3 to 5 different DVJs using a 2D video analysis procedure might not be a plausible option. Although the findings of the present study also report the presence of systematic shifts between the scores of both systems and for the KASR (systematic bias = -0.12 ± 0.22; effect size = 0.37 [small]) and KMD measures (systematic bias = 0.7 ± 2.2 cm; effect size = 0.22 [small]), their magnitudes may be considered as small according to the cutoffs described by Cohen[221]. However, and unlike to what happened to the KMD measure, the measurement error of the 2D KASR, although small and homoscedastic, was big enough to generate numerous disagreements between both systems (Kappa correlation = 0.42) in the participants´ diagnoses of showing knee valgus or varus during the DVJs and hence, a clinically different cut-off score should be established for this 2D measure.

On the other hand, the findings of this study also showed moderate validity scores for the hip (standardized $TE_{EST} = 0.62$ [moderate] and $r = 0.85$ [moderate]) and knee (standardized $TE_{EST} = 0.56$ [small], $r = 0.87$ [moderate]) flexion ROM measures obtained during a bilateral DVJ and using a 2D video analysis technique and with respect to their counterpart criterion measures registered simultaneously through a 3D motion analysis system. Slightly higher correlational results were reported by Myer et al.[70] and for knee flexion ROM (r = 0.95). As the current study has been the first (to the best of the authors´ knowledge) to explore the criterion-related validity of the sagittal plane hip flexion ROM measure, comparisons with previously published works were not possible. Similar to that found for the measures of frontal plane knee alignment, the presence of systematic bias was also reported in these two measures of sagittal plane hip (systematic bias = 9.4 ± 10.5º; effect size = 0.60 [moderate]) and knee (systematic bias = -5.3 ± 6.9º; effect size = -0.38 [small]) flexion ROMs. Only the knee flexion ROM measure showed clinically acceptable Kappa agreement scores between the 2D and 3D systems (k = 0.74). Consequently, as the systematic error was homoscedastic (similar in magnitude for the higher and lower scores), different cut-off scores seem to be needed for the hip flexion ROM measure obtained using a 2D video analysis procedure to detect altered or abnormal hip movement patters in the sagittal plane.

5.6. Limitations

This study is not without limitations. First, the criterion-related validity of the 2D measures was only examined in uninjured futsal players and further studies are required to identify if these or different validity scores would occur in other cohorts of athletes with and without knee injuries. Second, all kinematic measures were recorded during a DVJ and hence, the validity scores cannot be generalizable to other dynamic tasks. Third, only the FPPA for the right leg was calculated. While this was appropriate for the purpose of this study, it may be recommended that future studies assess both legs because an asymmetry in knee abduction angle between sides was found to be a predictor of ACL injury status[60].

5.7. Conclusions

The main findings of the current study indicate that, unlike FPPA, the KASR but preferable KMD measures calculated during a bilateral DVJ task and using a 2D video analysis procedure might be considered as valid and feasible alternatives to their respective 3D criterion for quantifying the frontal plane knee alignment of asymptomatic futsal players. Likewise, the results of this study also support the use of 2D video analysis procedures to quantify the hip and knee flexion ROM during the landing phase of a DVJ. However, different cut-off values need to be established in order to detect altered or abnormal frontal plane knee alignment and sagittal plane movement patters from the KASR and hip flexion ROM measures calculated using 2D videos analysis procedures, respectively.

CHAPTER 6

Study 4

A field-based approach to determine soft tissue injury risk in elite futsal using novel machine learning techniques

Iñaki Ruiz-Pérez, Alejandro López-Valenciano, Sergio Hernández-Sánchez, José M. Puerta-Callejón, Mark De Ste Croix, Francisco Ayala

Under review in Journal of Sports Sciences

CHAPTER 6

Study 4

A field-based approach to determine soft tissue injury risk in elite futsal using novel machine learning techniques

Iñaki Ruiz-Pérez, Alejandro López-Valenciano, Sergio Hernández-Sánchez, José M. Puerta-Callejón, Mark De Ste Croix, Francisco Ayala

6.1. Abstract

Objective: Lower extremity non-contact soft tissue (LE-ST) injuries are prevalent in elite futsal. The purpose of this study was to analyze and compare the individual and combined ability of several measures obtained from questionnaires and field-based tests to prospectively predict LE-ST injuries after having applied a range of supervised Machine Learning techniques.

Method: One hundred and thirty-nine elite futsal players underwent a pre-season screening evaluation that included individual characteristics; measures related to sleep quality, athlete burnout, psychological characteristics related to sport performance and self-reported perception of chronic ankle instability. A number of neuromuscular performance measures obtained through three field-based tests (isometric hip strength, dynamic postural control [Y-Balance] and lower extremity joints range of motion [ROM-Sport battery]) were also recorded. Injury incidence was monitored over one competitive season.

Results: There were 25 LE-ST injuries. Only those groups of measures from two of the field-based tests (ROM-Sport battery and Y-Balance), as independent data sets, were able to build robust models (area under the receiver operating characteristic curve [AUC] score ≥ 0.7) to identify elite futsal players at risk of sustaining a LE-ST injury. Unlike the measures obtained from the five questionnaires selected, the neuromuscular performance measures

did build robust prediction models (AUC score ≥ 0.7). The inclusion in the same data set of the measures recorded from all the questionnaires and field-based tests did not result in models with significantly higher performance scores.

Conclusions: The models developed might help coaches, physical trainers and medical practitioners in the decision-making process for injury prevention in futsal.

Key words: Injury prevention, modeling, screening, decision-making, algorithm, decision tree

6.2. Introduction

Despite the substantive efforts made by the scientific community and sport practitioners, lower extremity non-contact soft tissue (muscle, tendon and ligament) (LE-ST) injuries are very common events in intermittent team sports such as soccer[71], futsal[72], rugby[73], bat (i.e. cricket and softball) and stick (i.e. field hockey and lacrosse) sports[74]. One of the main reasons that has been suggested to explain why LE-ST injury rates are still high is that none of the currently available screening models (based on potential risk factors), designed to identify athletes at high risk of suffering a LE-ST injury, have adequate predictive properties (i.e. accuracy, sensitivity and specificity)[27].

Perhaps the lack of available valid screening models to predict LE-ST injuries could be attributed to the use of statistical techniques (e.g.: traditional logistic regression) that have not been specifically designed to deal with class imbalance problems, such as the LE-ST injury phenomenon, in which the number of injured players (minority class) prospectively reported is always much lower than the non-injured players (majority class)[75–78]. Thus, in many scenarios including LE-ST injury, traditional screening models are often biased (for many reasons) towards the majority class (known as the "negative" class) and therefore there is a higher misclassification rate for the minority class instances (called the "positive" examples). Other issue with the current body of the literature is that the external validity of the screening models available may be limited because they are built and validated using the same date set (i.e. cohort of athletes). Apart from resulting in overly optimistic models´ performance scores, this evaluation approach does not indicate the true ability of the models to predict injuries in different data sets or cohort of athletes, which may be very low and consequently, not acceptable for injury prediction purposes. This appears to be supported by the fact that the injury predictors identified by some prospective studies have not been replicated by others using similar designs and assessment methodologies but with different samples of athletes[28,31,32,40,47,49,79–81]. These limitations have led some researchers to suggest that injury prediction may be a waste of time and resources[27].

In Machine Learning and Data Mining environments, some methodologies (e.g.: pre-processing, cost-sensitive learning and ensemble techniques) have been specially designed to deal with complex (i.e. non-lineal interactions among features or factors), multifactorial and class imbalanced scenarios[75–78]. These contemporary methodologies along with the use of resampling methods to assess models´ predictive power (i.e., cross-validation, bootstrap and leave-one-out) may overcome the limitations inherent to the current body of knowledge and enable the ability to build robust, interpretable and generalizable models to predict LE-ST injuries. In fact, recent studies have used these contemporary methodologies and resampling methods as alternatives to the traditional logistic regression techniques to predict injuries in elite team sport athletes[82]. Unlike previous studies that used traditional logistic regression techniques to build prediction models[47,81,83–88], most of these recent studies[29,30,89–93], although not all[50,94], have reported promising results (area under the receiver operator characteristics [AUC] scores > 0.700) to predict injuries.

However, one of the main limitations of most of these models built by the application of modern Machine Learning techniques lies in the fact that their use seems to be restricted to research settings (and not to applied environments) because sophisticated and expensive instruments (e.g.: isokinetic dynamometers, force platforms and GPS devices), qualified technicians and time-consuming testing procedures are required to collect such data. To the authors´ knowledge, there is only one study that has built a robust screening model using Machine Learning techniques (extreme gradient boosting algorithms) with data from field-based tests. Rommers et al.[95] built a model to predict injury in elite youth soccer players based on preseason anthropometric (stature, weight and sitting height) and motor coordination and physical fitness (strength, flexibility, speed, agility and endurance) measures obtained through field-based tests and reported an AUC score of 0.850.

If Machine Learning techniques could build "user friendly" models with adequate predictive properties and exclusively using data obtained from questionnaires and / or cost-effective, technically undemanding and time-efficient field-based tests, then injury prediction would not be a waste of time and resource in applied settings. In case these techniques provided a trustworthy positive response, coaches, physical trainers and medical practitioners may know whether any of the currently available questionnaires and field-based tests to predict injuries itself works and a hierarchical rank could be developed based on their individual predictive ability of those that showed reasonably high AUC, TP and TN scores. Furthermore, this knowledge might be used to analyze the cost-benefit (balance between the time required to assess a single player and the predictive ability of the measures recorded) of including measures in the screening sessions for injury prediction.

Therefore, the main purpose of this study was to analyze and compare the individual and combined ability of several measures obtained from different questionnaires and field-based tests to prospectively predict LE-ST injuries after having applied supervise Machine Learning techniques in elite male and female futsal players.

6.3. Method

To conduct this study, guidelines for reporting prediction model and validation studies in Health Research (Transparent Reporting of a multivariable prediction model for Individual Prognosis or Diagnosis [the TRIPOD statement]) were followed[222]. The TRIPOD checklist is presented in Appendix 6.1.

6.3.1. Participants

A convenience sample of 139 (72 [age: 22.5 ± 5.2 y, stature: 1.75 ± 0.7 m, body mass: 72.9 ± 6.9 kg] males and 67 [age: 22.4 ± 5.5 y, stature: 1.64 ± 0.5 m, body mass: 59.4 ± 5.1 kg] females) elite futsal players from 12 different teams (56 players [24 males and 32 females] from six club engaged in the First [top] National Spanish Futsal division and 83 players [48 males and 35 females] from six clubs engaged in the Second National Futsal division) completed this study. Elite futsal players were selected in this study because a recent published meta-analysis on injury epidemiology reported that this sport present high incidence rates of injuries (5.3 injuries per 1000 hours of players exposure)[72] and hence, urgent preventive measures are needed.

To be included in this study, all players had to be free of pain at the time of the study and currently involved in futsal-related activities. Players were excluded if: a) they reported the presence of orthopedic problems that prevented the proper execution of one or more of the neuromuscular performance tests or (b) were transferred to another club and were not available for follow up testing at the end of 9-months. Only first injuries were used for any player sustaining multiple LE-ST injuries. The study was conducted at the end of the pre-season phase in 2015 (39 players from four teams), 2016 (44 players from four teams), 2017 (30 players from three teams) and 2018 (26 players from two teams) (September). Before any participation, experimental procedures and potential risks were fully explained to the players and coaches in verbal and written form and written informed consent was obtained from players. An Institutional Research Ethics committee approved the study protocol prior to data collection (DPS.FAR.01.14) conforming to the recommendations of the Declaration of Frontera.

6.3.2. Study design

A prospective cohort design was used to address the purpose of this study. In particular, all LE-ST injuries accounted for within the 9 months following the initial testing session (in-season phase) were prospectively collected for all players.

Players underwent a pre-season evaluation of a number of personal, psychological, self-perceived chronic ankle instability and neuromuscular performance measurements, most of them considered potential sport-related injury risk factors. In each futsal team, the testing session was conducted at the end of the pre-season phase or beginning (within the first three weeks) of the in-season phase of the year. The testing session was divided into three different parts. The first part of the testing session was used to obtain information related to the participants' personal or individual characteristics. The second part was designed to assess psychological measures related to sleep quality, athlete burnout and psychological characteristics related to sport performance. The subjective perception of each player regarding his/her chronic ankle joints instability was also recorded in this second part. Finally, the third part of the session was used to assess a number of neuromuscular performance measures through three field-based tests. Each of the four testers who took part in this study had more than six years of experience in athletes′ screening assessment.

6.3.3. Personal or individual measures

The ad hoc questionnaire designed by Olmedilla, Laguna, & Redondo[223] was used to record personal or individual measures that have been defined as potential non-modifiable risk factors for sport injuries. In this questionnaire sport-related background (player position [goalkeeper or outfield player], current level of play [First or Second division], dominant leg [defined as the player's kicking leg]) and demographic (sex, age, body mass and stature) measures were recorded. In addition, the presence within the last season (yes or no) of LE-ST injuries with total time taken to resume full training and competition > 8 days were also recorded (self-reported).

Appendix 6.2 displays a description of the personal risk factor recorded.

6.3.4. Psychological risk factors

Sleep quality, athlete burnout and psychological characteristics related to sport performance measures were measured through three validated and widely used Likert scales. The Spanish version of the Karolinska Sleep Diary[224] was used to measure the sleep quality of players. The Spanish version of the Athlete Burnout Questionnaire[225] was used to assess the three different dimensions that comprise athlete burnout: (a) physical/emotional exhaustion, (b) reduced sense of accomplishment and (c) sport devaluation. The Spanish version of the Psychological Characteristics Related to Sport Performance Questionnaire designed by Gimeno, Buceta & Pérez-Llanta[226] was used to assess five different factors: (a) stress control, (b) influence of sport evaluation, (c) motivation, (d) mental skills and (e) group / team cohesion.

Appendix 6.3 displays a description of the psychological risk factor recorded.

6.3.5. Self-perceived chronic ankle instability

The subjective perception of chronic ankle instability was measured using the Cumberland Ankle Instability Tool (CAIT). The CAIT has been shown to be a simple, reliable, and valid questionnaire for discriminating and measuring the severity of functional ankle instability[227]. The final score was discretized into three categories of severity following the thresholds suggested by De Noronha et al.[99]: severe instability (< 22 points), moderate instability (from 22 to 27 points) and minor or no instability (> 27 points).

6.3.6. Neuromuscular risk factors

Prior to the neuromuscular risk factor assessment, all participants performed the dynamic warm-up designed by Taylor et al.[210]. The overall duration of the entire warm-up was approximately 15–20 min. The assessment of the neuromuscular risk factors was carried out 3–5 min after the dynamic warm-up.

Neuromuscular capability was determined from two different performance field-based tests: 1) isometric hip abduction and adduction strength test[228] and 2) Y-Balance test (dynamic postural control)[229]. The ROM-Sport field-based battery was also carried out to assess players´ lower extremity joints range of motion[230].

For a matter of space, the testing maneuvers are not described below, and the reader is to refer to their original sources. Furthermore, appendixes 6.4 to 6.6 display a description of the three field-based testing maneuvers carried and the measures recorded from each of them.

The order of the tests was consistent for all participants and was established with the intention of minimizing any possible negative influence among variables. A 5-min rest interval was given between consecutive testing maneuvers.

6.3.7. Injury Surveillance

For the purpose of this study, an injury was defined as any non-contact, soft tissue (muscle, tendon and ligament) injury sustained by a player during a training session or competition which resulted in a player being unable to take a full part in future football training or match play[231].

These injuries were confirmed by team doctors. Players were considered injured until the club medical staff (medical doctor or physiotherapist) allowed for full participation in training and availability for match selection. Only thigh muscle (hamstrings, quadriceps and adductors) and knee and ankle ligament injuries were considered for the analysis as these injuries are more likely to be preventable and influenced by the investigated variables.

The team medical staff of each club recorded LE-ST injuries on an injury form that was sent to the study group each month. For all LE-ST injuries that satisfied the inclusion criteria, team medical staff provided the following details to investigators: thigh muscle (hamstrings, quadriceps and adductors), knee or ankle ligament, leg injured (dominant/nondominant), injury severity based on lay-off time from futsal [slight/minimal (0–3 d), mild (4–7 d), moderate (8–28 d), and severe (>28 d)], date of injury, moment (training or match), whether it was a recurrence (defined as a soft tissue injury that occurred in the same extremity and during the same season as the initial injury) and total time taken to resume full training and competition. At the conclusion of the 9-month follow-up period, all data from the individual clubs were collated into a central database, and discrepancies were identified and followed up at the different clubs to be resolved. Some discrepancies among medical staff teams were found to diagnose minimal LE-ST injuries and to record their total time lost. To resolve these inconsistencies in the injury surveillance process (risk of misclassification of the players), only ST-LE injuries showing a time lost of >8 d (moderate to severe) were selected for the subsequent statistical analysis.

6.3.8. Statistical analysis

After having completed an exhaustive data cleaning process (detected outliers were removed using boxplots [16 cases] and missing data [2.3%] were replaced by the mean value of the corresponding variable according to the sex [male or female] of the players) we had an imbalanced (showing an imbalance ratio of 0.22) and a high-dimensional data set comprising of 72 male and 67 female futsal players (instances) and 66 potential risk factors (features).

Previous studies have documented that the discretization of continuous variables may be an effective measure to improve the performance of some classifiers[232]. Therefore, and before the data processing stage was carried out, continuous variables were discretized using the unsupervised discretization algorithm available in Weka repository, selecting the option "optimize the number of equal-width bins" (a maximum of 10 bins were allowed per variable) through a leave-one-out cross validation technique.

Afterward, eleven data sets were built. In particular, five data sets were built using the personal (data set [DS] 1 – personal variables), psychological (DS 2 – sleep quality, DS 3 – athlete burnout and DS 4 – psychological characteristics related to sport performance) and self-perceived (DS 5 – player´s self-perceived chronic ankle joint stability) measures recorded from each of the five questionnaires selected in this study. Likewise, three data sets were also built using the data from each of the three field-based tests carried out (DS 6 – ROM-Sport battery, DS 7 – isometric hip abduction and adduction strength test and DS 8 – Y-Balance test). Finally, three extra data sets were built, one that grouped all the measures obtained from the questionnaires (DS 9 – questionnaire-based personal, psychological and self-perceived measures), another one that included all the neuromuscular performance measures recorded from the field-based tests (DS 10 – neuromuscular performance measures from field-based tests) and finally one that contained all personal, psychological, self-perceived chronic ankle instability and neuromuscular performance measures (DS 11 – global).

Due to the fact that this study addressed a class imbalance problem, the taxonomy for external (resampling techniques), internal (ensemble techniques) and cost-sensitive methods for learning with imbalanced data sets proposed by Galar et al.[76] and Lopez et al.[78] was applied in each data set. Furthermore, this taxonomy was implemented with the approach recently proposed by Elkarami et al.[233] because of the good results (in term of predictive performances) showed to handle imbalanced data sets.

Four classifiers based on different paradigms, namely decision trees with C4.5[234] and ADTree[235], Support Vector Machines with SMO[236] and the well-known k-Nearest Neighbor (KNN)[237] as an Instance-Based Learning approach were selected to be used in the resampling, ensemble and cost-sensitive learning methodologies as base classifiers. The configuration of each base classifier was optimized through the use of the metaclassifier MultiSearch (it performs a search of an arbitrary number of parameters of a classifier and chooses the best pair found for the actual filtering and training) with the AUC score as evaluation criterion for evaluate classifier performance) (C4.5: confidence factor [from 0.05 to 0.75], ADTree: number of interactions [from 5 to 50], SMO: complexity [from 1 to 10] and ridge [from -10 to 5], KNN: number of neighbors [from 1 to 5]).

A description of the resampling, ensemble and cost-sensitive learning algorithms selected in this study has been written in the appendix 6.7

Due to the high dimensionality of the DS 10 - neuromuscular measures from field-based tests (47 variables) and DS 11 - Global (66 variables), before running the algorithms included in the taxonomy just described, a feature selection process was carried out in order to help base classifiers to reduce the feature space and eliminate irrelevant, weakly relevant and/or redundant features. In particular, we used the metaclassifier "attribute selected classifier" available in Weka´s repository to address this issue. In this sense, we selected as attribute evaluator the classify subset evaluator filter[238] because it extracts features from the data without any learning involved, which avoids any risk of overfitting the models and the GreedyStepwise as search technique (It performs a conservative greedy forward search through the space of attribute subsets).

To evaluate the performance of the algorithms, the fivefold stratified cross-validation technique was used[239]. That is, we split the data set into five stratified folds maintaining the class distribution, each one containing 20% of the patterns of the data set. For each fold, the algorithm was trained with the examples contained in the remaining folds (111 or 112 instances) and then tested with the current fold (n = 27 or 28 instances). This value is set up with the aim of having enough positive class instances in the different folds, hence avoiding additional problems in the data distribution. Because K-fold cross validation is based on random splitting of the data, there is also variation in the K-fold validation estimates[240,241]. Therefore, the fivefold stratified cross validation was repeated a hundred times and results were averaged over the runs to obtain a more reliable estimate for the generalization ability.

The AUC was used as a measure of a classifier´s performance for evaluating which models showed high (0.90–1.00), moderate (0.70-0.90 low (0.50-0.70) and fail (<50) scores[242]. Only those algorithms whose performance scores (AUC) were higher than 0.70 were considered as acceptable for the purposes of this study and included in the intra and inter dataset comparisons analyses. Furthermore, two extra measures from the confusion matrix were also used as evaluation criteria: (a) TP rate = TP / (TP + FN) also called sensitivity or recall, is the proportion of actual positives that are predicted to be positive, and (b) TN rate = TN / (TN + FP) or specificity, that is, the proportion of actual negatives that are predicted to be negative. In imbalanced domains, when the AUC has reached a high score (> 0.70), the classification performance may not be as perfect as the AUC value reflects because plenty of "trash" negative samples exist in the dataset. These trash negative samples may raise the AUC value, but a few other negative samples remain mixed with the positive samples, which are difficult to distinguish. These few remaining negative samples may diminish performance, including precision and recall, while very slightly influencing the

AUC score. Consequently, Zou et al.[243] suggest to employ the F-score together with the AUC as a classification measurement for imbalanced problems. The F-score is a trade-off between precision [P = TP / (TP + FP)] and recall (R).

In order to compare the performance of the algorithms ran in each data set (intra data set comparisons) and whose AUC scores were > 0.70, the F score was selected as criterion measure. These comparisons were conducted using separate Bayesian inference analyses. The Bayesian factor (BF_{10}) was used to quantify the relative degree of evidence for supporting the null hypothesis (H_0 = no differences across algorithms´ performance scores) or alternative hypothesis (H_1 = presence of differences across algorithms' performance scores[244,245]). The BF_{10} was interpreted using the evidence categories suggested by Lee & Wagenmakers[246]: $< \frac{1}{100}$ = extreme evidence for H_0, from $\frac{1}{100}$ to $< \frac{1}{30}$ = very strong evidence for H_0, from $\frac{1}{30}$ to $< \frac{1}{10}$= strong evidence for H_0, from $\frac{1}{10}$ to $< \frac{1}{3}$ = moderate evidence for H_0, from $\frac{1}{3}$ to <1 anecdotical evidence for H_0, from 1 to 3 = anecdotical evidence for H_1, from >3 to 10 = moderate evidence for H_1, from >10 to 30 = strong evidence for H_1, from > 30 to 100 = very strong evidence for H_1, > 100 extreme evidence for H_1. In those data sets in which (at least) a strong evidence for rejecting H_0 was found (BF_{10} >10), a post hoc procedure was carried out to identify the best performing model. In the cases in which either there would not be a strong evidence for rejecting H_0 or a group of algorithms showed the highest F-score results (without any relevant difference [BF_{10} < 10] among then), the best-performing algorithm for this dataset would be the one that showed the highest F-scores.

Finally, the best performing algorithm of each of the data sets were compared (inter dataset comparisons) using the same statistical approach in order to know which questionnaire, field-based test or combination showed the best ability to predict moderate LE-ST injuries in elite male and female futsal players.

6.4. Results

6.4.1. Soft-tissue lower extremity injuries epidemiology

There were 31 (16 in males and 15 in females) soft tissue injuries over the follow-up period, 17 (54.8%) of which corresponded to thigh muscles (seven hamstrings, four quadriceps and six adductors) injuries, eight (25.8%) to knee ligament and six (19.3%) to ankle ligament. Injury distribution between the legs was 74.1% dominant leg and 25.9% nondominant leg. A total of 13 injures occurred during training and 18 during competition. In terms of severity, most injures were categorized as moderate (n = 23), whereas only eight cases were considered severe injuries (five anterior cruciate ligament injuries). Five players sustained multiple soft tissue non-contact lower extremity injuries during the observation period, so their first injury was used as the index injury in the analyses. Consequently, 25 soft-tissue injuries were finally used to develop the prediction models.

6.4.2. Prediction models for soft tissue lower extremity injuries

6.4.2.1. Intra data set comparisons

As displayed in the appendixes 6.8 to 6.18, only four (DS 6 – lower extremity joint ranges of motion, DS 8 – dynamic postural control, DS 10 – neuromuscular performance measures from field-based tests and DS 11 – Global) out of 11 data sets resulted in the ability of the classification algorithms to build prediction models for LE-ST injuries with AUC scores ≥ 0.7.

For the DS 6 - lower extremity joint ranges of motion, a total of 23 learning algorithms showed AUC scores ≥ 0.7. The Bayesian inference analysis carried out with these 23 algorithms (Bayesian ANOVA) reported the presence of relevant differences (BF_{10} > 100 [extreme evidence for supporting H_1]) among their prediction performance scores. The subsequent post hoc analysis identified a sub-group of four algorithms whose F-scores were similar among them (F-scores ranging from 0.422 to 0.450) and also statistically higher (BF_{10} >10) than the rest. Among these four algorithms, the one that showed the highest F-score was the CS-Classifier technique with ADTree as base classifier (table 1). In particular, this model generated by the CS-Classifier technique with ADTree as base classifier was comprised for just an ADTree decision tree whose size or total number of nodes was 88 and its number of leaves or predictor nodes was 59 (figure 1).

Table 6.1. Features selected (displayed for order of importance) after having applied the classify subset evaluator filter to the data sets (DS) 10 and 11

Neuromuscular measures from field-based tests (DS – 10)
ROM-HF_{KE} [dominant leg]
ROM-$AKDF_{KE}$ [dominant leg]
ROM- $AKDF_{KF}$ [dominant leg]
ROM-BIL- HABD
Global (DS – 11)
ROM-HF_{KE} [dominant leg]
ROM-$AKDF_{KE}$ [dominant leg]
ROM- $AKDF_{KF}$ [dominant leg]
ROM-BIL- HABD
Self-perceived chronic ankle instability [non-dominant leg]
History of lower extremity soft tissue injury last season

ROM: range of motion; HF_{KE}: hip flexion with the knee extended; HABD: hip abduction at 90º of hip flexion; $AKDF_{KE}$: ankle dorsi-flexion with the knee extended; $AKDF_{KF}$: ankle dorsi-flexion with the knee flexed; BIL: bilateral ratio.

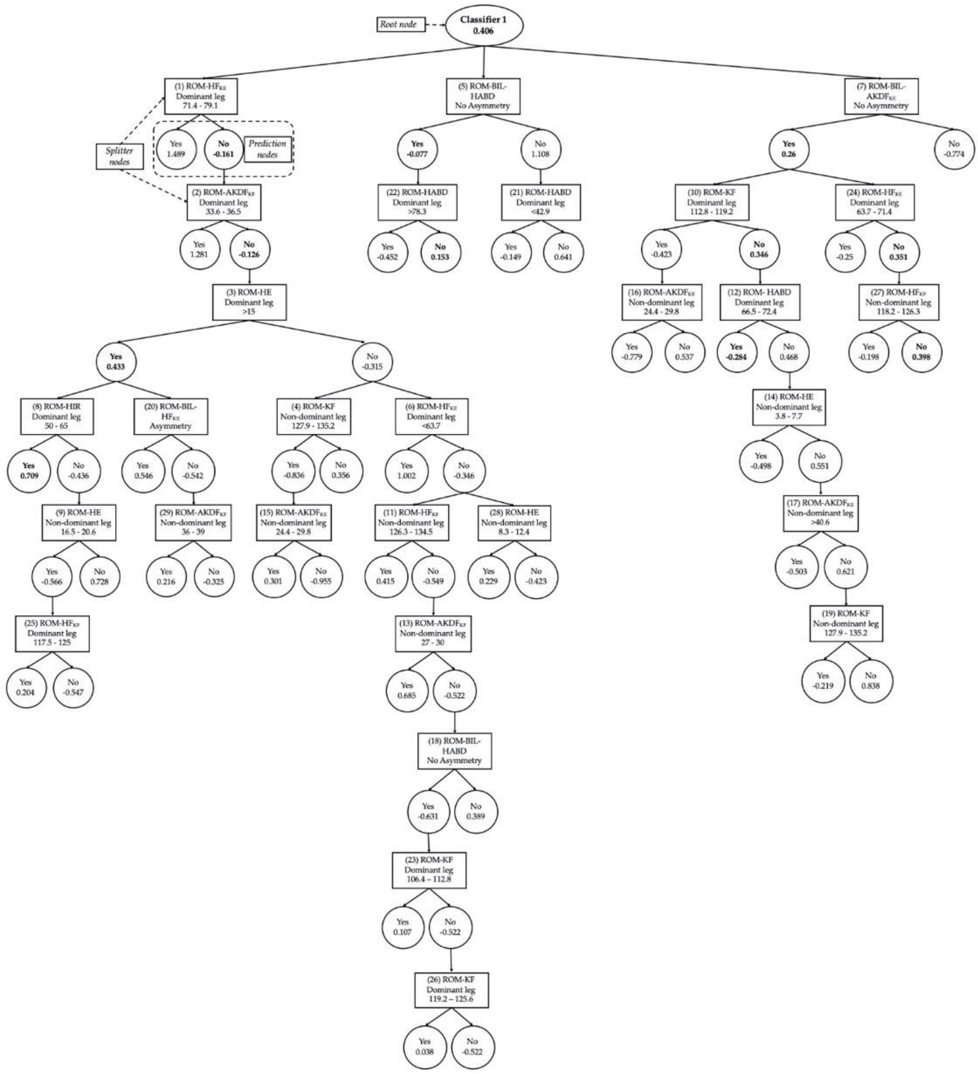


Figure 6.1. Graphical representation of the first classifier of the DS 6 (lower extremity joint ranges of motion). Prediction nodes are represented by ellipses and splitter nodes by rectangles. Each splitter node is associated with a real valued number indicating the rule condition, meaning: If the feature represented by the node satisfies the condition value, the prediction path will go through the left child node; otherwise, the path will go through the right child node. The numbers before the feature names in the prediction nodes indicate the order in which the different base rules were discovered. This ordering can to some extent indicate the relative importance of the base rules. The final classification score

produced by the tree is found by summing the values from all the prediction nodes reached by the instance, with the root node being the precondition of the classifier. If the summed score is greater than zero, the instance is classified as true (low risk of LE-ST injury).

For its part, the DS 8 – dynamic postural control only allowed to the class-balanced ensemble CS-UBAG with C4.5 as base classifier building a model with AUC scores ≥ 0.7 (AUC = 0.701 ± 0.112). In this sense, this model is comprised for 100 different C4.5 decision trees (figure 2 shows an example of one of these C4.5 decision trees, the rest can be got upon request to the authors).

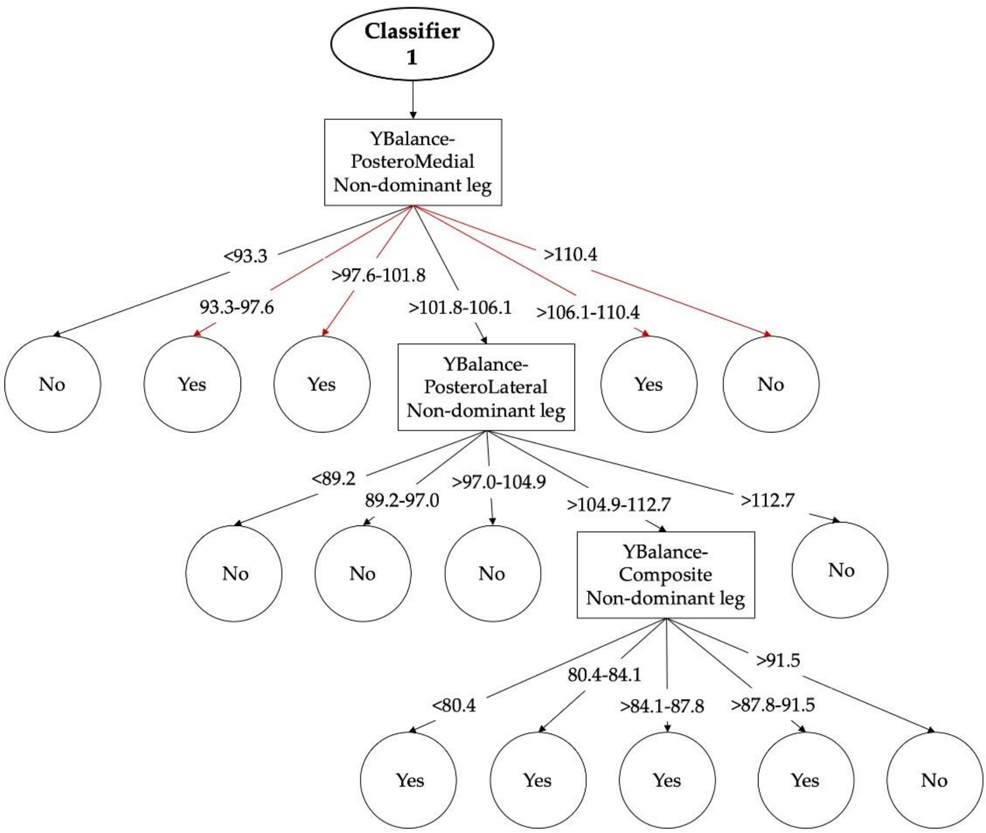


Figure 6.2. Graphical representation of the first classifier of the DS 8 (dynamic postural control). The arrows show the single pathway (transverse to the tree) through the classifier

that should be followed according to participant´s scores in order to achieve a dichotomic output (high [Yes] or low [No]) risk of LE-ST injury.

The feature selection process carried out in the DS 10 – neuromuscular measures from field-based tests identified a subset of four ROM measures as the most relevant (considering the individual predictive ability of each feature along with the degree of redundancy among them) on which was subsequently applied the taxonomy of learning algorithms described in the method section. Thus, a total of 66 algorithms built (using this subset of features) prediction models with AUC scores ≥ 0.7. The Bayesian analysis conducted with these 66 algorithms documented the existence of relevant differences (with an extreme degree of evidence [BF_{10} > 100]) among their predictive ability scores. The subsequent post hoc analysis reported that a group of three algorithms showed similar F-scores among them (ranging from 0.458 to 0.474) but significantly higher than the rest. Therefore, the selection of the best performing algorithm of this DS 10 was based on the highest F-score. Thus, the algorithm CS-UBAG with SMO as base classifier was the one that showed the highest F-score (0.474 ± 0.111) and hence, it was selected for the inter data set comparisons. Figure 6.3 displays an example of the 100 predictors than this prediction model is comprised (the rest can be got upon request to the authors).

Classifier 1 of the field-based tests model (CS-UBAG [SMO])

Equation → $f(x) = (w_1x_1 + ... + w_dx_d) + b = \langle w,x \rangle + b$

1. (0.999 * [normalized] ROM-HF$_{KE}$ dominant leg [< 63.7]) +
2. (-1.0003 * [normalized] ROM-HF$_{KE}$ dominant leg [63.7 - 71.4]) +
3. (1.0007 * [normalized] ROM-HF$_{KE}$ dominant leg [71.4 – 79.1]) +
4. (-0.9994 * [normalized] ROM-HF$_{KE}$ dominant leg [>79.1]) +
5. (-0.002 * [normalized] ROM-AKDF$_{KE}$ dominant leg [>44.5]) +
6. (1.3336 * [normalized] ROM-AKDF$_{KF}$ dominant leg [< 30]) +
7. (-0.6663 * [normalized] ROM-AKDF$_{KF}$ dominant leg [30 – 40]) +
8. (-0.6673 * [normalized] ROM-AKDF$_{KE}$ dominant leg [>40]) +
9. (1.9992 * [normalized] ROM-BIL- HABD [Asymmetry]) +

0.6668 (b)

Classification:

- Negative score = Yes
- Positive score = No

Normalized: scale from 0 to 1, ROM: range of motion, HF: hip flexion, KE: knee extension, KF: knee flexion, BIL: bilateral ratio, AKDF: ankle dorsiflexion, HABD: hip abduction.

Figure 6.3. Description of the first classifier of the DS 10 (field-based tests).

The DS 11, that comprised of the 66 personal (n = 8), psychological (n = 9), self-perceived chronic ankle instability (n = 2) and neuromuscular performance (47) features was reduced to a subset of six features by the feature selection metaclassifier selected, from which four were ROM measures, one was a self-perceived chronic ankle instability measure and the last one belonged to the group of personal measures (table 2). This sub-set of features allowed 59 algorithms building prediction models showing AUC scores ≥ 0.7. Finally, and it is showed in the table 1, the Bayesian inference and the subsequent post hoc analyses identified the class-balanced ensemble CS-UBAG with C4.5 as base classifier as the best-performing algorithm (AUC = 0.749 ±0.105, TP rate = 75.5% ±23.6, TN rate = 62.7 ±11.5, F-score = 0.436 ±0.122). An example of the 100 C4.5 decision trees that comprised this model is presented in figure 6.4.

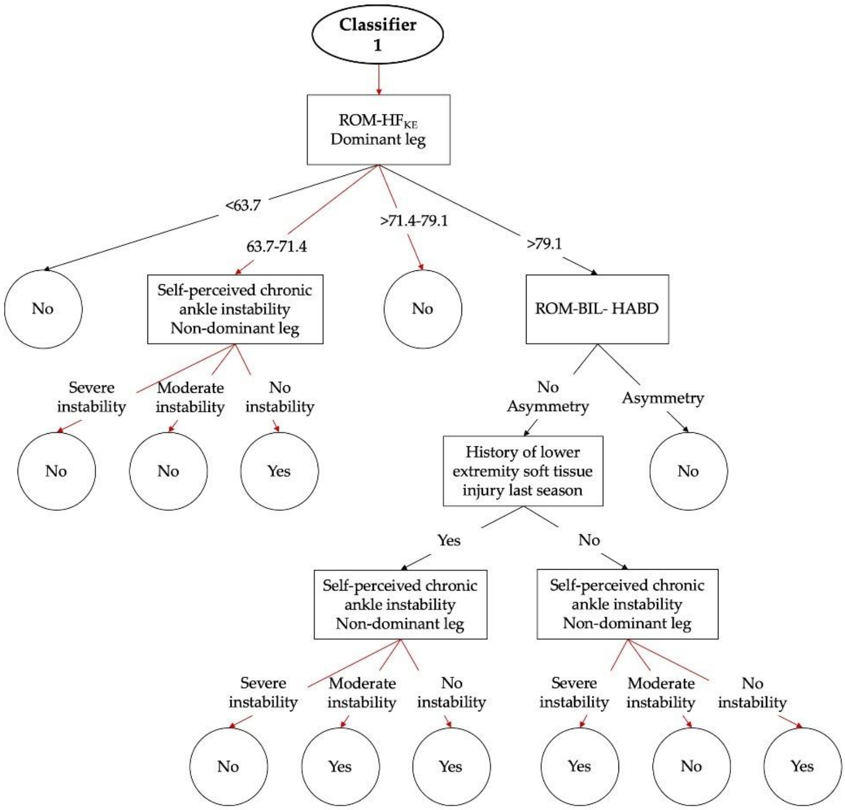


Figure 6.4. Graphical representation of the first classifier of the DS 11 (global). The arrows show the single pathway (transverse to the tree) through the classifier that should be followed according to participant´s scores in order to achieve a dichotomic output (high [Yes] or low [No]) risk of LE-ST injury.

Table 6.2. Best-performing sub-set of algorithms for those data sets (DS) that allowed building prediction models with AUC scores ≥0.7. Highlighted in bold are the algorithms selected in each DS for the posterior inter-group comparative analysis

Technique	Performance measures							
	AUC		TP rate (%)		TN rate (%)		F-score	
	Lower extremity joint ranges of motion (DS – 6)							
ADTree	0.754	±0.122	35.8	±21.6	93.4	±6.3	0.433	±0.195
ROS [ADTree]	0.745	±0.126	46.1	±23.5	87.4	±8.3	0.442	±0.188
CS-Classifier [ADTree]	**0.757**	**±0.124**	**44.7**	**±23.2**	**89.1**	**±8.4**	**0.450**	**±0.184**
CS-UBAG [ADTree]	0.737	±0.106	48.3	±21.5	83.0	±8.1	0.422	±0.161
	Dynamic postural control (DS – 8)							
CS-UBAG [C4.5]	**0.701**	**±0.114**	**64.9**	**±21.1**	**63.3**	**±10.4**	**0.388**	**±0.109**
	Neuromuscular measures from field-based tests (DS – 10)							
CS-OBAG [SMO]	0.760	±0.103	83.3	±22.9	62.9	±10.0	0.469	±0.115
CS-UBAG [C4.5]	0.748	±0.089	87.6	±20.3	57.2	±10.7	0.458	±0.100
CS-UBAG [SMO]	**0.767**	**±0.096**	**85.1**	**±21.4**	**62.1**	**±9.8**	**0.474**	**±0.111**
	Global (DS – 11)							
OBAG [SMO]	0.742	±0.125	51.3	±25.5	79.5	±9.6	0.410	±0.179
UBAG [SMO]	0.737	±0.121	54.7	±25.6	76.3	±10.2	0.410	±0.171
CS-OBAG [C4.5]	0.751	±0.107	60.9	±28.2	73.2	±10.6	0.418	±0.163
CS-OBAG [SMO]	0.747	±0.121	65.1	±27.9	70.1	±11.3	0.423	±0.151
CS-UBAG [C4.5]	**0.749**	**±0.105**	**75.5**	**±23.6**	**62.7**	**±11.5**	**0.436**	**±0.122**
CS-UBAG [ADTree]	0.741	±0.119	62	±27.3	72	±10.4	0.419	±0.161
CS-UBAG [SMO]	0.747	±0.116	70.8	±26.1	66.5	±10.9	0.433	±0.137
CS-UBAG [IBK]	0.722	±0.124	71.8	±23.9	61.6	±12.3	0.413	±0.122
CS-SBAG [C4.5]	0.755	±0.115	55.7	±28.2	76.2	±11	0.409	±0.175
CS-SBAG [SMO]	0.750	±0.121	58.4	±27.2	74.7	±11.1	0.416	±0.164

AUC: area under the ROC curve; TP rate: true positive rate; TN rate: true negative rate.

6.4.2.2. Inter data set comparisons

The inter data set comparison analysis carried out with the best-performing algorithms of the DS 6 (CS-Classifier [ADTree]), 8 (CS-UBAG [C4.5]), 10 (CS-UBAG [SMO]) and 11 (CS-UBAG [C4.5]) showed that the algorithm of the DS 8 obtained significantly lower F-scores than the other three algorithms ($BF_{10} > 100$). However, there were no statistically differences among the algorithms from the DS 6, 10 and 11. Among these three algorithms, the one from the DS 10 demonstrated the highest F-score and was considered as the "winning model" (table 6.1). As stated before, models from DS 8, 10 and 11 are comprised by 100 classifiers. In term of practical applications, each classifier has a vote or decision (yes [high risk of LE-ST injury] or no [lower risk of LE-ST injury]), and the final decision regarding whether or not a player might suffer an injury is based on the combination of the votes of each individual classifier to each class (yes or no).

6.5. Discussion

The main findings of this study indicate that only those groups of measures from two of the field-based tests (ROM-Sport battery [AUC = 0.751 ± 0.124] and Y-Balance [AUC = 0.701 ± 0.114]), as independent data sets, can build robust models (AUC ≥ 0.7) to identify elite futsal players at risk of sustaining a LE-ST injury. One of the possible reasons why only the lower extremity ROM and dynamic postural control measures can separately build robust prediction models may be related to the fact that they play a significant role in the hazardous lower extremity movement patterns performed by futsal players. In particular the execution of numerous weight-bearing high intensity locomotive actions (e.g.: cutting, landing and sprinting) that may produce excessive dynamic valgus at the knee with limited hip and knee flexion ROMs, which have been identified as primary and modifiable LE-ST injury patterns[100,101,103,106,247,248]. The fact that the best-performing model built with the ROM data set (DS 6) showed a significantly higher prediction performance (and also less decision trees [1 vs. 100]) than its counterpart model built with the dynamic postural control data set (DS 7) (F-score = 0.450 vs. 0.388) may be due to the fact that the scores obtained thorough the Y-Balance test are widely influenced by hip and knee flexion and the ankle dorsiflexion ROM measures in the sagittal plane and to less extend by dynamic core stability (in the frontal plane) and isokinetic knee flexion strength measures[249]. Thus, the dynamic postural control measures obtained from the Y-Balance test might have allowed the construction of a model with an acceptable prediction ability mainly due to the influence of whole lower limb posterior kinetic chain ROMs in the distances reached. This hypothesis may also be supported by the fact that the feature selection process carried out in the data set in which all the neuromuscular performance measures were grouped (DS 10) and also in the data set that contained all the measures recorded in this study (DS 11) did not consider any of the dynamic postural control measures in contrast to the hip flexion and ankle dorsiflexion ROM measures that were considered LE-ST injury predictors.

Previous studies have explored the individual predictive ability of some (but not many) field-based tests (e.g.: Y-Balance[58], leg squat[83], side plank[84] and drop jump[70,250]) to identify athletes from intermittent team sports at high risk of LE-ST injury using traditional logistic regression techniques. Most of these studies have reported models exhibiting high sensitivity values (TN rates) but very low specificity values (TP rates) and hence, cannot be used for injury prediction. For example, O´Connor et al.[83] examined whether a standardized visual assessment of squatting technique and core stability can predict lower extremity injuries in a large sample of collegiate Gaelic players (n = 627). The logistic regression-based model generated revealed that while the TP rate was moderate to high (76%) the TN rate was low (44%). This circumstance reflects one of the main limitations inherent in traditional regression techniques, that is to say, they do not deal well with imbalanced data sets (their models usually are biased toward the majority class [true negative rates] to optimize the percentage of well-classified instances)[76]. Furthermore, the validation technique applied to the models generated in these studies may not be exigent enough to ensure that the phenomenon of over-fitting was minimized as the models were validated using the data from the population with whom the prediction equations were generated[27,251].

Due to their high cost (approximately 250€ per unit) currently available GPS systems may not be considered as accessible tools for most practitioners that work in applied sport settings, however, it should be noted that prediction models to identify team sport athletes (mainly soccer and rugby players) at risk of sustaining a LE-ST injury based exclusively on external training workload measures and built using learning algorithms are available[89,93,94]. However, only the model reported by[93] has shown AUC scores ≥ 0.7 after 16 weeks of data collection (AUC = 0.760). The predictive ability of the model built by Rossi et al.[93] is very similar to the predictive ability shown in our best-performing prediction model built using only lower extremity ROM measures (AUC = 0.757). Nevertheless, our prediction model based on ROM measures has a higher external validity for practitioners in applied environments due to two main aspects. Firstly, the low cost of the materials needed to conduct the assessment maneuvers (inclinometer with a telescopic arm = 200€, lumbar protection support = 50€). Secondly, our model was developed and validated using ROM measures from 139 elite futsal players from 12 different teams, whereas Rossi et al.[93] only assessed the external training workload of 26 elite soccer players all from the same team. Consequently, the model displayed by Rossi et al.[93] can only be used by the medical and performance staff of the team in which the external workload measures were collected due (among other factors) to the high inter-team differences in training and competitive calendars, drills prescribed in training sessions and tactical systems adopted throughout match play.

The results of this study also reported that the combination in the same data set (DS 9) of all the measures obtained from the five questionnaires selected did not permit classification algorithms to build prediction models with acceptable performance scores (AUC scores ranged from 0.443 to 0.558). Previous studies have documented the existence of significant associations between some personal characteristics (e.g.: age[31,32,40] and recent history of injury[28–31]), psychological constructs (e.g.: physical/emotional exhaustion, reduce sense of accomplishment, sports devaluation[52,53]) and self-perceived chronic ankle instability[227,252] measures and LE-ST injury. However, it may be possible that the magnitude of these associations between the questionnaire-based measures and LE-ST injury, neither individually nor collectively, are strong enough to build robust models with the aim of identifying elite futsal players at risk of LE-ST injury. On the contrary, the grouping in the same data set (DS 10) of all the neuromuscular performance measures obtained from the three field-based tests did permit prediction models to be built with moderate performance scores (AUC ≥ 0.7). The feature selection technique applied to this data set with the aim of reducing its dimensionality (46 features) through deleting redundant and not relevant measures (considered as noise) only selected four ROM measures, with whom the CS-UBAG method with SMO as base classifier built a prediction model with AUC and F-scores of 0.767 and 0.474, respectively. This model reported the highest performance scores, together with the fact that only two hip and two ankle ROM measures are needed to run the screen in a single player making it appropriate for applied scenarios. Finally, the inclusion in the same data set (DS 11) of all the eight groups of measures obtained from the five questionnaires and three field-based tests did not result in models with significantly higher performance scores and hence, the null hypothesis was rejected.

The prediction properties of the "model of best fit" of the current study were lower than that reported by the only other study that has used Machine Learning techniques to develop a screening model based on field-based measures (AUC = 0.767 vs 0.850, TP rate = 85% vs. 85%, TN rate = 62% vs. 85%)[95]. One of the potential reasons that may explain this difference in models´ predictive performance in favor of Rommers et al.´s[95] model can be attribute to its higher sample size (734 elite young soccer players vs. 139 elite adult futsal players) and the less rigorous resampling technique applied in its validation process (hold out with 20% of the sample [test data set] vs. 5-folds stratified cross validation). Although the predictive properties of our model are lower than Rommers et al.´s[95] model (but they are acceptable for an injury prediction standpoint), it should be highlighted that only four

ROM measures and 5 minutes are needed to run the screen in a single player, unlike Rommers et al.´s[95] model that requires 20 measures obtained from a questionnaire and five different field-based tests, which can take longer than 45 min to collect all of them in a single player.

6.6. Limitations

The current study has a number of limitations that must be acknowledged. The first potential limitation of the current study is the population used. The sport background of participants was elite futsal and the generalizability to other sport modalities and level of play cannot be ascertained. Although all the measures recorded during the screening session are purported as LE-ST injury risk factors, there are a number of other measures from different questionnaires and field-based tests not included in this study (due to time constraints) which have been associated with LE-ST injury (e.g.: back extensor [Biering-Sørensen test[253]] and flexor [Flexion-Rotation trunk test[254]] endurance measures, bilateral leg strength asymmetries [hop test battery[255]], relative leg stiffness and reactive strength index[256]) and that may have improved the ability to predict LE-ST injuries in this cohort of athletes. Despite the fact that the number of both futsal players assessed (n = 139) and LE-ST injuries recorded (n = 25) was large enough to build robust prediction models, the inclusion of more instances in the learning processes of the models may have improved their performance scores. In fact, simulations carried out in our laboratory using different percentages of the data set when creating training subsets (60, 70, 80 and 100% of the data available) showed that the learning curve did not show a plateau, hence, the inclusion of more instance in both the training and testing subsets may increase to some extent the models´ performance score. It should also be noted that the model is dependent on the predictors used in the training process, and hence, practitioners must follow the same assessment methodologies used in the current study to replicate the current results and to make it applicable in their populations. Finally, out of the 8^8 possible combinations of measures that could have been analyzed with the data from the five questionnaires and three field-based tests, only three of them were explored, from both a time perspective and based on those that would be most interesting from a practitioner perspective. Therefore, it is unknown if other combinations of measures, different from the ones analyzed in this study, may have provided prediction models with higher AUC scores.

6.7. Conclusions

Current statistical methods used to predict injury risk are limited but newer techniques that utilize machine learning approaches can provide meaningful data when exploring specific injuries. The current study has identified a range of simple, quick and easy to employ field-based measures can have good predictive power in determining LE-ST injuries in elite futsal players. Given that these field-based tests require little equipment and can be employed quickly by trained staff, they should be included as an essential component of the injury management strategy in elite futsal.

6.8. Appendixes

Appendix 6.1. TRIPOD Checklist: Prediction Model Development and Validation

Section/Topic	Item		Checklist Item	Page
Title and abstract				
Title	1	D-V	Identify the study as developing and/or validating a multivariable prediction model, the target population, and the outcome to be predicted.	183
Abstract	2	D-V	Provide a summary of objectives, study design, setting, participants, sample size, predictors, outcome, statistical analysis, results, and conclusions.	183
Introduction				
Background and objectives	3a	D-V	Explain the medical context (including whether diagnostic or prognostic) and rationale for developing or validating the multivariable prediction model, including references to existing models	185
	3b	D-V	Specify the objectives, including whether the study describes the development or validation of the model or both	187
Methods				
Source of data	4a	D-V	Describe the study design or source of data (e.g., randomized trial, cohort, or registry data), separately for the development and validation data sets, if applicable	188
	4b	D-V	Specify the key study dates, including start of accrual; end of accrual; and, if applicable, end of follow-up	189
Participants	5a	D-V	Specify key elements of the study setting (e.g., primary care, secondary care, general population) including number and location of centres.	187
	5b	D-V	Describe eligibility criteria for participants.	188
	5c	D-V	Give details of treatments received, if relevant.	-
Outcome	6a	D-V	Clearly define the outcome that is predicted by the prediction model, including how and when assessed.	191
	6b	D-V	Report any actions to blind assessment of the outcome to be predicted.	

Predictors	7a	D-V	Clearly define all predictors used in developing or validating the multivariable prediction model, including how and when they were measured.	189
	7b	D-V	Report any actions to blind assessment of predictors for the outcome and other predictors.	-
Sample size	8	D-V	Explain how the study size was arrived at.	-
Missing data	9	D-V	Describe how missing data were handled (e.g., complete-case analysis, single imputation, multiple imputation) with details of any imputation method.	192
Statistical analysis methods	10a	D	Describe how predictors were handled in the analyses.	192
	10b	D	Specify type of model, all model-building procedures (including any predictor selection), and method for internal validation.	193
	10c	V	For validation, describe how the predictions were calculated.	193
	10d	D-V	Specify all measures used to assess model performance and, if relevant, to compare multiple models.	193
	10e	V	Describe any model updating (e.g., recalibration) arising from the validation, if done.	194
Risk groups	11	D-V	Provide details on how risk groups were created, if done.	193
Development vs. validation	12	V	For validation, identify any differences from the development data in setting, eligibility criteria, outcome, and predictors.	193
Results				
Participants	13a	D-V	Describe the flow of participants through the study, including the number of participants with and without the outcome and, if applicable, a summary of the follow-up time. A diagram may be helpful.	-
	13b	D-V	Describe the characteristics of the participants (basic demographics, clinical features, available predictors), including the number of participants with missing data for predictors and outcome.	187
	13c	V	For validation, show a comparison with the development data of the distribution of important variables (demographics, predictors and outcome).	-
Model development	14a	D	Specify the number of participants and outcome events in each analysis.	187
	14b	D	If done, report the unadjusted association between each candidate	189

			predictor and outcome.	
Model specification	15a	D	Present the full prediction model to allow predictions for individuals (i.e., all regression coefficients, and model intercept or baseline survival at a given time point).	193
	15b	D	Explain how to the use the prediction model.	202
Model performance	16	D-V	Report performance measures (with CIs) for the prediction model.	appx.
Model-updating	17	V	If done, report the results from any model updating (i.e., model specification, model performance).	8-10-SInf
Discussion				
Limitations	18	D-V	Discuss any limitations of the study (such as non-representative sample, few events per predictor, missing data).	210
Interpretation	19a	V	For validation, discuss the results with reference to performance in the development data, and any other validation data.	207
	19b	D-V	Give an overall interpretation of the results, considering objectives, limitations, results from similar studies, and other relevant evidence.	207
Implications	20	D-V	Discuss the potential clinical use of the model and implications for future research.	207
Other information				
Supplementary information	21	D-V	Provide information about the availability of supplementary resources, such as study protocol, Web calculator, and data sets.	appx.
Funding	22	D-V	Give the source of funding and the role of the funders for the present study.	-

*Items relevant only to the development of a prediction model are denoted by D, items relating solely to a validation of a prediction model are denoted by V, and items relating to both are denoted D-V. We recommend using the TRIPOD Checklist in conjunction with the TRIPOD Explanation and Elaboration document.

Appendix 6.2. Description of the personal or individual injury risk factors recorded

Name	Labels
Player position	Goalkeeper or outfield player
Current level of play	1^{st} division or 2^{nd} division
Dominant leg	Right, left or two-footed
Sex	Male or female
Age	Sub21, sub23, senior (23-30 y) or veteran (> 30y)
Body mass (kg)	<50, 50-54.1, >54.1-58.2, >58.2-62.3, >62.3-66.4, >66.4-70.5 or >70.5
Stature (cm)	<148.5, 148.5-156.1, >156.1-163.7, >163.7-171.2, >171.2-178.8, >178.8-186.4 or >186.4
History of lower extremity soft tissue injury last season	Yes or no

Appendix 6.3. Description of the psychological risk factors recorded

Name	Labels
Sleep quality	<2.46, 2.46-3.02, >3.02-3.58, >3.58-4.14 or >4.14
Athlete Burnout	
a) Physical/emotional exhaustion	<1.5, 1.5-1.8, >1.8-2.1, >2.1-2.4 or >2.4
b) Reduced sense of accomplishment	<2.1 or >2.1
c) Sport devaluation	<1.3, 1.3-1.6, >(1.6-1.9, >1.9-2.2, >2.2-2.5, >2.5-2.8, >2.8-3.1, >3.1-3.4, >3.4-3.7 or >3.7
Psychological Characteristics Related to Sport Performance	
a) Stress control	<30.8, 30.8-42.6, >42.6-54.4, >54.4-66.2 or >66.2
b) Influence of sport evaluation	<20.8, >20.8-23.6, >23.6-26.4, >26.4-29.2, >29.2-32, >32-34.8 or >34.8
c) Mental skills	<13, 13-15, >15-17, >17-19, >19-21, >21-23 or >23
d) Motivation	<13.1, 13.1-15.2, >15.2-17.3, >17.3-19.4, >19.4-21.5, >21.5-23.6, >23.6-25.7 or >25.7
e) Team cohesion	<17, 17-23 or >23

Appendix 6.4. Description of the measures obtained from the isometric hip abduction and adduction strength test

Name	Labels	
	Dominant Leg	Non-Dominant Leg
PT_{ISOM}-HipAbd-Normalized	<1.64, 1.64-1.89, >1.89-2.14, >2.14-2.39, >2.39-2.63, >2.63-2.88 or >2.88	<1.85, 1.85-2.17, >2.17-2.5, >2.5-2.83, >2.83-3.16, >3.16-3.48 or >3.48
PT_{ISOM}-HipAdd- Normalized	<1.57, 1.57-1.84, >1.84-2.11, >2.11-2.37, >2.37-2.63, >2.63-2.9 or >2.9	<1.58, 1.58-1.86, >1.86-2.14, >2.14-2.42 or >2.42
UnRatio-ISOM-HipAbd/HipAdd	<0.74, 0.74-0.82, >0.82-0.91, >0.91-0.99, >0.99-1.08, >1.08-1.17, >1.17-1.25, >1.25-1.34, >1.34-1.42 or >1.42	<0.69, 0.69-0.83, >0.83-0.97, >0.97-1.11, >1.11-1.24 or >1.24
BilaRatio-PT_{ISOM}-HipAbd	No Asymmetry or Asymmetry	
BilaRatio-PT_{ISOM}-HipAdd	No Asymmetry or Asymmetry	

Bila: bilateral; Uni: unilateral; ISOM: isometric; PT: peak torque; Abd: abduction; Add: adduction.

Appendix 6.5. Description of the measures obtained from the Y-Balance test

Name	Labels	
	Dominant Leg	**No Dominant Leg**
Y-Balance-Anterior	<50.9, 50.9-55.7, >55.7-60.5, >60.55-65.4, >65.4-70.2 or >70.2	<51.3, 51.3-56.7, >56.7-62.2, >62.2-67.7, >67.7-73.1 or >73.1
Y-Balance-PosteroMedial	<83.1, 83.1-88.7, >88.7-94.4, >94.4-100.1, >100.1-105.8, >105.8-111.4 or >111.4	<93.3, 93.3-97.6, >97.6-101.8, >101.8-106.1, >106.1-110.4 or >110.4
Y-Balance-PosteroLateral	<81.7, 81.7-91.4, >91.4-101.1, >101.1-110.7 or >110.7	<89.2, 89.2-97.0, >97.0-104.9, >104.9-112.7 or >112.7
BilaRatio-Y-Balance-Anterior	No Asymmetry or Asymmetry	
BilaRatio-Y-Balance-PosteroMedial	No Asymmetry or Asymmetry	
BilaRatio-Y-Balance-PosteroLateral	No Asymmetry or Asymmetry	
Y-Balance-Composite	<78.4, 78.4-85.9, >85.9-93.3 or >93.3	<80.4, 80.4-84.1, >84.1-87.8, >87.8-91.5 or >91.5

Appendix 6.6. Description of the measures obtained from the lower extremity range of motion assessment tests

Name	Labels	
	Dominant Leg	Non-Dominant Leg
ROM-HF$_{KF}$	<117.5, 117.5-125, >125-132.5, >132.5-140, >140-147.5 or >147.5	<118.2, 118.2-126.3, >126.3-134.5, >134.5-142.7, >142.7-150.8 or >150.8
ROM-HF$_{KE}$	<63.7, 63.7-71.4, >71.4-79.1 or >79.1	<59, 59-68 or >68
ROM-HE	<0.1, 0.1-3.8, >3.8-7.7, >7.7-11.6, >11.6-15.5 or >15.5	<0.1, 0.1-4.2, >4.2-8.3, >8.3-12.4, >12.4-16.5, >16.5-20.6 or >20.6
ROM-HABD	<42.9, 42.9-48.8, >48.8-54.7, >54.7-60.6, >60.6-66.5, >66.5-72.4, >72.4-78.3 or >78.3	<46.5, 46.5-67, >67-87.5 or >87.5
ROM-HIR	<35, 35-50, >50-65 or >65	<30.9, 30.9-36.8, >36.8-42.7 or >42.7
ROM-HER	<40.8, 40.8-50.6, >50.6-60.4, >60.4-70.2 or >70.2	<42.8, 42.8-54.6, >54.6-66.4, >66.4-78.2 or >78.2
ROM-KF	<106.4, 106.4-112.8, >112.8-119.2, >119.2-125.6, >125.6-132, >132-138.4, >138.4-144.8 or >144.8	<98.4, 98.4-105.7, >105.7-113.1, >113.1-120.5, >120.5-127.9, >127.9-135.2, >135.2-142.6 or >142.6
ROM-AKDF$_{KE}$	<44.5 or >44.5	<24.4, 24.4-29.8, >29.8-35.2, >35.2-40.6 or >40.6
ROM- AKDF$_{KF}$	<24.9, 24.9-27.8, >27.8-30.7, >30.7-33.6, >33.6-36.5, >36.5-39.4, >39.4-42.3 or >42.3	<24, 24-27, >27-30, >30-33, >33-36, >36-39 or >39
ROM-BIL- HF$_{KF}$	No Asymmetry or Asymmetry	
ROM-BIL- HF$_{KE}$	No Asymmetry or Asymmetry	
ROM-BIL- HE	No Asymmetry or Asymmetry	
ROM-BIL- HABD	No Asymmetry or Asymmetry	
ROM-BIL- HIR	No Asymmetry or Asymmetry	
ROM-BIL- HER	No Asymmetry or Asymmetry	
ROM-BIL- KF	No Asymmetry or Asymmetry	
ROM-BIL- AKDF$_{KE}$	No Asymmetry or Asymmetry	
ROM-BIL- AKDF$_{KF}$	No Asymmetry or Asymmetry	

ROM: range of motion; HF$_{KF}$: hip flexion with the knee flexed; HF$_{KE}$: hip flexion with the knee extended; HE: Hip extension; HABD: hip abduction at 90º of hip flexion; HIR: hip internal rotation; HER: hip external rotation; KF: knee flexion; AKDF$_{KE}$: ankle dorsi-flexion with the knee extended; AKDF$_{KF}$: ankle dorsi-flexion with the knee flexed; BIL: bilateral ratio.

Appendix 6.7. Dascriptions' of the resampling, ensemble and cost-sensitive algorithms applied to the base classifiers.

With regard to the resampling techniques, four (two oversampling and two undersampling algorithms) of the most popular methodologies were selected, which are the synthetic minority oversampling technique (SMOTE)[257], random oversampling (ROS), random undersampling (RUS) and Wilson's edited nearest neighbor rule (ENN)[258]. In the four resampling techniques selected, a level of balance in the training data near the 40/60 was attempted. In addition, the interpolations that are computed to generate new synthetic data are made considering the k-5-nearest neighbors of minority class instances using the Euclidean distance.

Regarding ensemble learning algorithms, classic ensembles such as Bagging[259], AdaBoost[260] and AdaBoot.M1[261] were included in this study. Furthermore, the algorithm families designed to deal with skewed class distributions in data sets were also included: Boosting-based and Bagging-based. The Boosting based ensembles that were considered in the current study were SMOTEBoost[262] and RUSBoost[263]. Concerning Bagging based ensembles, it was included from the OverBagging group, OverBagging (which uses ROS)[264], UnderBagging (which uses RUS)[264] and SMOTEBagging[264]. The number of internal classifiers used within each ensemble learning algorithm was set 100 (always the same) base classifiers (C4.5, ADTree, SVM and KNN) by default.

Concerning the cost-sensitive learning algorithms, two different algorithms were used, namely MetaCost[265] and cost-sensitive classifier. Cost-sensitive learning solutions incorporating both the data (external) and algorithmic level (internal) approaches assume higher misclassification costs for samples in the minority class and seek to minimize the high cost errors. For the both cost-sensitive algorithms selected, the cox matrix set-up was to:

$c = \begin{Bmatrix} 0 & 2 \\ 1 & 0 \end{Bmatrix}$ where a false negative has a cost of 2 and false positive had a cost of 1.

The behavior of some specific combinations of class-balanced ensembles with cost-sensitive base classifiers was also studied. Finally, the algorithm Random Forest[266] in isolation and in combination with the resampling techniques was also explored due to its good results showed in previous studies[267].

For the sake of brevity and the lack of space, the code of the algorithms used in this study has not been written here. Instead, we have only specified the names and refer the reader to their original sources. Furthermore, all the classification algorithms used are available in Weka Data Mining software.

Appendix 6.8. AUC results (mean and standard deviation) of the personal or individual characteristics data set (DS 1) for the five base classifiers in isolation and after applying in them the resampling, ensemble (Classic, Boosting-based, Bagging-based and Class-balanced ensembles) and cost-sensitive learning techniques selected

Technique	Base classifiers									
	C4.5		ADTree		SMO		KNN		RF	
	AUC		AUC		AUC		AUC		AUC	
None	0.475	±0.091	0.579	±0.117	0.494	±0.016	0.504	±0.126	0.492	±0.111
Resampling Techniques										
SMOTE	0.474	±0.134	0.561	±0.123	0.488	±0.096	0.487	±0.120	0.522	±0.113
ROS	0.454	±0.117	0.570	±0.129	0.496	±0.100	0.488	±0.121	0.497	±0.114
RUS	0.495	±0.103	0.565	±0.131	0.505	±0.109	0.517	±0.129	0.490	±0.124
ENN	0.500	±0.006	0.563	±0.128	0.491	±0.027	0.505	±0.137	0.496	±0.121
Classic Ensembles										
ADB1	0.435	±0.117	0.472	±0.115	0.501	±0.101	0.476	±0.135	-	-
M1	0.454	±0.113	0.475	±0.120	0.511	±0.124	0.469	±0.109	-	-
BAG	0.496	±0.117	0.579	±0.109	0.512	±0.118	0.502	±0.120	-	-
Decorate	0.422	±0.124	0.501	±0.120	0.494	±0.016	0.433	±0.113	-	-
Boosting-based Ensembles										
SBO	0.483	±0.121	0.513	±0.122	0.509	±0.129	0.482	±0.118	-	-
RUSB	0.464	±0.124	0.486	±0.114	0.485	±0.128	0.458	±0.119	-	-
Bagging-based Ensembles										
OBAG	0.492	±0.112	0.573	±0.107	0.554	±0.116	0.483	±0.111	-	-
UBAG	0.528	±0.119	0.579	±0.106	0.568	±0.114	0.528	±0.119	-	-
SBAG	0.533	±0.112	0.583	±0.105	0.551	±0.116	0.524	±0.112	-	-
Cost-sensitive Classification										
MetaCost	0.499	±0.013	0.560	±0.117	0.485	±0.036	0.508	±0.135	-	-
CS-Classifier	0.480	±0.060	0.574	±0.122	0.474	±0.061	0.505	±0.125	-	-
Class-balanced Ensembles with a Cost-sensitive Classifier										
CS-OBAG	0.521	±0.111	0.574	±0.107	0.564	±0.116	0.485	±0.113	-	-
CS-UBAG	0.538	±0.112	0.581	±0.108	0.578	±0.114	0.528	±0.121	-	-
CS-SBAG	0.545	±0.109	0.584	±0.104	0.551	±0.116	0.523	±0.113	-	-

Appendix 6.9. AUC results (mean and standard deviation) of the sleep quality data set (DS 2) for the four base classifiers in isolation and after applying in them the resampling. ensemble (Classic, Boosting-based, Bagging-based and Class-balanced ensembles) and cost-sensitive learning techniques selected

Technique	Base classifiers									
	C4.5		ADTree		SMO		KNN		RF	
	AUC		AUC		AUC		AUC		AUC	
None	0.500	±0.000	0.458	±0.123	0.500	±0.000	0.461	±0.124	0.454	±0.122
	Resampling Techniques									
SMOTE	0.410	±0.127	0.409	±0.131	0.451	±0.092	0.409	±0.130	0.407	±0.131
ROS	0.475	±0.068	0.452	±0.131	0.492	±0.065	0.455	±0.128	0.444	±0.133
RUS	0.491	±0.044	0.459	±0.132	0.490	±0.074	0.460	±0.134	0.458	±0.134
ENN	0.500	±0.000	0.466	±0.132	0.498	±0.011	0.467	±0.134	0.463	±0.133
	Classic Ensembles									
ADB1	0.452	±0.111	0.458	±0.123	0.473	±0.088	0.458	±0.122	-	-
M1	0.454	±0.093	0.459	±0.122	0.459	±0.120	0.458	±0.122	-	-
BAG	0.485	±0.062	0.425	±0.117	0.523	±0.091	0.455	±0.122	-	-
Decorate	0.497	±0.032	0.433	±0.126	0.500	±0.000	0.451	±0.124	-	-
	Boosting-based Ensembles									
SBO	0.421	±0.126	0.421	±0.126	0.444	±0.106	0.422	±0.128	-	-
RUSB	0.461	±0.100	0.462	±0.129	0.456	±0.122	0.474	±0.126	-	-
	Bagging-based Ensembles									
OBAG	0.415	±0.119	0.407	±0.120	0.411	±0.118	0.416	±0.120	-	-
UBAG	0.477	±0.129	0.444	±0.120	0.509	±0.121	0.454	±0.122	-	-
SBAG	0.378	±0.119	0.376	±0.117	0.413	±0.117	0.375	±0.118	-	-
	Cost-sensitive Classification									
MetaCost	0.500	±0.000	0.503	±0.106	0.498	±0.012	0.576	±0.122	-	-
CS-Classifier	0.500	±0.000	0.458	±0.122	0.484	±0.030	0.461	±0.124	-	-
	Class-balanced Ensembles with a Cost-sensitive Classifier									
CS-OBAG	0.415	±0.118	0.407	±0.120	0.426	±0.118	0.416	±0.118	-	-
CS-UBAG	0.431	±0.125	0.438	±0.121	0.431	±0.121	0.433	±0.121	-	-
CS-SBAG	0.370	±0.117	0.374	±0.118	0.365	±0.115	0.373	±0.118	-	-

Appendix 6.10. AUC results (mean and standard deviation) of the Athlete Burnout data set (DS 3) for the four base classifiers in isolation and after applying in them the resampling. ensemble (Classic, Boosting-based, Bagging-based and Class-balanced ensembles) and cost-sensitive learning techniques selected

Technique	Base classifiers									
	C4.5		ADTree		SMO		KNN		RF	
	AUC		AUC		AUC		AUC		AUC	
None	0.500	±0.000	0.558	±0.127	0.495	±0.024	0.642	±0.117	0.633	±0.121
					Resampling Techniques					
SMOTE	0.543	±0.122	0.537	±0.126	0.511	±0.102	0.614	±0.114	0.598	±0.114
ROS	0.542	±0.123	0.568	±0.121	0.532	±0.102	0.642	±0.118	0.630	±0.120
RUS	0.494	±0.044	0.558	±0.123	0.525	±0.097	0.604	±0.121	0.592	±0.127
ENN	0.500	±0.000	0.553	±0.125	0.502	±0.038	0.619	±0.127	0.618	±0.128
					Classic Ensembles					
ADB1	0.577	±0.125	0.617	±0.126	0.523	±0.099	0.627	±0.127	-	-
M1	0.564	±0.123	0.615	±0.126	0.560	±0.122	0.630	±0.118	-	-
BAG	0.506	±0.106	0.579	±0.128	0.530	v0.118	0.636	±0.120	-	-
Decorate	0.521	±0.122	0.588	±0.133	0.495	±0.024	0.610	±0.124	-	-
					Boosting-based Ensembles					
SBO	0.596	±0.123	0.594	±0.126	0.570	±0.119	0.619	±0.122	-	-
RUSB	0.591	±0.122	0.612	±0.126	0.572	±0.122	0.624	±0.121	-	-
					Bagging-based Ensembles					
OBAG	0.610	±0.124	0.583	±0.126	0.588	±0.121	0.636	±0.120	-	-
UBAG	0.562	±0.133	0.577	±0.125	0.568	±0.119	0.617	±0.123	-	-
SBAG	0.585	±0.124	0.581	±0.126	0.570	±0.119	0.622	±0.116	-	-
					Cost-sensitive Classification					
MetaCost	0.500	±0.000	0.555	±0.125	0.512	±0.048	0.562	±0.138	-	-
CS-Classifier	0.500	±0.000	0.562	±0.125	0.523	±0.063	0.643	±0.118	-	-
					Class-balanced Ensembles with a Cost-sensitive Classifier					
CS-OBAG	0.592	±0.128	0.581	±0.128	0.580	±0.122	0.635	±0.119	-	-
CS-UBAG	0.564	±0.122	0.578	±0.127	0.568	±0.124	0.616	±0.125	-	-
CS-SBAG	0.583	±0.119	0.579	±0.127	0.565	±0.121	0.624	±0.116	-	-

Appendix 6.11. AUC results (mean and standard deviation) of the psychological characteristics related to sport performance data set (DS 4) for the four base classifiers in isolation and after applying in them the resampling. ensemble (Classic, Boosting-based, Bagging-based and Class-balanced ensembles) and cost-sensitive learning techniques selected

Technique	Base classifiers									
	C4.5		ADTree		SMO		KNN		RF	
	AUC		AUC		AUC		AUC		AUC	
None	0.500	±0.000	0.435	±0.122	0.492	±0.015	0.457	±0.105	0.379	±0.101
					Resampling Techniques					
SMOTE	0.458	±0.126	0.471	±0.135	0.490	±0.102	0.448	±0.116	0.417	±0.126
ROS	0.422	±0.122	0.441	±0.128	0.451	±0.090	0.458	±0.107	0.384	±0.104
RUS	0.494	±0.050	0.448	±0.132	0.450	±0.102	0.474	±0.126	0.408	±0.120
ENN	0.500	±0.000	0.450	±0.131	0.490	±0.023	0.477	±0.116	0.403	±0.111
					Classic Ensembles					
ADB1	0.419	±0.121	0.458	±0.114	0.463	±0.103	0.487	±0.105	-	-
M1	0.427	±0.125	0.446	±0.119	0.440	±0.121	0.414	±0.095	-	-
BAG	0.455	±0.115	0.431	±0.116	0.405	±0.112	0.468	±0.110	-	-
Decorate	0.487	±0.137	0.467	±0.121	0.492	±0.015	0.383	±0.120	-	-
					Boosting-based Ensembles					
SBO	0.451	±0.126	0.449	±0.123	0.452	±0.128	0.467	±0.122	-	-
RUSB	0.427	±0.121	0.435	±0.121	0.439	±0.128	0.464	±0.126	-	-
					Bagging-based Ensembles					
OBAG	0.417	±0.109	0.434	±0.117	0.440	±0.121	0.456	±0.113	-	-
UBAG	0.429	±0.113	0.430	±0.118	0.412	±0.119	0.474	±0.117	-	-
SBAG	0.436	±0.115	0.457	±0.119	0.459	±0.120	0.445	±0.115	-	-
					Cost-sensitive Classification					
MetaCost	0.500	±0.000	0.417	±0.118	0.480	±0.029	0.465	±0.105	-	-
CS-Classifier	0.500	±0.000	0.433	±0.121	0.463	±0.047	0.457	±0.105	-	-
					Class-balanced Ensembles with a Cost-sensitive Classifier					
CS-OBAG	0.426	±0.109	0.436	±0.118	0.434	±0.121	0.456	±0.113	-	-
CS-UBAG	0.437	±0.115	0.427	±0.117	0.427	±0.120	0.471	±0.115	-	-
CS-SBAG	0.447	±0.118	0.456	±0.120	0.448	±0.120	0.443	±0.116	-	-

Appendix 6.12. AUC results (mean and standard deviation) of the self-perceived chronic ankle instability data set (DS 5) for the four base classifiers in isolation and after applying in them the resampling. ensemble (Classic, Boosting-based, Bagging-based and Class-balanced ensembles) and cost-sensitive learning techniques selected

Technique	Base classifiers									
	C4.5		ADTree		SMO		KNN		RF	
	AUC		AUC		AUC		AUC		AUC	
None	0.500	±0.000	0.596	±0.108	0.497	±0.014	0.596	±0.109	0.598	±0.111
	Resampling Techniques									
SMOTE	0.572	±0.108	0.564	±0.107	0.520	±0.085	0.552	±0.108	0.556	±0.108
ROS	0.551	±0.100	0.597	±0.115	0.532	±0.079	0.592	±0.118	0.596	±0.118
RUS	0.517	±0.075	0.582	±0.118	0.530	±0.087	0.582	±0.120	0.588	±0.122
ENN	0.500	±0.000	0.590	±0.116	0.500	±0.019	0.589	±0.120	0.589	±0.120
	Classic Ensembles									
ADB1	0.595	±0.108	0.597	±0.109	0.526	±0.091	0.596	±0.110	-	-
M1	0.599	±0.113	0.595	±0.109	0.605	±0.115	0.595	±0.108	-	-
BAG	0.583	±0.111	0.600	±0.112	0.543	±0.085	0.597	±0.112	-	-
Decorate	0.519	±0.122	0.508	±0.117	0.497	±0.014	0.509	±0.118	-	-
	Boosting-based Ensembles									
SBO	0.558	±0.114	0.551	±0.112	0.559	±0.116	0.541	±0.110	-	-
RUSB	0.584	±0.111	0.593	±0.113	0.579	±0.123	0.590	±0.114	-	-
	Bagging-based Ensembles									
OBAG	0.588	±0.116	0.604	±0.114	0.604	±0.111	0.597	±0.115	-	-
UBAG	0.612	±0.118	0.599	±0.113	0.595	±0.123	0.594	±0.112	-	-
SBAG	0.567	±0.113	0.576	±0.113	0.606	±0.116	0.566	±0.115	-	-
	Cost-sensitive Classification									
MetaCost	0.499	±0.007	0.518	±0.123	0.498	±0.024	0.478	±0.126	-	-
CS-Classifier	0.501	±0.030	0.596	±0.109	0.532	±0.054	0.596	±0.110	-	-
	Class-balanced Ensembles with a Cost-sensitive Classifier									
CS-OBAG	0.589	±0.116	0.604	±0.113	0.604	±0.113	0.597	±0.115	-	-
CS-UBAG	0.608	±0.117	0.601	±0.113	0.599	±0.113	0.594	±0.114	-	-
CS-SBAG	0.555	±0.111	0.574	±0.113	0.602	±0.112	0.556	±0.113	-	-

Appendix 6.13. AUC results (mean and standard deviation) of the lower extremity joint ranges of motion data set (DS 6) for the five base classifiers in isolation and after applying in them the resampling, ensemble and cost-sensitive learning techniques selected

Technique	Base classifiers									
	C4.5		ADTree		SMO		KNN		RF	
	AUC		AUC		AUC		AUC		AUC	
None	0.629	±0.115	**0.754**	**±0.122**	0.567	±0.098	0.591	±0.125	0.690	±0.125
Resampling Techniques										
SMOTE	0.614	±0.121	**0.710**	**±0.126**	0.563	±0.101	0.601	±0.117	0.679	±0.117
ROS	0.620	±0.115	**0.745**	**±0.126**	0.567	±0.097	0.592	±0.120	**0.710**	**±0.111**
RUS	0.640	±0.122	0.692	±0.130	0.595	±0.117	0.624	±0.122	0.688	±0.121
ENN	0.602	±0.113	0.695	±0.130	0.561	±0.102	0.601	±0.126	0.674	±0.125
Classic Ensembles										
ADB1	0.602	±0.088	**0.750**	**±0.112**	0.575	±0.099	0.530	±0.121	-	-
M1	0.614	±0.092	**0.726**	**±0.121**	0.575	±0.099	0.556	±0.115	-	-
BAG	**0.742**	**±0.105**	**0.755**	**±0.110**	0.677	±0.111	0.609	±0.115	-	-
Decorate	0.681	±0.125	**0.738**	**±0.113**	0.569	±0.098	0.609	±0.124	-	-
Boosting-based Ensembles										
SBO	0.652	±0.113	0.669	±0.129	0.573	±0.098	0.577	±0.143	-	-
RUSB	0.672	±0.113	0.675	±0.128	0.616	±0.104	0.628	±0.126	-	-
Bagging-based Ensembles										
OBAG	**0.758**	**±0.088**	**0.755**	**±0.109**	0.677	±0.110	0.611	±0.114	-	-
UBAG	**0.758**	**±0.088**	**0.735**	**±0.107**	0.685	±0.107	0.652	±0.108	-	-
SBAG	**0.736**	**±0.092**	**0.735**	**±0.106**	0.681	±0.110	0.630	±0.116	-	-
Cost-sensitive Classification										
MetaCost	0.620	±0.115	**0.728**	**±0.125**	0.564	±0.096	0.605	±0.129	-	-
CS-Classifier	0.641	±0.112	**0.757**	**±0.124**	0.567	±0.098	0.500	±0.000	-	-
Class-balanced Ensembles with a Cost-sensitive Classifier										
CS-OBAG	**0.746**	**±0.083**	**0.755**	**±0.108**	0.677	±0.111	0.607	±0.113	-	-
CS-UBAG	**0.755**	**±0.086**	**0.737**	**±0.106**	0.686	±0.113	0.643	±0.114	-	-
CS-SBAG	**0.733**	**±0.089**	**0.735**	**±0.107**	0.681	±0.110	0.629	±0.116	-	-

In bold are highlighted those learning techniques that built prediction models with AUC scores >0.7.

Appendix 6.14. AUC results (mean and standard deviation) of the isometric hip abduction and adduction strength data set (DS 7) for the five base classifiers in isolation and after applying in them the resampling, ensemble (Classic, Boosting-based, Bagging-based and Class-balanced ensembles) and cost-sensitive learning techniques selected

Technique	**Base classifiers**									
	C4.5		**ADTree**		**SMO**		**KNN**		**RF**	
	AUC		**AUC**		**AUC**		**AUC**		**AUC**	
None	0.520	±0.095	0.510	±0.130	0.491	±0.040	0.614	±0.122	0.567	±0.123
Resampling Techniques										
SMOTE	0.563	±0.132	0.527	±0.135	0.479	±0.095	0.605	±0.119	0.562	±0.125
ROS	0.534	±0.117	0.522	±0.139	0.495	±0.104	0.621	±0.122	0.566	±0.123
RUS	0.539	±0.122	0.521	±0.141	0.498	±0.112	0.557	±0.139	0.558	±0.137
ENN	0.507	±0.096	0.512	±0.133	0.493	±0.055	0.591	±0.134	0.556	±0.130
Classic Ensembles										
ADB1	0.578	±0.133	0.524	±0.131	0.530	±0.118	0.600	±0.119	-	-
M1	0.569	±0.131	0.531	±0.132	0.524	±0.120	0.563	±0.122	-	-
BAG	0.501	±0.116	0.531	±0.128	0.496	±0.121	0.635	±0.124	-	-
Decorate	0.553	±0.124	0.572	±0.128	0.491	±0.040	0.568	±0.133	-	-
Boosting-based Ensembles										
SBO	0.540	±0.131	0.501	±0.132	0.521	±0.130	0.614	±0.128	-	-
RUSB	0.542	±0.134	0.533	±0.133	0.524	±0.131	0.568	±0.136	-	-
Bagging-based Ensembles										
OBAG	0.570	±0.124	0.535	±0.131	0.505	±0.118	0.638	±0.124	-	-
UBAG	0.538	±0.135	0.543	±0.129	0.501	±0.117	0.608	±0.132	-	-
SBAG	0.563	±0.122	0.531	±0.130	0.508	±0.118	0.626	±0.122	-	-
Cost-sensitive Classification										
MetaCost	0.501	±0.093	0.500	±0.135	0.494	±0.066	0.585	±0.129	-	-
CS-Classifier	0.522	±0.100	0.514	±0.130	0.492	±0.074	0.614	±0.123	-	-
Class-balanced Ensembles with a Cost-sensitive Classifier										
CS-OBAG	0.574	±0.125	0.535	±0.130	0.523	±0.118	0.637	±0.124	-	-
CS-UBAG	0.545	±0.123	0.526	±0.125	0.525	±0.119	0.608	±0.132	-	-
CS-SBAG	0.571	±0.127	0.533	±0.130	0.522	±0.117	0.628	±0.122	-	-

Appendix 6.15. AUC results (mean and standard deviation) of the dynamic postural control data set (DS 6) for the five base classifiers in isolation and after applying in them the resampling, ensemble and cost-sensitive learning techniques selected

Technique	Base classifiers									
	C4.5		ADTree		SMO		KNN		RF	
	AUC		AUC		AUC		AUC		AUC	
None	0.606	±0.127	0.644	±0.119	0.527	±0.091	0.587	±0.132	0.564	±0.133
Resampling Techniques										
SMOTE	0.634	±0.129	0.652	±0.115	0.623	±0.115	0.590	±0.138	0.571	±0.142
ROS	0.590	±0.123	0.640	±0.119	0.607	±0.117	0.564	±0.132	0.560	±0.141
RUS	0.619	±0.130	0.623	±0.127	0.601	±0.124	0.602	±0.136	0.610	±0.134
ENN	-	-	0.638	±0.128	0.533	±0.097	0.579	±0.143	0.575	±0.138
Classic Ensembles										
ADB1	0.618	±0.125	0.609	±0.130	0.578	±0.121	0.544	±0.127	-	-
M1	0.633	±0.125	0.674	±0.130	0.606	±0.121	0.564	±0.124	-	-
BAG	0.624	±0.123	0.675	±0.118	0.582	±0.127	0.591	±0.135	-	-
Decorate	0.508	±0.132	0.616	±0.133	0.518	±0.079	0.521	±0.139	-	-
Boosting-based Ensembles										
SBO	0.580	±0.135	0.574	±0.160	0.662	±0.139	0.571	±0.136	-	-
RUSB	0.594	±0.125	0.605	±0.132	0.600	±0.134	0.591	±0.136	-	-
Bagging-based Ensembles										
OBAG	0.642	±0.124	0.674	±0.122	0.630	±0.128	0.586	±0.134	-	-
UBAG	0.677	±0.115	0.677	±0.119	0.641	±0.129	0.619	±0.137	-	-
SBAG	0.641	±0.133	0.671	±0.120	0.628	±0.131	0.592	±0.140	-	-
Cost-sensitive Classification										
MetaCost	0.569	±0.113	0.659	±0.122	0.541	±0.101	0.585	±0.146	-	-
CS-Classifier	0.592	±0.126	0.644	±0.117	0.540	±0.105	0.591	±0.134	-	-
Class-balanced Ensembles with a Cost-sensitive Classifier										
CS-OBAG	0.663	±0.125	0.674	±0.120	0.647	±0.131	0.582	±0.134	-	-
CS-UBAG	**0.701**	**±0.114**	0.680	±0.117	0.657	±0.128	0.605	±0.139	-	-
CS-SBAG	0.663	±0.130	0.674	±0.120	0.638	±0.130	0.592	±0.138	-	-

In bold are highlighted those learning techniques that built prediction models with AUC scores >0.7

Appendix 6.16. AUC results (mean and standard deviation) of the measures obtained through questionnaires data set (DS 6) for the five base classifiers in isolation and after applying in them the resampling, ensemble (Classic, Boosting-based, Bagging-based and Class-balanced ensembles) and cost-sensitive learning techniques selected.

Technique	Base classifiers									
	C4.5		ADTree		SMO		KNN		RF	
	AUC		AUC		AUC		AUC		AUC	
None	0.460	±0.089	0.506	±0.133	0.518	±0.096	0.496	±0.136	0.443	±0.131
Resampling Techniques										
SMOTE	0.508	±0.137	0.528	±0.137	0.517	±0.100	0.458	±0.130	0.445	±0.135
ROS	0.451	±0.113	0.510	±0.133	0.527	±0.100	0.485	±0.134	0.446	±0.124
RUS	0.480	±0.125	0.515	±0.135	0.527	±0.125	0.517	±0.139	0.469	±0.131
ENN	0.474	±0.093	0.505	±0.131	0.518	±0.102	0.498	±0.140	0.467	±0.131
Classic Ensembles										
ADB1	-	-	0.505	±0.105	0.524	±0.113	0.489	±0.126	-	-
M1	0.479	±0.091	0.497	±0.107	0.527	±0.111	0.483	±0.121	-	-
BAG	0.489	±0.128	0.515	±0.130	0.548	±0.133	0.502	±0.133	-	-
Decorate	0.468	±0.135	0.494	±0.138	0.530	±0.099	0.455	±0.138	-	-
Boosting-based Ensembles										
SBO	0.504	±0.112	0.506	±0.122	-	-	0.470	±0.139	-	-
RUSB	0.495	±0.115	0.508	±0.104	0.530	±0.127	0.518	±0.134	-	-
Bagging-based Ensembles										
OBAG	0.468	±0.126	0.516	±0.129	0.549	±0.133	0.490	±0.130	-	-
UBAG	0.509	±0.134	0.529	±0.128	0.558	±0.136	0.519	±0.133	-	-
SBAG	0.537	±0.124	0.532	±0.128	0.544	±0.133	0.498	±0.134	-	-
Cost-sensitive Classification										
MetaCost	0.466	±0.087	0.500	±0.128	0.533	±0.105	0.478	±0.129	-	-
CS-Classifier	0.450	±0.102	0.507	±0.130	0.530	±0.102	0.496	±0.138	-	-
Class-balanced Ensembles with a Cost-sensitive Classifier										
CS-OBAG	0.477	±0.125	0.518	±0.128	0.550	±0.135	0.486	±0.132	-	-
CS-UBAG	0.515	±0.127	0.530	±0.131	0.556	±0.137	0.516	±0.135	-	-
CS-SBAG	0.537	±0.123	0.532	±0.128	0.548	±0.133	0.499	±0.135	-	-

Appendix 6.17. AUC results (mean and standard deviation) of the field-based tests of neuromuscular performance data set (DS 6) for the five base classifiers in isolation and after applying in them the resampling, ensemble and cost-sensitive learning techniques selected

Technique	Base classifiers									
	C4.5		ADTree		SMO		KNN		RF	
	AUC		AUC		AUC		AUC		AUC	
None	0.598	±0.097	**0.758**	**±0.084**	0.563	±0.075	**0.747**	**±0.098**	**0.742**	**±0.100**
					Resampling Techniques					
SMOTE	**0.718**	**±0.105**	**0.753**	**±0.088**	0.685	±0.112	**0.740**	**±0.101**	**0.737**	**±0.105**
ROS	**0.704**	**±0.110**	**0.760**	**±0.090**	0.685	±0.126	**0.749**	**±0.101**	**0.745**	**±0.100**
RUS	0.679	±0.118	**0.749**	**±0.093**	0.675	±0.124	**0.745**	**±0.100**	**0.742**	**±0.105**
ENN	0.584	±0.098	**0.756**	**±0.091**	0.559	±0.075	**0.747**	**±0.102**	**0.738**	**±0.105**
					Classic Ensembles					
ADB1	**0.756**	**±0.094**	**0.763**	**±0.086**	**0.776**	**±0.088**	**0.738**	**±0.101**	-	-
M1	**0.759**	**±0.086**	**0.751**	**±0.093**	**0.757**	**±0.091**	**0.748**	**±0.101**	-	-
BAG	**0.727**	**±0.088**	**0.763**	**±0.087**	0.661	±0.127	**0.756**	**±0.094**	-	-
Decorate	**0.710**	**±0.102**	**0.732**	**±0.095**	0.564	±0.075	**0.708**	**±0.108**	-	-
					Boosting-based Ensembles					
SBO	**0.739**	**±0.104**	**0.747**	**±0.104**	**0.749**	**±0.102**	**0.735**	**±0.102**	-	-
RUSB	**0.751**	**±0.091**	**0.759**	**±0.089**	**0.758**	**±0.089**	**0.745**	**±0.097**	-	-
					Bagging-based Ensembles					
OBAG	**0.753**	**±0.089**	**0.766**	**±0.087**	**0.750**	**±0.099**	**0.759**	**±0.096**	-	-
UBAG	**0.747**	**±0.084**	**0.755**	**±0.087**	**0.752**	**±0.094**	**0.758**	**±0.092**	-	-
SBAG	**0.769**	**±0.099**	**0.776**	**±0.092**	**0.771**	**±0.101**	**0.769**	**±0.100**	-	-
					Cost-sensitive Classification					
MetaCost	0.539	±0.081	**0.724**	**±0.110**	0.500	±0.000	0.519	±0.200	-	-
CS-Classifier	0.641	±0.112	**0.756**	**±0.087**	0.500	±0.000	**0.751**	**±0.099**	-	-
					Class-balanced Ensembles with a Cost-sensitive Classifier					
CS-OBAG	**0.759**	**±0.095**	**0.767**	**±0.088**	**0.760**	**±0.103**	**0.763**	**±0.097**	-	-
CS-UBAG	**0.748**	**±0.089**	**0.757**	**±0.088**	**0.767**	**±0.096**	**0.761**	**±0.095**	-	-
CS-SBAG	**0.770**	**±0.104**	**0.776**	**±0.092**	**0.768**	**±0.100**	**0.772**	**±0.101**	-	-

In bold are highlighted those learning techniques that built prediction models with AUC scores >0.7.

Appendix 6.18. AUC results (mean and standard deviation) of the global data set (DS 11) for the five base classifiers in isolation and after applying in them the resampling, ensemble (Classic, Boosting-based, Bagging-based and Class-balanced ensembles) and cost-sensitive learning techniques selected

Technique	**Base classifiers**									
	C4.5		**ADTree**		**SMO**		**KNN**		**RF**	
	AUC		**AUC**		**AUC**		**AUC**		**AUC**	
None	0.642	±0.124	**0.741**	**±0.119**	0.568	±0.086	**0.704**	**±0.131**	**0.713**	**±0.135**
	Resampling Techniques									
SMOTE	**0.709**	**±0.130**	**0.738**	**±0.121**	0.651	±0.128	**0.700**	**±0.129**	**0.711**	**±0.139**
ROS	0.694	±0.130	**0.738**	**±0.122**	0.659	±0.127	**0.704**	**±0.131**	**0.712**	**±0.136**
RUS	0.663	±0.131	**0.720**	**±0.126**	0.645	±0.129	0.698	±0.120	**0.708**	**±0.137**
ENN	0.637	±0.123	**0.731**	**±0.124**	0.567	±0.093	0.697	±0.130	**0.707**	**±0.136**
	Classic Ensembles									
ADB1	**0.746**	**±0.124**	**0.769**	**±0.131**	**0.722**	**±0.138**	0.691	±0.135	-	-
M1	**0.754**	**±0.110**	**0.742**	**±0.144**	**0.797**	**±0.131**	0.690	±0.136	-	-
BAG	**0.740**	**±0.115**	**0.743**	**±0.116**	0.694	±0.131	**0.716**	**±0.127**	-	-
Decorate	**0.709**	**±0.127**	**0.720**	**±0.124**	0.569	±0.087	0.676	±0.141	-	-
	Boosting-based Ensembles									
SBO	**0.715**	**±0.138**	**0.749**	**±0.061**	**0.740**	**±0.102**	**0.707**	**±0.132**	-	-
RUSB	**0.736**	**±0.121**	**0.748**	**±0.138**	**0.752**	**±0.118**	**0.710**	**±0.128**	-	-
	Bagging-based Ensembles									
OBAG	**0.744**	**±0.112**	**0.741**	**±0.116**	**0.742**	**±0.125**	**0.720**	**±0.126**	-	-
UBAG	**0.742**	**±0.111**	**0.739**	**±0.119**	**0.737**	**±0.121**	**0.719**	**±0.120**	-	-
SBAG	**0.751**	**±0.118**	**0.745**	**±0.119**	**0.750**	**±0.124**	**0.724**	**±0.125**	-	-
	Cost-sensitive Classification									
MetaCost	0.572	±0.120	0.698	±0.134	0.500	±0.000	0.604	±0.147	-	-
CS-Classifier	0.685	±0.129	**0.739**	**±0.124**	0.500	±0.000	**0.706**	**±0.128**	-	-
	Class-balanced Ensembles with a Cost-sensitive Classifier									
CS-OBAG	**0.751**	**±0.107**	**0.742**	**±0.115**	**0.747**	**±0.121**	**0.715**	**±0.126**	-	-
CS-UBAG	**0.749**	**±0.105**	**0.741**	**±0.119**	**0.747**	**±0.116**	**0.722**	**±0.124**	-	-
CS-SBAG	**0.755**	**±0.115**	**0.746**	**±0.119**	**0.750**	**±0.121**	**0.719**	**±0.127**	-	-

In bold are highlighted those learning techniques that built prediction models with AUC scores >0.7.

CHAPTER 7

Study 5

A Bayesian Network approach to study the relationships between several neuromuscular performance measures and dynamic postural control in futsal players

Iñaki Ruiz-Pérez, Francisco Ayala, José Miguel Puerta, José L. L. Elvira, Mark De Ste Croix, Sergio Hernández-Sánchez, Francisco José Vera-García

Published in PlosOne

CHAPTER 7

Study 5

A Bayesian Network approach to study the relationships between several neuromuscular performance measures and dynamic postural control in futsal players

Iñaki Ruiz-Pérez, Francisco Ayala, José Miguel Puerta, José L. L. Elvira, Mark De Ste Croix, Sergio Hernández-Sánchez, Francisco José Vera-García

7.1. Abstract

Objective: The purpose of this study was to analyse the relationship between several parameters of neuromuscular performance with dynamic postural control using a Bayesian Network Classifiers (BN) based analysis.

Methods: The Y-Balance test (measure of dynamic postural control), isokinetic (concentric and eccentric) knee flexion and extension strength, isometric hip abduction and adduction strength, lower extremity joint range of motion (ROM) and core stability were assessed in 44 elite male futsal players. A feature selection process was carried out before building a BN (using the Tabu search algorithm) for each leg. The BN models built were used to make belief updating processes to study the individual and concurrent contributions of the selected parameters of neuromuscular performance on dynamic postural control.

Results: The BNs generated using the selected features by the algorithms correlation attribute evaluator and chi squared reported the highest evaluation criteria (area under the receiver operating characteristic curve [AUC]) for the dominant (AUC = 0.899) and non-dominant (AUC = 0.879) legs, respectively.

Conclusions: The BNs demonstrated that performance achieved in the Y-Balance test appears to be widely influenced by hip and knee flexion and ankle dorsiflexion ROM measures in the sagittal plane, as well as by measures of static but mainly dynamic core stability in the frontal plane. Therefore, training interventions aimed at improving or maintaining dynamic postural control in elite male futsal players should include, among other things, exercises that produce ROM scores equal or higher than 127º of hip flexion, 132.5º of knee flexion as well as 34º and 30.5º of ankle dorsiflexion with the knee flexed and extended, respectively. Likewise, these training interventions should also include exercises to maintain or improve both the static and dynamic (medial-lateral plane) core stability so that futsal players can achieve medial radial error values lower than 6.69 and 8.79 mm, respectively.

Keywords: Y-Balance, injury, futsal, strength, core stability, performance, machine learning.

7.2. Introduction

The Y-Balance is a reliable[229,268], time efficient and portable (field-based) test widely used to assess dynamic postural control[96]. This test is usually included as part of an injury risk battery in both clinical and sporting contexts, primarily based on the fact that several studies[57,58,97–99], although not all[269,270], have reported that poor performance and bilateral asymmetries may be considered as valid predictors for identifying athletes at high risk of non-contact lower extremity injuries (mainly knee and ankle injuries). Thus, Butler et al.[58] found that collegiate football players were 3.5 times more likely to suffer a non-contact lower extremity injury when they reported Y-Balance normalized composite scores below 89.6%. Similarly, Calvo-Gonel et al.[98] reported that elite football players with bilateral asymmetries equal to or greater than 4 cm in the posteromedial direction of the Y-Balance test had a 3.86 greater probability of suffering a non-contact injury than those who did not. Furthermore, the Y-Balance test is sensitive enough to differentiate between different levels of competition[247,271,272] and sporting populations[273]. Elite football players have demonstrated better Y-Balance scores than their non-elite peers[271,272] and when compared with other sporting populations, footballers have performed better on either leg[273].

The Y-Balance test involves maintaining single-legged balance whilst simultaneously reaching as far as possible with the contralateral leg in three directions (anterior, posterolateral and posteromedial). Potentially, the execution of this test might require, among others, adequate levels of hip and knee strength, power, trunk or core stability, coordination and lower extremity ranges of motion (ROM). With the aim of improving the design of training interventions, some studies have explored the individual contribution of certain measures of knee strength[100–102], hip strength[102–104], lower extremity power[105], core stability[102] and lower extremity ROMs[102,106] on Y-Balance test performance using linear regression models in different cohorts of athletes. However, these studies have reported conflicting results that might not permit clinicians, physiotherapists and physical trainers to make general training recommendations. For example, Booysen, Gradidge & Watson[100] did not show any relationship between the isokinetic strength of the knee flexors and extensors and the Y-Balance test score in professional football players, whereas Lockie et al.[101] did find a positive and statistically significant correlation ($r = 0.50$; $p = 0.008$) between the isokinetic strength of the knee extensors and the Y-Balance test performance in amateur team sport athletes. The conflicting results might be partially attributed to the different sport modalities and levels of competition (i.e. amateur vs. professional or elite) of the athletes recruited in each study. In particular, the differences in technical skills, specific movements, training load and physical capacities among sports and levels of competition may predispose participants to individual chronic musculoskeletal adaptations, thus influencing some neuromuscular measures and their subsequent impact on the Y-Balance test performance.Therefore, it may be necessary a sport-specific and level of competition-based analysis of which neuromuscular parameters contribute to Y-Balance test performance in order to design effective dynamic postural control training interventions.

Despite being one of the most popular sports worldwide[1,160] and being ranked among the top ten non-contact lower extremity injury-prone sports[6], an analysis of the influence of the main modifiable measures of neuromuscular performance (i.e. hip and knee strength, core stability, lower extremity ROMs) on Y-Balance test scores in futsal players has not been undertaken. In terms of sport performance, futsal players might be a target group for dynamic postural control training programmes since they are required to perform repetitively high intensity unilateral movements such as sudden acceleration and deceleration tasks, rapid changes of direction, kicking and tackling[5,274].

The existing literature has predominantly used traditional lineal regression analyses to explore statistical associations and to our knowledge no studies have used contemporary statistical techniques, such as Bayesian Networks Classifiers (BNs) (also referred to as causal networks or belief networks) to provide evidence of relationships of dependency and conditional independence between different measures or variables[107]. In contrast to traditional statistics, BNs not only provide statistical models describing the relationships between variables from empirical data (as a way of representing uncertainty), but construct graphical probabilistic models (directed acyclic graphs) based on the underlying structure in which variables are represented by nodes and their relationships of dependency are symbolized by arrows or arcs[275]. Thus, the graphical representation of BNs captures the compositional structure of the relations and the general aspects of all probability distributions that factorize according to that structure[276]. Furthermore, BNs allow making inference or relevance analysis/reasoning in a natural manner and within a dynamic context to generate intercausal reasoning, that is to say, adding new evidence to the model in order to study the impact of the new relationships generated in the class variable. Therefore, the use of a BN based analysis to study the relationships of dependency and conditional independence between the main modifiable measures of neuromuscular performance and dynamic postural control and particularly the subsequent graph generated will help clinicians, physiotherapists and physical trainers to understand this complex phenomenon better. In addition, the BN model built could be used to make belief updating processes (by adding new evidence [the scores obtained by an athlete in the different neuromuscular performance tests]) in order to study the concurrent and individual contribution of the neuromuscular factors on the dynamic postural control of each futsal player and thus allowing the design of individualised training programs.

Therefore, the main purpose of the current study was to analyse the relationships between several parameters of neuromuscular performance with dynamic postural control (measured through the Y-Balance test) using a BN based analysis in a cohort of elite futsal players.

7.3. Methods

7.3.1. Participants

A total of 44 elite male futsal players from four different teams (16 players from a club engaged in the First [top] National Spanish Futsal division and 28 players from three clubs engaged in the Second National Futsal division) completed this cross-sectional study (convenience sampling). To be included, all participants had to be free of pain at the time of the study and currently involved in futsal-related activities. Participants were excluded if they reported the presence of any lower extremity injury within the last month, a current upper respiratory tract infection, any bone or joint abnormalities, any uncorrected visual and vestibular problems and/or a concussion within the last three months[100]. The study was conducted at the end of the pre-season phase in 2015 and 2016 (September). Before any participation, experimental procedures and potential risks were fully explained to the participants in verbal and written form, and written informed consent was obtained from participants. An Institutional Research Ethics committee approved the study protocol prior to data collection (DPS.FAR.01.14), conforming to the recommendations of the Declaration of Helsinki.

7.3.2. Testing procedure

Prior to the neuromuscular testing, all participants performed a standardised dynamic warm-up designed by Taylor et al.[210]. Three to 5 min after the dynamic warm-up was carried out, participants completed five different neuromuscular assessments in the following order: 1) dynamic postural control; 2) isometric hip abduction and adduction strength; 3) lower extremity joint ROMs; 4) core stability; and 5) isokinetic knee flexion and extension strength.

Dynamic postural control was measured using the Y-Balance test (Y-Balance Test, Move2Perform, Evansville, IN) (composite score) and followed the guidelines proposed by Shaffer et al.[229]. After having completed a 2 min practise of the testing procedure, players were allowed a maximum of five trials to obtain three successful trials for each reach direction (anterior, posteromedial and posterolateral). To obtain a global measure of the dynamic postural control performance, the greatest distance reached in each direction was normalised (by dividing by leg length) and then averaged (by multiplying by 100) to establish a composite balance score.

Isometric hip abduction and adduction peak torque of the dominant and non-dominant leg were assessed using a portable handheld dynamometer (Nicholas Manual Muscle Tester, Lafayette Indiana Instruments) with the participant lying in a supine position on a plinth with legs extended, following the methods described by Thorborg et al.[228]. Participants performed two practice trials (50 and 80% of the self-perceived isometric maximal voluntary contraction) and then three 5s isometric maximal voluntary contraction trials for each hip movement. The best trial was used for the subsequent statistical analyses.

Likewise, passive hip flexion with knee flexed and extended, extension, abduction, external and internal rotation; knee flexion; and ankle dorsiflexion with knee flexed and extended ROMs of the dominant and non-dominant leg were assessed following the methods previously described[230]. The best score for each test was used in the subsequent analyses.

An unstable sitting protocol was used to assess participant's core stability, determined as the ability to control trunk posture and motion while sitting, following the methods previously described by Barbado et al.[277]. Briefly, after a familiarization period (2 min), participants performed different static and dynamic tasks while sitting on an unstable seat. All tasks were performed twice. The duration of each trial was 70s and the rest period between trials was 1 min. The mean radial error was used as a global measure to quantify the trunk/core performance during the trials.

Finally, isokinetic concentric and eccentric torques during knee extension and flexion actions in both legs were determined (Biodex System-4, Biodex Corp., Shirley, NY, USA) following the methods employed by Ayala et al.[278]. In each of the three trials at each velocity (60º/s and 180º/s for concentric muscle actions and 30º/ and 60º/s for eccentric muscle actions), the peak torque was reported as the single highest torque value achieved. For each peak torque variable, the best of the three trials at each velocity was used for subsequent statistical analysis. When a variation >5% was found in the peak torque values between the three trials, the mean of the two most closely related torque values was used for the subsequent statistical analyses.

Appendix 7.1 summarizes the list of variables recorded from each assessment procedure (and it also shows the abbreviations that have been used within the manuscript). Each of the 6 testers who took part in this study conducted the same tests throughout all the testing sessions. All testers had more than 4 years of experience in using the neuromuscular assessments.

7.3.3. Statistical analysis

Prior to building the BN of each leg, all variables were discretized as this has been shown to be an effective measure to improve the performance of several BN and logistic regression techniques[279]. Thus, both class variables (Y-Balance composite score of the dominant and non-dominant legs) were discretized into two intervals (high risk and low risk of injury) according to the cut-off score of 89.6% reported by Butler et al.[58], in which composite scores below 89.6% indicate that players are 3.5 times more likely to suffer a non-contact lower extremity injury (100% of sensitivity and 71.7% of specificity). A statistician experienced in running BN analysis carried out the discretization of the continuous variables using a visual inspection of their histogram (in which each instance was colored [blue or red] according to their relationship to each interval of the class variable [high risk or low risk]) which allowed identification of a clear cut-off point. Thus, for the Y-Balance composite score of the dominant and non-dominant leg, six and eight variables were discretized into two intervals, respectively. For those variables in which a clear cut-off score was not visually identified, the unsupervised discretization algorithm available in the WEKA Data Mining software was applied using the equal frequency binning approach (three cut point intervals). Three intervals were selected in order to reflect taxonomy of low, moderate and high scores that might make the final models more comprehensible. Appendix 7.1 shows a description of all variables recorded to build the BNs.

In order to build the BN of each leg that allows the classification of futsal players into one of the two injury risk categories (low risk or moderate risk) previously defined according to their dynamic postural control scores, we used the well-known WEKA (Waikato Environment for Knowledge Analysis) Data Mining software. To build the BN the score + search approach was used[280]. Specifically, the Tabu search algorithm as a search engine[281] coupled with the BDeu score[282] was selected to build the structure of both BNs (dominant and non-dominant leg). This algorithm explores the search space starting from a network structure and adding, deleting, or reversing one arc at a time until the score can no longer be improved. Thus, the Tabu search algorithm is a modified hill climbing algorithm able to escape local optima by selecting a network that minimally decreases the score function. Neither expert knowledge nor prior knowledge of the system under study was taken into account in the model selection process in order to prevent the model from encoding the prior information instead of the information in the data. As the Tabu search is a stochastic algorithm, the final model was obtained by repeating the structure learning several times (in our case 1,000 times). A large number of network structures were explored (1,000 BNs) to reduce the impact of locally optimal (but globally suboptimal) network learning. The networks learned were averaged to obtain a more robust model. A conditional probability distribution was obtained for each node.

The performance of the BNs was assessed using a 5-fold stratified cross validation technique. That is, we split the dataset into 5 folds, each one containing 20% of the patterns of the dataset. For each fold, the BN was trained with the examples contained in the remaining folds and then tested with the current fold. A wide range of performance measures can be obtained from the stratified cross validation technique. A well-known approach to unify these measures and to produce an evaluation criterion is to use the area under the Receiver Operating Characteristic Curve (AUC). In particular, the AUC corresponds to the probability of identifying which one of the two stimuli is noise and which one is signal plus noise correctly[76]. Thus, the AUC was used as a single measure of BNs´ performance.

However, and before learning the BNs, a feature selection process was carried out to reduce the dimensionality of the feature space and eliminate irrelevant, weakly relevant and/or redundant features. In other words, the aim of this pre-learning process was to find the minimal subset of attributes such that the resulting probability distribution of data classes is close to the original distribution obtained using all attributes and that they do not decrease the accuracy of the model significantly[283]. Feature selection algorithms are separated into three categories: a) *the filters* which extract features from the data without any learning involved, b) *the wrappers* that use learning techniques to evaluate which features are useful, and c) *the embedded techniques* which combine the feature selection step and the classifier construction[284,285]. A priori it is not possible to determine with certainty which category of the feature selection algorithms might be applied to address each problem more accurately. Thus, it has been suggested that an appropriate approach may be to analyze and compare the accuracy of the models built for a given classifier (in our case the Tabu search algorithm) to which different feature selection techniques have been previously applied and then select the best performing BN-based feature selection method[286–288]. Accordingly, the behavior of numerous feature selection algorithms coming from the filter and wrapper categories were analyzed and compared (using the metaclassifier "attribute selected classifier" available in Weka´s repository) in order to select the best performing BN to describe the relationships between the main measures of neuromuscular performance and dynamic postural control. For those filter algorithms in which a ranker search technique is required (e.g. chi squared attribute evaluator and correlation attribute evaluator techniques), it was set up to select the top-10 ranked features so that a comprehensible and straightforward model could be developed. Once the top-10 ranked features were determined, the performance of these filter algorithms were assessed by using the top-10, 9, 8, 7 … and 2 features and then compared in order to find the minimal subset of features with the best performance. On the other hand, the search algorithms used for the wrapper algorithms were the Best First (backward direction) and Greedy Stepwise (backward direction) and as base classifier the following three classifier algorithms were selected: Naïve Bayes, C4.5 and Support Vector Machine. The accuracy scores of all the possible combinations for the wrapper algorithms were compared and the best performing model was finally selected.

The BNs were implemented using SAMIAM (Sensitivity Analysis Modeling Inference and More) software (2013) to obtain a graphical interface for manipulating the probabilistic network.

Once the BNs were built, different configurations of variable's values where entered with the aim of studying different intercausal (interactions among different causes of the same effect) and causal (predictions from causes to effects) reasoning scenarios.

7.4. Results

Tables 7.1 and 7.2 show the accuracy scores obtained by the 11 feature selection algorithms used to build different dynamic postural control BNs (Y-Balance test composite score) for the dominant and non-dominant leg, respectively. For the dynamic postural control of the dominant leg, the feature selection algorithm "correlation attribute evaluator" (which evaluates the worth of an attribute by measuring the correlation [Pearson's] between it and the class) belonging to the *filters* category was the algorithm that built the BN with the highest accuracy score (AUC = 0.899). The dynamic postural control BN built for the non-dominant leg after the application (pre-processing) of the "chi squared" feature selection algorithm (that evaluates the worth of an attribute by computing the value of the chi-squared statistic with respect to the class), also belonged to the filters category, and had the highest AUC scores (0.879). Furthermore, these two feature selection algorithms used six and ten variables to build the dynamic postural control BNs that showed the highest performance for the dominant and non-dominant leg, respectively.

Table 7.1. Comparisons among the accuracy scores obtained by all the BN-based feature selection methods for the dominant leg. In grey is highlighted the best performing BN

Feature selection algorithm	Search technique	AUC	Nº of features selected	Description in ascending (from more to less important/relevant) order
-	-	0.865	31	Appendix 7.1
Correlation-based feature subset evaluator	Best First	0.858	5	ISOK-PT-ECC-KF_{180}, CS-NF, CS-ML, ROM-HF_{KF} and ROM-KF
Chi squared attribute evaluator	Ranker	0.835	4	ROM-KF, ROM-HF_{KF}, CS-ML and ROM-HE
Classifier attribute evaluator (Naïve Bayes)	Ranker	0.874	7	ROM-KF, ROM-HF_{KF}, CS-NF, ISOK-PT-ECC-KF_{180}, ISOM-PT-Hip-Abd and CS-ML, CS-WF
Classifier subset evaluator (Naïve Bayes)	Best First	0.774	10	ISOK-PT-CON-KF_{60}, Stature, ISOK-PT-CON-KE_{180}, ISOK-PT-ECC-KF_{60}, ISOK-PTECC-KF_{180}, ISOK-PTECC-KE_{60}, ISOM-PT-Hip-Abd, CS-ML, ROM-HIR, ROM-HER, ROM-HE, ROM-KF, ROM-$AKDF_{KE}$ and ROM-$AKDF_{KF}$
Consistency subset evaluator	Best First	0.699	5	ROM-HIR, ROM-HER, ROM-HE, ROM-KF and ROM-$AKDF_{KF}$
Correlation attribute evaluator	Ranker	0.899	6	ROM-KF, ROM-HF_{KF}, CS-ML, Stature, CS-NF and CS-CD
CV Attribute evaluator	Ranker	0.697	7	CS-ML, Dominant-leg, ISOK-PTECC-KF_{60}, ROM-$AKDF_{KF}$, ISOK-PTECC-KF_{180}, ISOK-PTCON-KE_{240} and ISOK-PTECC-KE_{30}
Gain ratio attribute evaluator	Ranker	0.865	6	CS-ML, ROM-KF, ROM-HF_{KF}, Stature, ROM-HE and CS-CD

Info gain attribute evaluator	Ranker	0.874	6	ROM-KF, CS-ML, ROM-HF$_{KF}$, ROM-HE, CS-CD and ISOK-PTECC-KF$_{180}$
One R attribute evaluator	Ranker	0.857	7	ROM-KF, ROM-HF$_{KF}$, CS-NF, ISOK-PTECC-KF$_{180}$, CS-ML, ISOM-PT-Hip-Abd, CS-WF
Wrapper subset evaluator (Naïve Bayes)	Best First	0.851	9	Stature, ISOM-PT-Hip-Abd, CS-NF, CS-ML, CS-AP, ROM-HF$_{KF}$, ROM-HER, ROM-HE, ROM-KF

BN: Bayesian Network Classifiers; AUC: area under the receiver operating characteristic curve; ISOK: isokinetic; KE: knee extensors; CON: concentri eccentric; ISOM: isometric; PT: peak torque; Abd: abduction; ROM: range of motion; HF$_{KF}$: hip flexion with the knee flexed; HE: Hip extension; HIR: hip i rotation; HER: hip external rotation; KF: knee flexors; AKDF$_{KE}$: ankle dorsi-flexion with the knee extended; AKDF$_{KF}$: ankle dorsi-flexion with the knee fle core stability; NF: unstable sitting without feedback; WF: unstable sitting with feedback; ML: unstable sitting while performing medial-lateral displacemer feedback; AP: unstable sitting while performing anterior-posterior displacements with feedback; CD: unstable sitting while performing circular displac with feedback.

Table 7.2. Comparisons among the accuracy scores obtained by all the BN-based feature selection methods for the non-dominant leg. In grey is highlighted the best performing BN

Feature selection algorithm	Search technique	AUC	Nº of features selected	Description in ascending (from more to less important/relevant) order
-	-	0.821	31	Appendix 7.1
Correlation-based feature subset evaluator	Best First	0.817	8	Dominant-leg, ISOM-Hip-Abd, CS-WF, CS-ML, ROM-HE, ROM-KF, ROM-AKDF$_{KE}$ and ROM-AKDF$_{KF}$
Chi squared attribute evaluator	Ranker	0.879	10	ROM-AKDF$_{KE}$, ROM-AKDF$_{KF}$, ROM-KF, ROM-HE, CS-ML, CS-CD, CS-WF, ROM-HF$_{KF}$, ISOK-ECC-KF$_{180}$ and CS-NF
Classifier attribute evaluator (Naïve Bayes)	Ranker	0.809	10	ROM-AKDF$_{KF}$, ROM-KF, ROM-HE, ISOK-ECC-KF180, ROM-AKDF$_{KE}$, ROM-HF$_{KF}$, CS-WF, ISOK-ECC-KE$_{30}$, ISOK-ECC-KE$_{60}$ and CS-CD
Classifier subset evaluator (Naïve Bayes)	Best First	0.758	10	ISOK-ECC-KF$_{180}$, ISOK-ECC-KE$_{60}$, ISOM-Hip-Add, CS-NF, CS-WF, CS-CD, ROM-HE, ROM-KF, ROM-AKDF$_{KE}$ and ROM-AKDF$_{KF}$
Consistency subset evaluator	Best First	0.828	5	ROM-HABD, ROM-HIR, ROM-HER, ROM-KF and ROM-AKDF$_{KF}$
Correlation attribute evaluator	Ranker	0.853	9	ROM-AKDF$_{KE}$, ROM-AKDF$_{KF}$, ROM-KF, CS-ML, ROM-HF$_{KF}$, CS-WF, CS-NF, ISOM-Hip-Add and Dominant-leg
CV Attribute evaluator	Ranker	0.700	9	ROM-AKDF$_{KE}$, Dominant-leg, ISOK-ECC-KF$_{180}$, ISOK-ECC-$_{KF60}$, ISOK-ECC-KE$_{30}$, ISOK-CON-KE$_{240}$, ISOK-ECC-KE$_{60}$, ISOK-ECC-KF$_{30}$ and ROM-AKDF$_{KF}$
Gain ratio attribute evaluator	Ranker	0.853	10	ROM-AKDF$_{KE}$, ROM-AKDF$_{KF}$, ROM-KF, CS-ML, ROM-HF$_{KF}$, CS-WF, CS-NF, Dominant-leg, ISOM-Hip-Add and ROM-HE

Info gain attribute evaluator	Ranker	0.853	9	ROM-AKDF$_{KE}$, ROM-AKDF$_{KF}$, ROM-KF, CS-ML, ROM-HE, CS-CD, ROM-HF$_{KF}$, CS-WF, ISOK-ECC-KF$_{180}$ and CS-NF
One R attribute evaluator	Ranker	0.731	9	ROM-AKDF$_{KF}$, ROM-KF, ROM-HE, ISOK-ECC-KF$_{180}$, ROM-AKDF$_{KE}$, ISOK-ECC-KE$_{60}$, ISOK-ECC-KF$_{60}$, ISOK-CON-KF$_{240}$ and ISOK-CON-KF$_{180}$
Wrapper subset evaluator (Naïve Bayes)	Best First	0.809	22	ISOK-CON-KF$_{60}$, Body-mass, ISOK-CON-KE$_{180}$, ISOK-CON-KE$_{240}$, ISOK-ECC-KF$_{30}$, ISOK-ECC-KF$_{60}$, ISOK-ECC-KF$_{180}$, ISOK-ECC-KE$_{30}$, ISOK-ECC-KE$_{60}$, ISOM-Hip-Abd, ISOM-Hip-Add, CS-NF, CS-ML, CS-AP, CS-CD, ROM-HF$_{KF}$, ROM-HF$_{KE}$, ROM-HABD, ROM-HE, ROM-KF, ROM-AKDF$_{KE}$ and ROM-AKDF$_{KF}$

BN: Bayesian Network Classifiers; AUC: area under the receiver operating characteristic curve; ISOK: isokinetic; KE: knee extensors; CON: concentric; ECC: ec ISOM: isometric; PT: peak torque; Abd: abduction; ROM: range of motion; HF$_{KF}$: hip flexion with the knee flexed; HE: Hip extension; HIR: hip internal rotatio hip external rotation; KF: knee flexors; AKDF$_{KE}$: ankle dorsi-flexion with the knee extended; AKDF$_{KF}$: ankle dorsi-flexion with the knee flexed; CS: core stabil unstable sitting without feedback; WF: unstable sitting with feedback; ML: unstable sitting while performing medial-lateral displacements with feedback; AP: u sitting while performing anterior-posterior displacements with feedback; CD: unstable sitting while performing circular displacements with feedback.

Figure 7.1 presents the directed acyclic graphs (DAGs) corresponding to the dynamic postural control BNs built for the dominant (figure 7.1a) and non-dominant leg (figure 7.1b). In addition, both DAGs also show the a priori probability distributions (expressed in percentages), that is, without entering any observed value, for each of the two or three labels of the six and ten variables selected to build the dynamic postural control BNs. Thus, for the class variable of the dominant leg (Y-BALANCE_DOM), six child nodes or independent predictors were observed: knee flexion (ROM-KF_DOM) and hip flexion with knee flexed (ROM-HF$_{KF}$_DOM) ROMs, core stability measures recorded while performing medial-lateral (CS-ML) and circular (CS-CD) displacements with feedback, and also without displacement and nor feedback (CS-NF), and stature. Likewise, what can also be observed is the presence of connections between hip flexion ROM and the players′ stature (ROM-KF_DOM $\rightarrow$ Stature) as well as between the measures of core stability assessed while performing medial-lateral (CS-ML) and circular (CS-CD) displacements (CS-ML $\rightarrow$ CS-CD). The DAG corresponding to the dynamic postural control BN of the non-dominant leg shows the presence of nine child nodes, corresponding to five ROM (ankle dorsiflexion with knee extended [ROM-AKDF$_{KE}$_NODOM] and flexed [ROM-AKDF$_{KE}$_NODOM], knee flexion [ROM-KF_NODOM] and hip extension [ROM-HE_NODOM] and flexion with knee flexed [ROM-HF$_{KF}$_NODOM] ROMs), three core stability measured during both static (unstable sitting with [CS-WF] and without [CS-NF] feedback) and dynamic tasks (unstable sitting while performing medial-lateral displacements with feedback [CS-ML]) and one isokinetic strength (eccentric knee flexors peak torque [ISOK-ECC-KF$_{180}$_NODOM]) measures. Likewise, a number of connections among variables were also displayed in the DAG for the dynamic postural control BN of the non-dominant leg (e.g.: CS-NF $\rightarrow$ ISOK-ECC-KF$_{180}$_NODOM, ROM-KF_NODOM $\rightarrow$ ROM-HF$_{KF}$_NODOM). Another child node was observed, the measure of core stability assessed while performing circular displacements with feedback (CS-CD), that acts as descendent of another measure of core stability, in its case the one measured while performing medial-lateral displacements (CS-ML).

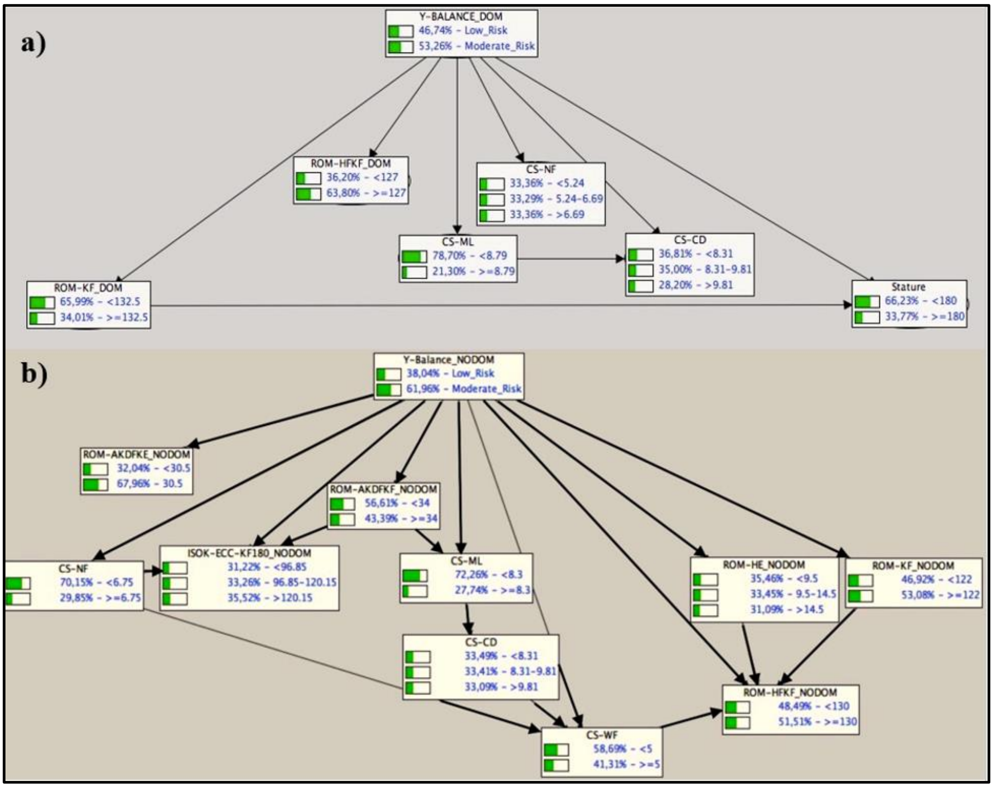


Figure 7.1. Directed acyclic graphs corresponding to the dynamic postural control BNs built for the dominant leg (figure 7.1a) and non-dominant leg (figure 7.1b). The a priori probability distributions for each feature are given, where the likelihood for each feature's label is expressed in percentage.

The individual contribution of each label of the different variables finally selected on the probability of having the class variable (Y-Balance test composite score) in its low and moderate risk states is shown in table 7.3 for both the dominant and non-dominant legs. Knee flexion ROM (≥132.5º) and core stability assessed while performing medial-lateral displacements with feedback (≥8.79 mm) measures were the ones that presented the highest impact on the probability of having the class variable of the dominant leg in its low (84.34%) and moderate risk (95.01%) states, respectively. Hip extension (≥14.5º) and ankle dorsiflexion with knee extended (<30.5º) ROM measures were also the predictors with the highest contribution to have the class variable of the non-dominant leg in its low (62.84%) and moderate risk (96.7%) states, respectively.

Table 7.3. Individual contribution of each level of the final variables selected on the probability of having the class variable (Y-Balance composite score) of the non-dominant leg in its low and moderate risk states. In grey are highlighted the labels of the variables that present the highest individual contribution of having the class variable in its low and moderate risk scores

	Y-Balance (composite score)	
	Low risk	**Moderate risk**
	Dominant leg	
No instantiations	46.74	53.26
ROM-KF (º)		
▪ <132.5	27.36	72.64
▪ ≥132.5	84.34	15.66
ROM-HF_{KF} (º)		
▪ <127	14.67	85.33
▪ ≥127	64.94	35.06
CS-ML (CoP mm)		
▪ <8.79	58.04	41.96
▪ ≥8.79	4.99	95.01
Stature (cm)		
▪ <180	56.55	43.45
▪ ≥180	23.27	76.73
CS-NF (CoP mm)		
▪ <5.24	34.25	65.75

▪ 5.24 – 6.09	71.76	28.24
▪ ≥6.09	34.25	65.75
CS-CD (CoP mm)		
▪ <8.31	52.04	47.96
▪ 8.31 – 9.81	62.74	37.26
▪ ≥9.81	18.92	81.8
	Non-dominant leg	
No instantiations	38.04	61.96
ROM-AKDF$_{KE}$ (º)		
▪ <30.5	3.3	96.7
▪ ≥30.5	54.42	45.58
ROM-AKDF$_{KF}$ (º)		
▪ <34	18.23	81.77
▪ ≥34	61.79	38.21
ROM-KF (º)		
▪ <122	15.77	84.23
▪ ≥122	57.74	42.26
ROM-HE (º)		
▪ <9.5	31.8	68.11
▪ 9.5 – 14.5	21.52	78.48
▪ ≥14.5	62.84	37.16
CS-ML (CoP mm)		
▪ <8.3	48.26	51.74
▪ ≥8.3	11.43	88.57
CS-CD (CoP mm)		
▪ <8.31	47.13	52.87
▪ 8.31 – 9.81	42.6	57.4

▪ ≥9.81	24.25	75.75
CS-WF (CoP mm)		
▪ <5	47.97	52.03
▪ ≥5	25.56	74.44
ROM-HF$_{KF}$ (º)		
▪ <130	25.61	74.39
▪ ≥130	52.26	47.74
ISOK-ECC-KF$_{180}$ (Nm)		
▪ <96.85	20.95	79.05
▪ 96.85 – 120.15	56.45	43.55
▪ ≥120.15	35.45	64.55
CS-NF (CoP mm)		
▪ <6.75	46.7	53.3
▪ ≥6.75	17.7	82.3

ISOK: isokinetic; KE: knee extensors; ECC: eccentric; ROM: range of motion; HFKF: hip flexion with the knee flexed; HE: Hip extension; KF: knee flexors; AKDFKE: ankle dorsi-flexion with the knee extended; AKDFKF: ankle dorsi-flexion with the knee flexed; CS: core stability; NF: unstable sitting without feedback; WF: unstable sitting with feedback; ML: unstable sitting while performing medial-lateral displacements with feedback; CD: unstable sitting while performing circular displacements with feedback.

In table 7.4 it can be seen that by mean of a belief updating process which uses two different configurations (i.e.: the process by which new evidence is introduced in some target variables of the model), it was possible to achieve the maximal hypothetical probability (98.98%) that a futsal player will show a limited (moderate risk) dynamic postural control performance of the dominant leg, which implies a "jump" of approximately 45 percentage points from the initial value shown within the studied population. Table 7.4 also displays how through three instantiations it is possible to achieve the maximal hypothetical probability that a player would have a dynamic postural control performance of the dominant leg that might be categorized as "low risk for lower-extremity injuries" (98.08%), with an increase of approximately 52 percentage points from the initial value. Similarly, table 7.5 presents another step-by-step belief updating process carried out to maximize both labels (low risk and moderate risk) of the class variable for the dynamic postural control model of the non-dominant leg. In particular, only two variables need to be observed (fixed) to achieve the greatest hypothetical probability (99.29%) that a player would have a limited dynamic postural control performance (moderate risk). However, the correct value must be entered for 5 variables to maximize the probability (98.65%) that a player would have a dynamic postural stability performance categorized as "low risk for lower-extremity injuries", which suppose an increase of approximately 60 percentage points with respect to its initial probability (38.04%). For the belief updating process carried out in both BNs and shown in tables 7.4 and 7.5, an intercausal reasoning (when different causes of the same effect can interact) was applied. From each step, the variable and the state that induces the greatest increase in the likelihood of the class variable to show a low and moderate state were chosen.

Table 7.4. Step-by-step instantiations leading to maximization of the likelihood of having the class variable (Y-Balance) of the dominant leg in its low and moderate risk categories

Step	Instantiate variable	Label	Y-Balance
			Moderate risk
1	None		53.26%
2	CS-ML	≥8.79	95.01%
3	ROM-HF_{KF}_DOM	<127	98.98%
			Low risk
1	None		46.74%
2	ROM-KF_DOM	≥132.5	84.34%
3	ROM-HF_{KF}_DOM	≥127	91.91%
4	CS-NF	5.24 – 6.69	97.05%

CS: core stability; ML: unstable sitting while performing medial-lateral displacements with feedback; ROM: range of motion; HF_{KF}: hip flexion with the knee flexed; KF: knee flexors; DOM: dominant leg; NF: no feedback.

Table 7.5. Step-by-step instantiations leading to maximization of the likelihood of having the criterion variable (Y-Balance) of the non-dominant leg in its low and moderate risk states.

Step	Instantiate variable	Label	Y-Balance
			Moderate risk
1	None		61.96%
2	ROM-AKDF$_{KE}$_NONDOM	<30.5	96.7%
3	CS-ML	≥8.3	99.29%
			Low risk
1	None		38.04%
2	ROM-HE_NODOM	>14.5	63.84%
3	ISOK-ECC-KF$_{180}$_NODOM	96.85-120.15	81.54%
4	ROM-AKDF$_{KF}$_NONDOM	≥34	94.32%
5	ROM-AKDF$_{KE}$_NONDOM	≥30.5	97.03%
6	ROM-KF_NONDOM	≥122	98.65%

CS: core stability; ML: unstable sitting while performing medial-lateral displacements with feedback; ROM: range of motion; KF: knee flexors; AKDF$_{KE}$: ankle dorsi-flexion with the knee extended; AKDF$_{KF}$: ankle dorsi-flexion with the knee flexed; HE: hip extension; ISOK: isokinetic strength; ECC: eccentric; NONDOM: non-dominant leg.

Finally, figures 7.2 (dominant leg) and 7.3 (non-dominant leg) show a top-down reasoning for the dynamic postural control BNs in which in both cases, the class variable (Y-Balance composite scores) was instantiated in their two labels in order to define / predict a profile. For the dynamic postural control BN of the dominant leg, figure 7.2 shows that when the class variable is instantiated at is maximum of “low risk” (figure 7.2a), three variables or father nodes show a clearly imbalanced distribution of probabilities in favor of one of their labels (ROM-HF$_{KF}$_DOM, CS-ML and stature). In particular, a futsal player with a dynamic postural control performance categorized as "low risk" is very likely to have a hip flexion with knee flexed ROM higher than 127º, a core stability score (measured while performing medial-lateral displacements) lower than 8.79 mm (mean radial error) and a stature shorter than 180 cm. Subsequently, figure 7.2b also shows that when the label "high risk" of the class variable is instantiated, only knee flexion ROM reported a clear imbalance in the distribution of probabilities between its two labels (in favour to the label "<132.5°") and hence, a high-risk profile was not visually clear. Regarding the dynamic postural control BN of the non-dominant leg, figure 7.3 shows that when the class variable is instantiated in its "low risk" label (figure 7.3a), seven out of nine variables present a clearly imbalanced distribution orientated to one of their labels. Thus, there seems to be a low risk profile characterised by moderate to high ROM values for the ankle, knee and hip (flexion) joints alongside with a high core stability performance during static and dynamic tasks. Contrarily, when the moderate risk label was instantiated (figure 7.3b), it was not possible to find a clear profile

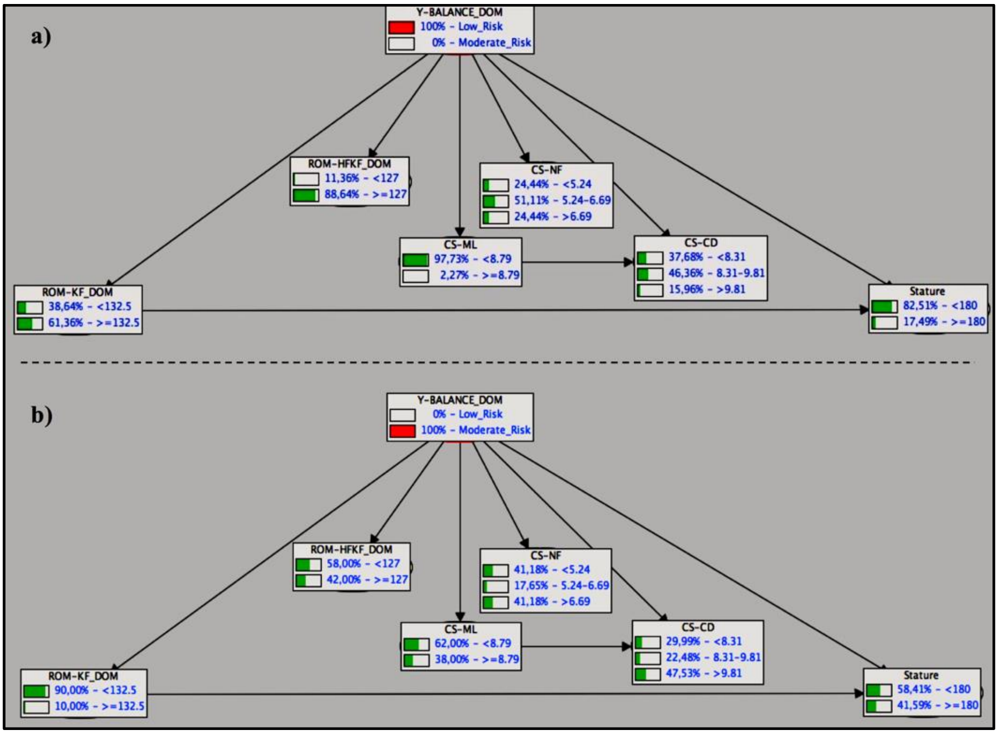


Figure 7.2. A top-down reasoning for the dynamic postural control BNs of the dominant leg in which the class variable (Y-Balance composite scores) was instantiated in their two labels: a) low risk and b) moderate risk.

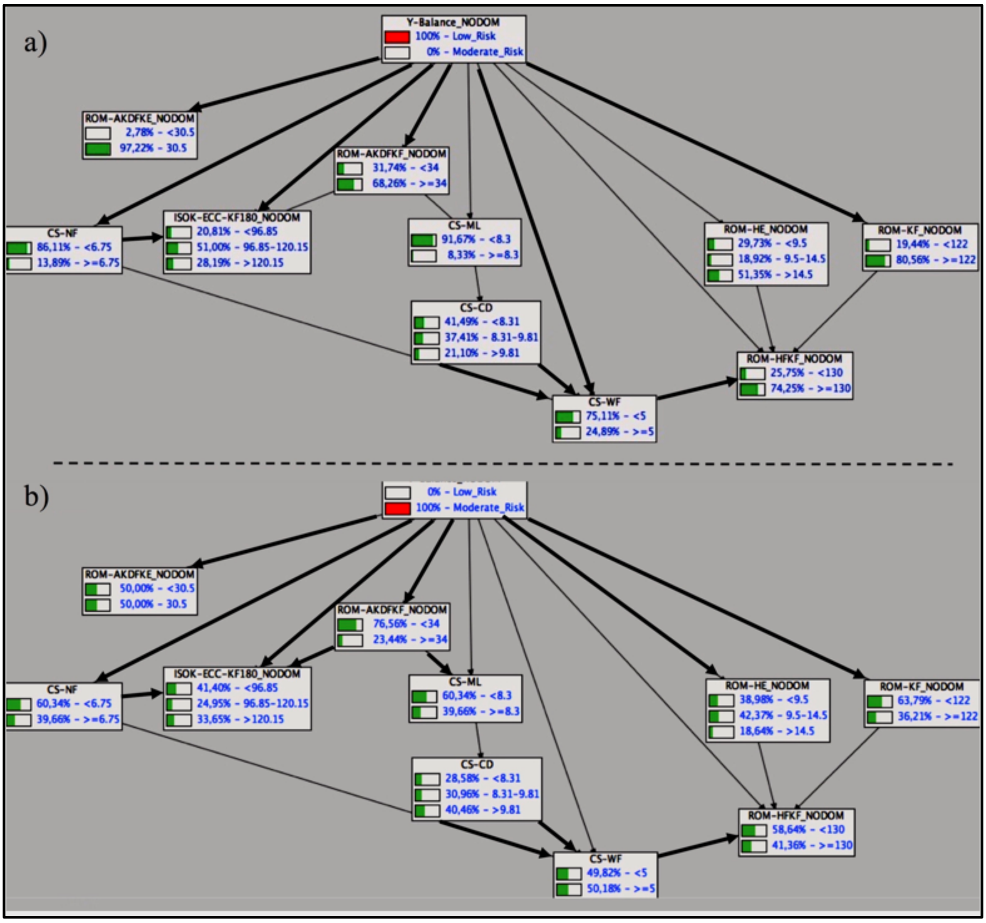


Figure 7.3. A top-down reasoning for the dynamic postural control BNs of the non-dominant leg in which the class variable (Y-Balance composite scores) was instantiated in their two labels: a) low risk and b) moderate risk.

7.5. Discussion

The BNs generated using the selected features by the algorithms correlation attribute evaluator and chi squared reported the highest evaluation criteria for the dominant (AUC = 0.899) and non-dominant (AUC = 0.879) legs, respectively. The ability of both BNs to classify the instances correctly into one of the two categories of the class variable (low risk vs. moderate risk) cannot be compared with the models developed (through regression logistic techniques) in previous studies because neither of them reported any measure of their global ability or accuracy.

The BN built for the dynamic postural control of the dominant leg identified six independent predictors: knee flexion and hip flexion with the knee flexed ROMs, stature, and one static (with feedback) and two dynamic (assessed while performing medial-lateral and circular displacements with feedback) core stability measures. On the contrary, the feature selection-based BN of the dynamic postural control of the non-dominant leg shows nine father nodes or independent predictors for the distance reached in the Y-Balance test: five of them were ROMs (hip flexion and extension with knee flexed, knee flexion and ankle dorsiflexion with knee flexed and extended), three were static (with and without feedback) and dynamic (assessed while performing medial-lateral displacements) core stability measures and one was a measure of the isokinetic eccentric strength of the knee flexors. Therefore, the performance achieved in the Y-Balance test (independent of the leg) and consequently, the dynamic postural control, appears to be widely influenced by the hip and knee flexion and the ankle dorsiflexion ROM measures, all in the sagittal plane, as well as by measures of static but mainly dynamic core stability in the frontal plane. In particular, the highest label of the dynamic core stability measure (the higher the value the worse the core stability) recorded while performing medial-lateral displacements (≥8.9 mm) and the lowest label of the hip flexion with knee flexed ROM (<127°) were the two neuromuscular parameters that presented the largest individual contribution (an increase of 41.7 and 32.1 percentage points, respectively) to the probability that the class variable of the dominant leg (Y-Balance composite score) would adopt its moderate risk category. For the non-dominant leg, the two measures that have the highest impact on the probability of having the class variable in its moderate risk category were the lowest label of the ankle dorsiflexion with knee extended ROM (<30.5°) and again, the highest label of the dynamic core stability measure recorded while performing medial-lateral displacements (≥8.3 mm).

These results are in agreement with the findings reported by previous studies[102,106,248] which found that the hip and knee flexion and ankle dorsiflexion ROMs individually determined a meaningful proportion of the explained variance (R^2) for the Y-Balance test (ranging from 5 to 30% of the composite score) in different cohorts of athletes. These findings may support the hypothesis that those athletes with limited hip and knee flexion and ankle dorsiflexion ROMs might show a sub-optimal dynamic postural control while performing explosive actions (i.e., kicking and changes of direction) due to a smaller anterior displacement of their center of mass, which may increase the likelihood of losing stability.

Although core stability has been proposed as a crucial factor for Y-Balance test[289], only López-Valenciano et al.[102] have confirmed this link in professional female football players. In particular, this study found that the measure of core stability recorded while players were performing medial-lateral displacements on an unstable seat explained a large percentage (31.1%) of the performance achieved in the composite score of the Y-Balance test in female, but not in male professional football players. These sex-related differences found by López-Valenciano et al.[102] in the identification of this variable as an independent predictor for the Y-Balance test performance, but not in the absolute distances reached (composite scores), may be partially attributed to the fact that female players reported better results (statistically significant) in the core stability measures (with the exception of the static stability measure with feedback [CS-WF]) in comparison with their counterpart male football players (e.g.: CS-NF: 6.1 mm [males] – 4.3 mm [females], CS-CD: 10.8 mm [males] – 9.2 mm [females]). These differences in the core stability results in favor of the female players might have allowed them to develop different neuromuscular strategies to control the trunk in the frontal plane more efficiently while performing functional unilateral movements (e.g. changes of direction, kicking). Consequently, the individual contribution of the different measures of neuromuscular performance on dynamic postural control might have been modified, so core stability may have now adopted a more relevant role in such cohort of female players in contrast to other parameters (e.g. ROM). This hypothesis seems to be supported by the results reported in the current study, in which the scores obtained by the male futsal players in the core stability tasks were similar or even slightly better to those reported by López-Valenciano et al.[102] for the female players, and both BNs also selected some of these measures as independent predictors for the dynamic postural control performance.

Thanks to the fact that BNs have the ability to make simulations or instantiations when new evidence is introduced in the model, it was possible to carry out the study of the simplest step-by step combination of instanced variables (in term of the number of instantiations made) to maximize the probability for the class variable (composite score) to have its low and moderate category for the dominant (table 7.4) and non-dominant legs (table 7.5). The combination of poor dynamic core stability scores (medial-lateral displacement) (≥8.79 and 8.3 mm for the dominant and non-dominant leg, respectively) with limited hip flexion with knee flexed (dominant leg) (<127º) or ankle dorsiflexion with knee flexed (non-dominant leg) (<30.5º) ROM measures presented a strong probabilistic and negative relationship with dynamic postural control. On the contrary, the combination of high hip (>127º) and knee (>132.5 and 122º for the dominant and non-dominant leg, respectively) flexion and ankle dorsiflexion with knee flexed (>34º) and extended (>30.5º) ROM values seems to have presented the strongest probabilistic and positive impact on dynamic postural control.

7.6. Limitations

The current findings are limited to the participants' sport background (elite futsal players) so the extrapolation to other sport cohorts should be made with a certain degree of caution. Each sport modality and level of competition requires differences in technical skills, specific movements, training load and physical capacities, all of which predispose athletes to individual chronic musculo-skeletal adaptations, thus possibly developing different strategies for neuromuscular control and influencing subsequent Y-Balance test scores.

7.7. Conclusions

The BNs built (AUC = 0.899 and 0.879 for the dominant and non-dominant legs respectively) in the current study demonstrated that the dynamic postural control in elite male futsal players presents a strong relationship to the abilities to flex the hip, knee and ankle (dorsiflexion) joints in the sagittal plane and to control the core structures during static, but mainly during dynamic actions in the frontal plane. Therefore, training interventions aimed at improving or maintaining unilateral dynamic balance in professional male futsal players should include, among other things, exercises (i.e. stretching exercises for the major muscles of the posterior chain) that allow futsal players to achieve hip and knee flexion and ankle dorsiflexion with knee flexed and extended ROM scores equal or higher than 127º, 132.5º, 34º and 30.5º, respectively. Likewise, these training interventions should also include exercises to maintain or improve both the static (e.g. frontal, back and side planks) and dynamic medial-lateral (e.g. plank jacks and Russian twists, one-legged squats, lunges, airplane exercises) core stability so that futsal players can achieve medial radial error values lower than 6.69 and 8.79 mm, respectively.

7.8. Appendixes

Appendix 7.1. Description of the features recorded to build the Bayesian Networks.

Name	Labels	
	Dominant leg	**Non-dominant leg**
Y-Balance (composite score)	High risk (<89.6%) or Low risk (≥89.6%)	
Personal characteristics:		
1. Dominant leg	Left or right	
2. Stature (cm)	<180 or ≥180*	<173.55, 173.55-179.35 or >179.35
3. Body mass (kg)	<70.1, 70.1-74.95 or >74.95	<70.1, 70.1-74.95 or >74.95
Isometric hip abduction and adduction strength (N/kg):		
4. ISOM-Hip-Abd	<2.73, 2.73-2.93 or >2.93	<2.55, 2.55-2.81 or >2.81
5. ISOM-Hip-Abd	<2.61, 2.61-3.27 or >3.27	<3 or ≥3*
Lower extremity ranges of motion (º):		
6. ROM-HF$_{KF}$	<127 or ≥127*	<130 or ≥130*
7. ROM-HF$_{KE}$	<70.5, 70.5-79.5 or >79.5	<70.5, 70.5-81 or >81
8. ROM-HAB	<56, 56-63.5 or >63.5	<51.5, 51.5-60.5 or >60.5
9. ROM-HIR	<39.5, 39.5-44.5 or >44.5	<34.5, 34.5-44.5 or >44.5
10. ROM-HER	<51.5, 51.5-59.5 or >59.5	<49.5, 49.5-58 or >58
11. ROM-HE	<9, 9-14 or >14*	<9.5, 9.5-14.5 or >14.5

12. ROM-KF	<132.5 or ≥132.5*	<122 or ≥122*
13. ROM-AKDF$_{KE}$	<31 or ≥31*	<30.5 or ≥30.5*
14. ROM-AKDF$_{KF}$	<32.5, 32.5-37.5 or >37.5	<34 or ≥34*
Core stability (mm):		
15. CS-NF	<5.24, 5.24-6.69 or >6.69	<6.75 or ≥6.75*
16. CS-WF	<3.66, 3.66-5.34 or >5.34	<5 or ≥5*
17. CS-ML	<8.79 or ≥8.79*	<8.3 or ≥8.3
18. CS-AP	<6.88, 6.88-7.96 or >7.96	<6.88, 6.88-7.96 or >7.96
19. CS-CD	<8.31, 8.31-9.81 or >9.81	<8.31, 8.31-9.81 or >9.81
Isokinetic knee flexion and extension strength (Nm):		
20. ISOK-CON-KF$_{60}$	<98.95, 98.95-113.95 or >113.95	<92.45, 92.45-112 or >112
21. ISOK-CON-KF$_{180}$	<84.2, 84.2-106.05 or >106.05	<80.8, 80.8-106.65 or >106.65
22. ISOK-CON-KF$_{240}$	<82.65, 82.65-104 or >104	<80.35, 80.35-100.35 or >100.35
23. ISOK-CON-KE$_{60}$	<172.6, 172.6-220 or >220	<175.4, 175.4-204.15 or >204.15
24. ISOK-CON-KE$_{180}$	<124.85, 124.85-149.5 or >149.5	<127, 127-145.4 or >145.4
25. ISOK-CON-KE$_{240}$	<112, 112-142.65 or >142.65	<116.55, 116.55-134.05 >134.05
26. ISOK-ECC-KF$_{30}$	<98, 98-130.25 or >130.25	<97.45, 97.45-119.65 or >119.65
27. ISOK-ECC-KF$_{60}$	<79.95, 79.95-102.4 or >102.4	<101.3, 101.3-126.05 or >126.05
28. ISOK-ECC-KF$_{180}$	<103.4, 103.4-124.45 or >124.45	<96.85, 96.85-120.15 or >120.15

29. ISOK-ECC-KE_{30}	<218.9, 218.9-268.75 or >268.75	<222.45, 222.45-268.35 or >268.35
30. ISOK-ECC-KE_{60}	<217.75, 217.75-262.95 or >262.95	<223, 223-267.2 or >267.2
31. ISOK-ECC-KE_{180}	<191.75, 191.75-246.25 or >246.25	<188.95, 188.95-238.45 or >238.45

*: discretization based on visual inspection; N: Newton; m: meter, º: degrees; cm: centimeter; kg: kilograms; ISOM: isometric; PT: peak torque; Abd: abduction; Add: adduction; ROM: range of motion; HF_{KF}: hip flexion with the knee flexed; HF_{KE}: hip flexion with the knee extended; HE: Hip extension; HABD: hip abduction at 90º of hip flexion; HIR: hip internal rotation; HER: hip external rotation; KF: knee flexors; $AKDF_{KE}$: ankle dorsi-flexion with the knee extended; $AKDF_{KF}$: ankle dorsi-flexion with the knee flexed; CS: core stability; NF: unstable sitting without feedback; WF: unstable sitting with feedback; ML: unstable sitting while performing medial-lateral displacements with feedback; AP: unstable sitting while performing anterior-posterior displacements with feedback; CD: unstable sitting while performing circular displacements with feedback; ISOK: isokinetic; KE: knee extensors; CON: concentric; ECC: eccentric.

CHAPTER 8

Epilogue

CHAPTER 8

Epilogue

8.1. General conclusions

The studies included in this doctoral thesis: a) provide a deeper understanding of the injury incidence, characteristics and burden in futsal; b) confirm that the cost-effective, technically undemanding and portable 2D video analyses may be used as alternative to laboratory-based 3D motion analysis systems to quantify frontal plane knee alignment and hip and knee motion during drop vertical landings in male futsal players; c) present "user friendly" screening models to identify futsal players at high or low risk of non-contact lower extremity soft tissue injury by applying a novel Machine Learning approach; and d) improve the knowledge regarding the relationship between some neuromuscular performance measures and dynamic postural control through a Bayesian Network analysis.

Overall, the main findings of the current doctoral thesis may help clinicians, coaches and sports science specialists in the decision-making process of injury prevention.

The major contributions of the present doctoral thesis are listed below:

Study 1:

1. Professional futsal players are exposed to a substantial risk of sustaining injuries, especially during matches.
2. Male players´ risk of sustaining injuries during international tournaments is 8.5 times higher than during national tournaments.
3. Male players´ risk of sustaining injuries during matches in national competitions is similar to the female players´ risk.

4. Future studies should focus on studying the injury incidence and characteristic of male and female elite players during both national leagues and international tournaments.

Study 2:

1. Female players´ risk of sustaining injuries during matches is similar to incidence during training sessions.
2. Moderate injury incidence in female futsal players is most likely higher than other severities.
3. The overall time loss injury was 96 days loss per 1000 hours of exposure.
4. Outfield players showed higher incidence rate and amount of days off than goalkeepers.
5. The most frequent injury location was lower extremity and specifically knee and ankle.

Study 3:

1. Knee medial displacement and knee flexion ROM measures calculated during a bilateral drop vertical jump and using a 2D video analysis procedure might be considered as valid and feasible alternatives to their respective 3D criterion to quantify knee kinematics and to detect futsal players who demonstrated aberrant movement patterns in the frontal and sagittal planes, respectively.
2. New cut-off values need to be established to detect abnormal knee alignment and sagittal plane movements patterns using the 2D knee-to-ankle separation ratio and hip flexion range of motion.

Study 4:

1. Lower extremity soft-tissue injuries can be predicted with moderate accuracy through a combination of easy to employ field-based tests in elite futsal players

using machine learning techniques. The best performing model, which was built with just four ROM measures, reported an area under the curve score of 0.767 with true positive and negative rates of 85.1% and 62.1% respectively.

2. The measures obtained through the ROM-Sport battery and Y-Balance test, as independent data sets, could be used to predict lower extremity soft-tissue injuries in elite futsal players as they reported area under the curve scores of 0.757 and 0.701, true positive rate of 44.7% and 64.9%, true negative rate of 63.3 and 89.1%, respectively.
3. Futsal elite players screening through field-based tests, that requires little equipment, can be used quickly with an almost inexpensive tools by trained staff and analysed just once during the preseason, should be included as an essential component of the injury prevention.

Study 5:

1. Dynamic postural control has strong relationship with the abilities to flex the hip, knee and ankle, and with the control of the core structures during static but mainly dynamic tasks.
2. Training interventions focused on improving or maintaining unilateral dynamic balance should include exercises to stretch the major muscles of the posterior chain and to improve core stability during both static and dynamic tasks.

8.2. Thesis limitations and future research

As something inherent in any research, this doctoral thesis presents several limitations. Most of them were addressed in each of the five studies (chapters 3, 4, 5, 6, 7). Additionally, this section presents some limitations that may be the starting point for new studies and research projects.

1. *To collect and analyse injury incidence of different futsal populations*. This thesis has only analysed the epidemiology of injury in elite futsal players, which has allowed to know the main characteristics of the injuries and with that to establish prediction models on injuries with the highest burden. However, it could not be assured that these epidemiological data are the same in other age groups, levels of play and specially, in different team sports. Therefore, it is essential that future studies continue investigating injury incidence, characteristics and burden in futsal, focusing on female and young players. This knowledge will guide the development of prediction models according to the most burdensome injuries to each population.
2. *To analyse the criterion-related validity of 2D kinematic measures that may help to detect abnormal movement patterns during dynamic actions different to bilateral drop vertical landings*. This thesis has only explored the validity of 2D measures of frontal plane knee alignment and sagittal plane motion during drop vertical landing. However, the study of the criterion-related validity of 2D kinematic measures using more specific, but complex, futsal actions such as changes of direction or cutting manoeuvres might allow to identify abnormal movement patterns in more ecologically valid situations. Therefore, studies focusing on the validity of kinematic measures obtained with 2D video analysis and during futsal-related dynamic actions are warranted to help in the decision-making process of injury prediction.

3. *To evaluate the applicability of the prediction models developed in this doctoral thesis to different populations*. Due to the intrinsic characteristics of futsal (i.e. type and location of injuries with higher incidence, associated risk factors, physical requirements, etc.) it is possible that the models developed in the study four might not be generalizable to other sport modalities and level of play. Therefore, future lines of work should build prediction models in other high-performance sports as well as in different age groups, levels of play and sex. In this case, two doctoral theses which are being developed in our research group are trying to replicate the current Machine Learning approach to develop robust prediction models in other sports in both sexes.

4. *To improve complex statistical approaches coming from machine learning and data mining environments used in this thesis*. The screening models presented in study four still have some limitations, as having a model with good predictive accuracy is not enough if someone is interested in answering why an injury happened and what predictors are most closely associated with it. The base learning classifiers selected in this doctoral thesis cannot answer these questions, since they only allow to dichotomize the player. For example, someone might be interested in how much an injury likelihood will increase if hip abduction isometric strength imbalance between the player's legs increases or if there is a deficit in the ankle dorsiflexion range of motion, which could be estimated from statistical models such as Bayesian networks. Furthermore, the implementation of a SHAP type approach may provide a global overview of the most important features of a prediction model, which can also help to design preventive measures and risk mitigation strategies.

5. *To include more evidence-based risk factors in the prediction models in order to increase their ability to identify futsal players at high risk of LE-ST injury*. Although all the measures recorded during the screening session are purported as LE-ST injury risk factors, there are a number of other measures from different questionnaires and

field-based tests not included in the study four (due to time constraints) which have been associated with LE-ST injury (e.g.: back extensor [Biering-Sørensen test[253]] and flexor [Flexion-Rotation trunk test[254]] endurance measures, bilateral leg strength asymmetries [hop test battery[255]], relative leg stiffness and reactive strength index [256]) and that may have improved the ability to predict LE-ST injuries in this cohort of athletes.

6. *To develop prevention protocols once high-risk players are identified*. The injury prevention theory establishes that once the information about the problem (injury) and the main causes of injury are obtained, the next step is to propose preventive programs that ratify the data obtained and show the effectiveness of preventive strategies. Therefore, another limitation of this thesis, and future line of study, is the need to corroborate in a practical way the main results of the study four, establishing totally individualized preventive programs based on the identification of players with greater injury risk and the risk factors associated with each player.
7. *To study the relationships between neuromuscular performance measures and other complex movement skills with the aim of improving the design of training interventions*. The study five has quantitatively described and graphically represented the relationships of dependency and conditional independence between the main modifiable measures of neuromuscular performance and dynamic postural control, which have improved the understanding of this complex phenomenon and may guide the design of tailored training interventions. The efficacy of training interventions to enhance other complex skills such as cutting and lineal sprinting will be improved if the same statistical approach used in the study four would be used to explore the concurrent and individual contribution of the main neuromuscular factors that may play a role to perform them with a low risk of injury.

CAPÍTULO 9

Epílogo

CAPÍTULO 9

Epílogo

9.1. Conclusiones generales

Los estudios incluidos en esta tesis doctoral: a) aportan un mayor entendimiento en la incidencia de las lesiones, sus características y sus consecuencias (entendidas en días perdidos sin entrenar y jugar por lesión por cada 1000 horas de exposición a la práctica deportiva) en el fútbol sala; b) confirman que, los análisis de video 2D económicos, técnicamente poco exigentes y portátiles pueden usarse como alternativa a los sistemas de análisis de laboratorio de movimiento 3D para cuantificar la alineación de la rodilla en el plano frontal y el movimiento de la cadera y la rodilla durante aterrizajes verticales en jugadores masculinos de fútbol sala; c) presenta modelos de cribado "fáciles de usar" para identificar a los jugadores de fútbol sala con alto o bajo riesgo de lesiones de tejido blando de las extremidades inferiores en situaciones de no contacto mediante la aplicación de un nuevo enfoque de Aprendizaje Automático; y d) mejoran el conocimiento sobre la relación entre algunas medidas de rendimiento neuromuscular y el control postural dinámico a través de un análisis de redes bayesianas.

En general, los principales hallazgos de la presente tesis doctoral pueden ayudar a los médicos, entrenadores y profesionales en ciencias del deporte en el proceso de toma de decisiones para la prevención de lesiones.

A continuación, se enumeran las principales contribuciones de esta tesis doctoral:

Estudio 1:

1. Los jugadores profesionales de fútbol sala están expuestos a un gran riesgo de sufrir lesiones, especialmente durante los partidos.

2. El riesgo de los jugadores masculinos de sufrir lesiones durante los torneos internacionales es 8.5 veces mayor que durante los torneos nacionales.
3. El riesgo de los jugadores masculinos de sufrir lesiones durante los partidos en las competiciones nacionales es similar al riesgo de las jugadoras.
4. Futuros estudios deberían analizar la incidencia y características de las lesiones en jugadores de élite tanto masculinos como femeninos durante las ligas nacionales y los torneos internacionales.

Estudio 2:

1. El riesgo de las jugadoras de sufrir lesiones durante los partidos es similar a la incidencia durante las sesiones de entrenamiento.
2. La incidencia de lesiones de gravedad moderada es probablemente más alta que la de lesiones de otra severidad en jugadoras de fútbol sala.
3. La pérdida global de tiempo por lesión fue de 96 días por 1000 horas de exposición.
4. Las jugadoras de campo mostraron una mayor tasa de incidencias y cantidad de días perdidos que las porteras.
5. La localización de la lesión más frecuente fue en la extremidad inferior, específicamente la rodilla y el tobillo.

Estudio 3:

3. Las medidas de desplazamiento medial y el rango de movimiento de la flexión de la rodilla calculadas durante un salto vertical tras caída bilateral y el uso de un procedimiento de análisis de video 2D podrían considerarse como alternativas válidas y factibles a sus respectivas medidas criterio obtenidas a través de sistemas 3D para cuantificar la cinemática de la rodilla y detectar jugadores de fútbol sala que realizan movimientos inadecuados y potencialmente lesivos.

4. Se deben establecer nuevos valores de corte para detectar patrones anormales de alineación de la rodilla y de movimientos del plano sagital, utilizando la ratio de separación de rodilla-tobillo y el rango de movimiento de flexión de cadera obtenidos a través del análisis de sistemas 2D.

Estudio 4:

1. Las lesiones de tejido blando de las extremidades inferiores se pueden predecir con precisión moderada mediante una combinación de pruebas de campo fáciles de emplear en jugadores de fútbol sala de élite a través de técnicas de Aprendizaje Automático. El modelo que mejores resultados aportó, que fue construido con solo cuatro medidas de rango de movimiento, reportó un área bajo la curva de 0.767 con una tasa de verdaderos positivos y negativos de 85.1% y 62.1% respectivamente.
2. Las medidas obtenidas a través de la batería ROM-Sport y del test Y-Balance, como conjuntos de datos independientes, podrían usarse para predecir lesiones del tejido blando de extremidades inferiores en jugadores de fútbol sala de élite, ya que reportaron un área bajo la curva de 0.757 y 0.701, con una tasa de verdaderos positivos de 44.7% y 64.9%, y una tasa de verdaderos negativos de 63.3 y 89.1%, respectivamente.
3. El cribado de jugadores de élite de fútbol sala a través de pruebas de campo, que requieren poco equipamiento, pueden llevarse a cabo rápidamente con herramientas económicas por parte de personal capacitado y siendo analizado solamente una vez durante la pretemporada, debería incluirse como un componente esencial de la prevención de lesiones.

Estudio 5:

1. El control postural dinámico tiene una fuerte relación con habilidad para flexionar la cadera, la rodilla y el tobillo, con el control del tronco durante las tareas estáticas y sobre todo durante las tareas dinámicas.

2. Las intervenciones de entrenamiento enfocadas en mejorar o mantener el equilibrio dinámico unilateral deben incluir ejercicios para estirar los principales músculos de la cadena posterior y mejorar la estabilidad del tronco durante las tareas estáticas y dinámicas.

9.2. Limitaciones de la tesis y líneas futuras de investigación.

Como algo inherente a cualquier investigación, esta tesis doctoral presenta ciertas limitaciones. La mayoría de ellas han sido abordadas en los cinco estudios (capítulos 3, 4, 5, 6 y 7). Adicionalmente, esta sección presenta algunas limitaciones que pueden ser el punto de partida para nuevos estudios y proyectos de investigación.

1. *Recoger y analizar la incidencia de lesiones en diferentes poblaciones de fútbol sala.* Esta tesis solo ha analizado la epidemiología de las lesiones en jugadores de fútbol sala de élite, lo que ha permitido conocer las características principales de las lesiones y con eso establecer modelos de predicción sobre las lesiones con mayores consecuencias. Sin embargo, no se puede asegurar que estos datos epidemiológicos sean los mismos en otros grupos de edad, niveles de rendimiento y, especialmente, en diferentes deportes de equipo. Por lo tanto, es esencial que futuros estudios continúen investigando la incidencia, características y consecuencias de las lesiones, en el fútbol sala, centrándose en jugadores jóvenes. Este conocimiento permitirá el desarrollo de modelos de predicción de acuerdo con las lesiones más relevantes para cada población.

2. *Analizar la validez de criterio de las medidas cinemáticas 2D que pueden ayudar a detectar patrones de movimiento anormales durante acciones dinámicas diferentes a los aterrizajes verticales en caída bilateral tras salto desde cajón.* Esta tesis solo ha explorado la validez de las medidas 2D de la alineación de la rodilla en el plano frontal y del movimiento en el plano sagital durante el aterrizaje tras salto desde cajón. Sin embargo, el estudio de la validez criterio de las medidas cinemáticas 2D utilizando acciones de fútbol sala más específicas pero complejas, como cambios de dirección o recortes, podría permitir identificar patrones de movimiento anormales en situaciones más ecológicas. Por lo tanto, los estudios centrados en la validez de las medidas cinemáticas obtenidas con el análisis de video 2D y durante las acciones dinámicas

relacionadas con el fútbol sala son necesarios para ayudar en el proceso de toma de decisiones en la predicción de lesiones.

3. *Evaluar la aplicabilidad de los modelos de predicción desarrollados en esta tesis doctoral en diferentes poblaciones.* Debido a las características intrínsecas del fútbol sala (es decir, tipo y localización de las lesiones con mayor incidencia, factores de riesgo asociados, demandas físicas, etc.) es posible que los modelos desarrollados en el estudio cuatro no sean generalizables a otras modalidades deportivas y niveles de juego. Por lo tanto, líneas de trabajo futuras deben construir modelos de predicción en otros deportes de alto rendimiento, así como en diferentes grupos de edad, niveles de juego y sexo. En este caso, dos tesis doctorales que se están desarrollando en nuestro grupo de investigación están tratando de replicar el enfoque actual de Aprendizaje Automático para desarrollar modelos de predicción robustos en otros deportes y en ambos sexos.

4. *Mejorar los enfoques estadísticos complejos precedentes de entornos de Aprendizaje Automático y Minería de Datos utilizados en esta tesis.* Los modelos de detección presentados en el estudio cuatro todavía tienen algunas limitaciones, ya que tener un modelo con buena precisión predictiva no es suficiente si alguien está interesado en responder al por qué ocurrió una lesión y qué predictores están más estrechamente asociados con ella. Los clasificadores de aprendizaje seleccionados en esta tesis doctoral no pueden responder estas preguntas, ya que solo permiten dicotomizar al jugador. Por ejemplo, alguien podría estar interesado en cuánto aumentará la probabilidad de una lesión si aumenta el desequilibrio de la fuerza isométrica de la abducción de cadera entre las piernas del jugador o si hay un déficit en el rango de movimiento de dorsiflexión del tobillo, que podría estimarse a partir de modelos estadísticos como las redes Bayesianas. Además, la implementación de un enfoque de tipo SHAP puede proporcionar una visión global de las

características más importantes de un modelo de predicción, que también puede ayudar a diseñar medidas preventivas y estrategias de mitigación de riesgos.

5. *Incluir más factores de riesgo en los modelos de predicción basados en evidencia para aumentar su capacidad de identificar jugadores de fútbol sala con alto riesgo de lesión de tejido blando en la extremidad inferior.* Si bien todas las medidas registradas durante la sesión de evaluación se consideran factores de riesgo de lesiones de tejido blando en la extremidad inferior, existen otras medidas de diferentes cuestionarios y pruebas de campo que no se incluyen en el estudio cuatro (debido a limitaciones de tiempo) que se han asociado con estas lesiones (p. ej .: medidas de resistencia de extensores [test de Biering-Sørensen[253]] y flexores [prueba de flexo-rotación del tronco[254]] de tronco, asimetrías bilaterales de fuerza de las piernas [batería de test de salto[255]], rigidez relativa de la pierna e índice de fuerza reactiva[256]) y que pueden mejorar la capacidad de predecir lesiones de tejido blando de la extremidad inferior en esta cohorte de atletas.

6. *Desarrollar protocolos de prevención una vez identificados los jugadores en alto riesgo de sufrir una lesión.* La teoría de prevención de lesiones establece que una vez que se obtiene la información sobre el problema (la lesión) y las causas principales de la lesión, el siguiente paso es proponer programas que ratifiquen los datos obtenidos y muestren la efectividad de las estrategias preventivas. Así pues, otra limitación de esta tesis y, por lo tanto, otra futura línea de estudio es la necesidad de corroborar de manera práctica los principales resultados del estudio cuatro, estableciendo programas preventivos totalmente individualizados basados en la identificación de jugadores con mayor riesgo de lesiones y los factores de riesgo asociados a cada jugador.

7. *Estudiar las relaciones entre las medidas de rendimiento neuromuscular y otras habilidades de movimiento complejas con el objetivo de mejorar el diseño de las intervenciones de entrenamiento.* El estudio cinco ha descrito cuantitativamente y representado

gráficamente las relaciones de dependencia e independencia condicional entre las principales medidas modificables del rendimiento neuromuscular y el control postural dinámico, mejorando la comprensión de este complejo fenómeno y que pueden guiar el diseño de intervenciones de entrenamiento personalizadas. La eficacia de las intervenciones de entrenamiento para mejorar otras habilidades complejas, como el recorte y la carrera lineal, mejorará si se utiliza el mismo enfoque estadístico utilizado en el estudio para explorar la contribución simultánea e individual de los principales factores neuromusculares que pueden desempeñar un papel importante para realizarlos con un bajo riesgo de lesiones.

CHAPTER 10

References

CHAPTER 10

References

1. Tessitore A, Meeusen R, Pagano R, et al. Effectiveness of active versus passive recovery strategies after futsal games. *J Strength Cond Res*. 2008;22(5):1402-1412. doi:10.1519/JSC.0b013e31817396ac

2. Beato M, Coratella G, Schena F. Brief review of the state of art in futsal. *J Sports Med Phys Fitness*. 2016;56(4):428-432..

3. Castagna C, D'Ottavio S, Vera JG, Álvarez JCB. Match demands of professional Futsal: A case study. *J Sci Med Sport*. 2009;12(4):490-494. doi:10.1016/j.jsams.2008.02.001

4. Dogramaci SN, Watsford ML. A comparison of two different methods for time-motion analysis in team sports. *Int J Perform Anal Sport*. 2006;6(1):73-83. doi:10.1017/CBO9781107415324.004

5. Naser N, Ali A, Macadam P. Physical and physiological demands of futsal. *J Exerc Sci Fit*. 2017;15(2):76-80. doi:10.1016/j.jesf.2017.09.001

6. Junge A, Dvorak J. Injury risk of playing football in Futsal World Cups. *Br J Sports Med*. 2010;44(15):1089-1092. doi:10.1136/bjsm.2010.076752

7. Verrall GM, Kalairajah Y, Slavotinek JP, Spriggins AJ. Assessment of player performance following return to sport after hamstring muscle strain injury. *J Sci Med Sport*. 2006;9(1-2):87-90. doi:10.1016/j.jsams.2006.03.007

8. Hägglund M, Waldén M, Magnusson H, Kristenson K, Bengtsson H, Ekstrand J. Injuries affect team performance negatively in professional football: An 11-year follow-up of the UEFA Champions League injury study. *Br J Sports Med*. 2013;47(12):738-742. doi:10.1136/bjsports-2013-092215

9. Podlog L, Buhler CF, Pollack H, Hopkins PN, Burgess PR. Time trends for injuries and illness, and their relation to performance in the National Basketball Association. *J Sci Med Sport*. 2015;18(3):278-282. doi:10.1016/j.jsams.2014.05.005

10. Drew MK, Raysmith BP, Charlton PC. Injuries impair the chance of successful performance by sportspeople: A systematic review. *Br J Sports Med*. 2017;51(16):1209-1214. doi:10.1136/bjsports-2016-096731

11. Woods C, Hawkins R, Hulse M, Hodson A. The Football Association Medical Research Programme - analysis of preseaon injuries. *Thr Br J Sport Med*. 2002;(36):436-441.

12. Cumps E, Verhagen E, Armenians L, Meeusen R. Injury rate and socioeconomic costs resulting from sports injuries in Flanders: data derived from sports insurance statistics 2003. *Br J Sports Med*. 2008;42(9):767-772. doi:10.1136/bjsm.2007.037937

13. Hickey J, Shield AJ, Williams MD, Opar DA. The financial cost of hamstring strain injuries in the Australian Football League. *Br J Sports Med*. 2014;48(8):729-730. doi:10.1136/bjsports-2013-092884

14. van Mechelen W, Hlobil H, Kemper HCG. Incidence, Severity, Aetiology and Prevention of Sports Injuries: A Review of Concepts. *Sport Med An Int J Appl Med Sci Sport Exerc*. 1992;14(2):82-99. doi:10.2165/00007256-199214020-00002

15. Finch C. A new framework for research leading to sports injury prevention. *J Sci Med Sport*. 2006;9(1-2):3-9. doi:10.1016/j.jsams.2006.02.009

16. Van Tiggelen D, Wickes S, Stevens V, Roosen P, Witvrouw E. Effective prevention of sports injuries: A model integrating efficacy, efficiency, compliance and risk-taking behaviour. *Br J Sports Med*. 2008;42(8):648-652. doi:10.1136/bjsm.2008.046441

17. Bolling C, van Mechelen W, Pasman HR, Verhagen E. Context Matters: Revisiting the First Step of the 'Sequence of Prevention' of Sports Injuries. *Sport Med*.

2018;48(10):2227-2234. doi:10.1007/s40279-018-0953-x

18. Bittencourt NFN, Meeuwisse WH, Mendonça LD, Nettel-Aguirre A, Ocarino JM, Fonseca ST. Complex systems approach for sports injuries: moving from risk factor identification to injury pattern recognition—narrative review and new concept. *Br J Sports Med*. 2016;50(21):1309-1314. doi:10.1136/bjsports-2015-095850

19. Roe M, Malone S, Blake C, et al. A six stage operational framework for individualising injury risk management in sport. *Inj Epidemiol*. 2017;4(1). doi:10.1186/s40621-017-0123-x

20. Álvarez Medina J, Murillo Lorente V, Giménez Salillas L, Manonelles Marqueta P. Modificación del volumen–intensidad como medida preventiva de lesiones en fútbol sala. *Rev Int Med y Ciencias la Act Fis y del Deport*. 2016;16(61):85-97. doi:10.15366/rimcafd2016.61.007

21. Angoorani H, Haratian Z, Mazaherinezhad A, Younespour S. Injuries in Iran futsal national teams: A comparative study of incidence and characteristics. *Asian J Sports Med*. 2014;5(3):0-4. doi:10.5812/asjsm.23070

22. Hamid MSA, Jaafar Z, Ali ASM. Incidence and characteristics of injuries during the 2010 FELDA/FAM national futsal league in Malaysia. *PLoS One*. 2014;9(4):2-7. doi:10.1371/journal.pone.0095158

23. Ribeiro RN, Oliveira L, Costa P. Epidemiologic analysis of injuries occurred during the 15 th Brazilian Indoor Soccer (Futsal) Sub20 Team Selection Championship. *Rev Bras Med do Esporte*. 2006;12(31):9-12.

24. Larruskain J, Lekue JA, Diaz N, Odriozola A, Gil SM. A comparison of injuries in elite male and female football players: A five-season prospective study. *Scand J Med Sci Sport*. 2018;28(1):237-245. doi:10.1111/sms.12860

25. Fuller CW. Injury Risk (Burden), Risk Matrices and Risk Contours in Team Sports:

A Review of Principles, Practices and Problems. *Sport Med*. 2018;48(7):1597-1606. doi:10.1007/s40279-018-0913-5

26. Bahr R, Clarsen B, Ekstrand J. Why we should focus on the burden of injuries and illnesses, not just their incidence. *Br J Sports Med*. 2017;0(0):bjsports-2017-098160. doi:10.1136/bjsports-2017-098160

27. Bahr R. Why screening tests to predict injury do not work-and probably never will.: A critical review. *Br J Sports Med*. 2016;50(13):776-780. doi:10.1136/bjsports-2016-096256

28. Brockett CL, Morgan DL, Proske U. Predicting Hamstring Injury in Elite Athletes. *Med Sci Sports Exerc*. 2004;36(3):379-387. doi:10.1249/01.MSS.0000117165.75832.05

29. López-Valenciano A, Ayala F, Puerta JosM, et al. A Preventive Model for Muscle Injuries: A Novel Approach based on Learning Algorithms. *Med Sci Sports Exerc*. 2018;50(5):915-927. doi:10.1249/MSS.0000000000001535

30. Ayala F, López-Valenciano A, Gámez Martín JA, et al. A Preventive Model for Hamstring Injuries in Professional Soccer: Learning Algorithms. *Int J Sports Med*. 2019;40(05):344-353. doi:10.1055/a-0826-1955

31. Hägglund M, Waldén M, Ekstrand J. Previous injury as a risk factor for injury in elite football: A prospective study over two consecutive seasons. *Br J Sports Med*. 2006;40(9):767-772. doi:10.1136/bjsm.2006.026609

32. Arnason A, Sigurdsson SB, Gudmundsson A, Holme I, Engebretsen L, Bahr R. Risk Factors for Injuries in Football. *Am J Sports Med*. 2004;32(1_suppl):5-16. doi:10.1177/0363546503258912

33. Hauge Engebretsen A, Myklebust G, Holme I, Engebretsen L, Bahr R. Intrinsic risk factors for hamstring injuries among male soccer players: A prospective cohort study. *Am J Sports Med*. 2010;38(6):1147-1153. doi:10.1177/0363546509358381

34. Hosea TM, Carey CM, Harrer MM. The Gender Issue: Epidemiology of Ankle Injuries in Athletes Who Participate in Basketball. *Clin Orthop Relat Res*. 2000;372(372):45-49.

35. Tan SHS, Lau BPH, Khin LW, Lingaraj K. The Importance of Patient Sex in the Outcomes of Anterior Cruciate Ligament Reconstructions. *Am J Sports Med*. 2016;44(1):242-254. doi:10.1177/0363546515573008

36. Sutton KM, Bullock JM. Anterior cruciate ligament rupture: Differences between males and females. *J Am Acad Orthop Surg*. 2013;21(1):41-50. doi:10.5435/JAAOS-21-01-41

37. Giza E, Mithöfer K, Farrell L, Zarins B, Gill T, Drawer S. Injuries in women's professional soccer. *Br J Sports Med*. 2005;39(4):212-216. doi:10.1136/bjsm.2004.011973

38. Borowski LA, Yard EE, Fields SK, Comstock RD. The Epidemiology of US High School Basketball Injuries, 2005–2007. *Am J Sports Med*. 2008;36(12):2328-2335. doi:10.1177/0363546508322893

39. Best G. Epidemiology and Incidence of Injury in Elite Netball Players – an Injury Audit of the 2016 Netball Superleague Season. *Br J Sports Med*. 2017;51(4):297.1-297. doi:10.1136/bjsports-2016-097372.34

40. Dauty M, Menu P, Fouasson-Chailloux A, Ferréol S, Dubois C. Prediction of hamstring injury in professional soccer players by isokinetic measurements. *Muscles Ligaments Tendons J*. 2016;6(1):116-123. doi:10.11138/mltj/2016.6.1.116

41. Hägglund M, Waldén M, Ekstrand J. Injuries among male and female elite football players. *Scand J Med Sci Sport*. 2009;19(6):819-827. doi:10.1111/j.1600-0838.2008.00861.x

42. Mallo J, González P, Veiga S, Navarro E. Injury incidence in a spanish sub-elite

professional football team: A prospective study during four consecutive seasons. *J Sport Sci Med*. 2011;10(4):731-736.

43. Falese L, Della Valle P, Federico B. Epidemiology of football (soccer) injuries in the 2012/2013 and 2013/2014 seasons of the Italian Serie A. *Res Sport Med*. 2016;24(4):426-432. doi:10.1080/15438627.2016.1239105

44. Woods C, Hawkins RD, Maltby S, Hulse M, Thomas A, Hodson A. The Football Association Medical Research Programme: An audit of injuries in professional football - Analysis of hamstring injuries. *Br J Sports Med*. 2004;38(1):36-41. doi:10.1136/bjsm.2002.002352

45. Junge A, Dvorak J, Graf-Baumann T, Peterson L. Football Injuries during FIFA Tournaments and the Olympic Games, 1998-2001: Development and Implementation of an Injury-Reporting System. *Am J Sports Med*. 2004;32(SUPPL. 1):1998-2001. doi:10.1177/0363546503261245

46. Ekstrand J, Hägglund M, Waldén M. Epidemiology of muscle injuries in professional football (soccer). *Am J Sports Med*. 2011;39(6):1226-1232. doi:10.1177/0363546510395879

47. Fousekis K, Tsepis E, Poulmedis P, Athanasopoulos S, Vagenas G. Intrinsic risk factors of non-contact quadriceps and hamstring strains in soccer: A prospective study of 100 professional players. *Br J Sports Med*. 2011;45(9):709-714. doi:10.1136/bjsm.2010.077560

48. Wilk KE, Macrina LC, Fleisig GS, et al. Factors associated with increased propensity for hamstring injury in English Premier League soccer players. *Am J Sports Med*. 2015;43(10):2379-2385. doi:10.1177/0363546515594380

49. Croisier J-LL, Ganteaume S, Binet J, Genty M, Ferret J-MM. Strength imbalances and prevention of hamstring injury in professional soccer players: A prospective study. *Am J Sports Med*. 2008;36(8):1469-1475. doi:10.1177/0363546508316764

50. Ruddy JD, Shield AJ, Maniar N, et al. Predictive Modeling of Hamstring Strain Injuries in Elite Australian Footballers. *Med Sci Sports Exerc*. 2018;50(5):906-914. doi:10.1249/MSS.0000000000001527

51. Zazulak BT, Hewett TE, Reeves NP, Goldberg B, Cholewicki J. Deficits in neuromuscular control of the trunk predict knee injury risk: A prospective biomechanical-epidemiologic study. *Am J Sports Med*. 2007;35(7):1123-1130. doi:10.1177/0363546507301585

52. Moen F, Myhre K, Sandbakk Ø, Moen F. Psychological Determinants of Burnout, Illness and Injury among Elite Junior Athletes. *Sport J*. 2016.

53. Cresswell SL, Eklund RC. The nature of player burnout in rugby: Key characteristics and attributions. *J Appl Sport Psychol*. 2006;18(3):219-239. doi:10.1080/10413200600830299

54. Hägglund M, Zwerver J, Ekstrand J. Epidemiology of patellar tendinopathy in elite male soccer players. *Am J Sports Med*. 2011;39(9):1906-1911. doi:10.1177/0363546511408877

55. Shelbourne KD, Kerr B. The relationship of femoral intercondylar notch width to height, weight, and sex in patients with intact anterior cruciate ligaments. *Am J Knee Surg*. 2001;14(2):92-96.

56. Uhorchak JM, Scoville CR, Williams GN, Arciero RA, St. Pierre P, Taylor DC. Risk Factors Associated with Noncontact Injury of the Anterior Cruciate Ligament. A Prospective Four-Year Evaluation of 859 West Point Cadets. *Am J Sports Med*. 2003;31(6):831-842. doi:10.1177/03635465030310061801

57. Plisky PJ, Rauh MJ, Kaminski TW, Underwood FB. Star excursion balance test as a predictor of lower extremity injury in high school basketball players. *J Orthop Sport Phys Ther*. 2006;36(12):911-919. doi:10.2519/

58. Butler RJ, Lehr ME, Fink ML, Kiesel KB, Plisky PJ. Dynamic balance performance and noncontact lower extremity injury in college football players: an initial study. *Sports Health*. 2013;5(5):417-422. doi:10.1177/1941738113498703

59. Chung PYM, Ng GYF. Comparison between an accelerometer and a three-dimensional motion analysis system for the detection of movement. *Physiother (United Kingdom)*. 2012;98(3):256-259. doi:10.1016/j.physio.2011.06.003

60. Hewett TE, Myer GD, Ford KR, et al. Biomechanical Measures of Neuromuscular Control and Valgus Loading of the Knee Predict Anterior Cruciate Ligament Injury Risk in Female Athletes: A Prospective Study. *Am J Sports Med*. 2005;33(4):492-501. doi:10.1177/0363546504269591

61. McLean SG, Walker K, Ford KR, Myer GD, Hewett TE, Van Den Bogert AJ. Evaluation of a two dimensional analysis method as a screening and evaluation tool for anterior cruciate ligament injury. *Br J Sports Med*. 2005;39(6):355-362. doi:10.1136/bjsm.2005.018598

62. Myer GD, Ford KR, Di Stasi SL, Foss KDB, Micheli LJ, Hewett TE. High knee abduction moments are common risk factors for patellofemoral pain (PFP) and anterior cruciate ligament (ACL) injury in girls: Is PFP itself a predictor for subsequent ACL injury? *Br J Sports Med*. 2015;49(2):118-122. doi:10.1136/bjsports-2013-092536

63. Paterno M V., Schmitt LC, Ford KR, et al. Biomechanical measures during landing and postural stability predict second anterior cruciate ligament injury after anterior cruciate ligament reconstruction and return to sport. *Am J Sports Med*. 2010;38(10):1968-1978. doi:10.1177/0363546510376053

64. Willson JD, Davis IS. Utility of the Frontal Plane Projection Angle in Females With Patellofemoral Pain. *J Orthop Sport Phys Ther*. 2008;38(10):606-615. doi:10.2519/jospt.2008.2706

65. Gwynne CR, Curran SA. Quantifying frontal plane knee motion during single limb squats: reliability and validity of 2-dimensional measures. *Int J Sports Phys Ther*. 2014;9(7):898-906.

66. Herrington L, Alenezi F, Alzhrani M, Alrayani H, Jones R. The reliability and criterion validity of 2D video assessment of single leg squat and hop landing. *J Electromyogr Kinesiol*. 2017;34:80-85. doi:10.1016/j.jelekin.2017.04.004

67. Mizner RL, Chmielewski TL, Toepke JJ, Tofte KB. Comparison of 2-Dimensional Measurement Techniques for Predicting Knee Angle and Moment During a Drop Vertical Jump. *Clin J Sport Med*. 2012;22(3):221-227. doi:10.1097/JSM.0b013e31823a46ce

68. Ortiz A, Rosario-Canales M, Rodríguez A, Seda A, Figueroa C, Venegas-Ríos H. Reliability and concurrent validity between two-dimensional and three-dimensional evaluations of knee valgus during drop jumps. *Open Access J Sport Med*. Published online 2016:65. doi:10.2147/OAJSM.S100242

69. Sorenson B, Kernozek TW, Willson JD, Ragan R, Hove J. Two- and Three-Dimensional Relationships Between Knee and Hip Kinematic Motion Analysis: Single-Leg Drop-Jump Landings. *J Sport Rehabil*. 2015;24(4):363-372. doi:10-1123/jsr.2014-0206

70. Myer GD, Ford KR, Khoury J, Succop P, Hewett TE. Development and Validation of a Clinic-Based Prediction Tool to Identify Female Athletes at High Risk for Anterior Cruciate Ligament Injury. *Am J Sports Med*. 2010;38(10):2025-2033. doi:10.1177/0363546510370933

71. López-Valenciano A, Ruiz-Pérez I, Garcia-Gómez A, et al. Epidemiology of injuries in professional football: a systematic review and meta-analysis. *Br J Sports Med*. Published online June 6, 2019:bjsports-2018-099577. doi:10.1136/bjsports-2018-099577

72. Ruiz-Pérez I, López-Valenciano A, Elvira JLL, García-Gómez A, de Ste Croix M, Ayala F. Epidemiology of injuries in elite male and female futsal: a systematic review and meta-analysis. *Press*. 2020.

73. Williams S, Trewartha G, Kemp S, Stokes K. A meta-analysis of injuries in senior men's professional Rugby Union. *Sport Med*. 2013;43(10):1043-1055. doi:10.1007/s40279-013-0078-1

74. Panagodage Perera NK, Joseph C, Kemp JL, Finch CF. Epidemiology of Injuries in Women Playing Competitive Team Bat-or-Stick Sports: A Systematic Review and a Meta-Analysis. *Sport Med*. 2018;48(3):617-640. doi:10.1007/s40279-017-0815-y

75. Fernández A, del Río S, Chawla N V., Herrera F. An insight into imbalanced Big Data classification: outcomes and challenges. *Complex Intell Syst*. 2017;3(2):105-120. doi:10.1007/s40747-017-0037-9

76. Galar M, Fernandez A, Barrenechea E, Bustince H, Herrera F. A review on ensembles for the class imbalance problem: Bagging-, boosting-, and hybrid-based approaches. *IEEE Trans Syst Man Cybern Part C Appl Rev*. 2012;42(4):463-484. doi:10.1109/TSMCC.2011.2161285

77. Haixiang G, Yijing L, Shang J, Mingyun G, Yuanyue H, Bing G. Learning from class-imbalanced data: Review of methods and applications. *Expert Syst Appl*. 2017;73:220-239. doi:10.1016/j.eswa.2016.12.035

78. López V, Fernández A, García S, Palade V, Herrera F. An insight into classification with imbalanced data: Empirical results and current trends on using data intrinsic characteristics. *Inf Sci (Ny)*. 2013;250:113-141. doi:10.1016/j.ins.2013.07.007

79. Croisier JL, Forthomme B, Namurois MH, Vanderthommen M, Crielaard JM. Hamstring muscle strain recurrence and strength performance disorders. *Am J Sports Med*. 2002;30(2):199-203. doi:10.1177/03635465020300020901

80. Timmins RG, Bourne MN, Shield AJ, Williams MD, Lorenzen C, Opar DA. Short biceps femoris fascicles and eccentric knee flexor weakness increase the risk of hamstring injury in elite football (soccer): A prospective cohort study. *Br J Sports Med*. 2016;50(24):1524-1535. doi:10.1136/bjsports-2015-095362

81. Van Dyk N, Bahr R, Whiteley R, et al. Hamstring and Quadriceps Isokinetic Strength Deficits Are Weak Risk Factors for Hamstring Strain Injuries. *Am J Sports Med*. 2016;44(7):1789-1795. doi:10.1177/0363546516632526

82. Claudino JG, Capanema D de O, de Souza TV, Serrão JC, Machado Pereira AC, Nassis GP. Current Approaches to the Use of Artificial Intelligence for Injury Risk Assessment and Performance Prediction in Team Sports: a Systematic Review. *Sport Med - Open*. 2019;5(1). doi:10.1186/s40798-019-0202-3

83. O'Connor S, McCaffrey N, Whyte EF, Moran KA. Can a Standardized Visual Assessment of Squatting Technique and Core Stability Predict Injury? *J strength Cond Res*. 2020;34(1):26-36. doi:10.1519/JSC.0000000000003262

84. Hegedus EJ, McDonough S, Bleakley C, et al. Physical performance tests predict injury in National Collegiate Athletic Association athletes: A three-season prospective cohort study. *Br J Sports Med*. 2016;50(21):1333-1337. doi:10.1136/bjsports-2015-094885

85. Lee JWY, Mok KM, Chan HCK, Yung PSH, Chan KM. Eccentric hamstring strength deficit and poor hamstring-to-quadriceps ratio are risk factors for hamstring strain injury in football: A prospective study of 146 professional players. *J Sci Med Sport*. 2018;21(8):789-793. doi:10.1016/j.jsams.2017.11.017

86. Opar DA, Williams MD, Timmins RG, Hickey J, Duhig SJ, Shield AJ. Eccentric hamstring strength and hamstring injury risk in Australian footballers. *Med Sci Sports Exerc*. 2015;47(4):857-865. doi:10.1249/MSS.0000000000000465

87. Van Dyk N, Bahr R, Burnett AF, et al. A comprehensive strength testing protocol

offers no clinical value in predicting risk of hamstring injury: A prospective cohort study of 413 professional football players. *Br J Sports Med*. 2017;51(23):1695-1702. doi:10.1136/bjsports-2017-097754

88. Zvijac JE, Toriscelli TA, Merrick S, Kiebzak GM. Isokinetic concentric quadriceps and hamstring strength variables from the NFL scouting combine are not predictive of hamstring injury in first-year professional football players. *Am J Sports Med*. 2013;41(7):1511-1518. doi:10.1177/0363546513487983

89. Bartlett JD, O'Connor F, Pitchford N, Torres-Ronda L, Robertson SJ. Relationships Between Internal and External Training Load in Team-Sport Athletes: Evidence for an Individualized Approach. *Int J Sports Physiol Perform*. 2017;12(2):230-234. doi:10.1123/ijspp.2015-0791

90. Ertelt T, Solomonovs I, Gronwald T. Enhancement of force patterns classification based on Gaussian distributions. *J Biomech*. 2018;67:144-149. doi:10.1016/j.jbiomech.2017.12.006

91. Ge S. Research on the factors of basketball injury in physical teaching based on artificial neural network. *Rev la Fac Ing*. 2017;32(3):415-422.

92. Kautz T, Groh BH, Hannink J, Jensen U, Strubberg H, Eskofier BM. Activity recognition in beach volleyball using a Deep Convolutional Neural Network. *Data Min Knowl Discov*. 2017;31(6):1678-1705. doi:10.1007/s10618-017-0495-0

93. Rossi A, Pappalardo L, Cintia P, Iaia FM, Fernàndez J, Medina D. Effective injury forecasting in soccer with GPS training data and machine learning. Sampaio J, ed. *PLoS One*. 2018;13(7):e0201264. doi:10.1371/journal.pone.0201264

94. Thornton HR, Delaney JA, Duthie GM, Dascombe BJ. Importance of Various Training-Load Measures in Injury Incidence of Professional Rugby League Athletes. *Int J Sports Physiol Perform*. 2017;12(6):819-824. doi:10.1123/ijspp.2016-0326

95. Rommers N, Rössler R, Verhagen E, et al. A Machine Learning Approach to Assess Injury Risk in Elite Youth Football Players. *Med Sci Sport Exerc*. Published online February 2020:1. doi:10.1249/MSS.0000000000002305

96. Gribble PA, Hertel J, Plisky P. Using the star excursion balance test to assess dynamic postural-control deficits and outcomes in lower extremity injury: A literature and systematic review. *J Athl Train*. 2012;47(3):339-357. doi:10.4085/1062-6050-47.3.08

97. Attenborough AS, Sinclair PJ, Sharp T, et al. The identification of risk factors for ankle sprains sustained during netball participation. *Phys Ther Sport*. 2017;23:31-36. doi:10.1016/j.ptsp.2016.06.009

98. Calvo-Gonell A, Pina-Romero JA, Maciá-Soler L. Relationship Between the Y Balance Test Scores and Soft Tissue Injury Incidence in a Soccer Team. *Int J Sports Phys Ther*. 2015;10(7):955-966.

99. Noronha M, França LC, Haupenthal A, et al. Intrinsic predictive factors for ankle sprain in active university students: A prospective study. *Scand J Med Sci Sports*. 2012;23(5). doi:10.1111/j.1600-0838.2011.01434.x

100. Booysen MJ, Gradidge PJ-LL, Watson E. The relationships of eccentric strength and power with dynamic balance in male footballers. *J Sports Sci*. 2015;33(20):2157-2165. doi:10.1080/02640414.2015.1064152

101. Lockie RG, Schultz AB, Callaghan SJ, Jeffriess MD, Berry SP. Reliability and validity of a new test of change-of-direction speed for field- based sports: The change-of-direction and acceleration test (CODAT). *J Sport Sci Med*. 2013;12(1):88-96. doi:10.2478/v10078-012-0053-1

102. López-Valenciano A, Ayala F, De Ste Croix M, Barbado D, Vera-Garcia FJ. Different neuromuscular parameters influence dynamic balance in male and female football players. *Knee Surgery, Sport Traumatol Arthrosc*. 2018. doi:10.1007/s00167-018-5088-y

103. Ambegaonkar JP, Mettinger LM, Caswell S V, Burtt A, Cortes N. Relationships between core endurance, hip strength, and balance in collegiate female athletes. *Int J Sports Phys Ther*. 2014;9(5):604-616.

104. Wilson BR, Robertson KE, Burnham JM, Yonz MC, Ireland ML, Noehren B. The Relationship Between Hip Strength and the Y Balance Test. *J Sport Rehabil*. 2018;27(5):445-450. doi:10.1123/jsr.2016-0187

105. Ozmen T. Relationship between core stability, dynamic balance and jumping performance in soccer players. *Turkish J Sport Exerc*. 2016;18(1):110. doi:10.15314/tjse.93545

106. Overmoyer G V., Reiser RF. Relationships Between Lower-Extremity Flexibility, Asymmetries, and the Y Balance Test. *J Strength Cond Res*. 2015;29(5):1240-1247. doi:10.1519/JSC.0000000000000693

107. Bielza C, Larrañaga P. Discrete Bayesian Network Classifiers. *ACM Comput Surv*. 2014;47(1):1-43. doi:10.1145/2576868

108. Ekstrand J, Hägglund M, Fuller CW. Comparison of injuries sustained on artificial turf and grass by male and female elite football players. *Scand J Med Sci Sport*. 2011;21(6):824-832. doi:10.1111/j.1600-0838.2010.01118.x

109. Hahn T, Foldspang A. The Q angle and sport. *Scand J Med Sci Sports*. 1997;7(1):43-48.

110. Komi P V., Karlsson J. Skeletal muscle fibre types, enzyme activities and physical performance in young males and females. *Acta Physiol Scand*. 1978;103(2):210-218. doi:10.1111/j.1748-1716.1978.tb06208.x

111. Wojtys EM, Huston LJ, Lindenfeld TN, Hewett TE, Greenfield ML. Association between the menstrual cycle and anterior cruciate ligament injuries in female athletes. *Am J Sports Med*. 1998;26(5):614-619. doi:10.1177/0363546506295699

112. Crossley KM, Patterson BE, Culvenor AG, Bruder AM, Mosler AB, Mentiplay BF.

Making football safer for women: A systematic review and meta-analysis of injury prevention programmes in 11 773 female football (soccer) players. *Br J Sports Med*. 2020;(2):1-12. doi:10.1136/bjsports-2019-101587

113. Taylor JB, Ford KR, Nguyen AD, Terry LN, Hegedus EJ. Prevention of Lower Extremity Injuries in Basketball: A Systematic Review and Meta-Analysis. *Sports Health*. 2015;7(5):392-398. doi:10.1177/1941738115593441

114. Smith AM. Psychological Impact of Injuries in Athletes. *Sport Med*. 1996;22(6):391-405. doi:10.2165/00007256-199622060-00006

115. Bateman A, Morgan KAD. The Postinjury Psychological Sequelae of High-Level Jamaican Athletes: Exploration of a Posttraumatic Stress Disorder–Self-Efficacy Conceptualization. *J Sport Rehabil*. 2019;28(2):144-152. doi:10.1123/jsr.2017-0140

116. Eirale C, Tol JL, Farooq A, Smiley F, Chalabi H. Low injury rate strongly correlates with team success in Qatari professional football. *Br J Sports Med*. 2013;47(12):807-808. doi:10.1136/bjsports-2012-091040

117. Ekstrand J. Keeping your top players on the pitch: The key to football medicine at a professional level. *Br J Sports Med*. 2013;47(12):723-724. doi:10.1136/bjsports-2013-092771

118. Hutton B, Catalá-López F, Moher D. The PRISMA statement extension for systematic reviews incorporating network meta-analysis: PRISMA-NMA. *Med Clínica (English Ed)*. 2016;147(6):262-266. doi:10.1016/j.medcle.2016.10.003

119. Moher D, Tricco AC. Issues related to the conduct of systematic reviews: A focus on the nutrition field. *Am J Clin Nutr*. 2008;88(5):1191-1199. doi:10.3945/ajcn.2008.26255

120. Fuller CW, Ekstrand J, Junge A, et al. Consensus statement on injury definitions and data collection procedures in studies of football (soccer) injuries. *Clin J Sport Med*. 2006;16(2):97-106. doi:10.1097/JSM.0b013e31803220b3

121. Hägglund M, Waldén M, Bahr R. Methods for epidemiological study of injuries to professional football players: developing the UEFA model. *Br J Sport Med*. 2005;39:340-346. doi:10.1136/bjsm.2005.018267

122. Lupo C, Tessitore A, Minganti C, Capranica L. Notational Analysis of Elite and Sub-Elite Water Polo Matches. *J Strength Cond Res*. 2010;24(1):223-229. doi:10.1519/JSC.0b013e3181c27d36

123. Maly T, Zahalka F, Mala L. Muscular strength and strength asymmetries in elite and sub-elite professional soccer player. *Sport Sci*. 2014;7(1):26-33.

124. Cometti G, Maffiuletti NA, Pousson M, Chatard JC, Maffulli N. Isokinetic strength and anaerobic power of elite, subelite and amateur French soccer players. *Int J Sports Med*. 2001;22(1):45-51. doi:10.1055/s-2001-11331

125. Rodseth R, Marais L. Meta-analysis: Everything you wanted to know but were afraid to ask. *SA Orthop J*. 2016;15(4):31-36. doi:10.17159/2309-8309/2016/v15n4a4

126. von Elm E, Altman DG, Egger M, Pocock SJ, Gøtzsche PC, Vandenbroucke JP. The strengthening the reporting of observational studies in epidemiology (STROBE) statement: Guidelines for reporting observational studies. *Int J Surg*. 2014;12(12):1495-1499. doi:10.1016/j.ijsu.2014.07.013

127. Olmos M, Antelo M, Vazquez H, Smecuol E, Mauriño E, Bai JC. Systematic review and meta-analysis of observational studies on the prevalence of fractures in coeliac disease. *Dig Liver Dis*. 2008;40(1):46-53. doi:10.1016/j.dld.2007.09.006

128. Ruiz-Pérez I, López-Valenciano A, Jiménez-Loaisa A, Elvira JLLL, De Ste Croix M, Ayala F. Injury incidence, characteristics and burden among female sub-elite futsal players: a prospective study with three-year follow-up. *PeerJ*. 2019;7:e7989. doi:10.7717/peerj.7989

129. Zeng C, Gao S guang, Wei J, et al. The influence of the intercondylar notch

dimensions on injury of the anterior cruciate ligament: A meta-analysis. *Knee Surgery, Sport Traumatol Arthrosc*. 2013;21(4):804-815. doi:10.1007/s00167-012-2166-4

130. Saragiotto BT, Yamato TP, Hespanhol Junior LC, Rainbow MJ, Davis IS, Lopes AD. What are the main risk factors for running-related injuries? *Sport Med*. 2014;44(8):1153-1163. doi:10.1007/s40279-014-0194-6

131. Gao J, Wei W, Wang G, Zhou H, Fu Y, Liu N. Circulating vitamin D concentration and risk of prostate cancer: A dose-response meta-analysis of prospective studies. *Ther Clin Risk Manag*. 2018;14:95-104. doi:10.2147/TCRM.S149325

132. Doherty C, Delahunt E, Caulfield B, Hertel J, Ryan J, Bleakley C. The incidence and prevalence of ankle sprain injury: A systematic review and meta-analysis of prospective epidemiological studies. *Sport Med*. 2014;44(1):123-140. doi:10.1007/s40279-013-0102-5

133. Pantelis B, Nikolopoulos K, Bagos PG, Nikolopoulos GK. Mixed-effects poisson regression models for meta-analysis of follow-up studies with constant or varying durations. *Int J Biostat*. 2009;5(1):1-35. doi:10.2202/1557-4679.1168

134. Higgins JPT, Thompson SG. Quantifying heterogeneity in a meta-analysis. *Stat Med*. 2002;21(11):1539-1558. doi:10.1002/sim.1186

135. Viechtbauer W. Conducting meta-analyses in R with the metafor. *J Stat Softw*. 2010;36(3):1-48.

136. Hopkins W. A spreadsheet for deriving a confidence interval, mechanistic inference and clinical inference from a p value. *Sportscience*. 2007;11:16-20.

137. Hopkins WG. Linear Models and Effect Magnitudes for Research , Clinical and Practical Applications. *Sportscience*. 2010;14(October):49-57.

138. Batterham AM, Hopkins WG. Making meaningful inferences about magnitudes. *Int J Sports Physiol Perform*. 2006;1(1):50-57. doi:10.1123/ijspp.1.1.50

139. Gabbett TJ. Science of rugby league football: A review. *J Sports Sci*. 2005;23(9):961-976. doi:10.1080/02640410400023381

140. Mónaco M, Rincón JAG, Ronsano BJM, Whiteley R, Sanz-Lopez F, Rodas G. Injury incidence and injury patterns by category, player position, and maturation in elite male handball elite players. *Biol Sport*. 2019;36(1):67-74. doi:10.5114/biolsport.2018.78908

141. Faude O, Junge A, Kindermann W, Dvorak J. Risk factors for injuries in elite female soccer players. *Br J Sports Med*. 2006;40(9):785-790. doi:10.1136/bjsm.2006.027540

142. Tegnander A, Olsen OE, Moholdt TT, Engebretsen L, Bahr R. Injuries in Norwegian female elite soccer: A prospective one-season cohort study. *Knee Surgery, Sport Traumatol Arthrosc*. 2008;16(2):194-198. doi:10.1007/s00167-007-0403-z

143. Le Gall F, Carling C, Reilly T. Injuries in young elite female soccer players: An 8-season prospective study. *Am J Sports Med*. 2008;36(2):276-284. doi:10.1177/0363546507307866

144. Junge A, Dvorak J. Injuries in female football players in top-level international tournaments. *Br J Sports Med*. 2007;41(SUPPL. 1):3-8. doi:10.1136/bjsm.2007.036020

145. Bonato M, Benis R, La Torre A. Neuromuscular training reduces lower limb injuries in elite female basketball players. A cluster randomized controlled trial. *Scand J Med Sci Sports*. 2018;28(4):1451-1460. doi:10.1111/sms.13034

146. Barbero-Alvarez JC, Soto VM, Barbero-Alvarez V, Granda-Vera J. Match analysis and heart rate of futsal players during competition. *J Sports Sci*. 2008;26(1):63-73. doi:10.1080/02640410701287289

147. Dogramaci SN, Watsford ML, Murphy AJ. Time-motion analysis of international and national level futsal. *J Strength Cond Res*. 2011;25(3):646-651. doi:10.1519/JSC.0b013e3181c6a02e

148. Bangsbo J, Mohr M, Krustrup P. Physical and metabolic demands of training and match-play in the elite football player. *J Sports Sci*. 2006;24(7):665-674.

149. Bengtsson H, Ekstrand J, Hägglund M. Muscle injury rates in professional football increase with fixture congestion: An 11-year follow-up of the UEFA Champions League injury study. *Br J Sports Med*. 2013;47(12):743-747. doi:10.1136/bjsports-2013-092383

150. Bengtsson H, Ekstrand J, Waldén M, Hägglund M. Muscle injury rate in professional football is higher in matches played within 5 days since the previous match: A 14-year prospective study with more than 130 000 match observations. *Br J Sports Med*. 2018;52(17):1116-1122. doi:10.1136/bjsports-2016-097399

151. Carling C, McCall A, Le Gall F, Dupont G. The impact of short periods of match congestion on injury risk and patterns in an elite football club. *Br J Sports Med*. 2016;50(12):764-768. doi:10.1136/bjsports-2015-095501

152. Ekstrand J, Waldén M, Hägglund M. A congested football calendar and the wellbeing of players: Correlation between match exposure of European footballers before the World Cup 2002 and their injuries and performers during that World Cup. *Br J Sports Med*. 2004;38(4):493-497. doi:10.1136/bjsm.2003.009134

153. Carling C, Le Gall F, McCall A, Nédélec M, Dupont G. Squad management, injury and match performance in a professional soccer team over a championship-winning season. *Eur J Sport Sci*. 2015;15(7):573-582. doi:10.1080/17461391.2014.955885

154. McKay GD, Goldie PA, Payne WR, Oakes BW, Watson LF. A prospective study of injuries in basketball: A total profile and comparison by gender and standard of competition. *J Sci Med Sport*. 2001;4(2):196-211. doi:10.1016/S1440-2440(01)80030-X

155. Leite WSS. Physiological Demands in Football, Futsal and Beach Soccer: A Brief Review. *Eur J Phys Educ Sport Sci*. 2016;2(2):1-10. doi:10.5281/ZENODO.205160

156. McInnes SE, Carlson JS, Jones CJ, McKenna MJ. The physiological load imposed on basketball players during competition. *J Sports Sci*. 1995;13(5):387-397. doi:10.1080/02640419508732254

157. Bloomfield J, Polman R, O'Donoghue P. Physical demands of different positions in FA Premier League soccer. *J Sport Sci Med*. 2007;6(1):63-70.

158. Lystad RP, Pollard H, Graham PL. Epidemiology of injuries in competition taekwondo: A meta-analysis of observational studies. *J Sci Med Sport*. 2009;12(6):614-621. doi:10.1016/j.jsams.2008.09.013

159. Lystad RP, Gregory K, Wilson J. The epidemiology of injuries in mixed martial arts: A systematic review and meta-analysis. *Orthop J Sport Med*. 2014;2(1):1-10. doi:10.1177/2325967113518492

160. FIFA C. FIFA Big Count 2006: 270 million people active in football. *FIFA Commun Div Inf Serv*. 2007;31:1-12.

161. Gorostiaga EM, Llodio I, Ibáñez J, et al. Differences in physical fitness among indoor and outdoor elite male soccer players. *Eur J Appl Physiol*. 2009;106(4):483-491. doi:10.1007/s00421-009-1040-7

162. Beato M, Coratella G, Schena F, Hulton AT. Evaluation of the external & internal workload in female futsal players. *Biol Sport*. 2017;34(3):227-231. doi:10.5114/biolsport.2017.65998

163. van Mechelen W, Hlobil H, Kemper HC. Incidence, severity, aetiology and prevention of sports injuries. A review of concepts. *Sports Med*. 1992;14(2):82-99.

164. Asker M, Holm LW, Källberg H, Waldén M, Skillgate E. Female adolescent elite handball players are more susceptible to shoulder problems than their male counterparts. *Knee Surgery, Sport Traumatol Arthrosc*. 2018;26(7):1892-1900. doi:10.1007/s00167-018-4857-y

165. Peck KY, Johnston DA, Owens BD, Cameron KL. The Incidence of Injury Among Male and Female Intercollegiate Rugby Players. *Sports Health*. 2013;5(4):327-333. doi:10.1177/1941738113487165

166. Almeida SA, Williams KM, Shaffer RA, Brodine SK. Epidemiological patterns of musculoskeletal injuries and physical training. *Med Sci Sports Exerc*. 1999;31(8):1176-1182.

167. Brooks JHM, Fuller CW, Kemp SPT, Reddin DB. An assessment of training volume in professional rugby union and its impact on the incidence, severity, and nature of match and training injuries. *J Sports Sci*. 2008;26(8):863-873. doi:10.1080/02640410701832209

168. Askling CM, Tengvar M, Saartok T, Thorstensson A. Acute first-time hamstring strains during high-speed running: A longitudinal study including clinical and magnetic resonance imaging findings. *Am J Sports Med*. 2007;35(2):197-206. doi:10.1177/0363546506294679

169. Ekstrand J, Hägglund M, Kristenson K, Magnusson H, Waldén M. Fewer ligament injuries but no preventive effect on muscle injuries and severe injuries: an 11-year follow-up of the UEFA Champions League injury study. *Br J Sports Med*. 2013;47(12):732-737. doi:10.1136/bjsports-2013-092394

170. Faul F, Erdfelder E, Lang A-G, Buchner A. G*Power 3: a flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behav Res Methods*. 2007;39(2):175-191.

171. Erdfelder E, Faul F, Buchner A, Lang AG. Statistical power analyses using G*Power 3.1: Tests for correlation and regression analyses. *Behav Res Methods*. 2009;41(4):1149-1160. doi:10.3758/BRM.41.4.1149

172. Videbæk S, Bueno AM, Nielsen RO, Rasmussen S. *Incidence of Running-Related Injuries Per 1000 h of Running in Different Types of Runners: A Systematic Review and*

Meta-Analysis. Vol 45. Springer International Publishing; 2015:1017-1026. doi:10.1007/s40279-015-0333-8

173. Wells G, Shea B, O'Connell D, et al. The Newcastle-Ottawa Scale (NOS) for assessing the quality of nonrandomised studies in meta-analyses. 2013.

174. Dvorak J, Junge A, Derman W, Schwellnus M. Injuries and illnesses of football players during the 2010 FIFA World Cup. *Br J Sports Med*. 2011;45(8):626-630. doi:10.1136/bjsm.2010.079905

175. Junge A, Dvořák J. Football injuries during the 2014 FIFA World Cup. *Br J Sports Med*. 2015;49(9):599-602. doi:10.1136/bjsports-2014-094469

176. Noya Salces J, Gomez-Carmona PM, Moliner-Urdiales D, Gracia-Marco L, Sillero-Quintana M. An examination of injuries in Spanish Professional Soccer League. *J Sports Med Phys Fitness*. 2014;54(6):765-771. doi:10.1007/s11816-009-0104-9

177. Stubbe JH, van Beijsterveldt A-MMC, van der Knaap S, et al. Injuries in Professional Male Soccer Players in the Netherlands: A Prospective Cohort Study. *J Athl Train*. 2015;50(2):211-216. doi:10.4085/1062-6050-49.3.64

178. Waldén M, Hägglund M, Ekstrand J. Football injuries during European Championships 2004–2005. *Knee Surgery, Sport Traumatol Arthrosc*. 2007;15(9):1155-1162. doi:10.1007/s00167-007-0290-3

179. Gabbett TJ. The training-injury prevention paradox: Should athletes be training smarter and harder? *Br J Sports Med*. 2016;50(5):273-280. doi:10.1136/bjsports-2015-095788

180. Gabbett TJ. Influence of training and match intensity on injuries in rugby league. *J Sports Sci*. 2004;22(5):409-417. doi:10.1080/02640410310001641638

181. Bouaziz T, Makni E, Passelergue P, et al. Multifactorial monitoring of training load in elite rugby sevens players: Cortisol/cortisone ratio as a valid tool of training load

monitoring. *Biol Sport*. 2016;33(3):231-239. doi:10.5604/20831862.1201812

182. Elloumi M, Makni E, Moalla W, et al. Monitoring training load and fatigue in rugby sevens players. *Asian J Sports Med*. 2012;3(3):175-184.

183. Tsigilis N, Hatzimanouil D. Injuries in handball: Examination of the risk factors. *Eur J Sport Sci*. 2005;5(3):137-142. doi:10.1080/17461390500221610

184. Ekstrand J, Lundqvist D, Davison M, D'Hooghe M, Pensgaard AM. Communication quality between the medical team and the head coach/manager is associated with injury burden and player availability in elite football clubs. *Br J Sports Med*. Published online August 13, 2018:bjsports-2018-099411. doi:10.1136/bjsports-2018-099411

185. Lausic D, Tennebaum G, Eccles D, Jeong A, Johnson T. Intrateam communication and performance in doubles tennis. *Res Q Exerc Sport*. 2009;80(2):281-290. doi:10.1080/02701367.2009.10599563

186. Petersen J, Thorborg K, Nielsen MB, Budtz-Jørgensen E, Hölmich P. Preventive Effect of Eccentric Training on Acute Hamstring Injuries in Men's Soccer. *Am J Sports Med*. 2011;39(11):2296-2303. doi:10.1177/0363546511419277

187. Lees A, Nolan L. The biomechanics of soccer: A review. *J Sports Sci*. 1998;16(3):211-234. doi:10.1080/026404198366740

188. Hewett TE. Biomechanical Measures of Neuromuscular Control and Valgus Loading of the Knee Predict Anterior Cruciate Ligament Injury Risk in Female Athletes: A Prospective Study. *Am J Sports Med*. 2005;33(4):492-501. doi:10.1177/0363546504269591

189. Rahnama N, Reilly T, Lees A, Graham-Smith P. Muscle fatigue induced by exercise simulating the work rate of competitive soccer. *J Sports Sci*. 2003;21(11):933-942. doi:10.1080/0264041031000140428

190. Miloski B, Freitas VH, Barra-Filho MG. Monitoring of the internal training load in futsal players over a season. *Brazilian J Kinanthropometry Hum Perform*. 2012;14(6):671-679. doi:10.5007/1980-0037.2012v14n6p671

191. Petersen J, Thorborg K, Nielsen MB, Hölmich P. Acute hamstring injuries in Danish elite football: A 12-month prospective registration study among 374 players. *Scand J Med Sci Sport*. 2010;20(4):588-592. doi:10.1111/j.1600-0838.2009.00995.x

192. Waldén M, Hägglund M, Werner J, Ekstrand J. The epidemiology of anterior cruciate ligament injury in football (soccer): a review of the literature from a gender-related perspective. *Knee Surgery, Sport Traumatol Arthrosc*. 2011;19(1):3-10. doi:10.1007/s00167-010-1172-7

193. Agel J, Arendt E, Bershadsky B. Anterior Cruciate Ligament Injury in National Collegiate Athletic Association Basketball and Soccer: A 13-Year Review. *Am J Sports Med*. 2005;33(4):524-531. doi:10.1177/0363546504269937

194. Janssen KW, Orchard JW, Driscoll TR, van Mechelen W. High incidence and costs for anterior cruciate ligament reconstructions performed in Australia from 2003-2004 to 2007-2008: Time for an anterior cruciate ligament register by Scandinavian model? *Scand J Med Sci Sport*. 2012;22(4):495-501. doi:10.1111/j.1600-0838.2010.01253.x

195. Hewett TE, Myer GD, Ford KR. Anterior cruciate ligament injuries in female athletes: Part 1, mechanisms and risk factors. *Am J Sports Med*. 2006;34(2):299-311. doi:10.1177/0363546505284183

196. Boden BP, Griffin LY, Garrett WE. Etiology and prevention of noncontact ACL injury. *Phys Sportsmed*. 2000;28(4):53-60. doi:10.3810/psm.2000.04.841

197. Ireland ML. Anterior Cruciate Ligament Injury in Female Athletes: Epidemiology. *J Athl Train*. 1999;34(2):150-154.

198. Starkey C. Injuries and Illnesses in the National Basketball Association: A 10-Year Perspective. *J Athl Train*. 2000;35(2):161-167.

199. Powers CM. The Influence of Abnormal Hip Mechanics on Knee Injury: A Biomechanical Perspective. *J Orthop Sport Phys Ther*. 2010;40(2):42-51. doi:10.2519/jospt.2010.3337

200. Dai B, Mao D, Garrett WE, Yu B. Anterior cruciate ligament injuries in soccer: Loading mechanisms, risk factors, and prevention programs. *J Sport Heal Sci*. 2014;3(4):299-306. doi:10.1016/j.jshs.2014.06.002

201. Dierks TA, Manal KT, Hamill J, Davis I. Lower extremity kinematics in runners with patellofemoral pain during a prolonged run. *Med Sci Sports Exerc*. 2011;43(4):693-700. doi:10.1249/MSS.0b013e3181f744f5

202. Herrington L. Knee valgus angle during single leg squat and landing in patellofemoral pain patients and controls. *Knee*. 2014;21(2):514-517. doi:10.1016/j.knee.2013.11.011

203. Hewett TE, Paterno M V, Myer GD. Strategies for enhancing proprioception and neuromuscular control of the knee. *Clin Orthop Relat Res*. 2002;(402):76-94. doi:10.1097/01.blo.0000026962.51742.99

204. Koga H, Nakamae A, Shima Y, Bahr R, Krosshaug T. Hip and Ankle Kinematics in Noncontact Anterior Cruciate Ligament Injury Situations: Video Analysis Using Model-Based Image Matching. *Am J Sports Med*. 2018;46(2):333-340. doi:10.1177/0363546517732750

205. Leppänen M, Pasanen K, Kujala UM, et al. Stiff Landings Are Associated With Increased ACL Injury Risk in Young Female Basketball and Floorball Players. *Am J Sports Med*. 2017;45(2):386-393. doi:10.1177/0363546516665810

206. McLean SG, Walker KB, van den Bogert AJ. Effect of gender on lower extremity

kinematics during rapid direction changes: An integrated analysis of three sports movements. *J Sci Med Sport*. 2005;8(4):411-422. doi:10.1016/S1440-2440(05)80056-8

207. Shultz SJ, Schmitz RJ, Benjaminse A, Collins M, Ford K, Kulas AS. ACL research retreat VII: An update on anterior cruciate ligament injury risk factor identification, screening, and prevention March 19-21, 2015; Greensboro, nc. *J Athl Train*. 2015;50(10):1076-1093. doi:10.4085/1062-6050-50.10.06

208. Norris BS, Olson SL. Concurrent validity and reliability of two-dimensional video analysis of hip and knee joint motion during mechanical lifting. *Physiother Theory Pract*. 2011;27(7):521-530. doi:10.3109/09593985.2010.533745

209. Hopkins WG. Measures of reliability in sports medicine and science. *Sports Med*. 2000;30(1):1-15.

210. Taylor K-LL, Sheppard JM, Lee H, Plummer N. Negative effect of static stretching restored when combined with a sport specific warm-up component. *J Sci Med Sport*. 2009;12(6):657-661. doi:10.1016/j.jsams.2008.04.004

211. Kadaba MP, Ramakrishnan HK, Wootten ME. Measurement of lower extremity kinematics during level walking. *J Orthop Res*. 1990;8(3):383-392. doi:10.1002/jor.1100080310

212. Onate J, Cortes N, Welch C, Van Lunen B. Expert versus Novice Interrater Reliability and Criterion Validity of the Landing Error Scoring System. *J Sport Rehabil*. 2010;19(1):41-56. doi:10.1123/jsr.19.1.41

213. McMahon JJ, Jones PA, Comfort P. A Correction Equation for Jump Height Measured Using the Just Jump System. *Int J Sports Physiol Perform*. 2016;11(4):555-557. doi:10.1123/ijspp.2015-0194

214. Myer GD, Ford KR, Brent JL, Hewett TE. An Integrated Approach to Change the Outcome Part I. *J Strength Cond Res*. 2012;26(8):2265-2271.

doi:10.1519/JSC.0b013e31825c2b8f

215. J.M.Bland, D.G.Altman, Bland JM, Altman DG, J.M.Bland, D.G.Altman. Statistical methods for assessing agreement between two methods of clinical measurement. *Lancet*. 1986;1(8476):307-310. doi:10.1016/S0140-6736(86)90837-8

216. Fong CM, Blackburn JT, Norcross MF, McGrath M, Padua DA. Ankle-dorsiflexion range of motion and landing biomechanics. *J Athl Train*. 2011;46(1):5-10. doi:10.4085/1062-6050-46.1.5

217. Landis JR, Koch GG. The measurement of observer agreement for categorical data. *Biometrics*. 1977;33(1):159-174.

218. Maykut JN, Taylor-Haas JA, Paterno M V, DiCesare CA, Ford KR. Concurrent validity and reliability of 2d kinematic analysis of frontal plane motion during running. *Int J Sports Phys Ther*. 2015;10(2):136-146.

219. Krosshaug T, Nakamae A, Boden BP, et al. Mechanisms of anterior cruciate ligament injury in basketball: Video analysis of 39 cases. *Am J Sports Med*. 2007;35(3):359-367. doi:10.1177/0363546506293899

220. Olsen OE, Myklebust G, Engebretsen L, Bahr R. Injury mechanisms for anterior cruciate ligament injuries in team handball: A systematic video analysis. *Am J Sports Med*. 2004;32(4):1002-1012. doi:10.1177/0363546503261724

221. Cohen J. *Statistical Power Analysis for the Behavioural Sciences*. 2.ª ed. Ac.; 1988.

222. Network E. TRIPOD Checklist : Prediction Model Development and Validation. *Equator Netw*. Published online 2016. doi:10.4028/www.scientific.net/SSP.183.163

223. Olmedilla A, Laguna M, Blas Redondo A. Injury and psychological characteristics in handball players. *Rev Andal Med Deport*. 2011;4(1):6-12.

224. Cervelló E, Peruyero F, Montero C, Moreno-murcia VJBJA. Ejercicio, bienestar psicológico, calidad de sueño. *Cuad Psicol del Deport*. 2014;14:31-38.

225. Arce C, De Francisco C, Andrade E, Seoane G, Raedeke T. Adaptation of the Athlete Burnout Questionnaire in a Spanish Sample of Athletes. *Span J Psychol*. 2012;15(3):1529-1536. doi:10.5209/rev_SJOP.2012.v15.n3.39437

226. Gimeno F, Buceta JM, Pérez-Llanta MDC. El cuestionario «Características Psicológicas Relacionadas con el Rendimiento Deportivo» (CPRD): Características psicométricas. *Análise Psicológica*. 2012;19(1):93-113. doi:10.14417/ap.346

227. Hiller CE, Refshauge KM, Bundy AC, Herbert RD, Kilbreath SL. The Cumberland Ankle Instability Tool: A Report of Validity and Reliability Testing. *Arch Phys Med Rehabil*. 2006;87(9):1235-1241. doi:10.1016/j.apmr.2006.05.022

228. Thorborg K, Petersen J, Magnusson SP, Hölmich P. Clinical assessment of hip strength using a hand-held dynamometer is reliable. *Scand J Med Sci Sports*. 2009;20(3):493-501. doi:10.1111/j.1600-0838.2009.00958.x

229. Shaffer SW, Teyhen DS, Lorenson CL, et al. Y-Balance Test: A Reliability Study Involving Multiple Raters. *Mil Med*. 2013;178(11):1264-1270. doi:10.7205/MILMED-D-13-00222

230. Cejudo A, Sainz de Baranda P, Ayala F, Santonja F. Normative data of Lower-limb muscle flexibility in futsal players . *Rev Int Med y Ciencias la Act Fis y del Deport*. Published online 2014. doi:10.1159/000115004

231. Bahr R, Clarsen B, Derman W, et al. International Olympic Committee Consensus Statement: Methods for Recording and Reporting of Epidemiological Data on Injury and Illness in Sports 2020 (Including the STROBE Extension for Sports Injury and Illness Surveillance (STROBE-SIIS)). *Orthop J Sport Med*. 2020;8(2). doi:10.1177/2325967120902908

232. Hacibeyoglu M, Arslan A, Kahramanli S. Improving Classification Accuracy with Discretization on Datasets Including Continuous Valued Features. Published online 2011.

233. Elkarami B, Alkhateeb A, Rueda L. Cost-sensitive classification on class-balanced ensembles for imbalanced non-coding RNA data. In: *2016 IEEE EMBS International Student Conference (ISC)*. IEEE; 2016:1-4. doi:10.1109/EMBSISC.2016.7508607

234. Quinlan JR. Learning decision tree classifiers. *ACM Comput Surv*. 1996;28(1):71-72. doi:10.1145/234313.234346

235. Freund Y, Mason L. *The Alternating Decision Tree Learning Algorithm*. Morgan Kaufmann Publishers, Inc.; 1999.

236. Gove R, Faytong J. Machine Learning and Event-Based Software Testing: Classifiers for Identifying Infeasible GUI Event Sequences. *Adv Comput*. 2012;86:109-135. doi:10.1016/B978-0-12-396535-6.00004-1

237. Steinbach M, Tan PN. kNN: k-nearest neighbors. In: *The Top Ten Algorithms in Data Mining*. Chapman an. ; 2009:165-176.

238. Hall MA, Smith LA. Practical feature subset selection for machine learning. *Comput Sci*. Published online 1998.

239. Refaeilzadeh P, Tang L, Liu H. Cross-Validation. In: LIU L, ÖZSU MT, eds. *Encyclopedia of Database Systems*. Springer US; 2009:532-538. doi:10.1007/978-0-387-39940-9_565

240. Krstajic D, Buturovic LJ, Leahy DE, Thomas S. Cross-validation pitfalls when selecting and assessing regression and classification models. *J Cheminform*. 2014;6(1):1-15. doi:10.1186/1758-2946-6-10

241. Kohavi R. A Study of Cross-Validation and Bootstrap for Accuracy Estimation and Model Selection. *Int Jt Conf Artif Intell*. 1995;(January 1995).

242. Altman DG, Bland JM. Diagnostic tests 3: receiver operating characteristic plots. *BMJ*. 1994;309(6948):188-188. doi:10.1136/bmj.309.6948.188

243. Zou Q, Xie S, Lin Z, Wu M, Ju Y. Finding the Best Classification Threshold in

Imbalanced Classification. *Big Data Res*. 2016;5:2-8. doi:10.1016/j.bdr.2015.12.001

244. Wagenmakers EJ, Marsman M, Jamil T, et al. Bayesian inference for psychology. Part I: Theoretical advantages and practical ramifications. *Psychon Bull Rev*. 2018;25(1):35-57. doi:10.3758/s13423-017-1343-3

245. Rouder JN, Morey RD, Speckman PL, Province JM. Default Bayes factors for ANOVA designs. *J Math Psychol*. 2012;56(5):356-374. doi:10.1016/J.JMP.2012.08.001

246. Lee MD, Wagenmakers EJ. *Bayesian Cognitive Modeling: A Practical Course*.; 2013. doi:10.1017/CBO9781139087759

247. Thorpe, JL. Ebersole K, Thorpe JL, Ebersole KT. Unilateral balance performance in female collegiate soccer athletes. *J Strength Cond Res*. 2008;22(5):1429-1433. doi:10.1519/JSC.0b013e31818202db

248. Robinson R, Gribble P. Kinematic predictors of performance on the Star Excursion Balance Test. *J Sport Rehabil*. 2008;17(4):347-357. doi:10.1123/jsr.17.4.347

249. Ruiz-Pérez I, Ayala F, Puerta JM, et al. A Bayesian Network approach to study the relationships between several neuromuscular performance measures and dynamic postural control in futsal players. Steinberg N, ed. *PLoS One*. 2019;14(7):e0220065. doi:10.1371/journal.pone.0220065

250. Myer GD, Ford KR, Hewett TE. New method to identify athletes at high risk of ACL injury using clinic-based measurements and freeware computer analysis. *Br J Sports Med*. 2011;45(4):238-244. doi:10.1136/bjsm.2010.072843

251. Jovanovic M. Uncertainty Heuristics and Injury Prediction. *Aspetar Sport Med J*. 2017;6(1):18-24.

252. Hiller CE, Kilbreath SL, Refshauge KM. Chronic ankle instability: Evolution of the model. *J Athl Train*. 2011;46(2):133-141. doi:10.4085/1062-6050-46.2.133

253. Biering-Sørensen F. Physical measurements as risk indicators for low-back trouble

over a one-year period. *Spine (Phila Pa 1976)*. 1984;9(2):106-119. doi:10.1097/00007632-198403000-00002

254. Brotons-Gil E, García-Vaquero MP, Peco-González N, Vera-Garcia FJ. Flexion-Rotation Trunk Test to Assess Abdominal Muscle Endurance. *J Strength Cond Res*. 2013;27(6):1602-1608. doi:10.1519/JSC.0b013e31827124d9

255. Grindem H, Logerstedt D, Eitzen I, et al. Single-Legged Hop Tests as Predictors of Self-Reported Knee Function in Nonoperatively Treated Individuals With Anterior Cruciate Ligament Injury. *Am J Sports Med*. 2011;39(11):2347-2354. doi:10.1177/0363546511417085

256. Lloyd RS, Oliver JL, Hughes MG, Williams CA. Reliability and validity of field-based measures of leg stiffness and reactive strength index in youths. *J Sports Sci*. 2009;27(14):1565-1573. doi:10.1080/02640410903311572

257. Chawla N V., Bowyer KW, Hall LO, Kegelmeyer WP. SMOTE: Synthetic minority over-sampling technique. *J Artif Intell Res*. 2002;16(February 2017):321-357. doi:10.1613/jair.953

258. Wilson DL. Asymptotic Properties of Nearest Neighbor Rules Using Edited Data. *IEEE Trans Syst Man Cybern*. 1972;2(3):408-421. doi:10.1109/TSMC.1972.4309137

259. Breiman L. Bagging Predictors. *Mach Learn*. 1996;24(2):123-140. doi:10.1023/A:1018054314350

260. Freund Y, Schapire RE. A Decision-Theoretic Generalization of On-Line Learning and an Application to Boosting. *J Comput Syst Sci*. 1997;55(1):119-139. doi:10.1006/jcss.1997.1504

261. Schapire RE, Singer Y. Improved Boosting Algorithms Using Confidence-rated Predictions. *Mach Learn*. 1999;37(3):297-336. doi:10.1023/A:1007614523901

262. Chawla N V., Lazarevic A, Hall LO, Bowyer KW. SMOTEBoost: Improving

prediction of the minority class in boosting. In: *Lecture Notes in Artificial Intelligence (Subseries of Lecture Notes in Computer Science)*. Vol 2838. Springer, Berlin, Heidelberg; 2003:107-119. doi:10.1007/978-3-540-39804-2_12

263. Seiffert C, Khoshgoftaar TM, Van Hulse J, Napolitano A. RUSBoost: A hybrid approach to alleviating class imbalance. *IEEE Trans Syst Man, Cybern Part ASystems Humans*. 2010;40(1):185-197. doi:10.1109/TSMCA.2009.2029559

264. Wang S, Yao X. Diversity analysis on imbalanced data sets by using ensemble models. In: *2009 IEEE Symposium on Computational Intelligence and Data Mining, CIDM 2009 - Proceedings*. IEEE; 2009:324-331. doi:10.1109/CIDM.2009.4938667

265. Domingos P. Metacost: A general method for making classifiers cost-sensitive. In: *Proceedings of the Fifth ACM SIGKDD International Conference on Knowledge Discovery and Data Mining - KDD '99*. ACM Press; 1999:155-164. doi:10.1145/312129.312220

266. Breiman L. Random forests. *Mach Learn*. 2001;45(1):5-32. doi:10.1023/A:1010933404324

267. Bergeron MF, Landset S, Maugans TA, et al. Machine Learning in Modeling High School Sport Concussion Symptom Resolve. *Med Sci Sports Exerc*. 2019;51(7):1362-1371. doi:10.1249/MSS.0000000000001903

268. Hertel J, Miller SJ, Denegar CR. Intratester and Intertester Reliability during the Star Excursion Balance Tests. *J Sport Rehabil*. 2000;9(2):104-116. doi:10.1123/jsr.9.2.104

269. Lai WC, Wang D, Chen JB, Vail J, Rugg CM, Hame SL. Lower Quarter Y-Balance Test Scores and Lower Extremity Injury in NCAA Division I Athletes. *Orthop J Sport Med*. 2017;5(8):232596711772366. doi:10.1177/2325967117723666

270. Smith CA, CHIMERA NJ, Warren M. Association of Y balance test reach asymmetry and injury in Division I Athletes. *Med Sci Sports Exerc*. 2015;47(1):136-141. doi:10.1249/MSS.0000000000000380

271. Butler RJ, Southers C, Gorman PP, Kiesel KB, Plisky PJ. Differences in soccer players' dynamic balance across levels of competition. *J Athl Train*. 2012;47(6):616-620. doi:10.4085/1062-6050-47.5.14

272. Paillard T, Noé F, Rivière T, Marion V, Montoya R, Dupui P. Postural performance and strategy in the unipedal stance of soccer players at different levels of competition. *J Athl Train*. 2006;41(2):172-176.

273. Bressel E, Yonker JC, Kras J, Heath EM. Comparison of static and dynamic balance in female collegiate soccer, basketball, and gymnastics athletes. *J Athl Train*. 2007;42(1):42-46.

274. Makaje N, Ruangthai R, Arkarapanthu A, Yoopat P. Physiological demands and activity profiles during futsal match play according to competitive level. *J Sports Med Phys Fitness*. 2012;52(4):366-374.

275. Larrañaga P, Moral S. Probabilistic graphical models in artificial intelligence. In: *Applied Soft Computing Journal*. Vol 11. ; 2011:1511-1528. doi:10.1016/j.asoc.2008.01.003

276. Glymour C. *The Mind's Arrows : Bayes Nets and Graphical Causal Models in Psychology*.; 2001. doi:10.1093/mind/112.446.340

277. Barbado D, Lopez-Valenciano A, Juan-Recio C, Montero-Carretero C, van Dieën JH, Vera-Garcia FJ. Trunk Stability, Trunk Strength and Sport Performance Level in Judo. *PLoS One*. 2016;11(5):e0156267. doi:10.1371/journal.pone.0156267

278. Ayala F, De Ste Croix M, Sainz de Baranda P, Santonja F. Absolute reliability of isokinetic knee flexion and extension measurements adopting a prone position. *Clin Physiol Funct Imaging*. 2013;33(1):45-54. doi:10.1111/j.1475-097X.2012.01162.x

279. Ekbal A. Improvement of prediction accuracy using discretization and voting classifier. *Proc - Int Conf Pattern Recognit*. 2006;2:695-698. doi:10.1109/ICPR.2006.698

280. Neapolitan RE. Chapter 10.3.1. *Learn Bayesian Networks*. Published online 2003:600-603. doi:10.1145/1327942.1327961

281. Glover F. Artificial Intelligence, Heuristic Frameworks and Tabu Search. *Manag Decis Econ*. 1990;11(5):365-375.

282. Buntine W. *Theory Refinement on Bayesian Networks*. Morgan Kaufmann Publishers, Inc.; 1991. doi:10.1.1.52.1068

283. Kumar V, Minz S. Smart Computing Review Feature Selection: A literature Review. *Smart Comput Rev*. 2014;4(3). doi:10.6029/smartcr.2014.03.007

284. Blum AL, Langley P. Selection of relevant features and examples in machine learning. *Artif Intell*. 1997;97(1-2):245-271. doi:10.1016/S0004-3702(97)00063-5

285. Das S. Filters, Wrappers and a Boosting-Based Hybrid for Feature Selection. In: Brodley CE, Danyluk AP, eds. *Proceedings of the Eighteenth International Conference on Machine Learning {(ICML} 2001), Williams College, Williamstown, MA, USA, June 28 - July 1, 2001*. Morgan Kaufmann; 2001:74-81.

286. Kabir R, Abdur DB, Onik R, Bangladesh D, Samad T. *A Network Intrusion Detection Framework Based on Bayesian Network Using Wrapper Approach*. Vol 166.; 2017.

287. Onik AR, Haq NF, Dhaka T, et al. An Analytical Comparison on Filter Feature Extraction Method in Data Mining using J48 Classifier An analytical survey on E-commerce Security using Cryptographic algorithm View project An Analytical Comparison on Filter Feature Extraction Method in Data Mining using J48 Classifier. *Artic Int J Comput Appl*. 2015;124(13):975-8887. doi:10.5120/ijca2015905706

288. Tang J, Alelyani S, Liu H. Feature selection for classification: A review. *Data Classif Algorithms Appl*. Published online 2014:37-64. doi:10.1201/b17320

289. Willson JD, Dougherty CP, Ireland ML, Davis IM. Core stability and its relationship to lower extremity function and injury. *J Am Acad Orthop Surg*. 2005;13(5):316-325.