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Injury prediction in sports using artificial intelligence (IPredict-AI)

Devant le jury composé de :

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LIST OF PUBLICATIONS

Related to the PhD

International peer-reviewed scientific journals

Spyridon Iatropoulos, **Pierre-Eddy Dandrieux**, David Blanco, Alexis Ruffault, Estelle Gignoux, Constance Mosser, Karsten Hollander, Laurent Navarro, and Pascal Edouard. Effect of an unsupervised multidomain intervention integrating education, exercises, psychological techniques and machine learning feedback, on injury risk reduction in athletics (track and field): protocol of a randomised controlled trial (i-reductai). *BMJ Open Sport & Exercise Medicine*, 11(1):e002501, January 2025. ISSN 2055-7647. doi: 10.1136/bmjsem-2025-002501. URL http://dx.doi.org/10.1136/bmjsem-2025-002501.

Pierre-Eddy Dandrieux, Laurent Navarro, David Blanco, Alexis Ruffault, Christophe Ley, Antoine Bruneau, Spyridon (Spyros) Iatropoulos, Joris Chapon, Karsten Hollander, and Pascal Edouard. Association between the use of daily injury risk estimation feedback (i-ref) based on machine learning techniques and injuries in athletics (track and field): results of a prospective cohort study over an athletics season. *BMJ Open Sport & Exercise Medicine*, 11(1):e002331, February 2025. ISSN 2055-7647. doi: 10.1136/bmjsem-2024-002331. URL http://dx.doi.org/10.1136/bmjsem-2024-002331.

Pierre-Eddy Dandrieux, Spyridon Iatropoulos, Jeanne Tondut, Laurent Navarro, Karsten Hollander, and Pascal Edouard. Predicting sports injuries using machine learning approaches: a scoping review. *BEFORE RESUBMISSON, TARGETED: Sports Medicine*, 08 2024a.

[SUBMITTED] Spyridon Iatropoulos, **Pierre-Eddy Dandrieux**, Pascal Edouard, and Laurent Navarro. Development and internal validation of machine learning prognostic models of sports injuries using self-reported data in athletics (track and field): the influence of quantity and quality of features. *Journal of Sports Sciences*, August 2024.

Pascal Edouard, **Pierre-Eddy Dandrieux**, Spyridon Iatropoulos, David Blanco, Pedro Branco, Joris Chapon, Davie Mulenga, Kenny Guex, Gael Guilhem, Jenny Jacobsson, Robert Mann, Ciara McCallion, Constance Mosser, Jean-Benoit Morin, Caroline Prince, Alexis Ruffault, Toomas Timpka, Juan-Manuel Alonso, Yuka Tsukahara, Laurent Navarro, and Karsten Hollander. Injuries in athletics (track and field): A narrative review presenting the current problem of injuries. *Deutsche Zeitschrift für Sportmedizin*, 75(4):132–141, June 2024. doi: 10.5960/dzsm.2024.601. URL http://dx.doi.org/10.5960/dzsm.2024.601.

Pierre-Eddy Dandrieux, Laurent Navarro, Joris Chapon, Jeanne Tondut, Michael Zyskowski, Karsten Hollander, and Pascal Edouard. Perceptions and beliefs on sports injury prediction as an injury risk reduction strategy: An online survey on elite athletics (track and field) athletes, coaches, and health

professionals. *Physical Therapy in Sport*, 66:31–36, March 2024b. ISSN 1466-853X. doi: 10.1016/j.ptsp.2024.01.007. URL http://dx.doi.org/10.1016/j.ptsp.2024.01.007.

Pierre-Eddy Dandrieux, Laurent Navarro, David Blanco, Alexis Ruffault, Christophe Ley, Antoine Bruneau, Joris Chapon, Karsten Hollander, and Pascal Edouard. Relationship between a daily injury risk estimation feedback (i-ref) based on machine learning techniques and actual injury risk in athletics (track and field): protocol for a prospective cohort study over an athletics season. *BMJ Open*, 13(5): e069423, May 2023. ISSN 2044-6055. doi: 10.1136/bmjopen-2022-069423. URL http://dx.doi.org/10.1136/bmjopen-2022-069423.

Laurent Navarro, **Pierre-Eddy Dandrieux**, Karsten Hollander, and Pascal Edouard. *Exploring Stakeholders' Perceptions of Interactions in Competitive Sports: A Study on the Introduction of AI in the Process*, pages 804–814. Springer Nature Switzerland, 2023. ISBN 9783031426223. doi: 10.1007/978-3-031-42622-3_57. URL http://dx.doi.org/10.1007/978-3-031-42622-3_57.

Laurent Navarro, **Pierre-Eddy Dandrieux**, Karsten Hollander, and Pascal Edouard. *Digitalization in Professional Football: An Opportunity to Estimate Injury Risk*, pages 366–375. Springer International Publishing, 2022. ISBN 9783031148446. doi: 10.1007/978-3-031-14844-6_30. URL http://dx.doi.org/10.1007/978-3-031-14844-6_30.

National peer-reviewed scientific journals

Jeanne Tondut, **Pierre-Eddy Dandrieux**, Benjamin Caumeil, Alexis Ruffault, Caroline Giroux, Gaël Guilhem, Laurent Navarro, and Pascal Edouard. Estimation du risque de blessures en utilisant le machine learning basée sur le monitoring de la perception des états physiques et mentaux des athlètes : étude préliminaire sur 110 athlètes de haut niveau suivis sur une période de 18 mois. *Journal de Traumatologie du Sport*, 40(2):74–80, June 2023a. ISSN 0762-915X. doi: 10.1016/j.jts.2023.04.002. URL http://dx.doi.org/10.1016/j.jts.2023.04.002.

Jeanne Tondut, **Pierre-Eddy Dandrieux**, Laurent Navarro, Christophe Ley, and Pascal Edouard. La prédiction des blessures en sport : fiction ou réalité ? *Journal de Traumatologie du Sport*, 40(2):62–68, June 2023b. ISSN 0762-915X. doi: 10.1016/j.jts.2023.03.006. URL http://dx.doi.org/10.1016/j.jts.2023.03.006.

Pierre-Eddy Dandrieux, Laurent Navarro, Joris Chapon, Jeanne Tondut, Karsten Hollander, and Pascal Edouard. Perceptions et croyances sur la prédiction des blessures en sports en tant que mesure de réduction des risques de blessure : une enquête en ligne sur les acteurs du sport de haut niveau (athlètes, entraîneurs, professionnels de santé). *Journal de Traumatologie du Sport*, 40(2):81–87, June 2023a. ISSN 0762-915X. doi: 10.1016/j.jts.2023.04.004. URL http://dx.doi.org/10.1016/j.jts.2023.04.004.

Pierre-Eddy Dandrieux, Jeanne Tondut, Ryu Nagahara, Jurdan Mendiguchia, Jean-Benoit Morin, Johan Lahti, Christophe Ley, Pascal Edouard, and Laurent Navarro. Prédiction des blessures des ischiojambiers en football à l'aide d'apprentissage automatique : étude préliminaire sur 284 footballeurs. *Journal de Traumatologie du Sport*, 40(2):69–73, June 2023b. ISSN 0762-915X. doi: 10.1016/j.jts.2023.04.003. URL http://dx.doi.org/10.1016/j.jts.2023.04.003.

National magazine

Pierre-Eddy Dandrieux, Laurent Navarro, Joris Chapon, Karsten Hollander, and Pascal Edouard. Prédire les blessures en athlétisme pour réduire leur risque de survenue, est-ce possible ? État des

lieux de l'étude IPredict-AI. *La Revue de l'Association des Entraîneurs Français d'Athlétisme*, 249: 34–37, January 2023.

Side to the PhD

International peer-reviewed scientific journals

Tom Kastner, **Pierre-Eddy Dandrieux**, Dominik Fohrmann, Florian Frohberg, Matjaz Turel, Maarit Valtonen, Pascal Edouard, Jörg Spörri, Bernd Wolfarth, Astrid Junge, and Karsten Hollander. Injuries and illnesses during the 54th fis nordic world ski championships 2023 in planica: a prospective cohort study. *BMJ Open Sport & Exercise Medicine*, mar 2025. doi: 10.1136/bmjsem-2024-002156. URL http://dx.doi.org/10.1136/bmjsem-2024-002156.

Bruno Lemarchand, Laurie Marrauld, **Pierre-Eddy Dandrieux**, Marine Sarfati, and Pascal Edouard. Planetary health: why not empower the sports and exercise medicine community to play the game of life well? *BMJ Open Sport & Exercise Medicine*, 11(1):e002409, January 2025. ISSN 2055-7647. doi: 10.1136/bmjsem-2024-002409. URL http://dx.doi.org/10.1136/bmjsem-2024-002409.

[SUBMITTED] Caroline Prince, Pierre Samozino, **Pierre-Eddy Dandrieux**, Joris Chapon, and Pascal Edouard. Biceps femoris muscle constraints of drills of the track-and-field warm-up. *TO DEFINED*, August 2024a.

[SUBMITTED] Caroline Prince, Pascal Edouard, **Pierre-Eddy Dandrieux**, Joris Chapon, and Pierre Samozino. Velocity-induced changes in biceps femoris muscle mechanical constraints within maximum acceleration sprinting. *Scandinavian Journal of Medicine and Science in Sports*, August 2024b.

Pascal Edouard, **Pierre-Eddy Dandrieux**, Milan Klöwer, Astrid Junge, Sébastien Racinais, Pedro Branco, Karsten Hollander, and Laurent Navarro. Association between feel-like temperatures and injury risk during international outdoor athletic championships: a prospective cohort study on 29 579 athlete starts during 10 championships. *British Journal of Sports Medicine*, pages bjsports–2023–108050, October 2024a. ISSN 1473-0480. doi: 10.1136/bjsports-2023-108050. URL http://dx.doi.org/10.1136/bjsports-2023-108050.

Pascal Edouard, Spyridon Iatropoulos, Laurent Navarro, Pedro Branco, Karsten Hollander, and **Pierre-Eddy Dandrieux**. Educating and promoting athletes' health protection through infographics on injury and illness prevention during an international competition: Prospective study during the 2024 european athletics championships. *BMJ Open Sport & Exercise Medicine*, September 2024b.

Spyridon Iatropoulos, **PierreEddy Dandrieux**, Laurent Navarro, David Blanco, and Pascal Edouard. The dose–response relationship of an exercise–based injury prevention program: A secondary analysis of a randomized controlled trial on athletics (track-and-field) athletes over a 39week followup. *Scandinavian Journal of Medicine & Science in Sports*, 34(9), September 2024. ISSN 1600-0838. doi: 10.1111/sms.14720. URL http://dx.doi.org/10.1111/sms.14720.

Pascal Edouard, Mulenga Davie, **Pierre-Eddy Dandrieux**, Florence Salati, Jessica Wallace, and Oluwatoyosi Owoeye. Coverage from medical teams and injury/illness epidemiology within youth athletics in africa: a prospective study during the 2023 african youth under 18/20 athletics championships. *Journal of Science and Medicine in Sport*, July 2024c. ISSN 1440-2440. doi: 10.1016/j.jsams.2024.07.014. URL http://dx.doi.org/10.1016/j.jsams.2024.07.014.

Pascal Edouard, **Pierre-Eddy Dandrieux**, Astrid Junge, Laurent Navarro, Caroline Giroux, Kenny Guex, Pedro Branco, Gaël Guilhem, and Karsten Hollander. Is the risk of muscle injuries higher in the finals than in previous rounds of the 100m, 200m and 400m sprints of international athletics championships? *Journal of Science and Medicine in Sport*, 27(5):302–306, May 2024d. ISSN 1440-2440. doi: 10.1016/j.jsams.2024.02.007. URL http://dx.doi.org/10.1016/j.jsams.2024.02.007.

Pascal Edouard, **Pierre-Eddy Dandrieux**, David Blanco, Jeanne Tondut, Joris Chapon, Laurent Navarro, Astrid Junge, and Karsten Hollander. How do sports injury epidemiological outcomes vary depending on athletes' response rates to a weekly online questionnaire? an analysis of 39week followup from 391 athletics (track and field) athletes. *Scandinavian Journal of Medicine & Science in Sports*, 34(3), March 2024e. ISSN 1600-0838. doi: 10.1111/sms.14589. URL http://dx.doi.org/10.1111/sms.14589.

Pascal Edouard, **Pierre-Eddy Dandrieux**, Karsten Hollander, and Michael Zyskowski. Injuries and illnesses at the munich 2022 european championships: a prospective study of 5419 athletes from 52 countries involved in 9 sports. *BMJ Open Sport & Exercise Medicine*, 10(1):e001737, February 2024f. ISSN 2055-7647. doi: 10.1136/bmjsem-2023-001737. URL http://dx.doi.org/10.1136/bmjsem-2023-001737.

Pascal Edouard, Jeanne Tondut, Karsten Hollander, **Pierre-Eddy Dandrieux**, Laurent Navarro, Antoine Bruneau, Astrid Junge, and David Blanco. Risk factors for injury complaints leading to restricted participation in athletics (track and field): a secondary analysis of data from 320 athletes over one season. *BMJ Open Sport & Exercise Medicine*, 9(4):e001718, December 2023a. ISSN 2055-7647. doi: 10.1136/bmjsem-2023-001718. URL http://dx.doi.org/10.1136/bmjsem-2023-001718.

Séréna Charpy, Pierre Billard, **Pierre-Eddy Dandrieux**, Joris Chapon, and Pascal Edouard. Epidemiology of injuries in elite women's artistic gymnastics: a retrospective analysis of six seasons. *BMJ Open Sport & Exercise Medicine*, 9(4):e001721, October 2023a. ISSN 2055-7647. doi: 10.1136/bmjsem-2023-001721. URL http://dx.doi.org/10.1136/bmjsem-2023-001721.

Séréna Charpy, Pierre Billard, **Pierre-Eddy Dandrieux**, Joris Chapon, Jeanne Tondut, and Pascal Edouard. Injuries in french high-level and national-level women artistic gymnastics: One-year prevalence and associated factors. *Applied Sciences*, 13(19):10600, September 2023b. ISSN 2076-3417. doi: 10.3390/app131910600. URL http://dx.doi.org/10.3390/app131910600.

Pascal Edouard, **Pierre-Eddy Dandrieux**, Jeanne Tondut, Joris Chapon, Laurent Navarro, Alexis Ruffault, Pedro Branco, Mickael Zyskowski, and Karsten Hollander. Injury risk reduction perceptions in athletics: Survey on elite athletes and stakeholders participating at the munich 2022 european championships. *Deutsche Zeitschrift für Sportmedizin*, 74(6):197–204, September 2023b. doi: 10.5960/dzsm.2023.572.

Pascal Edouard, **Pierre-Eddy Dandrieux**, Karsten Hollander, and Michael Zyskowski. Pre-participation injury and illness complaints of elite athletes participating at the munich 2022 european championships. *Deutsche Zeitschrift für Sportmedizin/German Journal of Sports Medicine*, 74(2):40–46, February 2023c. ISSN 2510-5264. doi: 10.5960/dzsm.2023.559. URL http://dx.doi.org/10.5960/dzsm.2023.559.

Thibault Besson, Frederic Sabater Pastor, Giorgio Varesco, Marilyne Berthet, Djahid Kennouche, **Pierre-Eddy Dandrieux**, Jeremy Rossi, and Guillaume Y. Millet. Elite vs. experienced male and female trail runners: Comparing running economy, biomechanics, strength, and power. *Journal of Strength and Conditioning Research*, 37(7):1470–1478, January 2023. ISSN 1064-8011. doi: 10.1519/jsc.0000000000004412. URL http://dx.doi.org/10.1519/jsc.0000000000004412.

Frederic Sabater Pastor, Thibault Besson, Marilyne Berthet, Giorgio Varesco, Djahid Kennouche, **Pierre-Eddy Dandrieux**, Jeremy Rossi, and Guillaume Y. Millet. Elite road vs. trail runners: Comparing

economy, biomechanics, strength, and power. *Journal of Strength and Conditioning Research*, 37 (1):181–186, February 2022. ISSN 1064-8011. doi: 10.1519/jsc.0000000000004226. URL http://dx.doi.org/10.1519/jsc.0000000000004226.

During my PhD I had the opportunity to work on several research projects and experimentations with different teams and make important contributions, such as:

- The injury and illness surveillance study during the Munich 2022 European Championships (Edouard et al., 2024f, 2023c,b) (**Dandrieux** et al., 2024b).
- The injury and illness surveillance study during the 54th FIS Nordic World Ski Championships 2023 in Planica (Kastner et al., 2025).
- The injury and illness surveillance study during the Roma 2024 European Athletics Championships (Edouard et al., 2024b).
- The experimental laboratory-setting study on maximal sprinting biomechanics (Prince et al., 2024b,a).
- The institutional collaboration in presence and distance with the MSH Medical School Hamburg, Germany with one of my supervisors, Prof. Karsten Hollander.
- The institutional collaboration in presence and distance with Mines Saint-Etienne with one of my supervisors, Dr. Laurent Navarro.

LIST OF COMMUNICATIONS

International communication related to the PhD

Pierre-Eddy Dandrieux and Laurent Navarro. Artificial intelligence in sports. Seminar, Departament de Fisioteràpia Facultat de Medicina i Ciències de la Salut Universitat Internacional de Catalunya (UIC), Barcelona, ***Oral***, December 2024.

Pierre-Eddy Dandrieux. Artificial intelligence and injury prevention. Medical seminar, Roma 2024 European Athletics Championships, ***Oral***, June 2024.

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Amount Awarded:	250,000€
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Title of Project:	I-Run-Healthy
Role on Project:	Co-investigator, Post-Doctoral

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Title of Project:	Injury prediction using artificial intelligence
Role on Project:	Principal investigator, visiting research student

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Title of Project:	Injury prediction using artificial intelligence
Role on Project:	Principal investigator, PhD

Table of contents

Page #

Acknowledgements **1**

List of publications **5**
Related to the PhD 5
International peer-reviewed scientific journals 5
National peer-reviewed scientific journals 6
National magazine 6
Side to the PhD 7
International peer-reviewed scientific journals 7

List of communications **11**
International communication related to the PhD 11
National communication sided to the PhD 12

List of grants **13**

Table of contents **15**

List of figures **18**

List of tables **21**

1 Introduction **22**

2 State of the art **25**
2.1 Injury prevention in sports 26
2.1.1 History and principles of epidemiology 26
2.1.2 Sports epidemiology 27
2.1.2.1 Health problem 27
2.1.2.2 Injury surveillance 28
2.1.2.3 Epidemiological outcome 29
2.1.2.4 Injury consequences 31
2.1.3 Sports injury prevention 33
2.1.3.1 Research framework on sports injury prevention 33
2.1.3.2 Aetiology of sports injuries 35
2.1.3.3 Sports injury prevention strategies 44
2.1.3.3.1 Context 44
2.1.3.3.2 Digital health the 'e'-volution 44
2.1.4 Summary 47
2.2 Artificial Intelligence 48
2.2.1 Context 48
2.2.2 Machine learning 50

2.2.2.1 Definition ... 50
2.2.2.2 Medicine and machine learning ... 52
2.2.2.3 Pipeline of machine learning in medicine ... 53
2.2.3 Sports injuries & machine learning ... 60
2.2.4 Summary ... 62
2.3 Injuries in athletics (track and field) ... 63
2.3.1 Specific context of athletics ... 63
2.3.2 Injury meaning in athletics ... 63
2.3.3 Injury surveillance in athletics ... 64
2.3.4 The extent of the injury problem in athletics ... 65
2.3.4.1 During championships ... 65
2.3.4.2 During seasons ... 66
2.3.5 The consequences of injuries in athletics ... 67
2.3.5.1 Performance-related consequences ... 67
2.3.5.2 Physical-related consequences ... 67
2.3.5.3 Psychological-related consequences ... 68
2.3.5.4 Career-related consequences ... 68
2.3.6 Factors that increase injury risk in athletics ... 68
2.3.7 Reducing the injury problem in athletics ... 69
2.3.7.1 Neuromuscular exercises and injury risk reduction ... 69
2.3.7.2 Education and injury risk reduction ... 70
2.3.7.3 Other injury risk reduction approaches ... 71
2.3.7.4 Adherence and injury risk reduction approaches ... 71
2.3.7.5 Exploring new injury prevention measures ... 73
2.3.8 Summary ... 74

3 Problematic and objectives ... 75
3.1 Rational flow ... 76
3.2 Objectives ... 77

4 Personal contributions ... 78
4.1 Sports injury prediction & machine learning techniques ... 80
4.1.1 Context ... 80
4.1.2 Scoping review: key findings ... 126
4.2 IPredict-AI: Protocol ... 127
4.2.1 Context ... 127
4.3 IPredict-AI: Results ... 138
4.3.1 Context ... 138
4.3.2 IPredict-AI: key findings ... 164
4.4 Injury prediction perception ... 165
4.4.1 Context ... 165
4.4.2 Injury prediction perception: key findings ... 173

5 General discussion ... 174
5.1 Global challenges ... 176
5.1.1 Towards study methodology improvement ... 176
5.1.2 Towards ethics and legal policies improvement ... 180
5.1.3 Towards a planetary crisis ... 181
5.2 A time challenge ... 182
5.2.1 Time and data collection ... 183
5.2.2 Time and data processing ... 184
5.2.3 Time and model validation ... 185

5.3 A field challenge 186
5.3.1 Be performant? 186
5.3.2 Be 'X'-plainable? 187
5.3.3 Be personalised? 188

6 Perspectives 190
6.1 Algorithm 191
6.2 Something human 191
6.3 Won't stand down 192
6.4 Futurism 193

7 Conclusion 195

8 References 198

List of figures

1 Illustration of the distribution of health problems by consequences (Bahr et al., 2020). 28

2 Injury prevalence in the Olympic (Figure 2a) and Netherlands population (Figure 2b). 33

3 The 'sequence of prevention' of sports injuries, adapted from (Van Mechelen et al., 1992). 34

4 Implementation models for injury prevention strategy. 34

5 Conceptual scheme for the causes of a hypothetical disease, adapted (Rothman, 1976). Factor A is a necessary component to complete a sufficient cause (Present in the three sufficient cause). However, factors B, C, and F are not necessary causes, as there are sufficient causes that can occur without them. 35

6 Scatter plots of associated but not correlated (a, b), non-associated (c, d) and correlated variables (e, f). Created based on (Altman and Krzywinski, 2015). 36

7 A multifactorial model of sports injury etiology, from (Meeuwisse, 1994). 38

8 Comprehensive model for injury causation. BMD, Body mass density; ROM, range of motion, from (Bahr and Krosshaug, 2005). 39

9 A dynamic, recursive model of aetiology in sports injury, from (Meeuwisse et al., 2007). 39

10 Complex model for sports injuries. The group of variables at the bottom forms a web of determinants with different weightings. Variables with darker lines have more interactions and greater influence on the outcome. Dashed lines indicate weak interaction, while thick lines indicate strong interaction. Arrows show the relationship between observable regularities and the emerging outcome, from (Bittencourt et al., 2016). 41

11 Recurrent dynamics of macro-injury formation based on the connectivity hypothesis (Pol et al., 2018). 42

12 Evolution of the injury paradigm, adapted from (Fonseca et al., 2020). 43

13 An integrated digital health approach that encapsulates various performance and health aspects of sports. Athletes, coaches and medical staff feed information into a system, from (Verhagen and Bolling, 2015). 46

14 The Foundations of Artificial Intelligence: Part of the ideas, viewpoints and techniques from different disciplines that have contributed to artificial intelligence. Created on the basis of (Russell and Norvig, 2021) 48

15 A conceptual overview of supervised machine learning, from (Rajkomar et al., 2019). 53

16 An example of a machine learning pipeline in healthcare, from (Strating et al., 2023). 57

17 Illustration of the distribution of injury locations by disciplines in athletics (track and field), from (Edouard et al., 2024d). 67

18 Illustration of the approaches and interests of sports injury prediction using machine learning techniques in sports medicine, with prognostic and diagnostic prediction. 106

19 PRISMA flowchart of the selection process of the studies included in the present systematic review 107

20 Risk of bias assessment using the Prediction model Risk Of Bias Assessment Tool (PROBAST) (Wolff et al., 2019) for the included studies in the different domains 108

21 Stratified pie chart of extracted data regarding the Machine Learning approach and techniques used in the 99 methods reported in the 28 included studies. Six levels of information are presented by each circle according to the items of data extracted: 1) data collection, 2) time management, 3) validation, 4) cross-validation, 5) resampling methods and 6) ensemble methods. Inner circles encompass the next level of data represented by outer circles. 109

22 Frequencies and percentages of metrics used in machine learning studies included in the systematic review. 110

23 Stratified pie chart of extracted data regarding the 106 Machine Learning models used in the systematic review. The assessment of models was conducted considering three criteria: "Study," "Type of data collection," and "Model." In cases where multiple results were obtained for a single study, only one was retained in the final selection. 111

24 Study design overview. IPredict-AI, Injury Prediction with Artificial Intelligence; IPrevApp, Injury Prevention Application; I-REF, Injury Risk Estimation Feedback. 130

25 I-REF Module on smartphone. 134

26 Flowchart of the IPredict-AI study. 141

27 The mean daily response rate proportion (n=112) over the 38 weeks of the follow-up. The mean daily response rate was 90.2 $\pm$ 29.9 on the first day of the initial period. It decreased steadily during the entire study period, until a mean daily response rate of 36.9 $\pm$ 29.4 on the last day of the predictive period. .. 145

28 Response rate threshold analysis including one generalised negative binomial linear model per each minimum response rate threshold (x-axis). For a minimum response rate threshold, the analysis was performed for all athletes whose response rate was equal to or above that threshold. The circular dots represent the estimate (e^{β}) for the covariate 'level of I-REF use' (left y-axis). Vertical dashed lines around the estimates represent 95% CI. The red colour indicates a statistically significant result (p<0.05). Vertical grey bars represent the number of athletes included in each response rate threshold (right y-axis). The horizontal blue line represents the null hypothesis ($e^{\beta} = 1$) 146

29 Comparisons of answers between elite athletics stakeholders regarding their perceived level of interest, intent to use, help and stress induced by sports injury prediction approaches 169

30 Thirteen proposed steps for developing a clinical prediction model, from (Efthimiou et al., 2024). 177

31 Checklists of the Transparent Reporting of a multivariable prediction model for Individual Prognosis Or Diagnosis with Artificial Intelligence (TRIPOD+AI) (Collins et al., 2024b). 178

32 Ethical principles identified in existing AI guidelines, from (Jobin et al., 2019). ... 180

33 Performance of different predictive machine learning models in an evolutive scenario. As the season goes by, we plot week by week the cumulative F1-score of predictive machine learning models DT, RF, LR, B1, . . ., B4 trained on the data collected up to that week. Black crosses indicate injuries that not detect by the DT model, red crosses indicate injures correctly predicted by the DT model. For every week i we highlight in red the number of injuries detected by the DT model up to week i., from (Rossi et al., 2018). 183

34 Injury as a phase transition preceded by increased fluctuations, from (Fonseca et al., 2020). 185

List of tables

1 Conditions under which antecedent factor (X) may cause an outcome (Y) (Porta, 2014). 36

2 Different types of machine learning approaches, adapted from (Reis et al., 2024). 51

3 Different types of machine learning models, from (Scott, 2021). 55

4 Different types of performance measures (i.e. metrics), from (Scott, 2021). 58

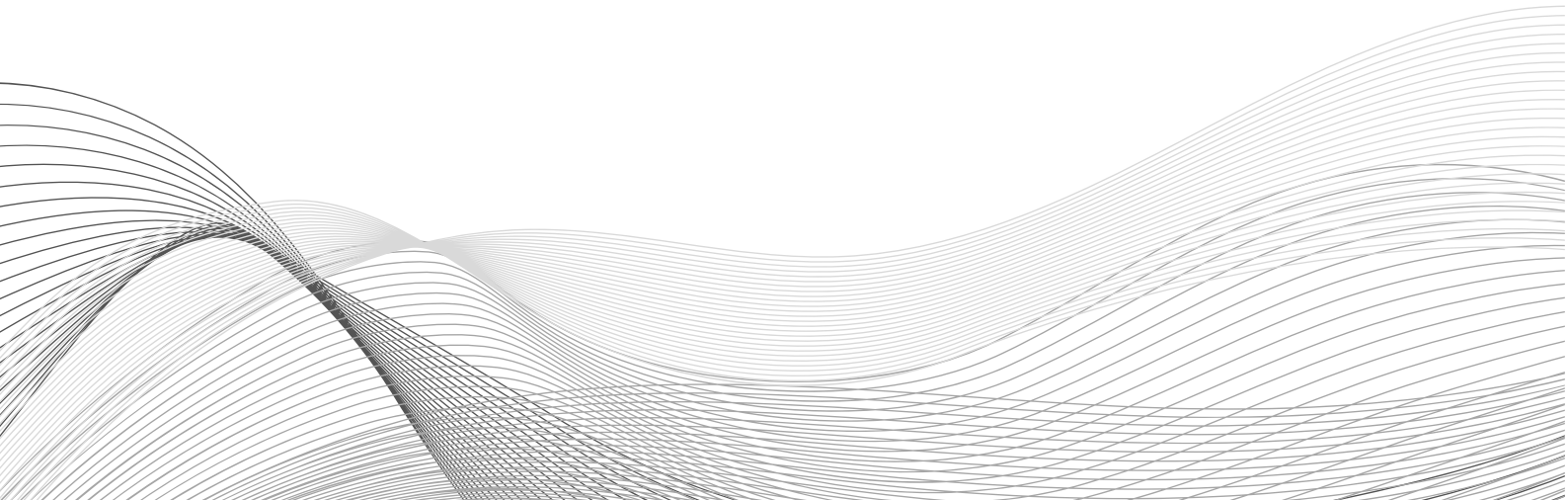
5 Injury risk factors in athletics (Edouard et al., 2024d) 69

6 Characteristics of the included participants. *The statistics for the ages of men medical team members were calculated using 21 and 17 responses in total due to one missing value encountered. 168

7 Results from the injury prediction perceptions questionnaires according to stakeholders. # Significantly different at a p-value of less than 0.05 when compared to the Athlete group. 168

Chapter 1

INTRODUCTION



This manuscript represents the research work carried out from October 2021 to October 2024. This work was funded by the University Jean-Monnet of Saint-Etienne in France and took place within the framework of a collaboration with two other institutions, namely the Mines Saint-Etienne in France and the MSH Medical School Hamburg in Germany.

Since ancient Greece, epidemiology has focussed on the study of the distribution and determinants of disease (Webb et al., 2019). Over the history, epidemiology has evolved to help to promote, protect, restore "a state of physical, mental and social well-being condition" supported by the translation of research findings into health policy (WHO, 1958).

In the 21st century, evidence-based recommendations on physical activity and its health benefits across the lifespan make physical activity a public health priority. The flip side of the coin in the pursuit of health and performance, is that physical activity can lead to health problems such as injuries (Clarsen et al., 2020). Injuries can have a physical, psychological and/or socio-economical impacts at any level of practice and at any age, with long-term effects being even more important in a young population (Emery and Pasanen, 2019; Palmer et al., 2020; Sytema et al., 2010). Therefore, there is a need to develop sports injury prevention strategies to minimise these injury-related effects and consequences (Engebretsen and Bahr, 2005).

In this goal, understanding the aetiology of injuries is an important step in developing effective injury prevention strategies (Van Mechelen et al., 1992). Since the beginning of the 21st century, there has been a paradigm shift in research into the causality of sports injuries. From monocausality to multifactorialism by investigating the additive accumulation of multiple risk factors over time (Meeuwisse, 1994; Bahr and Krosshaug, 2005; Meeuwisse et al., 2007), to recognise the complexity of a system of factors that interact with each other and influence the risk of injury integratively and recursively (Hulme and Finch, 2015; Bittencourt et al., 2016; Pol et al., 2018; Fonseca et al., 2020). This complexity should thus be taken into account in the injury prevention strategies development.

However, injury prevention strategies currently target only one or a few of these factors. Current injury prevention approaches are for instance: recommendations for protective equipment, education, rule changes, policy measures, or exercise-based injury prevention programmes

(Ross et al., 2020). There is thus still room in improvement of injury prevention strategies, mainly due to the challenges of developing, implementing and analysing interventions and better addressing the complexity and multifactorial nature of injuries. In addition, the strategies currently proposed to reduce the risk of injury are not widely used by the end-users involved (e.g., athletes, coaches, health professionals) and do not appear to be sufficiently effective in real-life. Thus, a more personalised approach that takes into account the multifactorial and complex nature of injuries, the individual deficits/risk factors of athletes, their environment, and potential changes over time of these factors, could be relevant to overcome the limits of the current injury prevention strategies. From this perspective, the use of artificial intelligence analyses through machine learning techniques in sports medicine could be a way to address the complexity of injuries, the digital transformation and the challenge of integrating injury prevention strategies in the field.

MAIN PROBLEMATIC

In this context, the overall goal of this PhD work was to explore the use of artificial intelligence and in particular machine learning in sports injury prevention, and specifically in athletics (track and field).

To answer this problematic, this PhD manuscript is structured as follows:

(i) The first part of this dissertation manuscript focuses on the basic theoretical concept of injury prevention in sports (section 2.1), the context of artificial intelligence (section 2.2) and the specific context of athletics (section 2.3).

(ii) The second part of this dissertation manuscript represents the personal contributions during the PhD, and aims to investigate the use of artificial intelligence in sports and athletics through clinical research studies presented in the Chapter 4.

Chapter 2

STATE OF THE ART

2.1 Injury prevention in sports

2.1.1 History and principles of epidemiology

One might think that epidemiological practice and reasoning began with the Greek physician Hippocrates of Kos (460-375 BC), who recognised that both environmental and behavioural factors can influence health (Webb et al., 2019). The term epidemiology is derived from the word "epidemic", which appears to have been derived from "epidemeion", as a description of a disease that was "visiting the people". The term epidemiology, which literally means "the study of what is upon the people", is derived from the Greek words epi "upon, among", demos "people, district" and logos "study, word, discourse". The introduction of more quantitative methods in epidemiology took place much later, in the 17th century, in biology and medicine, which were thus placed in the direct service of public health.

So what does epidemiology mean? The Concise Oxford Dictionary (1964) described it as "the science of epidemics". MacMahon and Pugh formulated it more concretely in 1970: "the study of the distribution and determinants of disease". Their definition succinctly describes the two core areas of traditional epidemiology: who develop diseases (where and when) and why do they develop them? The next definition, from the 2008 edition of the Dictionary of Epidemiology (Porta, 2008), went two steps further by broadening the scope to include health in general, not just disease, and emphasising the essential role of epidemiology in translating research findings into health policy and medical practice to control health in general. Finally, the most recent definition of epidemiology was published as "the study of the occurrence and distribution of health-related events, states and processes in specific populations, including the study of the determinants inuencing such processes, and the application of this knowledge to control relevant health problems" (Porta, 2014). In which:

- *study* includes observation, screening, hypothesis testing, analytic research, experiments, and prediction.
- *distribution* refers to analysis by time, place (or space) and population (i.e., classes or subgroups of affected individuals in an organisation, population or society, or at regional and global levels).
- *determinants* are the geophysical, biological, behavioural, social, cultural, economic and

political factors that influence health.

- *specified populations* are those with common contexts and identifiable characteristics.
- *Application... to control...* clarifies the goal of epidemiology - the promotion, protection and restoration of health and the advancement of scientific knowledge.

The primary "object of knowledge" of epidemiology as a scientific discipline is the causes of health-related events, conditions and processes in groups and populations (Webb et al., 2019). Health is defined by the World Health Organisation (WHO) (WHO, 1958) as a "state of physical, mental and social well-being". In practice, physical health is usually measured, and this focus is reflected in the content of most routine health data and measures we consider. However, some methods increasingly attempt to capture the more elusive mental and social well-being components. Rather than simply measuring "life expectancy", the WHO introduced the concepts of "health-adjusted life expectancy" (HALE) and later "disability-adjusted life years" (DALYs) to enable better international comparisons of the effectiveness of health systems. This recognises that it is not longevity per se that we are striving for, but a long and healthy life.

2.1.2 Sports epidemiology

The WHO 2020 guidelines (Bull et al., 2020) provide evidence-based public health recommendations on physical activity and its health benefits for children and adolescents (5-17), adults (18-64) and older adults (65 years and older). Consequently, as the WHO promoted (Bull et al., 2020), engaging in physical activity is better than not doing any at all. In this context, global and national physical activity guidelines are an important part of a comprehensive and coherent policy framework for public health action that recognises physical activity as a public health priority in the 21st century.

2.1.2.1 Health problem

People who engage in physical activities can be affected by health problems, while they are in the quest of health. This is especially true for those who engage in sports and competition given their quest for performance. Clarsen et al. (Clarsen et al., 2020) defined a health problem as "any condition that athlete consider to be a reduction in their normal state of full health, irrespective of its consequences on their sports participation or performance, or whether they have sought medical attention". This can include injuries, illnesses, pain or mental health conditions.

Health problems can have different consequences and can be categorised as either "medical attention" or "time-loss" health problems, depending on whether they require medical attention or prevent the athlete from participating in training or competition (Bahr et al., 2020). Broader definitions may be needed to capture all athlete health problems as not all health problems limit an athlete's ability to participate nor require medical attention. The illustration of the health problem can be found in Figure 1.

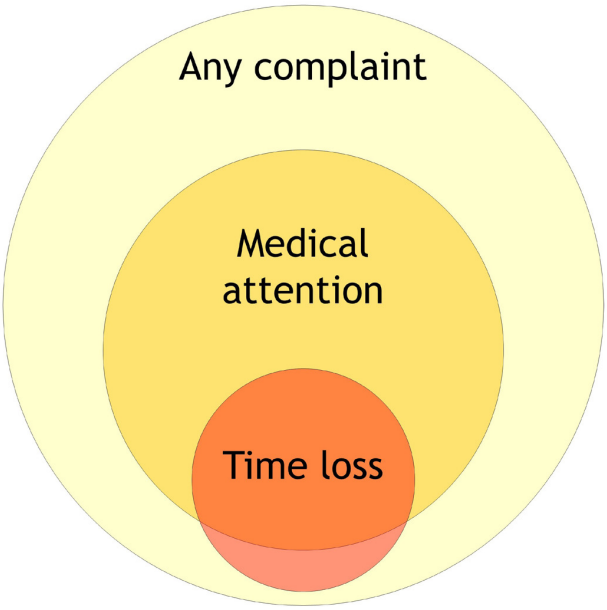


Figure 1: Illustration of the distribution of health problems by consequences (Bahr et al., 2020).

2.1.2.2 Injury surveillance

Surveillance of injury and illness is defined as "the systematic and continuous collection, analysis, and interpretation of data, closely integrated with the timely and coherent dissemination of the results and assessment to those who have the right to know so that action can be taken" (Porta, 2014). It is distinguished from monitoring by the notion that surveillance is continuous and ongoing, whereas monitoring tends to be more intermittent or episodic. It is an essential feature of epidemiological and public health practice. A surveillance system involves collecting, analysing and disseminating data related to public health programmes. The final stage of the surveillance process is to use the information for health promotion and disease prevention.

Defining what constitutes an injury is crucial for research studies in sports epidemiology to ensure standardised reporting and analysis and to reduce the lack of consistency in defin-

ing injuries, which can lead to inconsistent results and contradictory conclusions (Verhagen and van Mechelen, 2009). Despite the difficulties in defining injury, tissue damage or other derangement of normal physical function due to participation in sports, resulting from rapid or repetitive transfer of kinetic energy is currently the International Olympic Committee's consensus definition of injury (Bahr et al., 2020). Since 2005, the sports and exercise medicine community has also reached an international consensus on injuries in cricket (Orchard et al., 2005, 2016), football (Fuller et al., 2006; Waldén et al., 2023), rugby (Fuller et al., 2007), multisport events (Junge et al., 2008), tennis (Pluim et al., 2009; Verhagen et al., 2020), horse racing (Turner et al., 2011), athletics (track and field) (Timpka et al., 2014), aquatic sports (Mountjoy et al., 2015), endurance sports event (Schwellnus et al., 2019), golf (Murray et al., 2020), badminton (Gijon-Nogueron et al., 2022), circus (Greenspan et al., 2022), sports in general (Bahr et al., 2020), mental health (Mountjoy et al., 2023b,a), cycling (Clarsen et al., 2021). This aforementioned consensus statements have standardised the methodology and definitions for injury surveillance to enable a better understanding of injuries in different sports and situations and to compare studies with each other. Thus, the sports and exercise medicine community has methods and tools for conducting injury surveillance.

2.1.2.3 Epidemiological outcome

To quantify injury and illness risk in sports medicine exposure is fundamental (Van Mechelen et al., 1992; de Loës, 1997). In medicine, the "exposure" can be defined as "variable whose causal effect is to be estimated" (Porta, 2014). Epidemiological studies can assess exposure through environmental and lifestyle factors, socioeconomic and working conditions, medical treatments, and genetic traits. Exposures may be harmful or beneficialor even both. In sports medicine, the choice of exposure measures is heavily influenced by the research question, the sports-specific and contextual factors as well as which types of injuries are of interest (Bahr et al., 2020). Indeed, for injuries, exposure could be quantified as the time during which athletes are at risk of injury (e.g., hours of practice), distance covered or a count of the number of specified events (e.g., jumps, sprints, training sessions and game races). In order to consistently record and report injury risk, it's important to distinguish between training and competition exposures. This requires a clear definition of what constitutes training and what constitutes competition, and also considering situations where it may be difficult to apply these definitions.

Therefore "competition" is defined as "organised scheduled play between opposing athletes or teams of athletes, or athlete(s) competing (i) against time and/or (ii) to obtain a score (judged or measured)" and "training" as "physical activities performed by the athlete that are aimed at maintaining or improving their skills, physical condition and/or performance in their sports" (Bahr et al., 2020). In general, it is recommended to record individual exposure and sum all individuals to determine exposure at the sports or team level, which allows the researcher to analyse individual risk factors (Bahr et al., 2020). For example, the total exposure of the population could be given in Equation (1).

Exposure formula

$$E_{pop} = \sum_{i=1}^{n} T_i + \sum_{i=1}^{n} C_i \tag{1}$$

E_{pop} is the total population exposure,

n is the total number of individuals in the population,

T_i is the total duration of training session over specific period for individual i,

C_i is the total duration of competition over specific period for individual i

Rates and proportions are used to express injury risk and answer various research questions, e.g., "How many players have suffered an injury?", "What is the injury risk in a particular sports?" and "How does the injury risk in sports A compare to sports B?"(Bahr et al., 2020). In sports epidemiology, if "the occurrence" describing the frequency of injuries in a population (Porta, 2014). Therefore the frequency of injuries can be approach with proportions by using the injury prevalence (Equation (2)) which is the total number of individuals who have an injury at a particular time (or during a particular period) divided by the population at risk of having the injury at that time or midway through the period (Porta, 2014).

Prevalence formula

$$\text{Prevalence } (\%) = \frac{N_{cases}}{N_{total}} \times 100 \tag{2}$$

N_{cases} is the number of individuals with the condition at a specified point in time or during a particular period,

N_{total} is the total number of individuals in the population at a specified point in time or during a particular period

The frequency of injuries can also be approach with rates by using the incidence (Equation (3)) which is the number of new injured athletes in the population during a defined period of time (Bahr et al., 2020; Porta, 2014).

Incidence formula

$$\text{Incidence} = \frac{\text{Number of new events during a specific period}}{\text{Number of persons exposed to risk during a specific period}} \times 1000 \tag{3}$$

Measure and compare the overall impact of an injury in a specific population can be performed by using the burden (Bahr et al., 2020). The burden of injuries can be expressed using measures that combine their frequency and consequences (Equation (4)). For example, in football, rugby union and athletics, injury burden has been reported as the number of days of time loss per 1000 hours of player exposure (Brooks and Fuller, 2006; Edouard et al., 2021c).

Burden formula

$$\text{Burden} = \frac{\text{Number of time loss during a specific period}}{\text{Number of persons exposed to risk during a specific period}} \times 1000 \tag{4}$$

2.1.2.4 Injury consequences

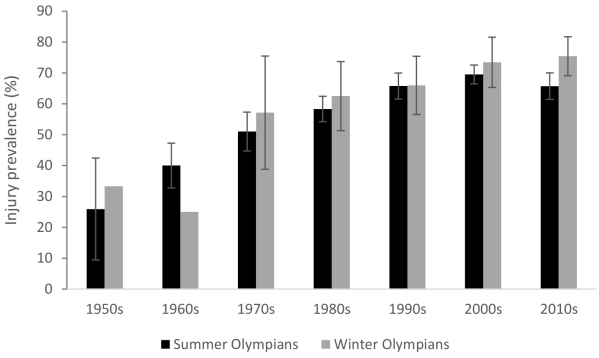
The practice of sports are important for maintaining a healthy lifestyle for people of all ages (Bull et al., 2020). However, sports-related injuries are of great importance. The US National Health Interview Survey characterised sports- and recreation-related injury episodes in the US population. From 1997 to 1999, Americans suffered an estimated annual average of 7.0 million sports- and recreation-related injuries, or an injury incidence rate of 25.9 per 1000 persons (95%CI 24.4 to 27.4 per 1000 persons), with sixty-four percent of these sports- and recreation-

related injuries occurring in persons aged 5-24 years (Conn et al., 2003). In the Netherlands, 25,120 single sports injuries cases were registered between 1990 and 2005 in an emergency department accounting for 20% of all injury events (Figure 2b) (Sytema et al., 2010).

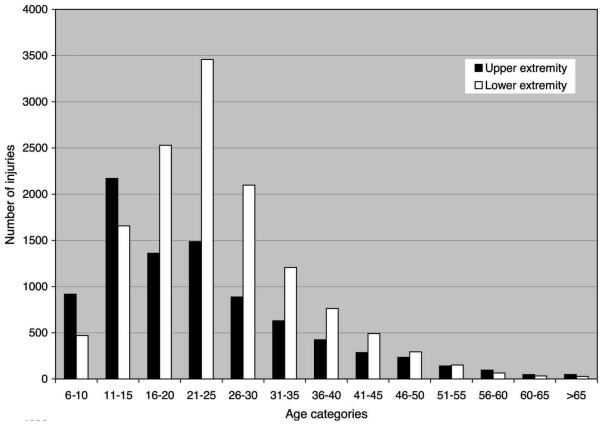
Participation and injury rates in sports are highest among adolescents and young adults. Sports are the leading cause of injury in youth with an estimated 20% of school-aged children miss at least one day of school per year due to sports-related injuries, and one-third of youth seek medical attention for a sports-related injury (Emery and Pasanen, 2019). It is also estimated that one third of working adults miss at least one day a year from work due to a sports-related injury (Conn et al., 2003). Sports injuries can also have a significant socioeconomic impact. The associated cumulative economic burden was $265 million for all sports injuries and $110 million for lower limb injuries over a 7-year period in Victoria, Australia (Finch et al., 2015).

Elite athletes are at risk of musculoskeletal injuries due to the intense training and competition they undergo. While former elite athletes generally have better overall health compared to the general population, they often experience ongoing pain and musculoskeletal issues (Figure 2a). Over thousand, throughout retired Olympians (winter and summer sports) 63% reported at least one significant injury related to their Olympic career, corresponding to 1.1 injuries per 10.4 years of participation (Palmer et al., 2020). Three quarters of this sample of Olympians pressured themselves to return to sports and one quarter recalled continuing to train/compete while injured, and one third of Olympians currently have pain and functional limitations that they attribute to an injury in their Olympic career (Palmer et al., 2020).

The burden of injuries in sports across the lifespan and at any level of practice highlights the need for evidence-informed injury prevention interventions to reduce the risk of injury as well as research evaluating injury prevention strategies in all sports and across all ages (Emery and Pasanen, 2019).



(a) Injury prevalence by decade of Olympic Games participation, from (Palmer et al., 2020).



(b) Number of sports injuries presented at the emergency department during the period 1990-2005, presented for upper and lower extremity with increasing age, from (Sytema et al., 2010).

Figure 2: Injury prevalence in the Olympic (Figure 2a) and Netherlands population (Figure 2b).

2.1.3 Sports injury prevention

2.1.3.1 Research framework on sports injury prevention

In view of the undesirable side effects of sporting activity, such as injuries, a preventive approach was needed to reduce sports injuries. This means that the understanding of sports injuries must be improved and a scientifically based prevention strategy developed. Thus, Willem van Mechelen (Van Mechelen et al., 1992) outlined steps in the sequence of prevention of sports injuries prevention in which (i) the extent of the problem is outlined by identifying and describing the frequency and severity of sports injuries, (ii) the risk factors or causes are identified, (iii) preventive measures are introduced based on the aetiological factors and the mechanisms identified in the second step, and (iv) the effectiveness of prevention is measured by returning to the first step.

The four-step model of sports injury prevention (Figure 3) is a valuable guide for injury research, but it does not adequately describe the directions required for injury prevention research implementation in the field (Finch, 2006). This is because the model did not take into account the need to research implementation issues after the proven effectiveness of prevention measures. To be effective, sports injury prevention measures must be accepted, adopted and complied by the target end-users, otherwise all prevention efforts will fail (Finch, 2006). Finch

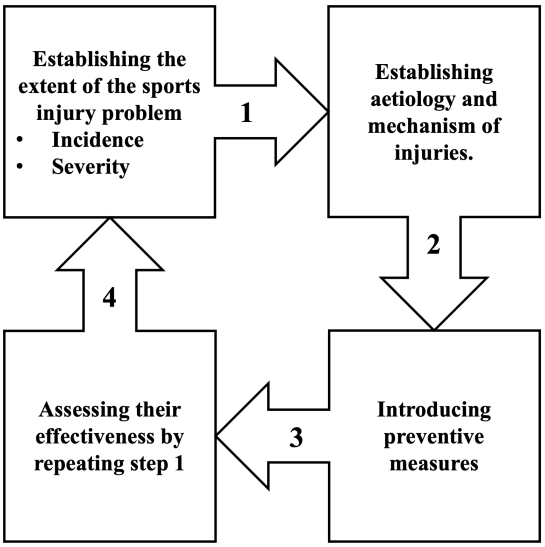
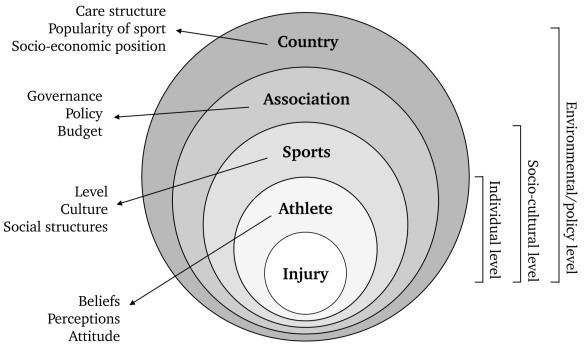


Figure 3: The 'sequence of prevention' of sports injuries, adapted from (Van Mechelen et al., 1992).

(Finch, 2006) extended the model of Van Mechelen et al. (Van Mechelen et al., 1992) with the 6-step Translating Research into Injury Prevention Practice (TRIPP) framework (Figure 4a), which considers implementation in research to ensure that prevention methods are adopted. Furthermore, by introducing "context" as part of the sports injury problem definition, and using a qualitative approach exploring the context could help to provide tailored intervention and thus, help research implementation (Figure 4b) (Bolling et al., 2018b).

Model stage	TRIPP	van Mechelen et al 4 stage approach [1]
1	Injury surveillance	Establish extent of the problem
2	Establish aetiology and mechanisms of injury	Establish aetiology and mechanisms of injury
3	Develop preventive measures	Introduce preventive measures
4	"Ideal conditions"/scientific evaluation	Assess their effectiveness by repeating stage 1
5	Describe intervention context to inform implementation strategies	
6	Evaluate effectiveness of preventive measures in implementation context	

(a) The Translating Research into Injury Prevention Practice (TRIPP) framework for research leading to real-world sports injury prevention (Finch, 2006).



(b) A socioecological view of sports injuries that includes context at multiple levels, i.e., individual, sociocultural and environmental, from (Bolling et al., 2018b).

Figure 4: Implementation models for injury prevention strategy.

2.1.3.2 Aetiology of sports injuries

In the framework proposed by Van Mechelen et al. (Van Mechelen et al., 1992) (Figure 3), understanding the aetiology and mechanism represent an important step. Literally, "aetiology" is the science of causes (Porta, 2014). Rothman (Rothman, 1976) defined "a cause" as "an act or event or a state of nature which initiates or permits, alone or in conjunction with other causes, a sequence of events resulting in an effect". Rothman (Rothman, 1976) also outlined the difference between necessary and sufficient causes (Figure 5). A necessary cause exists when a factor must always precede an effect and the outcome or disease cannot occur without the presence of this necessary factor. This is different from a sufficient cause, which is actually a collection or constellation of factors.

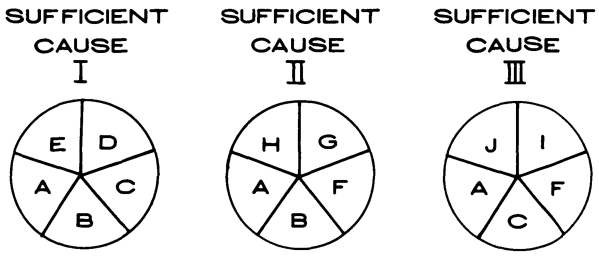


Figure 5: Conceptual scheme for the causes of a hypothetical disease, adapted (Rothman, 1976). Factor A is a necessary component to complete a sufficient cause (Present in the three sufficient cause). However, factors B, C, and F are not necessary causes, as there are sufficient causes that can occur without them.

When talking about causality, it is important to define the terms association and correlation in order to avoid misinterpretations. An association is defined as a "statistical dependence between two or more events, characteristics, or other variables. An association is present if the probability of occurrence of an event or characteristic, or the quantity of a variable, varies with the occurrence of one or more other events, the presence of one or more other characteristics, or the quantity of one or more other variables" (Porta, 2014). Overall, an association is a general relationship that is not to be confused with causality; if X is the cause of Y, then the two are associated (dependent). However, associations can arise between variables in the presence (i.e., X causes Y) and absence (i.e., they have a common cause) of a causal relationship (Altman and Krzywinski, 2015). A correlation is defined as "the degree to which variables change together. How closely two (or more) variables are related" (Porta, 2014). The term "correlation" is generally more specific and is used in statistics (e.g., Pearsons correlation coefficient), e.g.,

two variables are correlated if they show an increasing or decreasing trend. To summarise, a correlation implies an association, but not causation. Conversely, causation implies association but not correlation Figure 6 (Altman and Krzywinski, 2015).

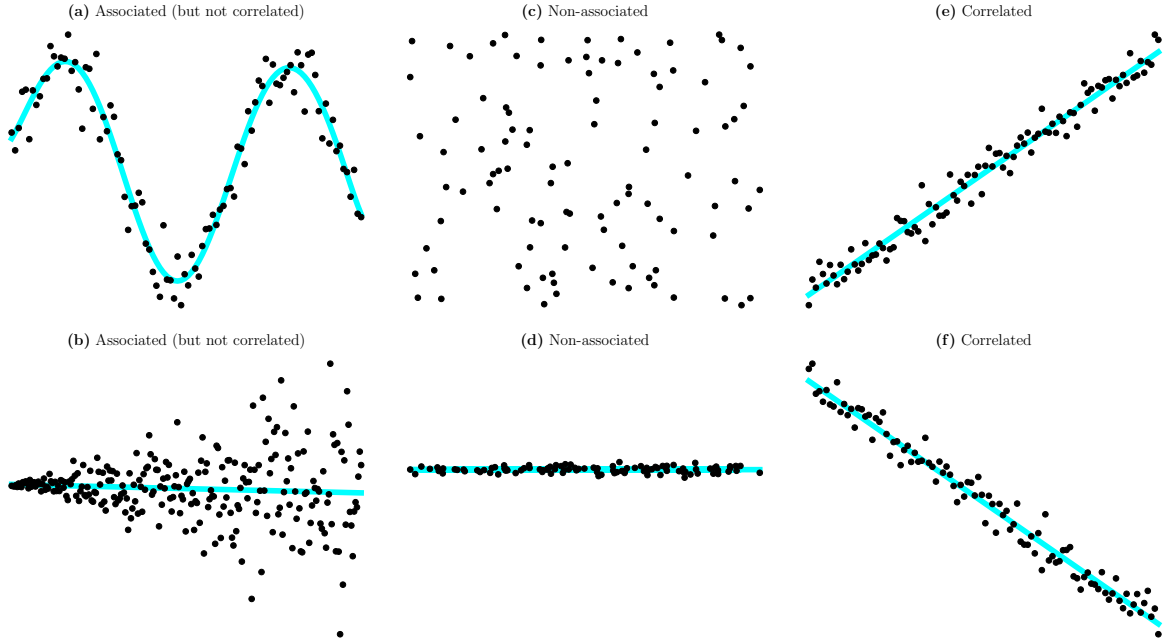


Figure 6: Scatter plots of associated but not correlated (a, b), non-associated (c, d) and correlated variables (e, f). Created based on (Altman and Krzywinski, 2015).

When investigating the causes of sports injuries, we always look back to a relevant time period for the factor we are interested in (Verhagen and van Mechelen, 2009). Additionally, comparing a specific group with a reference group for the factor (for example, comparing helmet wearers with non-wearers) is essential for assessing causality (Verhagen and van Mechelen, 2009). Furthemore, Porta (Porta, 2014) present four general conditions under which antecedent factor (X) may cause an outcome like an injury (Y) (Table 1).

Table 1: Conditions under which antecedent factor (X) may cause an outcome (Y) (Porta, 2014).

Conditions	X is necessary	X is sufficient	Causality
1.	+	+	X → Y
2.	+	−	X and Z → Y
3.	−	+	X → Y; Z → Y
4.	−	−	X and Z → Y; W and K → Y

1. **X is necessary and sufficient to cause Y**: *A direct blow to the knee (X) is necessary and sufficient to cause a knee contusion (Y)* In this case, a knee contusion (Y) always occurs

when there is a direct blow to the knee (X), and the contusion cannot occur without this specific trauma. If the blow occurs, the contusion will occur in any case and no other factor is needed.

2. **X is necessary but not sufficient to cause Y:** *Repeated loading on a bone (X) is necessary but not sufficient to cause a stress fracture (Y)* Repetitive loading of a bone is necessary for a stress fracture to occur, but not all athletes with repetitive loading develop a stress fracture. Other factors such as bone density, nutrition, rest, or training load (Z) also play a role in whether a stress fracture occurs.

3. **X is not necessary but sufficient to cause Y:** *A fall during a game (X) is not necessary but sufficient to cause a wrist sprain (Y)* A fall can cause a wrist sprain, but wrist sprains can also result from other causes such as overuse or a direct blow. A fall is therefore sufficient to cause the injury, but it is not the only possible cause.

4. **X is neither necessary nor sufficient to cause Y:** *Bad footwear (X) is neither necessary nor sufficient to cause Achilles tendinitis (Y)* Poor footwear can contribute to the development of Achilles tendinitis, but the injury can occur without poor footwear, and poor footwear alone does not guarantee the development of tendinitis. Additional factors such as training load, running surface and biomechanics (Z) also play a role.

Because sports injuries, like most diseases, are likely to have a multifactorial aetiology, examining each factors associated with injury (e.g., risk factors) individually without controlling for others would not provide a true picture of how each contributes to injury (Meeuwisse, 1994). Even when data on multiple factors were available, a univariate approach (a single risk factor) was typically used to assess causality. While the univariate approach has been able to delineate some of the risk factors, it has also limited progress in determining which factors or combinations of factors are truly causal.

Therefore, a multifactorial approach was developed to assess causality and explore factors interrelationship (Figure 7) (Meeuwisse, 1994). In sports injuries, risk factors are categorised as intrinsic (anthropometry, stage of maturity, somatotype, biomechanics, conditioning), extrinsic (weather, field conditions, rules and equipment), modifiable (body-weight, sleep duration), and non-modifiable (age, sex, genetics, ethnicity) (Taimela et al., 1990; Bahr and Krosshaug, 2005).

In Figure 7 predisposing intrinsic factors (i.e., factors that prepare, sensitise, condition an athlete to react in a certain way (Porta, 2014)) influence an individual to injury. As soon as the athlete has certain predispositions, external risk factors can affect him and enable the manifestation of injuries (Porta, 2014). The interaction of intrinsic and extrinsic factors can make the athlete susceptible to injury (Figure 7), but is usually not sufficient for an injury to occur. The final link in the causal chain is an inciting event (i.e., a necessary cause in section 2.1.3.2) that is related to the injury (Meeuwisse, 1994). By focussing on the precipitating events and the mechanism of injury, the sports medicine practitioner may pay less attention to other factors that precede the precipitating event (Meeuwisse, 1994).

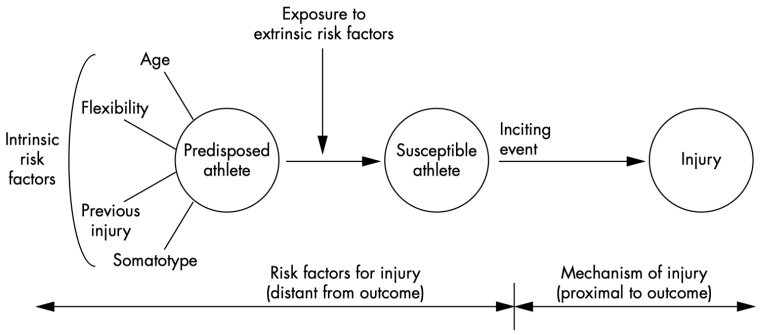


Figure 7: A multifactorial model of sports injury etiology, from (Meeuwisse, 1994).

A few years later, Bahr and Krosshaug (Bahr and Krosshaug, 2005) identified that the inciting event can be a complex set of key components including the game situation, player and opponent behaviour, the gross biomechanical description and the detailed biomechanical description. Therefore, they updated the model from Meeuwisse et al. (Meeuwisse, 1994) with a more comprehensive description of the mechanisms for a particular injury type in a particular sports to include the events leading up to the injury situation (game situation, player and opponent behaviour) and to add a description of the biomechanics of the whole body and joints leading up to and at the time of injury (Figure 8).

Traditional models used in cohort studies follow a linear paradigm in which events are observed sequentially from a starting point to an end point (Meeuwisse, 1994; Bahr and Holme, 2003; Bahr and Krosshaug, 2005). However, this approach has its limitations and cannot capture the complexity of diseases outcomes. In sports, injuries are often caused by a combination of risk factors and participation, which can vary in severity and frequency and do not always lead to permanent removal from participation (Meeuwisse et al., 2007). The linear approach used in the

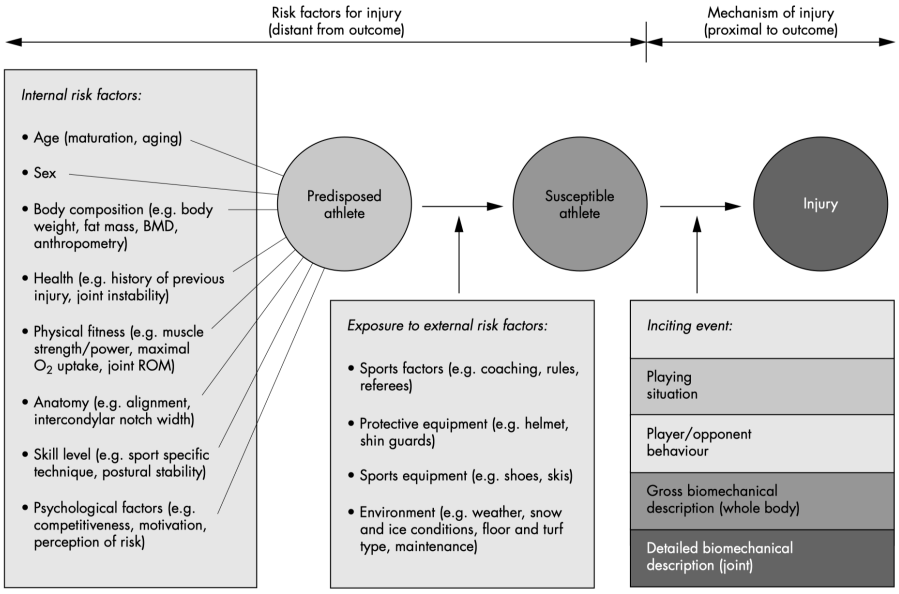


Figure 8: Comprehensive model for injury causation. BMD, Body mass density; ROM, range of motion, from (Bahr and Krosshaug, 2005).

previous models (Meeuwisse, 1994; Bahr and Krosshaug, 2005) with a start and an end point does not reect the true nature of injuries in sports. Therefore, Meeuwisse et al. (Meeuwisse et al., 2007) proposed an update to their original model, aiming for a dynamic approach that incorporates the consequences of repeated participation in sports, both with and without injury, by considering the cyclical nature of changing risk factors to create a dynamic, recursive picture of the aetiology of sports injuries (Figure 9).

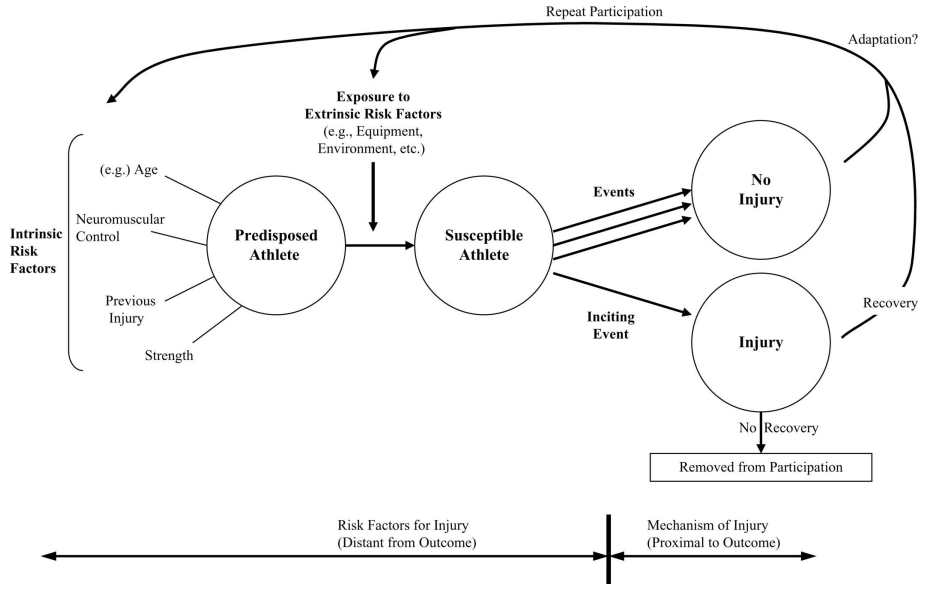


Figure 9: A dynamic, recursive model of aetiology in sports injury, from (Meeuwisse et al., 2007).

A few years later Hulme and Finch (Hulme and Finch, 2015) proposed a complementary and alternative conceptual approach to better understand the development and prevention of sports injuries with the help of systems thinking. Trochim et al. (Trochim et al., 2006) defined systems thinking as "a general conceptual orientation concerned with the interrelationships between parts and their relationships to a functioning whole, often understood within the context of an even greater whole. It is ancient in origin and familiar to us all, but it is also something very modern". Hulme and Finch (Hulme and Finch, 2015) raised the importance to reflect on how causal concepts in epidemiology have evolved over time, from monocausality to multifactorialism. In sports injury research, there has been a push to adopt a socioecological perspective (Hanson et al., 2005) and move to a systems paradigm.

Based on the paradigm of the conceptual system developed by Hulme and Finch (Hulme and Finch, 2015). Bittencourt et al. (Bittencourt et al., 2016) conceptualised and described sports injuries as complex systems with five characteristics:

1. **Open system:** Interaction with the environment and development over time lead to several paths that lead to similar injuries.

2. **Non-linearity:** Injury predictors are not proportional to the output and the outcome of a complex system are the result of interactions among units and are not equivalent to units themselves. For example, large changes in one factor do not necessarily produce a large effect on the outcome. Conversely, small changes may produce a large and sometimes unexpected effect on the injury.

3. **Recursive loop:** After an injury occurs, the system can change in unpredictable ways. In this case, the previous states of the so-called injury predictors are changed in such a way that they no longer have the same relationship to the outcome or even no longer exist at all.

4. **Self-organisation:** The emergence of properties that cannot be predicted solely on the basis of the behaviour of the factors leads to the spontaneous occurrence of order within the system.

5. **Uncertainty:** When new phenomena emerge, it is not always possible to predict them

by understanding the relationship between cause and effect. In these cases, prediction depends on determining the probability of the new phenomenon occurring.

Although the non-linear and recursive characteristics of sports injuries were recognised, the model described by Meeuwisse et al. (Meeuwisse et al., 2007) and its "web of causation" (Meeuwisse, 1994) was in fact insufficient to account for the complex interactions between multiple factors. The multifactorial and complex nature of sports injuries does not result from the linear combination of isolated and predictive factors, but from the interaction between the so-called 'web of determinants' (Figure 10). Bittencourt et al. (Bittencourt et al., 2016) defined the web of determinants as "an interacting units of a complex system, in which the units interact with each other in unpredictable and unplanned ways (frequently unknown). These complex interactions arise from the systems own history and form observable regularities (risk or protective prole), which in turn emerge as a global pattern (injury or adaptation). This emerging pattern constrains the interactions among the systems units (the models recursive loops) and will dynamically shape the existing interactions. In this case, the web of determinants may change according to the outcome they produce".

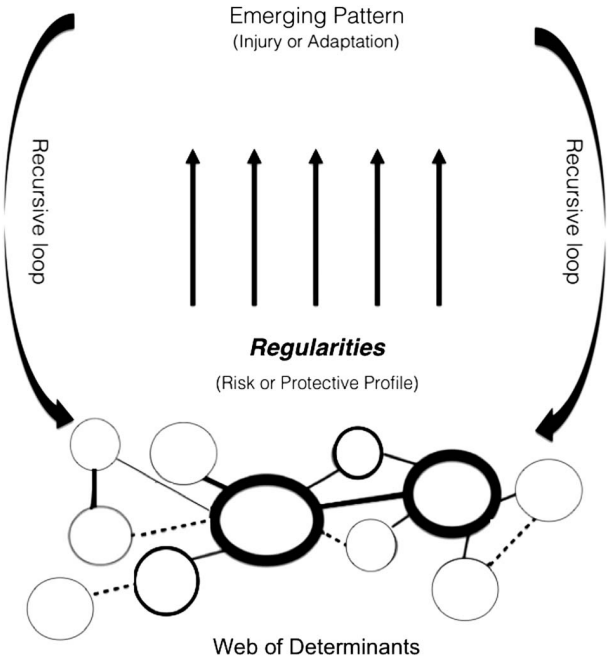


Figure 10: Complex model for sports injuries. The group of variables at the bottom forms a web of determinants with different weightings. Variables with darker lines have more interactions and greater influence on the outcome. Dashed lines indicate weak interaction, while thick lines indicate strong interaction. Arrows show the relationship between observable regularities and the emerging outcome, from (Bittencourt et al., 2016).

A few years later, Pol et al. (Pol et al., 2018) published a narrative review on the application of the complex dynamic systems approach in sports medicine based on the dynamic system theory from mathematics, which incorporates constraints, non-linearity and interaction at different levels and time scales that could influence the susceptibility to injury (Figure 11). Based on the connectivity theory, they assumed that susceptibility to sports injury is defined as the responsiveness of the musculoskeletal system to micro-injuries (i.e., at the microscopic level). When the musculoskeletal system is stable, susceptibility to injury is low and a large perturbation is needed to cause an injury. Near instability, susceptibility increases dramatically and a new micro-injury can be enough to cause a macro-injury (e.g., a muscle tear).

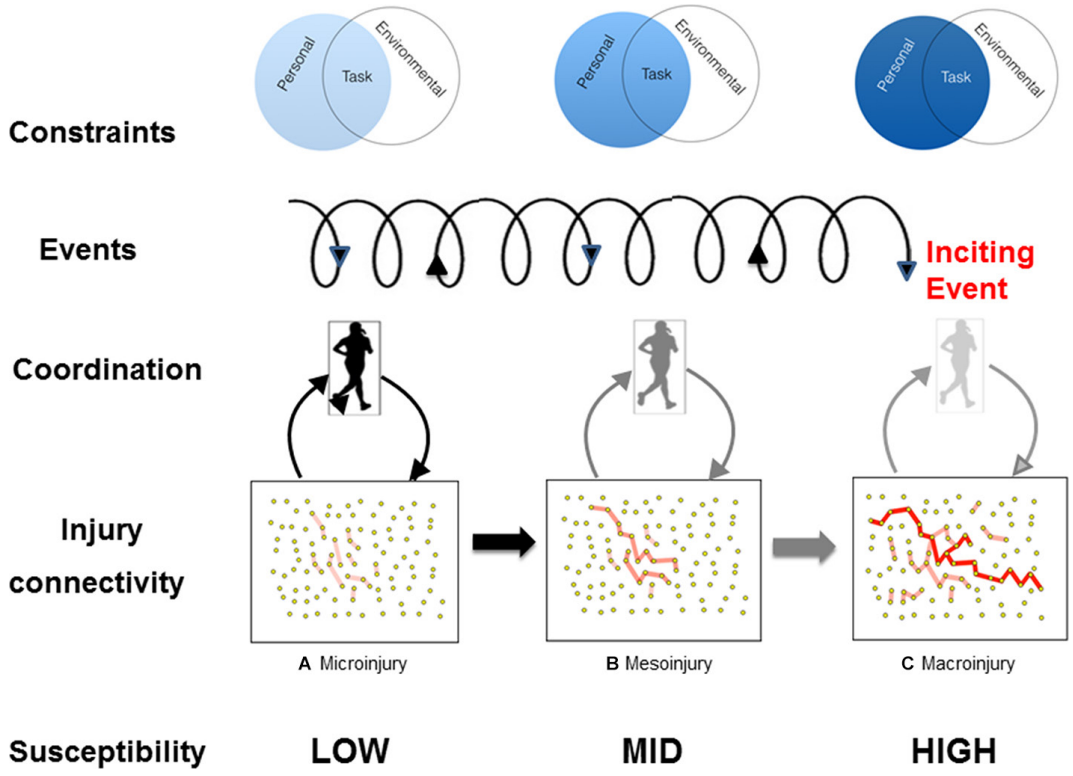


Figure 11: Recurrent dynamics of macro-injury formation based on the connectivity hypothesis (Pol et al., 2018).

Recently, Fonseca et al. (Fonseca et al., 2020) explained the complexity of injuries using a synergetic approach that assumes that the interactions between the elements of the injury are mostly unknown. However, this unknown behaviour at the element level can lead to ordered behaviour at the macroscopic level, which can be captured by an order parameter. Thus, injury complexity requires the identification of the correct proper order parameter and its temporal evolution that could lead to an emerging pattern (Fonseca et al., 2020).

Finally, a paradigm shift in the study of sports injury causality was made during the last decade, from monocausality to multifactorialism, recognising the complexity of a system of factors that interact with each other and have an integrative and recurrent influence on injury risk (Figure 12).

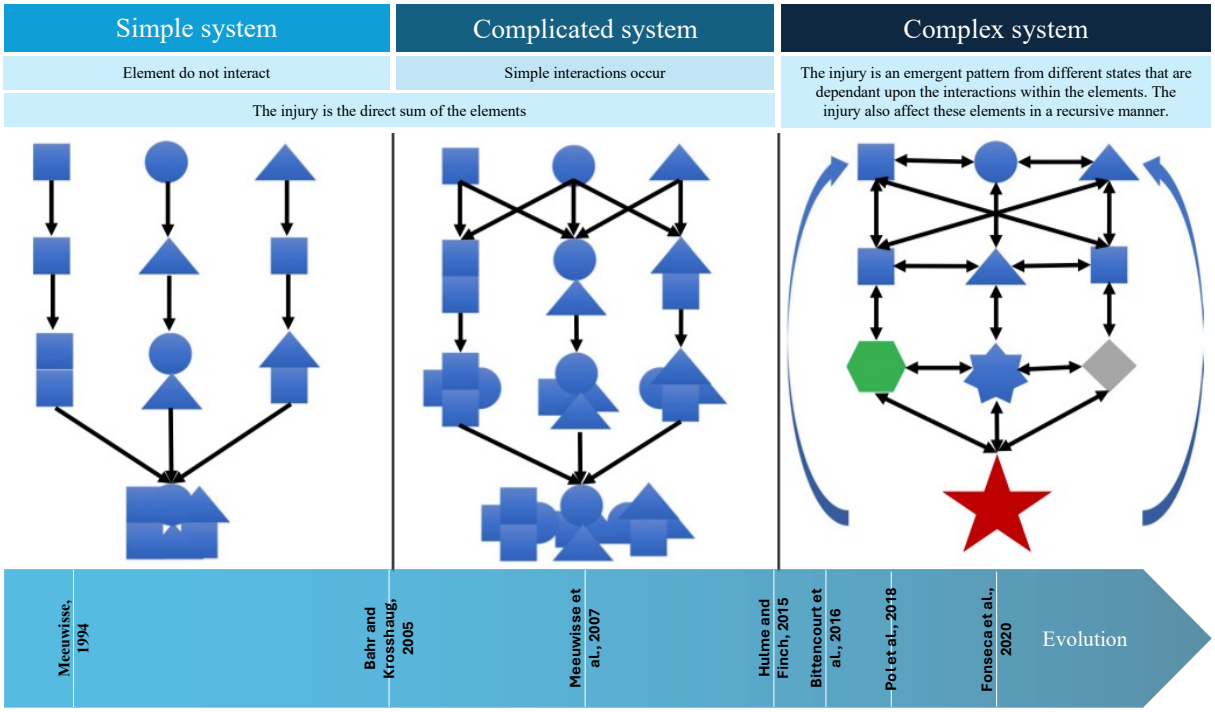


Figure 12: Evolution of the injury paradigm, adapted from (Fonseca et al., 2020).

2.1.3.3 Sports injury prevention strategies

2.1.3.3.1 Context

Public health stakeholders and policy makers are aware that up to one in three adults are physically inactive and have high rates of obesity worldwide (Guthold et al., 2018; Bull et al., 2020). Thus, it is to engage and participating regularly in physical activities (Bull et al., 2020). While there are benefits to participating in sporting activities, it also increases the risk of sports injuries, with a significant impact on adults (Emery and Pasanen, 2019). In the area of public health, strategies to reduce the risk of injury are legitimate and could therefore be implemented nationwide. Indeed, various types of injury risk reduction measures have been adopted, targeting one or more primary prevention interventions, such as recommendations for protective equipment, education, rule and policy changes, or exercise-based injury prevention programmes (Ross et al., 2020). Exercise-based injury prevention programmes is the most studied strategy (Liddle et al., 2023; Kilic et al., 2017; Crossley et al., 2020). There is still a need to investigate the efficacy of injury prevention strategies using rigorous scientific methods such as randomised controlled trials. Investigating the efficacy of an injury prevention strategy face some challenges in terms of intervention development, intervention implementation and intervention analysis that could lead to biased results (Iatropoulos et al., 2024). Therefore, injury prevention approaches need to be broadened to address the multifaceted and complex nature of injuries (Section 2.1.3.2).

2.1.3.3.2 Digital health the 'e'-volution

To better match the complexity of injuries, the use of a digital approach could be an opportunity. Indeed, in 2023, the International Telecommunication Union reported that almost 70% of the world's population (more than 90% in Europe) had access to the internet (International Telecommunication Union, 2023). The use of electronic processes and communication has found its way into our daily lives and also into health policy. In 2021, the WHO global strategy on digital health 2020-2025 (World Health Organization, 2021) defined 'Digital health' as "the field of knowledge and practice associated with the development and use of digital technologies to improve health. Digital health expands the concept of eHealth to include digital consumers, with a wider range of smartdevices and connected equipment. It also encompasses other uses

of digital technologies for health such as the Internet of things, artificial intelligence, big data and robotics". Despite this recent definition, sports medicine began using digital health in the 2010s as part of injury and illness surveillance research (Grindem et al., 2013; Ekegren et al., 2014). Verhagen et al. (Verhagen et al., 2013) have addressed some positive aspects of digital health towards the registration of data:

- **Automated database creation:** Respondents enter the data directly into a database. This eliminates the need for manual data entry by researchers, which increases efficiency and data accuracy.
- **Restricted questions:** Data fields can be predefined to contain only a certain range of possibilities to avoid incorrect and out-of-range data.
- **Maximise response rates:** Respondents can receive a notification when questions are skipped, reducing the amount of missing data.
- **Branching questions:** Guiding respondents through a questionnaire based on their answers) minimises the time burden on respondents and increases the likelihood of further study participation.

Verhagen et al. (Verhagen et al., 2013) also pointed to the possibility of using real-time data analysis to adjust a treatment protocol based on daily clinical outcomes reported by patients and, from a research perspective, such streaming data can be used for real-time predictive modelling. Unfortunately, digital health is not magic, and caution is needed regarding the validity of the content of available sports injury prevention apps, as in 2013, 20% of such prevention app contained evidence-based statements (Van Mechelen et al., 2013). Online surveys should also be used carefully to maximise their use and effectiveness (Verhagen et al., 2013; Evans and Mathur, 2005).

Digital health is neither magical nor efficient and autonomous if its use is not well designed. This is why Verhagen and Bolling (Verhagen and Bolling, 2015) have presented an integrated approach to digital health that encompasses research, implementation and care (Figure 13). Centralised, digitised information enables the athlete's entire care team to review data and make informed decisions. In addition, tailored feedback can be provided to athletes and coaches, allowing for better communication and improved overall athlete performance and health. Such an integrated approach provides scientific tools to solve enigmas in sports medicine research

and optimise injury prevention, management, and rehabilitation (Verhagen and Bolling, 2015).

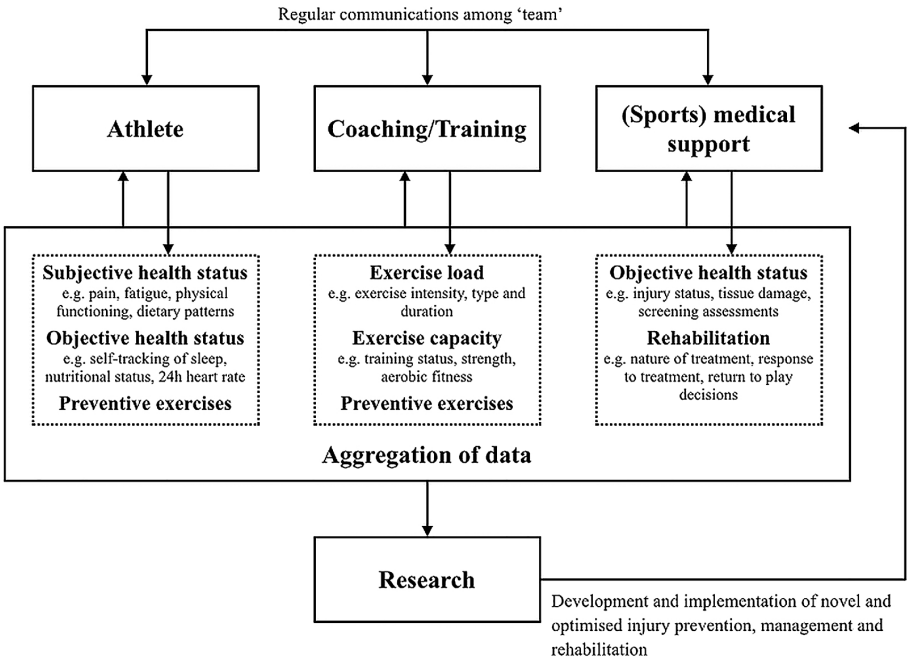


Figure 13: An integrated digital health approach that encapsulates various performance and health aspects of sports. Athletes, coaches and medical staff feed information into a system, from (Verhagen and Bolling, 2015).

The approach described above represents the current state of sports medicine with the technologies available to advance our field. Studies investigating the effects of such online interventions on injuries are limited and have mixed results. Hespanhol et al. (Hespanhol et al., 2017) showed a positive effect of online tailored injury prevention advice on injuries in trail runners. In contrast, other studies showed no effect of online intervention programme on injury occurrence (Fokkema et al., 2019; Dan der Does et al., 2023). It was suggested that this could be due to the fact that the intervention was too general (Fokkema et al., 2019) or not sufficiently adapted to the target population (Dan der Does et al., 2023). At the grassroots youth level, digital platforms could also offer new opportunities to efficiently support the development of safe sports practices (Jacobsson et al., 2022). Therefore, the use of digital health could be an opportunity for injury prevention measures.

2.1.4 Summary

CONTEXT OF INJURY PREVENTION

- The primary 'object of knowledge' of epidemiology as a scientific discipline is the causes of health-related events, conditions and processes in groups and populations.
- International and national guidelines on physical activity are an important part of a comprehensive and coherent policy framework for public health action that recognises physical activity as a public health priority in the 21st century.
- Athletes who engage in physical activities can be affected by health problems, such as injuries.
- Injury surveillance system has been developed in sports medicine based on injury consensus guidelines and the quantification of injury in sports could be performed by using metrics like prevalence, incidence, burden and exposure.
- The importance and impact of injuries in sports across the lifespan and at any level of practice highlights the need for evidence-informed injury prevention interventions to reduce the risk of injury as well as research evaluating injury prevention strategies.
- Framework for research leading to sports injury prevention is necessary and were developed to guide research on injury prevention.
- Understanding the injury is directly related to investigating the causes of the injury, i.e., the aetiology of sports injuries.
- A paradigm shift in the study of sports injury causality was made during the last decade, from monocausality to multifactorialism, recognising the complexity of a system of factors that interact with each other and have an integrative and recurrent influence on injury risk.
- Injury risk reduction measures have been adopted in sports, targeting one or more primary prevention interventions, such as recommendations for protective equipment, education, rule and policy changes, or exercise-based injury prevention programmes.
- The field of knowledge and practice associated with the development and use of digital technologies to improve health (digital health) is in the center of interest.
- In sports medicine, studies investigating the use of online technologies as an injury risk reduction measured is limited and with mixed results.

2.2 Artificial Intelligence

2.2.1 Context

There is no generally recognised definition of artificial intelligence in the literature. Despite this, Russel and Norvig (Russell and Norvig, 2021) tried to provide a simple definition of this concept as "the field of artificial intelligence is concerned not only with understanding, but also with building intelligent entities - machines that can compute how to act effectively and safely in a variety of novel situations".

One explanation for the difficulty in clearly defining artificial intelligence could lie in the numerous disciplines that have more or less dealt with the concept of intelligence and machine throughout history, which was given the name 'AI' in the 19th century (Figure 14).

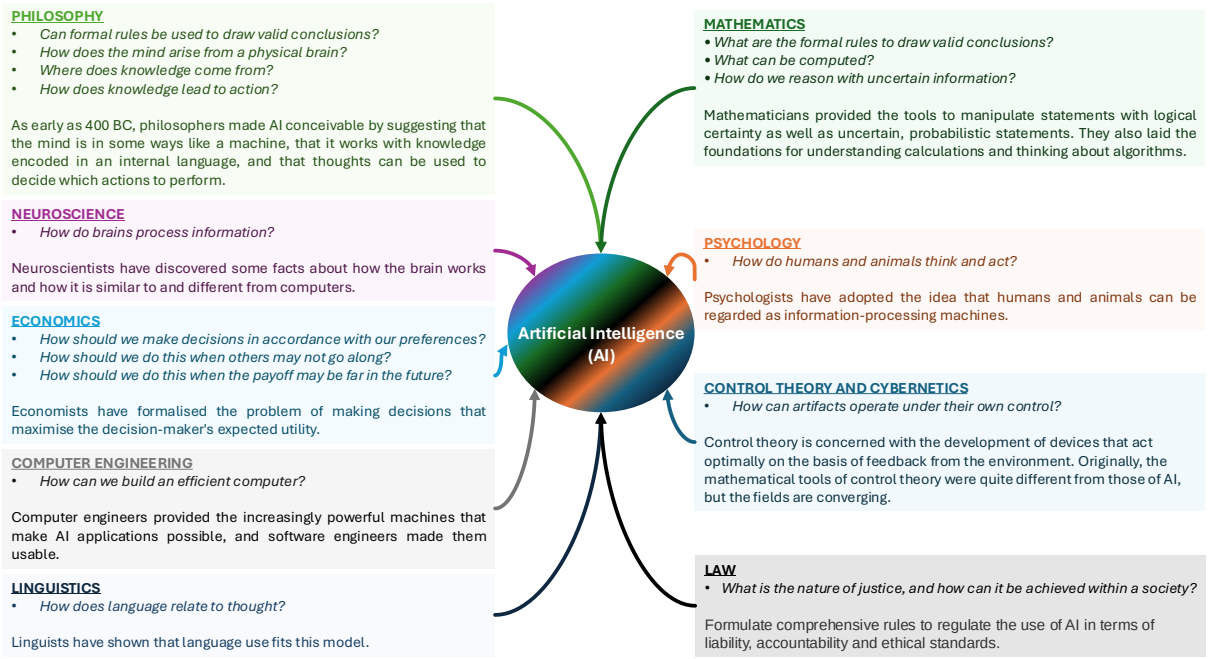


Figure 14: The Foundations of Artificial Intelligence: Part of the ideas, viewpoints and techniques from different disciplines that have contributed to artificial intelligence. Created on the basis of (Russell and Norvig, 2021)

Alan Turing, an English mathematician, was the first person to carry out extensive research in the field he called "machine intelligence", particularly during the Second World War (Russell and Norvig, 2021). Artificial intelligence was established as an academic discipline in 1956, in particular through research into artificial neurons based on the physiology of the brain and logic theory, which showed that computable functions and logical connections could be implemented

by networks of connected neurons (Russell and Norvig, 2021).

The field of artificial intelligence went through several cycles of optimism. In the 1950s, while the intellectual establishment believed that machines could never do certain tasks, artificial intelligence researchers proved otherwise by demonstrating their abilities in games, puzzles, maths and IQ tests. This period was known as "Look, Ma, no hands!". In the 1960s, the traditional approach to problem-solving in artificial intelligence involved general search mechanisms, but these "weak methods" were not effective for large or difficult problems. A more powerful alternative was the use of domain-specific knowledge, known as "expert systems", which allowed for larger reasoning steps and better handling of common cases within a given domain on a given task (e.g., recognising cancer cells in medicine).

In contrast, there were also periods of disappointment and loss of funding in the field of artificial intelligence, known as the "AI winter" between 1960 and 1990. This was mainly because the development of expert systems failed due to difficulties in dealing with uncertainty and the inability to learn from experience.

Funding and interest increased enormously after 2011, when deep learning surpassed all previous artificial intelligence techniques (Krizhevsky et al., 2012) based on the creation of very large data sets (big data) since the 2000s (Halevy et al., 2009). This led to the artificial intelligence boom of the early 2020s, with companies, universities and laboratories, mostly based in the United States, making significant advances in the field of artificial intelligence (e.g., ChatGPT).

The increasing use of artificial intelligence in the 21st century has been influencing social and economic change towards automation, data-driven decision-making and the integration of artificial intelligence systems into various economic sectors and areas of society, such as robotic vehicles (Thrun et al., 2006), legged locomotion (Ackerman and Guizzo, 2016), autonomous planning and scheduling (Nowak, 2016), machine translation (Wu et al., 2016), speech recognition (Xiong et al., 2018), recommendations (Zhang et al., 2019), gaming (Jaderberg et al., 2019), image understanding (Vinyals et al., 2017), medicine (Liu et al., 2019), and climate science (Rolnick et al., 2022) with implications for markets, healthcare, government, industry, education, and communication. This raises questions about the long-term effects, ethical implications and risks of artificial intelligence and prompts discussions about regulatory measures to

ensure the safety and benefits of this technology (Jobin et al., 2019).

2.2.2 Machine learning

2.2.2.1 Definition

Learning happens when a person improves their performance by making observations about the world (Russell and Norvig, 2021). There are endless examples of learning situations. Learning can be, for example, taking your first steps, writing or playing badminton. When a computer learns, this is called machine learning. This means that the computer observes data, creates a model based on these data and then uses this model both as a hypothesis about the world and as software to solve problems (Russell and Norvig, 2021). Machine learning is a subfield of artificial intelligence where every component of a computer programme can be improved. The improvements and the techniques used for this depend on various factors (Russell and Norvig, 2021):

- Which component is to be improved (e.g., recognising a task or learning a task, an image or an event such as the injury)
- What previous knowledge the programme had (i.e., database).
- What data and feedback on this data is available (i.e., which data on the database).

The use of intelligence in a computer mainly involves the construction of an algorithm, i.e., a sequence of instructions to perform a specific task. The machine learning algorithm is able to "learn", i.e., create a model that predicts output data from the input data. The database, which contained the initial input data, is called a "learning database" (Tondut et al., 2023). When the model has learnt, it can be confronted with new data whose output is unknown. If the learning was efficient, the model is able to make a more or less accurate prediction of the desired output. Machine learning is therefore a branch of artificial intelligence that develops algorithms (using mathematics, statistics, logic and computer programming) that are able to recognise patterns in data that improve automatically through experience, i.e., without being specifically programmed (Reis et al., 2024). This is known as automatic learning, as the machine learning model must first be trained to fulfil its task on an initial data (i.e., train) set before it can become autonomous on a second data set (i.e., test). In fine, this model will be able to autonomously predict output data based on input data, where the degree of uncertainty associated with such a prediction is

given by (Tondut et al., 2023).

The input (i.e., features) is a factorised representation, a vector of attribute values. The input can also be any data structure (e.g., time series, images, text, tables). The output (i.e., the label) can be of different types. If it is a finite set of values (e.g., sunny/cloudy/rainy, true/false, binary like 0 or 1), the learning problem is called classification. If the output is a number (e.g., tomorrows temperature measured either as an integer or as a real number), the learning problem is a function approximation or a numerical prediction called regression.

The task of learning in machine learning can be performed in different ways such as supervised, semi-supervised, unsupervised, and reinforced (Russell and Norvig, 2021) (Table 2).

Table 2: Different types of machine learning approaches, adapted from (Reis et al., 2024).

Learning	**Definition**	**Target variable (output)**	**Learning problem**
Supervised	The data set consists of pairs of input- output values. The input data is labelled, i.e. it is linked to an output so that the algorithm can create a prediction that links an output to a new input.	Known output label Variable type: continuous	Regression
		Known output label Variable type: categorical	Classification
		Known output label Variable type: numeric, dichotomous, categorical	Articifical neural network and deep learning
Semi-supervised	The combination of supervised and unsupervised learning (e.g. situations in which the collected data provides labelled and unlabelled results).	Labelled and unlabelled data	Classification Clustering
Unsupervised	The analysis is carried out without human intervention. It is used to extract generative features, recognise meaningful trends and structures, group results and exploratory purposes.	Unknown output: unlabelled	Clustering Association rule learning Dimension reduction and feature learning
Reinforcement	The machine must perform an action in a specific environment. The machine evaluates the optimal behaviour based on the immediate reward. The goal is to increase the long-term reward and reduce the risk (learning by trial and error).	Interaction with the environment	Positive or negative reinforcement

2.2.2.2 Medicine and machine learning

Rajkomar et al. (Rajkomar et al., 2019) presented the promise of machine learning in medicine as the wisdom contained in the decisions of almost every clinician and the outcomes of billions of patients that could be incorporated into the treatment of every patient. Authors also explained that every diagnosis, every treatment decision and every therapy could be personalised in real time based on all known information about a patient, incorporating the insights from collective experience (Rajkomar et al., 2019). Another way to justify why machine learning is growing in medicine is that every patient is now a "big data and complexe challenge", with vast amounts of information on past trajectories and current states (Obermeyer and Lee, 2017). The capabilities of the human mind and the complexity of medicine do not develop in the same period of time and with the same resources. A few years ago, microscopes and stethoscopes were developed to compensate for human limitations. Similarly, in the era of time and skill shortages in healthcare and the important and growing amount of medical information, computers are being developed that are able to process and synthesise medical data more effectively than the human mind (Obermeyer and Lee, 2017).

Supervised machine learning is usually used in medicine because the outcome is known, such as myocardial infarction (Muntner et al., 2014), clinical deterioration in the next 24 hours (Escobar et al., 2016), detection of metastases (Ehteshami Bejnordi et al., 2017). Rajkomar et al. (Rajkomar et al., 2019) presented a conceptual overview of supervised machine learning in three steps (Figure 15).

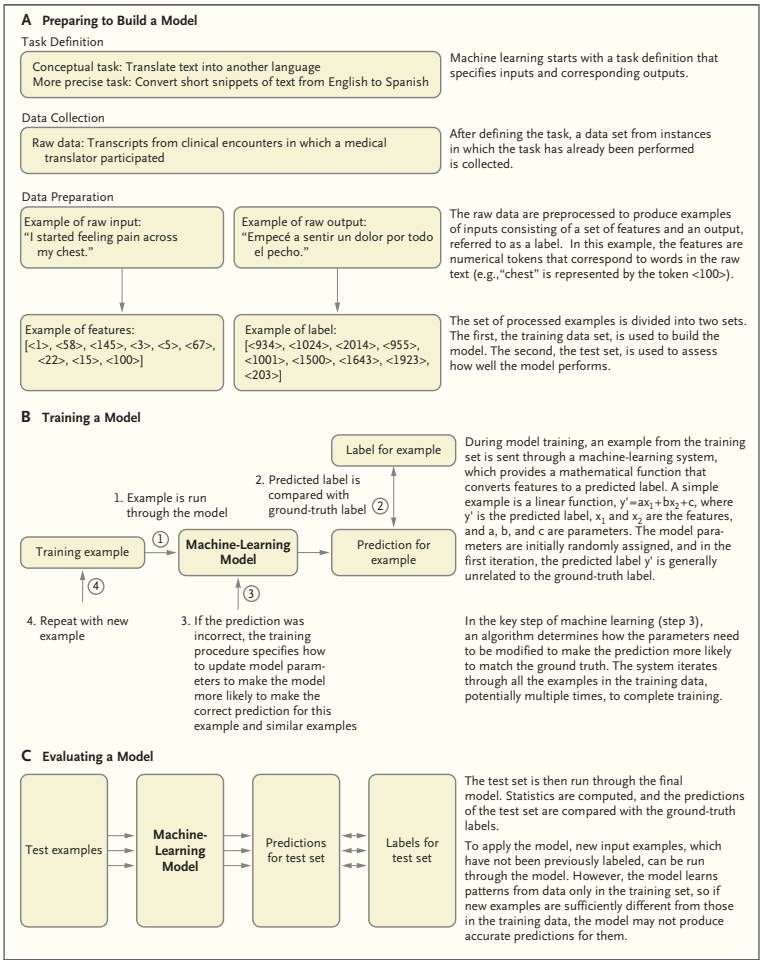


Figure 15: A conceptual overview of supervised machine learning, from (Rajkomar et al., 2019).

2.2.2.3 Pipeline of machine learning in medicine

A representation of key stages of the machine learning pipeline from computer-based development to real-world deployment is represented in Figure 16:

1. **Data collection:** The first step in creating a machine learning model is to collect data. The data can be anything that can be encoded in a format that the computer can understand (e.g., numbers, text, audio or images) and that could potentially help to predict the outcome either on its own or in combination with other data. The selection of the outcome is determined by the question that our model is supposed to answer. The result can therefore be binary (yes/no), categorical, probabilistic or otherwise continuous. The features (i.e., the data used to predict the outcome) should be a decision-making process based on the experience and knowledge of stakeholders around the target issue. Important considerations during this step should be how the data is collected (e.g., autonomous

vs. self-reported), the method of collection (e.g., digital devices vs. paper), the frequency of collection (e.g., annual vs. daily).

2. **Data preparation:** Similarly, data preparation is the step where part of the collected data is prepared (e.g., categorical data such as the injury is coded as 0 'not injured' or 1 'injured') to be put into computable formats.

3. **Feature selection and engineering:** During feature selection, the variable of interest are selected to train the model. This step can be performed during data collection or here if the database used to build a machine learning pipeline was not originally created for this purpose. Both the quantity and quality of features is important. The number of features should be determined based on the number of available outcome, as too many features could drown the model. However, apart from general "rules of thumb", there is no clear guidance on how many features are too many.

   Feature engineering is the construction of new features by using existing features, and domain knowledge can be used to construct features that facilitate the ability of the models to find patterns on the data (Zheng and Casari, 2018).

4. **Model training:** There are numerous machine learning models that are trained on labelled data and provide predictions for unlabelled data (Rajkomar et al., 2019). A model can be built as a unit (e.g., logistic regression, linear, decision trees, support vector machines, neural networks) or it can use ensemble methods, which means that multiple models contribute to the final prediction (Scott, 2021). The use of ensemble methods offers various possibilities. A model can be trained in series (i.e., boosting), where a single "weak" model is transformed into a strong model in an iterative process. Multiple models can also be trained in parallel (i.e., bagging), where the combination of multiple "weak" models contributes to the final prediction (i.e., "wisdom of the crowd"). Finally, ensemble methods can be used to train models on how best to combine the predictions of multiple powerful machine learning models (i.e., stacking), where an "additional" model is trained to learn from the results of the others. Even though some models perform better than others for certain tasks, such as image processing, there is no clear a priori guide for choosing the most suitable model. However, the choice should primarily depend on whether the

selected outcome is continuous or discrete (e.g., binary), which would require regression or classification algorithms.

Table 3: Different types of machine learning models, from (Scott, 2021).

Models	Description
Support vector machine (SVM)	Transforms input data into two or more classes or categories by choosing the boundary (line or plane or hyperplane) that separates them to the maximal degree, with the data points closest to the boundary being termed support vectors.
Naïve Bayes classifiers	Use Bayesian theory to categorise data and predict outcome probability as the product of probabilities of the features (or predictors), assuming these are independent from each other (hence the term naïve).
k-nearest neighbour	Partitions data along a decision boundary by identifying the number of features (k) sharing some common trait that are the nearest neighbours to a designated point within the feature space (e.g., if k = 3, 2 of 3 neighbours with commonalities will be sufficient to constitute a certain feature class).
Decision trees	Branching inverted tree-like structures comprising if-then decision points (nodes) connected by branches, with the leaves representing terminal output nodes. Tree is recursively constructed until all training examples in a subregion have been assigned the same class, or the minimum number of examples per subregion is reached.
Regression models	Linear and logistic regression models; polynomial regression for non-linear relationships; generalised linear models containing a generalisation that accommodates non-normally distributed variables.
k-means clustering	Identifies clusters or groups in the data with k equal to the number of groups formed based on similarity of traits while minimizing the distance between data points using distance formulas that yield k feature vectors called cluster centroids.
Principal component analysis	Identifies features most important for classification, thereby reducing a large set of features into a low-dimensional representation for incorporation into regression models or used for data visualisation or pre-processing.
Convolutional neural networks (CNNs)	Composed of many layers of nodes (up to 100) and used for classification (lesion present or absent); segmentation (specifying an area of interest); detection (predicting an area of interest). Each node has two or more inputs and an activation function which sums the inputs and uses a threshold (or weighting) and a bias value to produce an output of varying strength and direction, which then serves as the input data for the next layer of nodes. Convolution (or filtering) layer or matrix slides across the image and transforms collections of spatially separated pixels into features on an output feature map; the succeeding pooling layer reduces the dimensions and resolution of the data, but retains rich, important attributes; this new feature map then acts as input for the next convolutional layer, and so on; initial layers deal with basic image features (edges, shapes, lines); subsequent layers focus on abstract features (contrast, texture, colour).
Recurrent neural networks (RNNs)	Contain feedback loops between the nodes of each layer such that each node acquires memory of features (known as long-short-term memory) and can recall longer-term dependencies which may be non-linear.

Models	Description
Generative adversarial networks (GANs)	Comprise two competing networks: a generator of new examples and a discriminator assessing these examples for their authenticity. Generator tries to increase probability of the discriminator mistaking its inputs as real, while the discriminator keeps testing and forcing the generator to produce more authentic (i.e., accurate) images; hence the two networks simultaneously co-train and improve each others performance.

5. **Model validation:** Internal validation is the first test of a model's predictive performance using the same training data set. However, predicting with the exact same data that a model was trained with very often leads to overestimated results (i.e., overfitting). There are three well-described techniques for obtaining unbiased estimates of predictive performance during internal validation (Collins et al., 2024a).

   (a) Split sample validation: The data is divided (usually randomly) into two parts: one is used to develop the model, the other to evaluate the model's performance.

   (b) Cross-validation: The performance of the model is evaluated by splitting the data into k groups, using k-1 groups to develop a (preliminary) model (repeating the modelling steps used to develop the model for all data) and using the omitted group to evaluate the performance of the preliminary model. This process is repeated k times, omitting a different group each time, resulting in k values for each performance measure. The performance of the developed model is then taken as the average (or median) across the k performance measures.

   (c) Bootstrapp: Bootstrapping is a resampling technique, in which a bootstrap sample is created by randomly sampling (with replacement) from the original data. In extended bootstrap, a model is developed in each bootstrap sample (repeating the steps to develop the model for all data) and its performance is evaluated in that sample as well as in the original dataset to obtain an estimate of the optimism of the model performance. This process is repeated many times and the average optimism is calculated, which is then subtracted from the apparent performance.

   In a second step, the estimation of model performance using a different data sample than the one used to develop the model is called 'external validation'. The data may come from the same (or similar) population or environment as that used for model develop-

ment (reproducibility assessment) or from a different population or setting (assessing transportability). Another type of validation involves researchers assessing the performance of the model in multiple populations and settings, each relevant to the intended use (assessing generalisability) (Collins et al., 2024a).

To objectively evaluate how a predictive model has fulfilled its classification or regression tasks, regardless of whether it is an internal or external validation, various performance metrics are available, which are presented in Table 4.

6. **Deployment and post-deployment:** The model is undergo prospective validation using dynamic live (or near-live) data in a form that reflects future use in the real world, integrated into a prototype application and evaluated for its feasibility in clinical workflows (Strating et al., 2023). Then, its clinical utility is assessed in clinical trials comparing the application-led patient care and outcomes with the current standard of care (Strating et al., 2023).

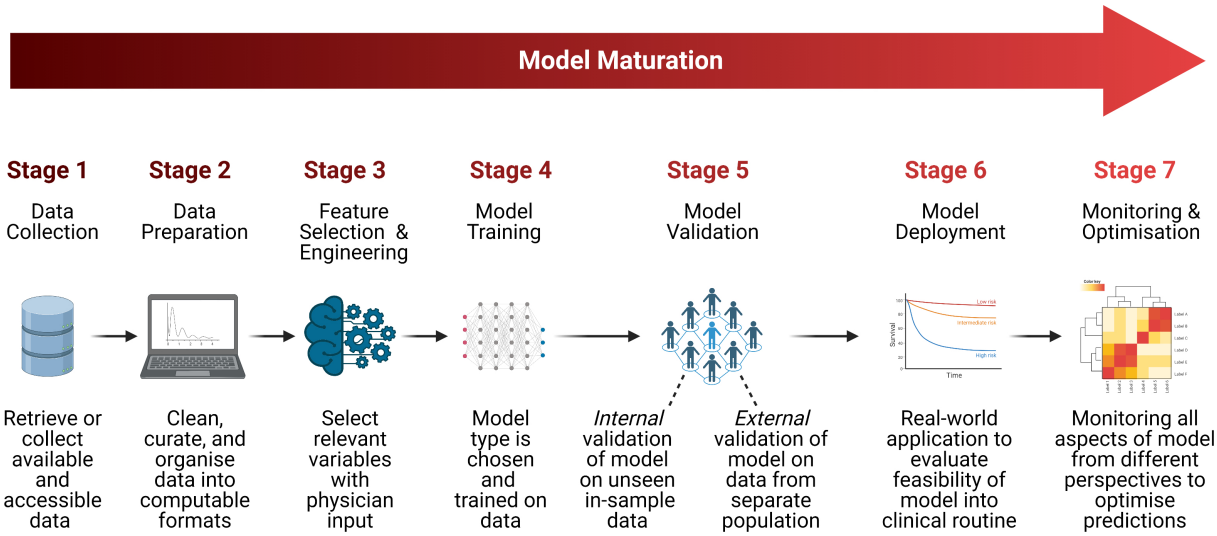
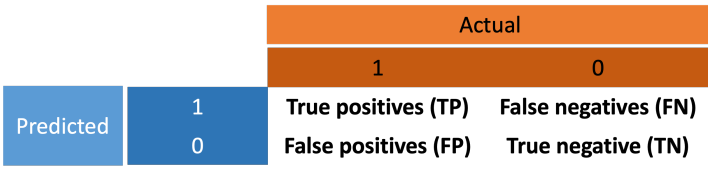


Figure 16: An example of a machine learning pipeline in healthcare, from (Strating et al., 2023).

Table 4: Different types of performance measures (i.e. metrics), from (Scott, 2021).

Metrics	**Indicative values of performance**
Confusion matrix *(classification)*  An N X N matrix, where N is the number of classifications (2 or more) being predicted, and which yields the following metrics: • **Accuracy:** the proportion of the total number of predictions that are correct (Equation (5)). $$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (5)$$ • **Positive Predictive Value (PPV) or Precision:** the proportion of positive predictions that are true positives (Equation (6)). $$\text{Precision} = \frac{TP}{TP+FP} \quad (6)$$ • **Sensitivity or Recall:** the proportion of all positive examples which are correctly identified as positive (Equation (7)). $$\text{Recall} = \frac{TP}{TP+FN} \quad (7)$$ • **Specificity:** the proportion of all negative examples which are correctly identified as positive (Equation (8)). $$\text{Specificity} = \frac{TN}{FP+TN} \quad (8)$$ • **F1 score:** harmonic (or weighted) average of precision and recall, reflecting how well the model maximises both precision and recall (Equation (9)). $$\text{F1} = \frac{2*TP}{2*TP+FP+FN} \quad (9)$$ Accuracy, PPV and NPV are prevalence-dependent metrics which means that they vary in value according to the frequency of the disease or event of interest whereas AUROC (see below), sensitivity and specificity are prevalence-independent.	Values ranging between 0 or 1 as performance improves.

Metrics	Indicative values of performance
Area under (AU) Receiver Operating Characteristic (ROC) Curve *(classification)* For binary outcomes, the ROC curve plots the true positive rate (sensitivity or precision) against the false positive rate (1-specificity) for a series of different prediction thresholds used to separate the two outcomes.	AUROC of 0.5 means the model predicts no better than chance
Precision-Recall (PR) Curve *(classification)* The PR curve plots precision against recall to show the trade-off between them for different feature or parameter settings. For classification tasks involving datasets with very few positive cases, the area under the PR curve (AUPRC) could be a better measure of accuracy than AUROC.	Value of 0.5 is preferred
Mean absolute error (MAE) *(regression)* Mean of the absolute differences (or residuals) between actual and predicted values, which can be either positive (predicted > actual; overprediction) or negative (predicted < actual; under-prediction) (Equation (10)). $$\text{MAE} = (\frac{1}{n}) * \sum_{i=1}^{n} \lvert x_i - y_i \rvert \quad (10)$$ $\sum$: Symbol representing the sum, x_i: The observed value for the ith observation, y_i: The predicted value for the ith observation, n: The total number of observations.	Values close to zero indicate better performance
Mean squared error (MSE) *(regression)* Calculated by summing the differences between actual and predicted values, squaring the results, and dividing by the total number of examples, thus producing sign-less measures of overall deviation from the mean, irrespective of their direction (Equation (11)). $$\text{MAE} = (\frac{1}{n}) * \sum_{i=1}^{n} \lvert x_i - y_i \rvert^2 \quad (11)$$ $\sum$: Symbol representing the sum, y_i: The observed value for the ith observation, x_i: The actual value for the ith observation, n: The total number of observations.	Values close to zero are preferred
Root mean squared error (RMSE) *(regression)* Represents the standard deviation of all errors and measures how well predicted outcomes are concentrated around the regression line, assuming errors are unbiased and normally distributed with very few outliers (Equation (12)). $$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n} \lvert x_i - y_i \rvert^2}{n}} \quad (12)$$ $\sum$: Symbol representing the sum, y_i: The observed value for the ith observation, x_i: The actual value for the ith observation, n: The total number of observations.	Values close to zero are preferred.
Coefficient of determination (R^2) *(regression)* Measure of how much the variation in the output variable (or Y dependent variable) is explained by variation in input variables (X independent variables).	Values >0.6 are preferred.

Metrics	Indicative values of performance
Calibration tests *(classification and regression)* Calibration refers to the assessment of whether observed and predicted values agree (Van Calster et al., 2016). For example, if the average predicted risk is higher than the total event rate, the algorithm generally overestimates the risk. Conversely, an underestimation occurs if the observed event rate is higher than the average predicted risk Van Calster et al. (2019).	The perfect calibration is represented by a diagonal regression line.

2.2.3 Sports injuries & machine learning

In sports medicine, predicting (Van Eetvelde et al., 2021) or forecasting (Rossi et al., 2018) the injury (there is no clear distinction between the two in the literature) was performed using machine learning since 2010s in majority in team sports (Claudino et al., 2019). In this thesis, the terms predicting or forecasting refers to a set of criteria used to estimate the probability of a specific outcome e.g., the injury to occur (Porta, 2014). In 2021, a recent systematic review conducted by Van Eetvelde al. (Van Eetvelde et al., 2021) included 11 studies in the aim to described methods using machine learning in sports injury prediction and prevention. Authors raised that the three main machine learning model used were tree-based ensemble methods (n = 9), Support Vector Machines (n = 4) and Artificial Neural Networks (n = 2)) with an injury predictive performance ranged from poor (Accuracy = 0.52, AUC = 0.52) to strong (AUC = 0.87, f1-score = 0.85).

Machine learning models have the potential to act as an automated data analysis that can provide insight into the athletes condition. Therefore, machine learning models could support the clinical decision-making process for sports scientists, physicians and coaches when the data collected from various sources (e.g., wearable sensors and even questionnaires from smartphones) are transformed into accurate decisions about athletes' health, safety and performance. Indeed, machine learning methods could be used to identify athletes at higher risk of injury and recognise the key risk factors (Van Eetvelde et al., 2021). However, a recent systematic review of the methodology and performance of existing models for the prediction of musculoskeletal injuries in sports found that 98% of these models have a high risk of bias (Bullock et al., 2022b). This result is due to a flawed assessment process and lack of transparency in the reporting of the models, including incomplete descriptions of the equations and code (Bullock et al., 2022a). This flawed methodology can lead to limited generalisability of the results. In addition, current

systematic reviews on injury prediction had some limitations. They did not specifically target sports injuries by also including sports performance outcomes (Claudino et al., 2019). They did not use the latest recommendation guidelines (Wolff et al., 2019) to assess the risk of bias (Van Eetvelde et al., 2021). Or they did not specifically target machine learning methods and included also statistical modelling approaches without validation process of the models (Bullock et al., 2022b). Therefore, an update of the evidence would be helpful for researchers, practitioners and stakeholders to better align their methods, data collection strategies, model selection, correct interpretation of such results and intervention plans to effectively assess and address sports injury prediction using machine learning.

As shown in the Paragraph 2.1.3.3.2, the use of digital health could be an opportunity for injury prevention measures. This opportunity may include machine learning approaches and, in particular, injury prediction as an injury prevention measure.

2.2.4 Summary

CONTEXT OF ARTIFICIAL INTELLIGENCE

- Machine learning is a subfield of artificial intelligence that use a machine i.e., computer to observes data, creates a model based on this data and then uses this model both as a hypothesis about the world and as software to solve problems.
- The use of intelligence in a computer involves the construction of an algorithm that uses a learning database of input features, i.e., predictors, to solve a learning problem with an output, i.e., labelled data, through various learning problems, e.g., classification or regression.
- The use of supervised machine learning in medicine is a response to the growing amount of information available and the limited ability of the human brain to process this information in a short time.
- Machine learning is used in medicine from data collection to model deployment involving an important number of possibilities in terms of type of machine learning models and performance measures available.
- The use of machine learning in sports medicine for predicting and preventing injuries is based on the potential of machine learning models to automate data analysis and provide insights into athletes' conditions, supporting clinical decision-making for sports scientists, physicians, and coaches.
- Recent systematic review found that the majority of existing models for predicting musculoskeletal injuries in sports have a high risk of bias due to flawed assessment processes and lack of transparency in reporting.
- The recent systematic reviews also showed some methodological limitations that could be improved based on new published guidelines and a more precise focus on injury prediction by machine learning models.
- Finally, there is the possibility of using a predictive modelling approach through machine learning models to develop injury prevention measures.

2.3 Injuries in athletics (track and field)

2.3.1 Specific context of athletics

Athletics (Track and Field) is an Olympic sports that is practised all over the world. It is governed at the international level by World Athletics, to which a total of 214 countries or territories worldwide belong. This makes athletics an intercultural sports involving athletes of different genders, ages, ethnicities and socio-economic environments. Athletics consists of several different disciplines, including sprinting, hurdling, jumping, throwing, combined events, middle and long-distance running and race walking, and other disciplines (e.g., cross country, mountain, ultra, and trail running) that are not part of the Olympic Games and will not be covered in this report. Athletes, at any level, usually train throughout the season and their career to perform at their best, compete at the highest level and try to win medals. Like any physical and sporting activity, athletics has positive effects on health (Oja et al., 2015).

However, in the quest for optimal performance, athletes can be affected by injuries (Edouard et al., 2011), with potential physical, psychological and social consequences (Edouard et al., 2024f,g; Huxley et al., 2013; Palmer et al., 2020). Injuries can therefore be an important aspect of an athletes life and for all stakeholders involved in athletics (e.g., coaches, health professionals, administrative leaders).

2.3.2 Injury meaning in athletics

The term injury is used when referring to the damage and/or dysfunction and/or impairment of a system. In the present context of athletics, we usually refer to damage/dysfunction/impairment of the musculoskeletal system (i.e., muscles, tendons, bones, cartilage, ligaments and soft tissues). If the stress and strain resulting from Athletic practice exceeds the capabilities of the musculoskeletal system, there is a risk of musculoskeletal structure failure leading to injury (Edouard et al., 2023e; Hoenig et al., 2022; Millar et al., 2021).

Although the focus is on the musculoskeletal system, injury is a broad term that can encompass multiple concepts. In 2014, Timpka and colleagues proposed definitions of sports impairment concepts based on the term impairment used by the WHO. This resulted in different terms depending on the tissue involvement, the athlete's self-report or the consequences

(Timpka et al., 2014), and they analysed their occurrence in scientific publications (Timpka et al., 2015b). Bolling and colleagues (Bolling et al., 2018a) reported that the definition of sports injury was a fluid phenomenon and a context-dependent concept, and the main constructs used to define a sports injury as perceived by elite athletes, coaches and physiotherapists were: pain (Ahmed et al., 2015), performance level (Alonso et al., 2009) and availability to participate in sports (Askling et al., 2014). Bahr and colleagues (Bahr et al., 2020) reported that sports injuries can be defined as an event that leads to medical attention (i.e., an injury problem that results in an athlete receiving medical attention), time-loss (i.e., an injury problem that results in an athlete being unable to complete the current or future training session or competition), or it could be any type of complaint (i.e., a broader definition including all injury problem self-reported, symptom-based or performance-based whatever they lead to medical attention and/or time-loss). The most recent consensus statement on injury and illness definitions and data collection procedures for use in epidemiological studies in athletics defined an athletics injury as: A physical complaint or observable damage to body tissue produced by the transfer of energy experienced or sustained by an athlete during participation in athletics training or competition, regardless of whether it received medical attention or its consequences with respect to impairments in connection with competition or training (Timpka et al., 2014). This consensus indicates that the sub-definitions of medical attention, time-loss, or any complaint could also be used (Bahr et al., 2020). This variety of interpretations of the term injury shows how complex the definition of injury is. This emphasises the need for a clearer definition of this term when stakeholders from the field of athletics interact for clinical, administrative and/or research purposes.

2.3.3 Injury surveillance in athletics

Given the influence of the methodology of data collection on the quality of the data and thus the resulting information, greater attention should be paid to the methodology of epidemiological studies to be able to interpret and compare their results appropriately. The study design, the definition of the injury considered in the study and its characteristics, the exposure, the data collection procedures and the data analyses are key points of the methodology of epidemiological studies (Bahr et al., 2020; Timpka et al., 2014). In addition to the complex definition of

injuries, the sports of athletics contributes to specific challenges for injury data collection (e.g., individual sports, training structure, health-related culture, medical organisation) that should be considered when planning an injury data collection or an epidemiological study (Edouard et al., 2014a).

The definition of injury as medical attention and data collection by health professionals was used in athletics championships (Alonso et al., 2009; Junge et al., 2008). This methodological approach was associated with good participation of national medical teams (about 80% of registered medical teams participated), good coverage of athletes (about 80% of registered athletes), good response rate (89% on average), good completeness of reports (96% on average) (Edouard et al., 2016b) and the generation of reliable information (Edouard et al., 2018). Different methods were used to collect injury data throughout an athletics season (i.e., retrospective or prospective, self-report by athletes or health professionals diagnosis), making direct comparison between studies difficult (Edouard et al., 2016a). Therefore, the choice of methods may depend on the context (e.g., level, geographical), the population (e.g., gender, age, performance level) and the definition of the injury (e.g., time loss, medical attention).

2.3.4 The extent of the injury problem in athletics

2.3.4.1 During championships

During international athletics championships, the combination of data from several championships provides a clearer view of the injury problem (Edouard et al., 2015a, 2019a; Feddermann-Demont et al., 2014). In this context, significantly higher injury risk (+25%) in male than female athletes (110.3±6.8 vs. 88.5±6.7 injuries per 1000 registered athletes) have been reported (Edouard et al., 2015a). In addition, there was a significant variation in injury rates and characteristics between disciplines: thigh muscle injuries were the main injury diagnoses in sprints, hurdles, jumps, combined events and race walking, lower leg muscle injuries in marathons, lower leg skin injuries in middle and long distances, and trunk muscle and lower leg muscle injuries in throws (Edouard et al., 2019a). The most frequent injury was the hamstring muscle injury (about 17% of all injuries), with a higher proportion in disciplines that require sprint running (e.g., in sprints hamstring injuries represented 35% and 24% of all injuries in male and female athletes, respectively (Edouard et al., 2016a, 2021a). About 30% of athletes reported an

injury complaint within the four-week preparation period before the championships (Edouard et al., 2022d).

During the French national indoor and outdoor championships from 2014 to 2017, there were 53 injuries per 1000 registered athletes, with rates being fairly similar at each championship (Edouard and Depiesse, 2024). The thigh was the most common injury location (about 30% of all injuries) and the muscle was the first injury type (about 30% of all injuries) (Edouard and Depiesse, 2024). During three years of the Penn Relays Carnival, corresponding to the oldest and largest track and field competition in the United States, there were 9 injuries per 1000 registered athletes (Opar et al., 2015), with hamstring muscle strains accounting for 24% of injuries (Opar et al., 2013). In the 2016 Olympic athletics competitions, there were 60 injuries per 1000 registered athletes, with hamstring strains accounting for 17% of injuries (Bigouette et al., 2018).

2.3.4.2 During seasons

The athletics season represents a longer period in the lives of athletes during which they participate in athletics and are therefore exposed to a greater risk of injury than championships. Although the methods (i.e., study design, injury definition, data collection) are not the same as those of the studies in which data were collected throughout the athletics season, there appear to be some consistencies and similarities in the prevalence, incidence and characteristics of injuries (Edouard, 2021a). In general, about two-thirds of athletes had at least one injury during the entire athletics season (Bennell and Crossley, 1996; Carragher et al., 2019; D'Souza, 1994; Edouard et al., 2022c; Jacobsson et al., 2013; Martínez-Silván et al., 2020). The incidence was reported as 3.6-3.9 injuries per 1000 hours of track and field practice (Bennell and Crossley, 1996; D'Souza, 1994; Jacobsson et al., 2013). In the National Collegiate Athletic Association (NCAA), an overall injury rate of 2-4 injuries per 1000 athletic exposures was reported between 2010 and 2019 (Boltz et al., 2021; Hopkins et al., 2022). The location of injuries varied according to the disciplines, and are presented in Figure 17 (Edouard et al., 2024d). The injury mode of onset was more sudden in explosive disciplines (e.g., sprints, jumps) and more gradual in endurance disciplines (e.g., middle- and long-distance, marathon) Figure 17 (Edouard et al., 2024d). The hamstring muscle injury was also frequently reported as the first injury during the whole season (Edouard et al., 2016a, 2023a, 2022e; Iatropoulos and Wheeler, 2023; Kelly et al.,

2022; Pollock et al., 2015, 2021).

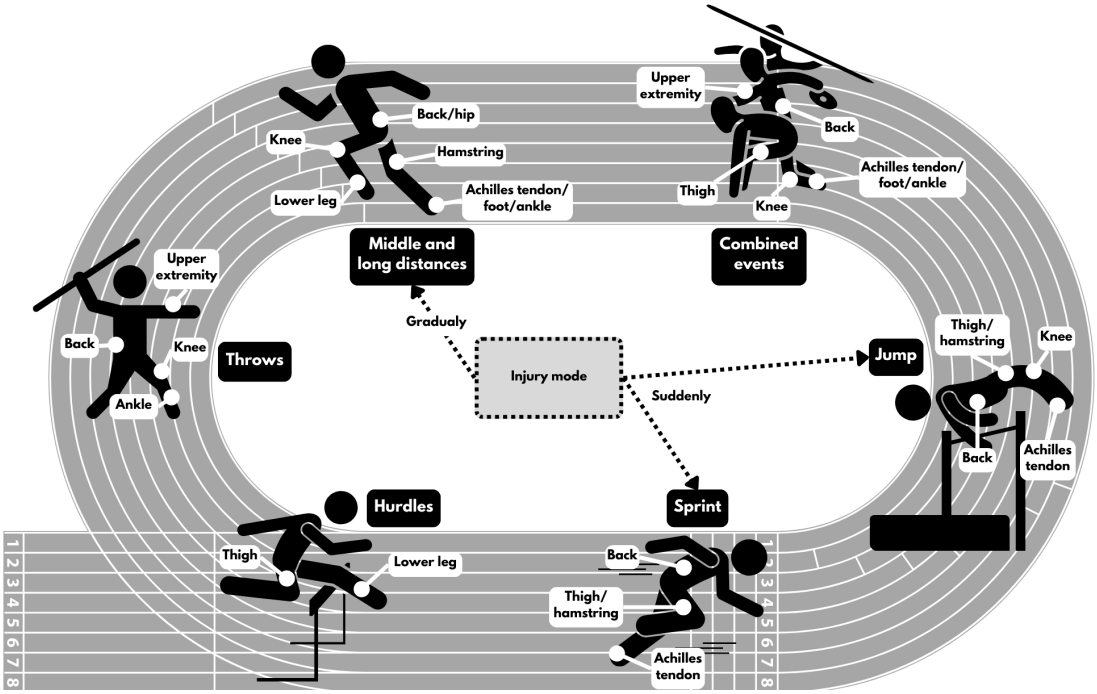


Figure 17: Illustration of the distribution of injury locations by disciplines in athletics (track and field), from (Edouard et al., 2024d).

2.3.5 The consequences of injuries in athletics

2.3.5.1 Performance-related consequences

Having no injury or illness seems to be especially important among the variables that can influence the athlete's performance (Drew et al., 2017). In athletics, many articles reported the negative effect of injuries on performance (e.g., during the context of championships, in the preparation of championships) (Chapon et al., 2022; Edouard et al., 2021b, 2019b; Raysmith and Drew, 2016).

2.3.5.2 Physical-related consequences

In general, damage to the musculoskeletal system can lead to pain and impairment of the musculoskeletal system, which can result in functional disorders, restricted movement and/or stability. This has negative consequences for daily life, physical activity (limitation of movement) due to pain and dysfunctionality (limitation of function) depending on the location, type and severity of the injury (Edouard et al., 2023e). Injuries can also lead to long-term sequelae depending on the initial damage and/or management, which can have long-term consequences for athletes

and are associated with an increased risk of subsequent injuries (Edouard et al., 2024f; Pollock et al., 2015).

2.3.5.3 Psychological-related consequences

In sports in general, it has been reported that sports injuries can lead to psychological consequences (Wiese-Bjornstal, 2010), and in athletics, athletes who experienced an injury reported negative emotions (Edouard et al., 2024g). Six typologies of injury narratives were identified specifically for elite athletes (Everard et al., 2021), providing insight into individual differences in the way an injury is experienced from a psychological perspective. The psychological consequences should be identified by physicians and treated in the same way as the physical consequences so that there are no relevant psychological sequelae that result in future performance limitations.

2.3.5.4 Career-related consequences

Injuries can lead to an interruption of the sports, but also to an interruption of the sports career due to a very severe injury, a repetition of injuries or the sequelae of an injury(s). This changes the sustainable practice of athletics (Edouard et al., 2024f; Palmer et al., 2020) and is likely to hurt the individuals athletic and social identity.

2.3.6 Factors that increase injury risk in athletics

Information on injury risk factors is of great interest when it comes to screen/detect athletes at potential risk of sustaining a new or recurrent injury and can also help develop injury prevention strategies. Current knowledge of injury risk factors in athletics is shown in Table 5. Although some factors are associated with higher injury rates (Table 5), our knowledge of injury risk factors in athletics remains limited, highlighting the need to continue to conduct studies that analyse potential risk factors for injury in athletics. Furthermore, a qualitative study reported that injuries in adolescent athletes are not exclusively due to single factors, but rather are the result of interactions between factors at different levels, including most notably: insufficient knowledge of athletic development in daily practice; short-sighted communities of practice and sports policies not adapted to youth, and societal health behaviours (Jacobsson et al., 2017).

Table 5: Injury risk factors in athletics (Edouard et al., 2024d)

	DURING THE ENTIRE ATHLETICS SEASON	DURING INTERNATIONAL ATHLETICS CHAMPIONSHIPS
Intrinsic non-modifiable risk factors	• **Previous injury:** a previous injury seems to be a risk factor for another injury (Edouard et al., 2023g; Jacobsson et al., 2013; Rebella et al., 2008; Rebella, 2015) • **Sex:** the influence of sex remains unclear, higher risk in male (Bennell and Crossley, 1996; D'Souza, 1994; Jacobsson et al., 2013) or in female athletes (Requa and Garrick, 1981; Watson and D, 1987) according to studies • **Age:** lower prevalence of injuries among juniors (<20 years) and higher among older athletes (Bennell and Crossley, 1996; D'Souza, 1994) • **Lifetime sexual and physical abuse** (Timpka et al., 2018) • **A history of illness within the season:** it was associated with a lower injury risk (Edouard et al., 2023g) • **Biomechanical pole vault patterns:** it was associated with a higher injury risk (Edouard et al., 2019c)	• **Injury before a championship:** an injury complaint in the 4 weeks before the championship is a risk factor for a new injury during the championship (Edouard et al., 2022d) • **Sex:** male athletes had higher injury rates than females (Edouard et al., 2015a) • **Age:** higher injury rates are reported in athletes over 30 years (Edouard et al., 2014c)
Intrinsic modifiable risk factors	• **Fitness status/fatigue:** a higher fitness subjective state at any time was associated with a lower injury risk (Edouard et al., 2023g) • **Performance level:** the influence of the performance level remains unclear, the injury incidence increased with increased level (Watson and D, 1987), or decreased with increased level (D'Souza, 1994), or no influence (Bennell and Crossley, 1996) • **Maladaptive coping practice of self-blame** was found to be associated with increased risk of overuse injuries (Timpka et al., 2015a)	
Extrinsic risk factors	• **Coach:** fewer injuries in athletes who trained with a coach compared to athletes training alone (D'Souza, 1994) • **Training load:** higher training load, calculated as volume x intensity, lead to higher injury rates in one study (Jacobsson et al., 2013) • **Spikes in training** (Ek et al., 2022)	• **Discipline type:** injury rates varied according to disciplines with higher injury rates in combined events, marathon, middle and long-distances (Edouard et al., 2019a) • **Training volume:** higher training volumes before championships were associated with higher injury rates during championships (based on a pilot study of 74 athletes) (Edouard et al., 2015b) • **Participation in finals** (Edouard et al., 2024e; Tsukahara et al., 2024) • **External temperature** (Tokutake and Kuramochi, 2020)

2.3.7 Reducing the injury problem in athletics

Given the extent and consequences of the injury, it is therefore logical to try to minimise the risk of injury. Athletics-related stakeholders share this overall goal and provide fertile ground for implementing injury prevention strategies (Edouard et al., 2023c, 2022f).

2.3.7.1 Neuromuscular exercises and injury risk reduction

To our knowledge, there is currently only one randomised controlled trial in athletics-related Olympic disciplines that has investigated the efficacy of a neuromuscular exercise programme to reduce the risk of injury. After a follow-up period of 39 weeks, no significant differences were

found between the control and intervention groups in terms of prevalence, burden, incidence and time to first injury (Edouard et al., 2021c). However, compliance with the programme was low (Edouard et al., 2021c) and/or there were potential confounding factors (Edouard et al., 2020). Based on the present results, it is not possible to promote the use of the programme and further efforts should be made to improve the programme itself and the implementation and adoption of interventions in general.

In the field of endurance running, which includes athletes participating in non-Olympic athletics disciplines, a recent systematic review and meta-analysis reported that exercise-based interventions do not appear to reduce the risk and rate of running-related injuries and emphasised the importance of exercise supervision to increase compliance (Wu et al., 2024).

Overall, there is little research on the development and analysis of the efficacy of injury risk reduction programmes through neuromuscular exercises, and that an existing programme is effective enough to reduce injury risk (Hübscher et al., 2010; Iatropoulos et al., 2024).

2.3.7.2 Education and injury risk reduction

Educating athletes, their entourage, and all stakeholders within athletics is widely seen as an approach to reducing the risk of injury (Bolling et al., 2019; Bonell Monsonís et al., 2021; Edouard et al., 2022a). In addition, adequate health literacy would be relevant for promoting healthy athletics activity. Health literacy corresponds to the degree to which individuals can obtain, process and understand the basic health information and services they need to make appropriate health decisions (Nutbeam, 1998). More specifically, health literacy could be defined as the ability of citizens to make informed health-related decisions in their daily lives at home, at work, in healthcare, in the marketplace and in politics (Sørensen et al., 2015).

Appropriate health literacy is not only important for athletes, as it aims to promote healthy athletics activity, but also for all those involved in their environment (i.e., coaches, health professionals and administrative leaders). The level of health literacy in relation to musculoskeletal health was found to be inadequate among world-leading track and field athletics athletes (Timpka et al., 2023) and mentors and school-aged children participating in athletics in Sweden (Jacobsson et al., 2021). A qualitative study of young Swedish athletes found that they were typically uncertain about how to acknowledge a sports-related injury and that they gained their knowledge of injuries partly by reflecting on the experiences of their peers (Jacobsson et al.,

2023). In terms of specific medical issues relating to female athletes, male coaches were less aware and less able to manage these, suggesting that coaches need to be better educated about these aspects (Tsukahara et al., 2023). So there is potential for improvement. For example, Jacobsson and colleagues (Jacobsson et al., 2022) reported on the effectiveness of a digital health platform with sports-specific training and health information (Jacobsson et al., 2020) in reducing injury risk in a cluster-randomised controlled trial with young athletes.

Another way to educate the athletics community is through social media, as a large majority of athletes and coaches are present on platforms such as Instagram and X (formerly Twitter), which are seen as a normal part of our society and lives (Ahmed et al., 2015). It is suggested that sports clinicians embrace social media as it can be used to effectively implement health interventions and even change public health policy through education. In the digital age, a lot of information about sports and health is circulating on social media. However, Marocolo et al. (Marocolo et al., 2021) concluded that prominent Brazilian Instagram influencers disseminate low-quality information about exercise and health, contributing to the widespread dissemination of misinformation to millions of followers. The inadequate knowledge of musculoskeletal health among world-leading Athletic athletes combined with low-quality information on social media should prompt us to develop an injury reduction strategy through education by dissemination of robust knowledge through various media such as social media.

2.3.7.3 Other injury risk reduction approaches

Other approaches to reducing the risk of injury may be relevant, although their efficacy has not yet been evaluated using the scientific method (Edouard, 2021b). These approaches may relate to athletes biomechanics, lifestyle, psychology (Gledhill et al., 2018), medical organisations (Dijkstra et al., 2014; Jacobsson et al., 2023), and federal policy (Dahlström et al., 2014; Timpka et al., 2021), or can consider an ecological (holistic-development-orientated) approach (Jacobsson et al., 2017).

2.3.7.4 Adherence and injury risk reduction approaches

Although injury risk reduction seems reasonable and relevant, and even if injury risk reduction represents a shared goal by the athletics-related stakeholders (Edouard et al., 2023c, 2022f) injury risk reduction approaches are seldom adopted. For example, a randomised controlled trial

reported that only 9% of athletes undertook the exercise-based injury risk reduction programme asked for in this study (Edouard et al., 2021c). One study also pointed out that <30% of the 7715 athletes self-reported that they had partially or fully adopted any exercise-based injury risk reduction programme during their lifetime (Ruffault et al., 2021). A better understanding of perceptions and beliefs related to injury risk reduction and the factors associated with adherence or nonadherence to injury prevention strategies may be one way to improve the adoption of injury risk reduction approaches (Donaldson et al., 2016; Edouard et al., 2022b). The athletes who had sustained more injuries and competed at a higher level were more likely to adopt an exercise-based injury risk reduction programme and scored higher on the socio-cognitive determinants (Ruffault et al., 2021). Another opportunity could be to take advantage of the fact that most athletes have suffered injuries in the past (Bolling et al., 2019; Bonell Monsonís et al., 2021; Edouard et al., 2022a). An online survey of 7,870 athletes found that athletes who had suffered at least one injury in their lifetime were more likely to adhere to injury prevention strategies than athletes who had never experienced an injury (Edouard et al., 2024g). In addition, individualisation of the injury risk reduction approach and its implementation could help to improve adherence to injury risk reduction approaches (Edouard et al., 2022b).

Another challenge for the development and implementation of effective prevention programmes within a sports can be that it is not always clear in which context they should be applied (Jacobsson and Timpka, 2015). Programmes can be classified either clinically on the basis of pathology or epidemiologically on the basis of identified risk factors. For example, a clinically based programme may be an effective hamstring rehabilitation program (Askling et al., 2014) and an epidemiologically based one a neuromuscular or educational programme (Edouard et al., 2021c; Jacobsson et al., 2022), these different programmes have different implementation contexts.

Assuming that it is probably impossible to eradicate sports injuries, Guex and Edouard (Edouard et al., 2023f; Guex et al., 2023) propose a more positive view of injuries. They suggest looking at what reducing the risk of injury can do for athletic performance (Edouard et al., 2023f; Guex et al., 2023). Specifically, these authors call for a more resilient and salutogenic approach that could help to better accept life with this risk of injury (Edouard et al., 2023f; Guex et al., 2023).

2.3.7.5 Exploring new injury prevention measures

As whown in Section 2.1, a paradigm shift in the study of sports injury causality was made during the last decade, from monocausality to multifactorialism, recognising the complexity of a system of factors that interact with each other and have an integrative and recurrent influence on injury risk. Thus, there is a need to developed injury prevention strategies that consider the complex nature of injuries. In this way, injury prevention strategies in athletics has benefits from the opportunity of using digital technology as shown by recent studies in running (Hespanhol et al., 2017; Fokkema et al., 2019; Jacobsson et al., 2022). The injury prevention strategy could also benefit from artificial intelligence, which is now considered part of digital health (Section 2.2.3). There is therefore an opportunity to address the complex nature of injuries in athletics with an extension of the existing injury prevention strategy through the use of injury prediction using machine learning techniques.

2.3.8 Summary

CONTEXT OF ATHLETICS

- In the quest for optimal performance, athletes can be affected by injuries in athletics.
- The choice of injury surveillance methods in athletics may depend on the context (e.g., level, geographical), the population (e.g., gender, age, performance level) and the definition of the injury (e.g., time loss, medical attention).
- Information on injury risk factors is of great interest when it comes to recognising athletes with a potential risk of a new or recurring injury and can also help in the development of injury prevention strategies.
- Various strategies have been used to reduce the risk of injury in athletics, such as neuromuscular exercises and but there are still very few studies investigating the efficacy of measures to reduce the risk of injury in athletics.
- Injury risk reduction approaches are seldom adopted, therefore maximising adherence to injury risk reduction approach is important and could be achieved by the individualisation of the injury risk reduction approach and its implementation, clarification about the context in which they should be applied.
- There is a need to further develop and evaluate injury prevention measures in athletics, utilising the opportunities offered by new digital health technologies such as machine learning to address the complexity of injuries.

Chapter 3

PROBLEMATIC AND OBJECTIVES

3.1 Rational flow

Based on the state-of-the-art (Chapter 2), we showed that:

- In the 21st century, physical activity has become a central theme in public health.
- The flip side of physical activity is that it can lead to health problems, such as injuries.
- Injury is of complex and multifactorial nature, which is recognised as a complex system with multiple factors that interact with each other and influence the risk of injury integratively and recursively.
- Injuries can have short-, mid- and long-term consequences at any age and any level of practice.
- To minimise injury-related effects and consequences, injury prevention strategies are needed.
- Injury prevention strategies should be improved mainly due to the challenges of developing, implementing and analysing interventions and better addressing the complexity and multifactorial nature of injuries.
- To address the challenges of injury prevention, the area of knowledge and practice related to the development and use of digital technologies to improve health (i.e., digital health) represents an opportunity.
- The need to efficiently process a large amount of information about athletes, which corresponds to the paradigm of complex systems, has allowed artificial intelligence and machine learning in particular to find its way into sports medicine.
- As a prognostic modelling approach, machine learning methods could be used to identify athletes at higher risk of injury and recognise the key risk factors by providing athlete with health status feedback.
- In sports medicine, studies investigating the use of online technologies as an injury risk reduction measured through health status feedback or tailored advices is limited and with mixed results.
- Therefore, the exploration of the role of artificial intelligence as an injury prevention strategy to enhance injury prediction and prevention is needed.
- Injuries are a widespread problem in athletics, significantly affecting both performance

and health. With two thirds of athletes suffering at least one injury per season, the risk of injury has become an integral part of athletic life.

- This omnipresent risk emphasises the need for a structured model that focuses on developing and testing injury prevention strategies to gain insights that can lead to better injury prevention practices in athletics.

3.2 Objectives

This rational flow conducted to the overall goal of this PhD work that was to explore the use of artificial intelligence and in particular machine learning in sports injury prevention, and specifically in athletics (track and field). In order to reply to this general problematic, we divided this PhD work into three objectives:

OBJECTIVE 1

To describe the current machine learning approaches used to develop prediction models for sports injuries (Section 4.1).

OBJECTIVE 2

To develop and assess the effectiveness of an injury prevention strategy using prediction models developed using machine learning in order to reduce the occurrence of sports injuries in the specific context of athletics (Sections 4.2 and 4.3).

OBJECTIVE 3

To explore perceptions and beliefs of elite athletics (track and field) athletes, coaches, and health professionals, towards the use of injury prediction as an injury prevention strategy (Section 4.4).

Chapter 4

PERSONAL CONTRIBUTIONS

Following the state of the art (Chapter 1) and the three objectives presented in the Chapter 3, this chapter 4 presents our personal contributions to reflect to the PhD problematic about the use of the use of artificial intelligence and in particular machine learning in the context of sports injury prevention and specifically in athletics (track and field). This chapter is organised into 4 parts:

- Section 4.1 is linked to the first objective (Section 3.2)
- Sections 4.2 and 4.3 are linked to the second objective (Section 3.2)
- Section 4.4 is linked to the third objective (Section 3.2)

For each part, the scientific articles published in a peer-reviewed journal (labelled 'PUBLISHED') or in a peer-review process (labelled 'DRAFT') are presented with their main findings.

4.1 Sports injury prediction & machine learning techniques

4.1.1 Context

- Based on the Section 2.2.2, sports injury prediction consists of developing a model able to predict sports injury outcome (i.e., injury, or no injury, or probability of injury).
- Machine learning is an artificial intelligence approach which allows to develop these prediction model.
- Different model using machine learning methods were developed to predict sports injuries (Section 2.2.3).
- Model development and machine learning pipeline involved different important stages like data collection, data preparation and model training and evaluation (Section 2.2.2).
- However, these steps lack clarity and transparency in their report of an injury prognosis (Section 2.2.2).
- Furthermore, the systematic evaluation of injury prognosis is dependent to the definition of machine learning used and recent published guidelines (Section 2.2.2).
- Thus, to describe the current machine learning approaches used to develop prediction models for sports injuries would be of help for researchers, practitioners, and stakeholders to better align their methodologies, data collection strategies, model selection, correctly interpreting such results, and intervention plans, to effectively estimate and address sports injury risks.

OBJECTIVE 1

In this context, our objective was to describe the current machine learning techniques used to develop prediction models for sports injuries.

Scoping Review

Predicting sports injuries using machine learning techniques: a scoping review

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ETHICAL APPROVAL

Not applicable

AUTHOR'S CONTRIBUTIONS

All authors conceived the study idea and were involved in design and planning. PED and JT performed the data extraction and analysis. JT, PED and PE wrote the first draft of the manuscript. Al authors critically revised the manuscript, and approved the final version of the manuscript.

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COMPETING INTERESTS STATEMENT

The authors declare having no conflict of interest. PE is an Associate Editor for the British Journal of Sports Medicine, the BMJ Open Sport & Exercise Medicine, and the Scandinavian Journal of Medicine & Science in Sports. KH is Editor for the German Journal of Sports Medicine and Associate Editor for the BMJ Open Sport & Exercise Medicine

ABSTRACT

Objectives:

To describe the machine learning (ML) techniques to develop ML prediction models for sports injuries.

Method:

We conducted a scoping review with a systematic search performed in December 2022 using Web of Science, Pubmed and Embase databases with the following inclusion criteria: original studies on competitive athletes; reporting sports-related musculoskeletal injury except for concussion; with ML injury prediction; and written in English. Risk of Bias was assessed using PROBAST. A descriptive analysis was performed on the data collection approaches, model development and validation.

Results:

Twenty-height studies were included; 96% had a high risk of bias and 4% had an unclear risk of bias. Regarding data collection, 43% of studies used screening, 43% monitoring, and 14% combined monitoring and screening data collections. Regarding model development, 86% of monitoring data collection studies considered time in the ML methods, compared to 50% in monitoring and screening, and 0% in screening. Regarding validation, internal validation was mainly used with 66% in screening and 26% in monitoring studies with 54% of monitoring studies having an unclear validation methods. ROC-AUC was the most reported metrics, presented in 70% of the included studies.

Conclusions:

Our scoping review showed that usually two data collections are usually used (i.e., screening and monitoring), which leads to different temporality and causes differences in the handling of model development and validation (e.g. time dependency, missing data, unbalanced classes).

Keywords: Injury risk estimation; injury prevention; artificial intelligence; track and field; epidemiology

1 INTRODUCTION

Sports injury rates and burden justify injury risk reduction strategies.[1] Among them, the prognostic prediction of sports injuries could represent a strategy by alerting athletes and their entourage about higher injury risk allowing them to implement appropriate individual preventative measures (Figure 1).[2, 3]

For that purpose, Machine Learning (ML) methods represent a promising approach.[4, 5] From a set of observations (each observation is an ordered pair composed of input data and outcome), ML allow to build a model capable to perform classification or regression tasks on new observations unknown to the model.[4, 5] Sports injury prediction thus consists of developing a model able to predict a sports injury outcome (i.e., injury, or no injury, or probability of injury) based on input data.[4, 5] Different ML methods exists to develop the model, but data (i.e., input data and outcome; and data collection and data preparation) stay the keystone. Then, a validation procedure of ML models is fundamental to abide ML concept rules and evaluate their performance to predict an outcome.[6] The validation process consists of evaluating the prediction compared to the ground truth, by splitting data into training and test sets.[6, 7] Two validation process can be identified: internal validation which consists of training and evaluating the model performance on the same population and external validation in which the model is evaluated on a new population unseen during the model training.[3, 7, 8] This comparison allows to calculate different performance metrics (Online supplemental appendix A).

Previous systematic reviews[4, 9, 10] synthesised the findings on sophisticated prognostic algorithms for the prediction of sports injuries. However, the most recent databases search is dated back to 24 June 2021 and additional articles were published in the meantime.[10] One systematic reviews did not specifically target sports injuries by also including sports performance outcomes.[9] One systematic reviews did not use the latest recommendation guidelines[11] to assess the risk of bias.[4] And one did not specifically target machine learning methods and included also statistical modelling approaches without validation process of the models.[10] Therefore, we believe that an update of the evidence would be helpful for researchers, practitioners and stakeholders to better align their methods, data collection strategies, model selection, correct interpretation of such results and intervention plans to

effectively assess and address sports injury prediction using machine learning.

In this context, we aimed to describe the ML techniques to develop ML prediction models for sports injuries.

2 METHODS

2.1 Protocol

We conducted a scoping review because this approach is superior to a systematic review for addressing an exploratory research question.[12, 13] We followed the methodological framework proposed by Arksey and O'Malley [12] and the Joanna Briggs Institute [14] when conducting and reporting this scoping review. Our research question was: "What are the different machine learning approaches to develop machine learning prediction models for sports injuries?".

2.2 Search strategy and inclusion/exclusion criteria

We conducted a systematic search on PubMed, Embase and Web of Science database, since the combination of these three database allows to reach 96% of all studies,[15] on 07 December 2022, to identify studies investigating sports injury prediction using ML techniques. The search strategy combined the following terms and Boolean operators:

#1 ("deep learning" OR "artificial intelligence" OR "machine learning" OR "neural network" OR "neural networks" OR "support vector machines" OR "nearest neighbour" OR "nearest neighbours" OR "random forest" OR "random forests" OR "trees" OR "elastic net" OR "ridge" OR "lasso" OR "boosting" OR "predictive modelling" OR "learning algorithms" OR "bayesian logistic regression" OR "prediction")

#2 ("sport" OR "sports" OR "athlete" OR "athletes")

#3 ("injury" OR "injuries" OR "injury risk")

#4 ("monitor" OR "monitoring" OR "screening" OR "screen" OR "baseline" OR "forecast" OR "forecasting" OR "detection").

#1 AND #2 AND #3 AND #4

The inclusion criteria were the following: (i) original studies reporting sports-related musculoskeletal injury except concussion; (ii) description of ML approaches predicting the injury upcoming and validated as defined in the Transparent Reporting of a multivariable prediction model for Individual Prognosis Or Diagnosis (TRIPOD) Types 2, 3 and 4;[16] (iii) written in English because no evidence bias if studies written in other languages than English

were excluded;[17, 18] (iv) original research such as observational studies, prospective, cohort studies and intervention studies; (v) studies including competitive athletes from recreational to international level. There was no restriction on the sport, country, sex, age, or level of the participants.

The exclusion criteria were the following: (i) ML techniques used to predict a diagnosis of sport injuries; and (ii) non-peer-reviewed articles, newspaper articles, opinion pieces, systematic reviews and meta-analyses, editorials, commentaries and letters to the editor, conference proceedings/abstracts, book chapters, descriptive studies, anecdotal studies, case studies, and case series.

2.3 Study selection

The study selection was performed using the Covidence reference management tool (Covidence, http://www.covidence.org). Titles and abstracts of all articles obtained from the electronic searches were first checked for redundancy, and duplicates were removed. Then, two independent reviewers (JT and PE) screened articles for eligibility based on the title and abstract using Covidence reference management platform. Full texts were then screened for inclusion in the scoping review by two reviewers (JT and PED), independently, also using Covidence. Any conflicts were solved during a consensus meeting, and a reviewer (LN) was available if needed. The reference lists of selected articles and of reviews not included in the present scoping review were searched to identify further relevant articles not selected by the database searches.

2.4 Data collection process

The data were extracted from the selected articles by two reviewers (JT and PED). Meeting was conducted with external data collectors (PE or LN) to solve disagreements. Extracted data were:

- Study design: prospective and retrospective study design;
- Population characteristics: sample size, sport, level of sport;
- Data collection type: The input data are usually collected in two different contexts depending on the period of the follow-up and its frequency: (i) data collected at a specific point in time named “screening”, and (ii) data collected prospectively based on regular

predetermined time points (e.g., daily, weekly) named “monitoring” (Figure 1);

- Number of observations, number of injured athletes and number of injuries;
- Time management data: This corresponds to the type of pre-processing applied to the data to consider time in a monitoring context: time-series analysis (i.e., series of data points indexed in time order like in moving averages) or time windows analysis (i.e., a fixed interval of time when the data stream is processed);
- Model development: internal or external validation, type of cross-validation (e.g., stratified, nested-stratified, monoid-cross-validation), details of any ensemble methods (bagging, boosting), and resampling methods (oversampling or under sampling);
- ML models;
- Metrics: type and performance metrics computed in models.

2.5 Risk of bias assessment

The Prediction model Risk Of Bias Assessment Tool (PROBAST) was used to assess the risk of bias of model studies by two authors (JT and PED).[11] A total of 20 questions about participants, predictors, outcome and analysis permitted the estimation of shortcomings in the study design, conduct or analysis.[11] Risk of bias is judged as low (+), high (-), or unclear if no sufficient information are given (?).

2.6 Data analyses

Descriptive analysis was performed to present the current state-of-scientific studies on ML approaches for sports injury prediction according the different machine learning steps: data collection, model development, validation. As data collection is the first step and can impact the next step of the ML approaches, it was decided to present the results of the scoping review according the potential different data collection approaches, if any. Also, different levels of analysis (i.e. different accounting strategies) were used to present the results inside each ML steps:

- Studies level: Presentation of the number of included study, allowing to present the study characteristics and metrics values.
- Methods level: Presentation of the number of methods employed in the included studies

regarding time management, method validation, cross-validation, resampling techniques, and ensemble methods.

- Models level: Presentation of the number of specific ML models used in the included studies.

Data were summarised using counts and percentages according to the three levels of analyses. A stratified sunburst chart was constructed to present the data items extracted according to the second level and thus included data collection, time management, validation process, type of cross-validation, resampling techniques, and ensemble methods if used.

3 RESULTS

3.1 Study selection

Based on our search strategy, a total of 1868 studies were found in the three databases. After removing the duplicates, 1319 studies were screened by title and abstract, then 165 full-text studies were screened, and finally 28 studies were included in the present scoping review (Figure 2). Excluded studies from full-text screening are available in Online supplemental appendix B.

3.2 Characteristics of included studies

The characteristics of the 28 included studies are presented in Online supplemental appendix C. The first included study was published in 2013 and the most recent studies in 2022; 71% of studies were published in 2020, 2021 and 2022 (Online supplemental appendix C). The study design was prospective in 22 (79%) studies [19–40] and retrospective in 6 (21%).[41–46] Twenty-nine percent of the studies were on football,[23, 24, 27, 30, 34, 36–38] 21% on multi-sports, [35, 39, 41, 42, 44, 46] 10% on Australian football,[20, 31, 33] 7% on American football,[28, 29] and basketball,[32, 45] 4% on each of the following sports: hockey,[43] cricket,[26] futsal,[21] short-track speed skating,[25] rugby,[19] and athletics,[22] and 4% did not specify any sport [40] (Online supplemental appendix C).

3.3 Study quality: risk of bias assessment

The overall risk of bias (RoB) was evaluated as high in 28 (97%) studies and unclear in one study (Figure 3 and online supplemental appendix D). For the participants domain, 55% of the studies presented a low RoB, and 45% unclear RoB. For the predictor's domain, 3% presented a low risk of bias, whereas 14% and 83% presented high and unclear RoB, respectively. For the outcome domain, 21% shown high RoB and 79% unclear RoB. For the analysis domain, 90% and 10% were high and unclear RoB, respectively.

3.4 Step 1: Data collection

Regarding the data collection approaches, 12 (43%) studies used a screening data collection,[20, 21, 27, 28, 35–37, 39–42, 46] (43%) studies a monitoring data collection,[19, 22, 25, 26, 29–32, 34, 43–45] and 4 (14%) studies combined monitoring and screening data collection[23, 24, 33,

38] (online supplementary appendix 4). In monitoring data collection, acquisition frequencies of data varied in a range from daily to monthly, and periods of follow-up ranged from a few weeks to 7 years. From the 28 studies, the number of observations were reported in 23 (82%) studies, and the number of outcomes in 27 (96%) studies.

3.5 Step 2: Model development

There was a total count of 28 studies, 99 different methods (Figure 4), and 106 different types of models (Online supplemental appendix E).

3.5.1 Methods level

Among the 99 different methods, 56 (57%) used screening data collection, 35 (36%) monitoring data collection, and 8 (8%) monitoring and screening data collection (Figure 4).

Time management In screening data collection, time management was not needed and thus none of the 56 methods (100%) reported time management. In monitoring data collection, the time was managed either with moving averages in 20 methods (57%), Time2Vec in 6 methods (17%), time windows processing in 2 methods (6%) or dynamic Bayesian network in 2 methods (6%); 7 (17%) did not specify any time management. In studies that used screening and monitoring data collections (n=8), 4 methods applied time windows processing, whereas the four other methods did not specify time management.

Resampling methods In screening data collection, synthetic minority oversampling technique (SMOTE) was applied in 16 (29%) methods, random undersampling (RUS) in 8 (14%), random oversampling (ROS) in 5 (9%), over-sampling in 2 (2%), under-sampling in 3 (5%), edited nearest neighbour undersampling (ENN) in 1 (2%) and 21 methods (38%) did not use any resampling technique. In monitoring data collection, 6 (17%) methods applied SMOTE, adaptative synthetic algorithm (ADASYN) in 4 (11%), over-sampling in 3 (8%), RUS in 2 (6%), weighting in 1 (3%) and 19 methods (54%) did not use any resampling technique. In monitoring and screening data collections, 2 methods used SMOTE, 1 method used ROS and 5 did not use any resampling technique.

Ensemble methods In screening data collection, bagging was applied in 18 (32%), boosting in 14 (25%), and no ensemble methods were used in 24 (43%). In monitoring data collection, bagging was applied in 15 (43%), boosting in 5 (14%), stacking in 1 (3%) and no ensemble methods were used in 14 (40%). In monitoring and screening data collections, boosting was used in 3 methods, bagging in 2 and 3 methods did not use any ensemble methods.

3.5.2 Models level

Among the 106 different models, 37 (35%) used screening data collection, 57 (54%) monitoring data collection, and 12 (11%) monitoring and screening data collection (Figure 6).

In screening studies, twelve (32%) used decision tree (DT), 6 (16%) used support vector machines (SVM), 5 (14%) random forest (RF), 4 (11%) logistic regression (LR), Artificial Neural Network (ANN), k-nearest neighbours (kNN), naive Bayes (NB), and extreme gradient boosting (XGBoost) in 2 (5%) models, 1 (3%) used linear discriminant analysis (LDA). One (3%) model was not specified (Figure 6).

In monitoring studies, RF were used in 12 (21%), LR in 7 (12%), XGboost in 6 (7%), DT, NB, and SVM in 5 (9%), Dummy classifier in 4 (8%), kNN in 3 (5%), Time-varying dynamic Bayesian network in 2 (3%), and auto regressive time varying netswork (ARTIVA), generalized equation estimation (GEE), Lasso, Multiple bidirectional Encoder Transformers for Injury Classification (METIC), Ridge, Rapid Incremental Search for time-varying associations (Rista), top 3 ensemble and voting in 1 (2%) (Figure 6).

In monitoring and screening studies, ANN and XGBoost were used in 2 (17%), DT, kNN, LDA, LR, NB, RF, Ridge and SVM were used in 1 (8%) (Figure 6).

3.6 Step 3: Validation

3.6.1 Methods level

Validation In screening data collection, internal validation was used in 30 methods (66%), 1 (2%) method used external validation, and 18 (32%) methods did not clearly mention the type of the population used to validate models (Figure 4). In monitoring data collection, internal validation was used in 9 (26%) methods, external validation in 7 (20%), whereas for 19 (54%) methods the population on which the validation was made was not specified (Figure 4). In

monitoring and screening data collections, 3 methods used internal validation and 5 did not mention the population used for validation (Figure 4).

Cross-validation In screening data collection, stratified cross-validation was used in 32 (60%) methods, cross-validation in 18 (32%), nested stratified cross-validation in 2 (3%), nested cross-validation in 1 (2%) and cross-validation was not used in 3 (5%) methods. In monitoring data collection, cross-validation was used in 14 (40%), stratified cross-validation in 12 (34%), recursive feature elimination with cross-validation in 2 (6%), and monoid cross-validation in 1 (3%); cross-validation was not used in 6 (17%) methods. In monitoring and screening data collections, 4 methods used cross-validation, 2 used stratified cross-validation and 2 used leave one-out with cross-validation.

Finally regarding the proportion of metrics used according to the studies, in screening data collection (n=12), ROC (receiver operating curve) AUC (Area Under the Curve) (also named C-statistic) was reported in 9 included studies, recall in 7, specificity in 6, accuracy in 2, and F1-score and precision in 1 (Figure 5). In monitoring data collection (n=12), ROC AUC and recall were reported in 8 studies, precision in 6, F1-score in 5, specificity in 4 and accuracy in 3 (Figure 5). In monitoring and screening data collection (n=4), ROC AUC and recall were reported in 3, accuracy and precision and specificity were reported in 2, and F1-score was never reported (Figure 5).

4 DISCUSSION

The main finding of our scoping review were that 1) one important characteristic of the different ML approaches to develop prediction ML models for sports injuries was the difference in data collections, highlighting two different approaches: screening and monitoring, and 2) these two data collections approaches induced differences in the development of sports injury prediction ML models and affected ML methods and metrics (e.g. time dependency, missing data, unbalanced classes).

4.1 Two data collection approaches with important implications

For the development and validation of ML prediction models, data (i.e., input data and outcome) is the keystone. Our results reported that, in sports injury prediction, the input data are usually collected in two different contexts depending on the period of the follow-up and its frequency: (i) data collected at a specific point in time named "screening", and (ii) data collected prospectively based on regular predetermined time points (e.g., daily, weekly) named "monitoring" (Figure 1). The outcome (i.e., sports injury) needs to be collected over a period of time (e.g., the season) through a prospective or retrospective approach.[47] The different acquisition frequencies of data between screening and monitoring data collections allow ML models to provide different injury predictions: (i) based on screening data collection ML models can theoretically provide an injury risk for an athlete at a given time (e.g., once at the beginning of the season) whereas (ii) monitoring data collection ML models can provide an injury risk estimation over time based on prospective surveillance and timely response (Figure 1). Our results showed differences in the ML approaches according to the data collection methods. Therefore, differentiating screening and monitoring data collections seems important for researchers, practitioners, and stakeholders to better align their methodologies, data collection strategies, model selection, and intervention plans to effectively estimate and address sports injury risks.

4.2 All is a question of time

As discussed above, the frequency of data collection had an impact on the ML model development, and the time should therefore be taken into account when developing the ML model. The time management was only applied to monitoring and the combination of

monitoring and screening data collection studies. It appears coherent for screening data collection that no time management was applied, since the input data are collected at a given time without any variation of the input data, and the outcome data are collected over a period of time without need of its temporality to predict this outcome. On the contrary, for monitoring data collection, input and outcome data are collected prospectively based on regular predetermined time points. Thus, data collected contains information to forecast future injuries and the time becomes a variable to consider. The time management is therefore of major importance for the validity of the ML prediction model.[48] Surprisingly, it remains unclear in 18% of monitoring studies and in 33% of monitoring and screening studies. This can represent a perspective of improvement to systematically detail time management in sports injury prediction using monitoring data collection.

In addition, a large variety of time management strategies were used in the included studies and can lead to differences in the time dependency of input data. We note that 6 studies have reported time window processing (i.e., when input data are processed in a fixed interval of time) in which the temporality is given in each time window, and thus, input is assumed to be independent because time is considered in the time window. However, methods using moving averages cannot consider independent input, since the output at the time t is computed according to the input and output at t – 1. Indeed, time series forecasting should consider temporality, seasonality, and trends in data to correctly predict future injuries. The time dependency has major consequences in validation process.

4.3 Time induces differences in the validation and cross-validation process and ensemble methods

Most of methods with internal validation used random splitting process to separate the population that was used either in train or test set. This process does not appear to be a problem in screening data collection since each sample is considered independent. However, it can lead to mistakes in monitoring data collection studies in which time should be considered to avoid mistakes. Indeed, future data cannot be used during model training to predict past injuries, and temporality must be respected. A temporal splitting seems to be the most appropriate as it was done in previous studies.[25, 31, 34]

Cross-validation is a commonly used technique to evaluate the performance of a machine learning model. It involves dividing the data into multiple subsets, called ”folds”, and performing model training and evaluation on different combinations of these folds.[46] In the case of time series data, it is crucial to respect the chronological order of the data when dividing it into folds. Time series data often exhibit dependencies and specific temporal structures related to the time evolution. Therefore, it is not appropriate to mix observations from different folds with different periods of time as it could lead to biased model evaluation. Classical cross-validation strategies should thus be adapted using temporal splitting, time-series cross-validation or time windows process.[49] Although, ensemble methods consisting in choosing the best classifier by voting based on different splitting of data could be adapted to take into account time dependency in data.[48–50]

4.4 Imbalance class problems can differ between screening and monitoring data collections

Our results also highlighted the problem of imbalanced class. This occurs when an outcome is over-represented compared to another (for instance, more non-injured than injured, or vice-versa).[8] This might lead to difficulties in the prediction of the non-dominant outcome (i.e., class). Different methods exist to help the model learn imbalanced classes.[7]

The imbalance class problem is increased in monitoring data collection contexts compared to screening. In the screening data collection, the number of observations is directly equal to the number of athletes included in the study. In the monitoring data collection, each observation is a measurement at a given time for an athlete associated with his injury status, and the number of observations is directly equal to the number of predetermined measurements multiplied by the number of athletes. Thereby, the imbalance class problem is accentuated in the monitoring data collection compared to the screening one. For example, in the context of daily monitoring, an athlete who had 10 days without injuries will increase the imbalanced class ratio with 10 examples without injuries comparing with injuries. Thus, the problem of imbalance class represents another major difference between screening and monitoring data collections.

To manage imbalanced data, resampling methods (54%) were applied in a large number of methods whatever the type of data collection and without any differences between screening and

monitoring data collections. However, these methods often consist in randomly splitting data in order to minimize bias. As already explained concerning the validation process in the monitoring data collection, random splitting can induce timeline breaks in the data if the model does not consider independent input. Thus, a revised version of resampling and ensemble methods considering time should be applied according to the data collection, and time management (either time series or time windows).[50]

4.5 Different metrics to better show the model performances

The reported metrics differed between screening and monitoring data collection studies: specificity was more reported in screening than monitoring data collection studies, and F1-score and precision in monitoring than in screening data collection studies. ROC AUC and recall were the most frequently reported metrics in both data collection contexts. Different metrics are commonly used in ML to present model performances and each metric presents its own characteristics and expresses a specific aspect of the prediction model (Online supplemental appendix A). Each metric is representative of one aspect of the algorithm prediction capabilities. For example, recall gives the true positive rate whereas specificity represents the true negative rate. Because of the rarity of events in the data set, models have difficulties predicting events that rarely occur. Predicting an event that never happens is trivial. Indeed, if one considers a model that always predicts non-event, if the event occurs 2% of the time, the accuracy of the model will be 98% which can be considered very good. However, the true positive rate (the recall) will be 0% because the model never predicts injury. For example, in monitoring data collection, a true negative rate (i.e., specificity) is given in only 7% of the studies with low scores of recall. This can be explained using oversampling on the minority class resulting in an overfitting of the injured label. The model might be constrained to predict injuries in an artificial way due to resampling processes using oversampling methods. However, controlling this overfitting might lead to better injury risk estimation by increasing recall. In this case, the specificity should be carefully controlled to avoid false positive detection. Only 8 (28,6%) studies of the 28 included presented both recall and specificity metrics, for example. The F1-score considers these two aspects of prediction but is rarely given in monitoring (41%), screening (8%) and monitoring and screening (0%) studies. And

none of the included studies, and whatever the data collection context, presents all the metrics available in the literature to give a global vision of the model performances. In ML sports injury prediction, it could be interesting to assess and present ML model performances by several metrics that represent the range of model capabilities, and not to only consider the best metric to assess the performance of the prediction model.

4.6 Limitations

Only three databases were used to search articles and only articles written in English have been considered. However, this selection strategy was chosen based on findings that in biomedical systematic reviews, the combination of Embase, MEDLINE and Web of Science or Google Scholar database reaches 95.9% of all studies[15] and no evidence bias if studies written in other languages than English were excluded.[17, 18] We used PROBAST[11] to assess the risk of bias of the included studies, which was not specifically developed to assess ML models, thus this may not perfectly fit with the ML approach inducing over or underrated assessments.

4.7 Practical implications and perspectives

This systematic review highlighted that there is no consensus on the appropriate ML approach based on the type of data collection. Our results also highlight the importance of time dependency when monitoring data collection for forecasting future injuries. Considering the prediction of future injuries requires accounting for time in data management and model development, including validation and resampling processes, specific development tools should be used to manage time in this context. If the data are time-dependent, classical methods like cross-validation, ensemble learning, and resampling can be employed by considering independence between samples in the input matrix. Alternatively, temporal approaches should be applied. While validation tools and strategies appear well-defined and utilized in the literature for screening sports injury prediction, further investigation is needed regarding time management and validation strategies in monitoring data collection context. This will help establish clear guidelines for ML development in this data collection context.

For the readers of studies presenting sports injury prediction using ML models, we think that it is important to evaluate if time was considered in the development of the ML models based on

monitoring data collection, and how, in order to evaluate the potential validity of the models. In addition, it is also of interest to look at the metrics and have in mind that several metrics allow to present the range of model capabilities and performances and that it is better not to only consider the best metric to assess the performance of the prediction model.

The monitoring data collection provided to the athlete with an estimation of the injury risk that can be updated at each new data entry. However, this raises the question of the frequency of the update of the ML model. How can we be sure that the ML model is still valid and stable with time and accumulation of new data? It would be interesting to know to what extent the arrival of continuous data does, or does not, give a better estimate of injury risk.

Finally, there is an increasing demand for high-performance and reliable prediction models to help athletes' training and injury prevention management. However, we sometimes overlook the focus on the athlete. It would be of interest to better understand the perception of the athletes, and their entourage, about the information of injury risk estimation.[51] How is such information accepted? What are the effects of injury prediction on their practice? How can they use this information? Besides technical and mathematical improvements needed on sports injury prediction, there are also very important questions that need to be addressed to better understand how to manage and implement injury prediction in real field practice.[52]

CONCLUSION

This scoping review showed that usually two data collections are usually used: screening and monitoring, which leads to different temporality and causes differences in the handling of model development and validation (e.g. time dependency, missing data, unbalanced classes). Consequently, it is necessary to adapt the ML approach for the prediction of sports injuries to the data collection of screening and monitoring. ML appears to be a promising tool for injury risk assessment, but if not used correctly, it can be misleading. We suggest developing clear guidelines for monitoring models based on the time dependence of the data to increase the performance and reliability of these models.

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FIGURES

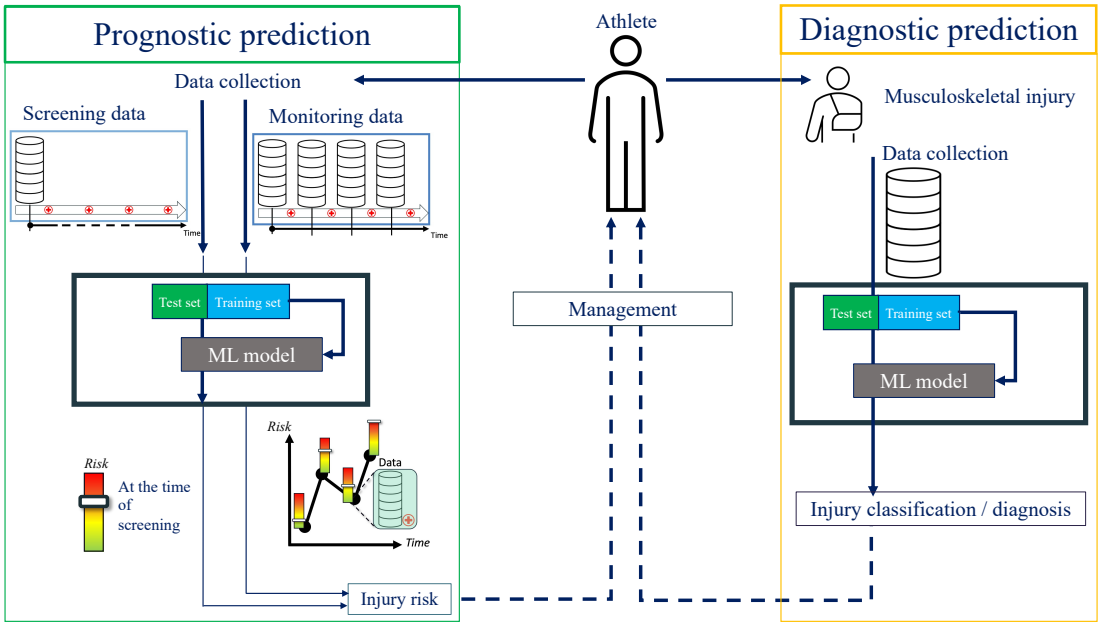


Figure 1: Illustration of the approaches and interests of sports injury prediction using machine learning techniques in sports medicine, with prognostic and diagnostic prediction. Diagnostic prediction aims at determining a class for a sports injury in order to help with the diagnosis, whereas prognostic prediction aims at detecting either athletes at high risk of injuries or an upcoming injury.[2] Prognosis prediction can be divided according to the data collection temporality into screening (input data collection at a time-point) or monitoring (input data collection throughout the time) leading to a different injury risk estimation. Data collected are split into test and training set, which are used either to develop or validate the model.

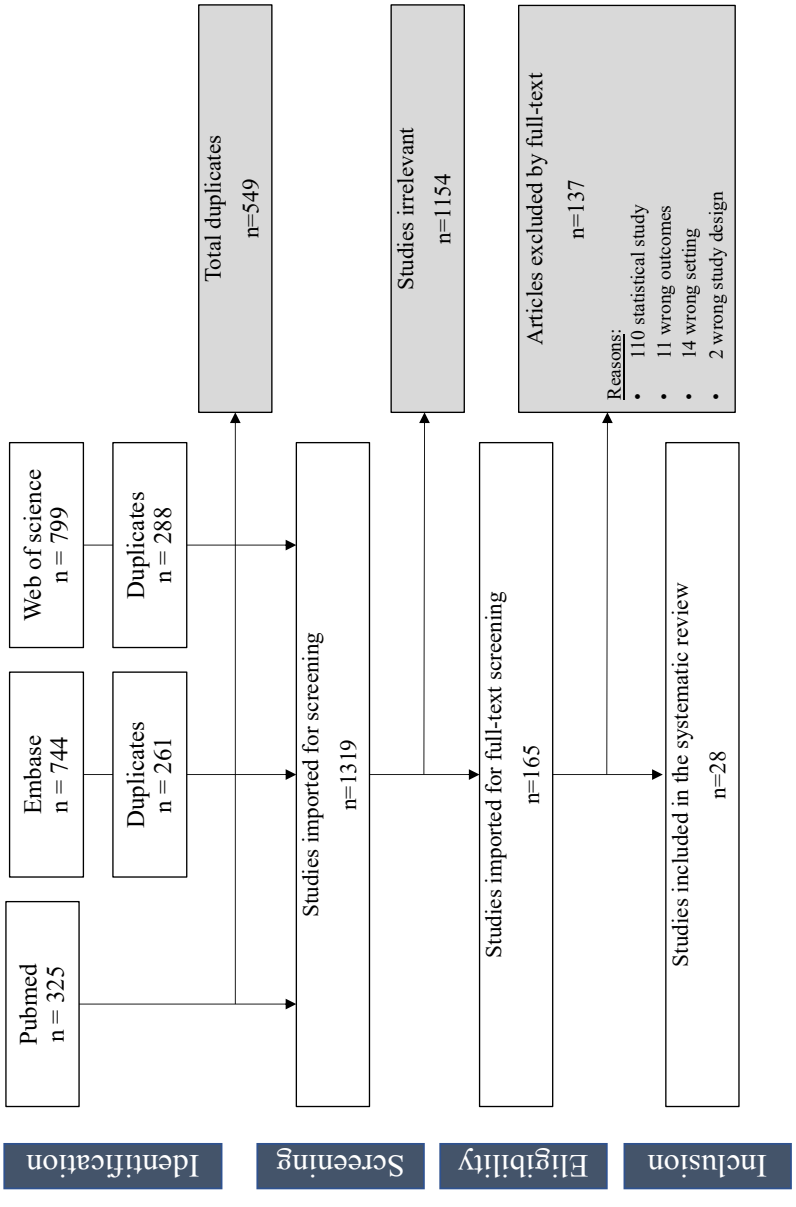


Figure 2: PRISMA flowchart of the selection process of the studies included in the present systematic review

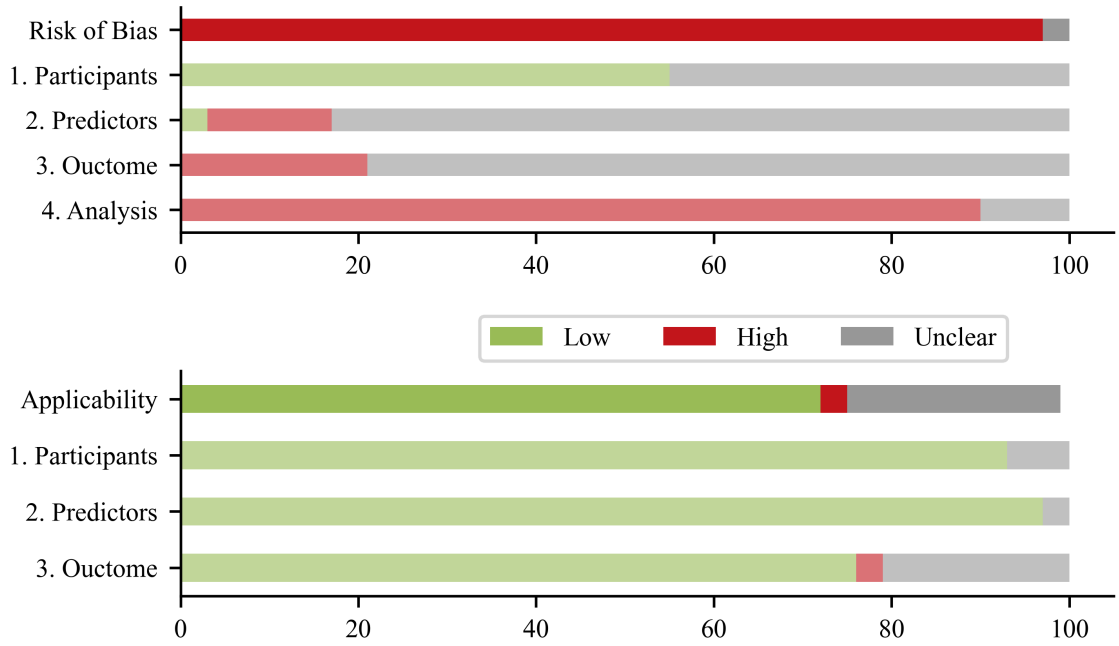


Figure 3: Risk of bias assessment using the Prediction model Risk Of Bias Assessment Tool (PROBAST) [11] for the included studies in the different domains

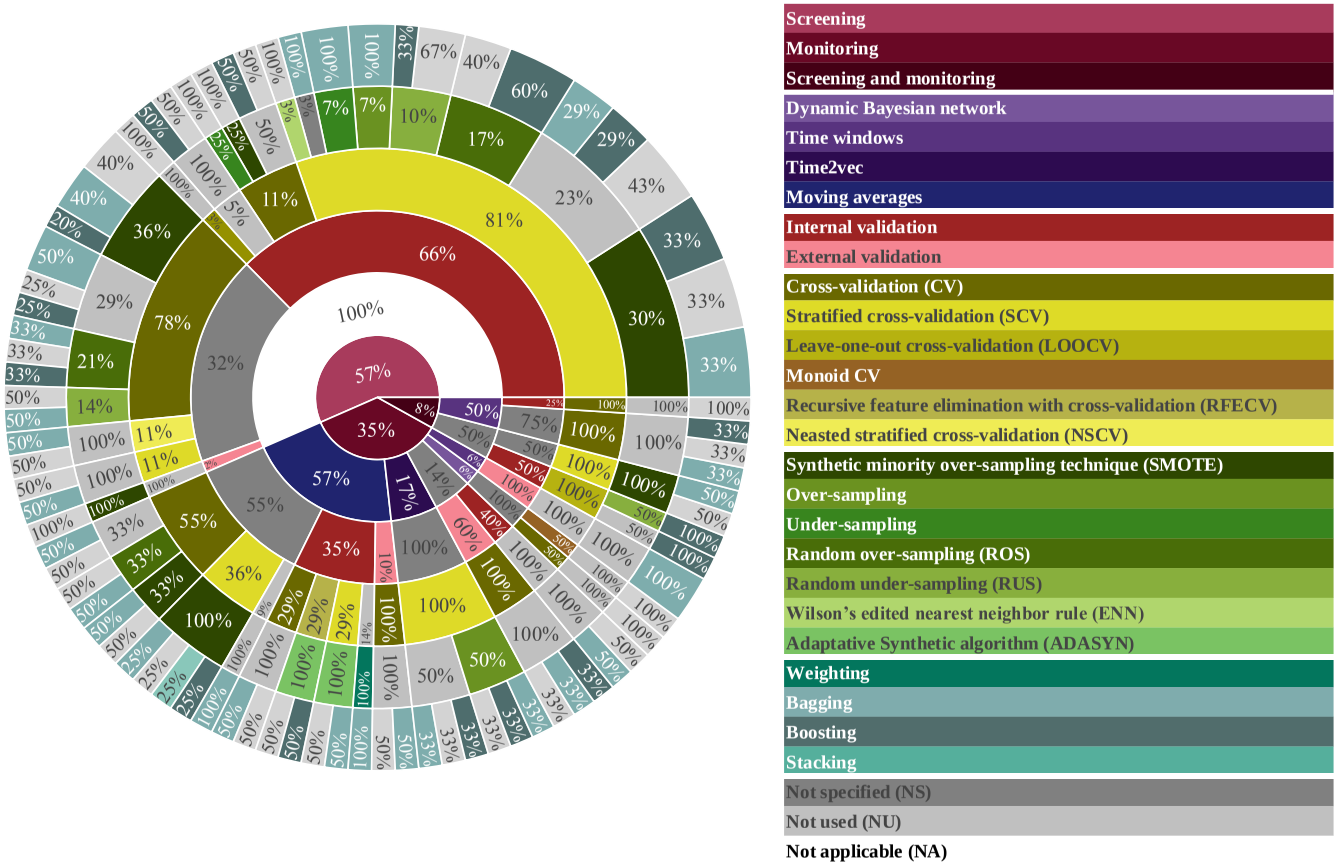


Figure 4: Stratified pie chart of extracted data regarding the Machine Learning approach and techniques used in the 99 methods reported in the 28 included studies. Six levels of information are presented by each circle according to the items of data extracted: 1) data collection, 2) time management, 3) validation, 4) cross-validation, 5) resampling methods and 6) ensemble methods. Inner circles encompass the next level of data represented by outer circles. Root percentages and absolute values are provided in the following html file: https://iprevapp.emse.fr/opendocs/Sunburst_methods_270623.html

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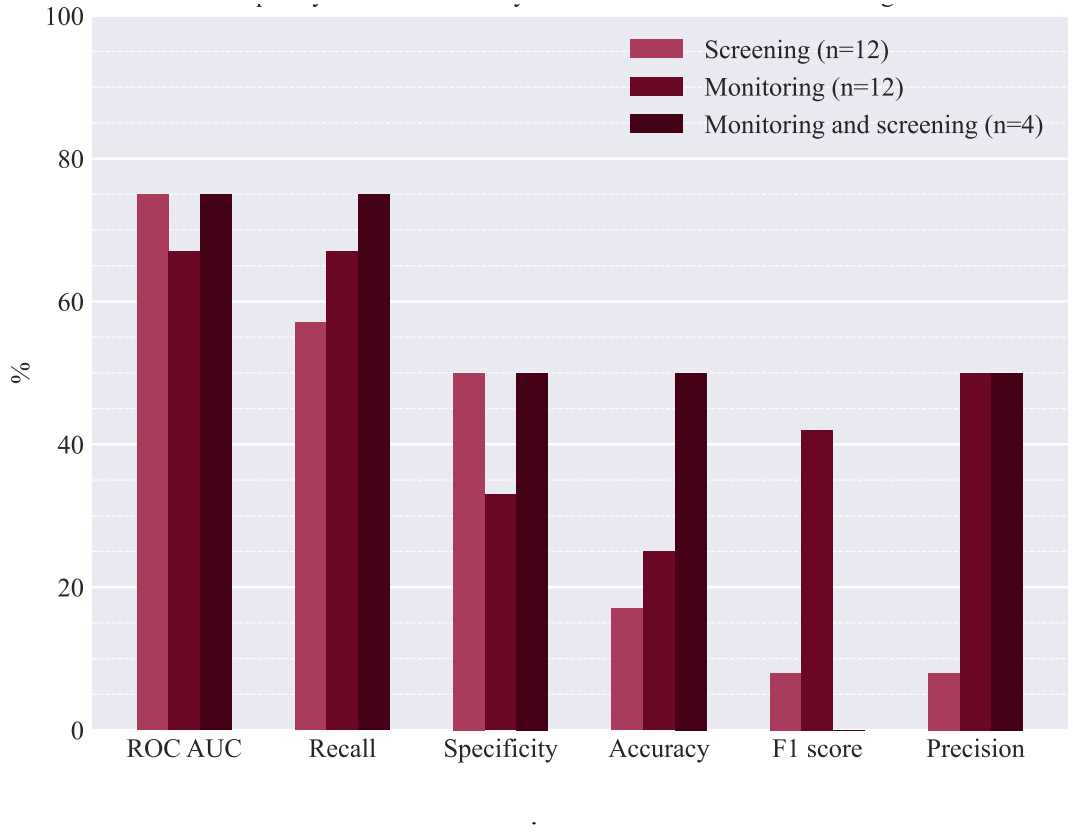


Figure 5: Frequencies and percentages of metrics used in ML studies included in the systematic review.

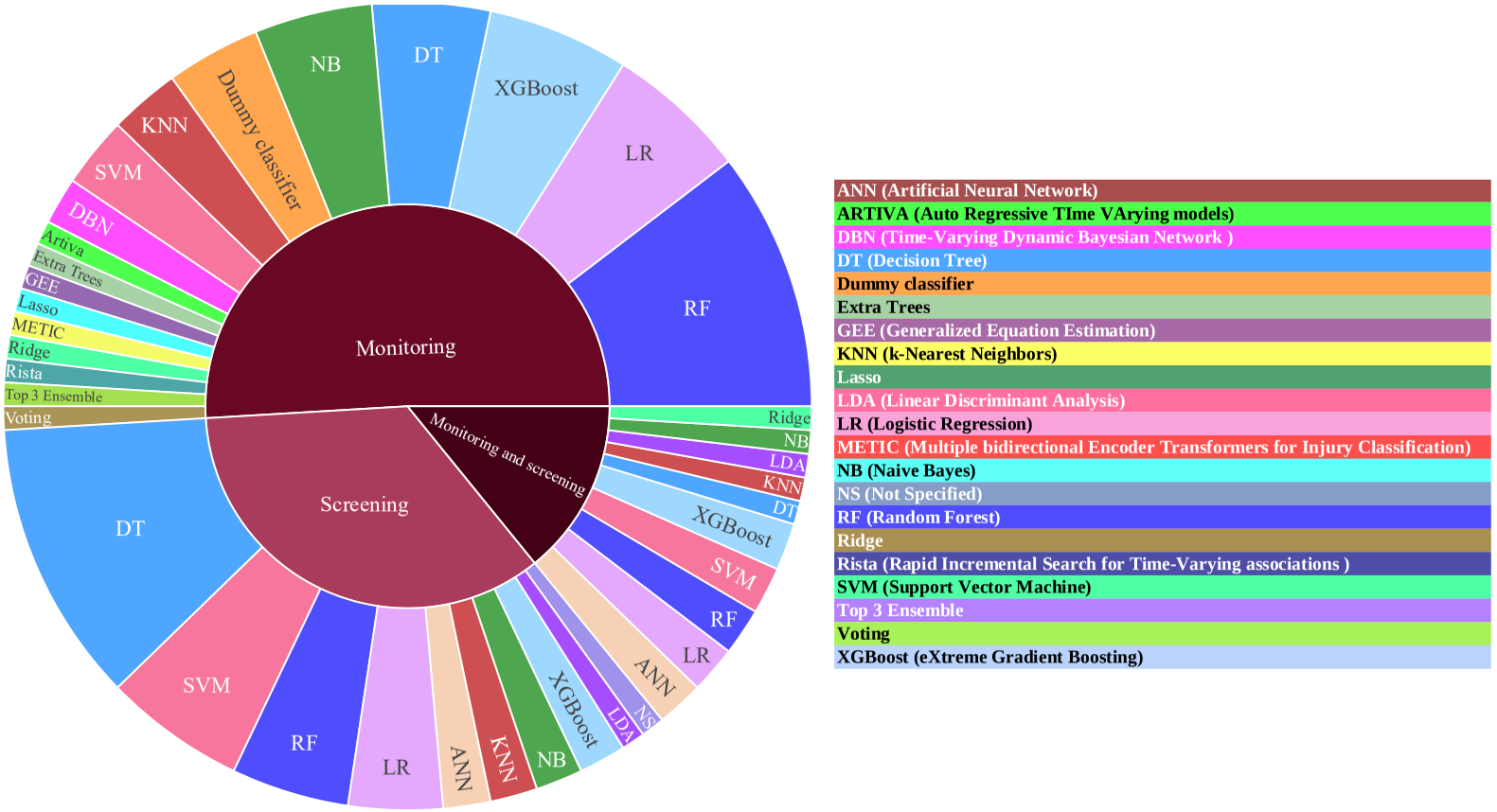


Figure 6: Stratified pie chart of extracted data regarding the 106 Machine Learning models used in the systematic review. The assessment of models was conducted considering three criteria: ”Study,” ”Type of data collection,” and ”Model.” In cases where multiple results were obtained for a single study, only one was retained in the final selection.

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A Online supplemental: The different performance metrics of machine learning models

Precision (or positive predictive value (PPV))	$= \frac{TP}{TP+FP}$	(1)
Recall (or sensitivity)	$= \frac{TP}{TP+FN}$	(2)
Specificity	$= \frac{TN}{TN+FP}$	(3)
Accuracy	$= \frac{TP+TN}{TP+TN+FP+FN}$	(4)
F1-score (corresponding to the harmonic mean of sensitivity and PPV)	$= 2 \times \frac{recall \times precision}{recall+precision}$	(5)

B Online supplemental: Details of full-text screening excluded studies and reasons

Authors	Title	Published Year	Journal	Volume	Issue	DOI	Study	Exclusion reason
Liu J; Tang X; Liao T; Huang Y	Duration Method of Athlete Joint Injury Based on Deep Learning Model.	2022	Comput Math Methods Med			10.1155/2022/8165380	Liu 2022	Wrong outcomes
Collings TJ; Diamond LE; Barrett RS; Timmins RG; Hickey JT; DU Moulin WS; Williams MD; Bourne MN	Strength and Biomechanical Risk Factors for Noncontact ACL Injury in Elite Female Footballers: A Prospective Study.	2022	Med Sci Sports Exerc	54	8	10.1249/MSS.0000000000002908	Collings 2022	Statistical study. No splitting data
Carbuhn AF; Vu D; Magee LM; McCulloch PC; Lambert BS	Anthropometric Factors Associated With Bone Stress Injuries in Collegiate Distance Runners: New Risk Metrics and Screening Tools?	2022	Orthop J Sports Med	10	2	10.1177/23259671211070308	Carbuhn 2022	Statistical study. No splitting data
Seda EY; Wanzi R; Matias AB; Tebldt UT; Sacco ICN	Predictive Effect of Pelvi-Kneown Risk Factors and Foo-Core Training in Lower Limb Running-Related Injuries in Recreational Runners: A Secondary Analysis of a Randomized Controlled Trial.	2022	Am J Sports Med	50	1	10.1177/03635465211056329	Seda 2022	Statistical study. No splitting data
Bruce SL; Wilkinson GB	Whole-Body Reactive Agility Metrics to Identify Football Players With a Command Lower Extremity Injury Risk.	2021	Front Sports Act Living	3		10.3389/fspor.2021.733567	Bruce 2021	Statistical study. No splitting data
Handaleidoi K; Sanfilippo J; McKay L; Watson AM	Duration of Sleep and Subjective Well-Being as Independent Predictors of Injury in Female Collegiate Volleyball Players.	2021	Orthop J Sports Med	9	9	10.1177/23259671211029285	Handaleidoi 2021	Statistical study. No splitting data
Stenlund CA; Cochran HJ; Schall R	Morphological and skill-related fitness components as potential predictors of injury in elite netball players: A cohort study.	2021	S Afr J Physiother	77	1	10.4102/sajp/v77i1.1524	Stenlund 2021	Statistical study. No splitting data
Filhström A; Kvist J; Brinnucot NFN; Mandelou LD; Hägglund M	Clinical Risk Profile for a Second Anterior Cruciate Ligament Injury in Female Soccer Players After Anterior Cruciate Ligament Reconstruction.	2021	Am J Sports Med	49	6	10.1177/03635465211999109	Filhström 202 1	Statistical study. No splitting data
Filhström A; Hägglund M; Hadevik H; Kvist J	Poor Validity of Functional Performance Tests to Predict Knee Injury in Female Soccer Players With or Without Anterior Cruciate Ligament Reconstruction.	2021	Am J Sports Med	49	6	10.1177/03635465211002354 1	Filhström 202 1	Statistical study. No splitting data
de Leeuw AW; van der Zwaard S; van Baar R; Knobbe A	Personalized machine learning approach to injury monitoring in elite volleyball players.	2022	Eur J Sport Sci	22	4	10.1080/17461391.2021.1887369	deLeeuw 2022	Statistical study. No splitting data
Hoover DL; Killian CB; Trinsey RA; Butler DM; Wilkinson SG; Esslinger FT; Judge LW	Predictive Validity of a Functional Movement Screen in Professional Basketball Players.	2020	Medicina (Kaunas)	56	12	10.3390/medicina56120724	Hoover 2020	Statistical study. No splitting data
Hughes T; Riley RD; Callaghan MJ; Sergeant JC	The Value of Pre-season Screening for Injury Prediction: The Development and Internal Validation of a Multivariable Prognostic Model to Predict Indirect Muscle Injury Risk in Elite Football (Soccer) Players.	2020	Sports Med Open	6	1	10.1186/s40798-020-00302-w#t	Hughes 2020	Statistical study. No splitting data
Tervo T; Ekstrup J; Nordström A; Tervo F	The 9+ screening test score does not predict injuries in elite football players.	2020	Scand J Med Sci Sports	30	7	10.1111/sms.13663	Tervo 2020	Statistical study. No splitting data
Karlsson J; Haljste A; von Rosen P	Handball anc movement screening - can non-contact injuries be predicted in adolescent elite handball players? A 1-year prospective cohort study.	2021	Phy siother Theory Pract	37	10	10.1080/09593985.2019.1681014	Karlsson 2021	Statistical study. No splitting data
O'Connor S; McCaffrey N; Whyte EF; Moran KA	Can a Standardized Visual Assessment of Squatting Technique and Core Stability Predict Injury?	2020	J Strength Cond Res	34	1	10.1519/JSC.0000000000003262	O'Connor 2020	Statistical study. No splitting data
Johnson WR; Mian A; Lloyd DG; Alderson JA	On-field player workload exposure and knee injury risk monitoring via deep learning.	2019	J Biomech	93		10.1016/j.jbiomech.2019.07.002	Johnson 2019	Wrong outcomes
De Blaiser C; De Ridder R; Willems T; Vanden Bossche L; Danneels L; Roosen P	Impaired Core Stability as a Risk Factor for the Development of Lower Extremity Overuse Injuries: A Prospective Cohort Study.	2019	Am J Sports Med	47	7	10.1177/0363546519837724	DeBlaiser 2019	Statistical study. No splitting data
Attia M; Tabor MF; Rahan Yousif A	Design and validation of a smart wearable device to prevent recurrent ankle sprain.	2018	J Med Eng Technol	42	6	10.1080/03091902.2018.1544342	Attia 2018	Wrong outcomes
Brund BBK; Bianna ssi S; Kersting UG; Arendt-Nielsen L; Palsso TS	Prediction of running-induced Achilles tendinopathy with pain sensitivity - a 1-year prospective study.	2019	Scand J Pain	19	1	10.1515/sjpain-2018-0084	Brun dBBK 2019	Statistical study. No splitting data
Lauridsen on J; Hejne A; Flodströ m F; Frohm A; von Rosen P	Can movement tests predict injury in elite orienteers? An 1-year prospective cohort study.	2020	Phy siother Theory Pract	36	8	10.1080/09593985.2018.1513106	Lauridsenon 2020	Statistical study. No splitting data
Philp F; Blana D; Chadwick EK; Stewart C; Stapleton C; Major K; Pandyan AD	Study of the measurement and predictive validity of the functional Movement Screen.	2018	BMJ Open Sport Exerc Med	4	1	10.1136/bmjsem-2018-000357	Philp 2018	Statistical study. No splitting data
Klemm D; Hawkins DA; Matsuoka MAC; McKillip M; Ochsner L; Caskey CF; Cro Bough CL	Accelerometer-based prediction of running injury in National Collegiate Athletic Association track athletes.	2018	J Biomech	73		10.1016/j.jbiomech.2018.04.001	Klemm 2018	Statistical study. No splitting data
Perugini AM; Dunmore A; Nilstad A; Solstad BE; Steffen K	Psychosocial stress factors, including the relationship with thoughts and their influences on acute and overuse injury risk in elite female football players.	2018	BMJ Open Sport Exerc Med	4	1	10.1136/bmjsem-2017-000317	Perugini 2018	Statistical study. No splitting data
Dowd IR; Long T; Shaffer S; Myer GD	The Functional Movement Screen as a Predictor of Injury in National Collegiate Athletic Association Division II Athletes.	2018	J Athl Train	53	1	10.4085/1062-6050-528-15	Dowd 2018	Statistical study. No splitting data
Bittig BV; Chen M; Devine RC; Collins CL; Diehl J; Burkam B	Functional Movement Screening and Injury Rate in High School and Collegiate Runners: A Retrospective Analysis of 3 Prospective Observational Studies.	2018	Clin J Sport Med	28	4	10.1097/JSM.0000000000000459	Bittig 2018	Statistical study. No splitting data
Schuermans J; Van Tiggelen D; Witvrouw E	Prestretch-Extension Muscle Recruitment is Associated with Hamstring Injury Risk in Amateur Soccer.	2017	Int J Sports Med	38	9	10.1055/s-0043-103016	Schuermans 2017	Statistical study. No splitting data
Hakkinen A; Turgut S; Ben T; Haile C; Farooq A; Tol R; Whiteley R; Khan KM; Ihsha R	The functional movement test 9+ is a poor screening test for forearm tendinopathies: An 1-year prospective cohort study.	2018	Br J Sports Med	52	16	10.1136/bjsports-2017-097730 T	Hakkinen 2018	Statistical study. No splitting data
Bond CW; Dorman JC; Olin ry TO; Roggenbuck SJ; Young SW; Mena TA	Evaluation of the Functional Movement Screen and a Novel Basketball Mobility Test as an Injury Prediction Tool for Collegiate Basketball Players.	2019	J Strength Cond Res	33	6	10.1519/JSC.0000000000001944	Bond 2019	Statistical study. No splitting data
Hulin JA; Stanton WR	Predicting football injuries using size and speed of the midfielder and quadriceps tendinosis muscles.	2017	Scand J Med Sci Sports	27	4	10.1111/sms.12643	Hulin 2017	Statistical study. No splitting data
Pau i BM; Zimny K; Schwartzk WI	Analysis of Gaunlet Test Performance and Injury Risk in Intercollegiate Division I Female Soccer (Football) Players: A Retrospective Study.	2017	J Sport Rehabil	26	6	10.1123/jsr.2017-0097	Nino 2017	Statistical study. No splitting data
Bacon CS; Manger AB	Prediction of Overuse Injuries in Professional U18-U21 Footballers Using Metrics of Training Distance and Intensity.	2017	J Strength Cond Res	31	11	10.1519/JSC.0000000000001744	Bacon 2017	Statistical study. No splitting data
Teo EC; Klinghiel JF; Collins R; Lambert ME; Cooper Y	Preseason Functional Movement Screen Component Tests Predict Severe Contact Injuries in Professional Rugby Union Players.	2016	J Strength Cond Res	30	11	10.1519/JSC.0000000000001422	Teo 2016	Statistical study. No splitting data
Martin C; Olivier B; Benjamin N	The Functional Movement Screen in the Prediction of Injury in Adolescent Cricket Pace Bowlers: An Observational Study.	2017	J Sport Rehabil	26	5	10.1123/jsr.2015-0073	Martin 2017	Wrong setting
Clay H; Manuel J; Tumey R	Association between rowing injuries and the functional movement screen™ in female collegiate division I rowers	2016	Int J Sports Phys Ther	11	3		Clay 2016	Statistical study. No splitting data
Chimera NJ; Warne M	Use of clinical movement screening tests to predict injury in sport.	2016	World J Orthop	7	4	10.5312/wjo.v7.i4.202	Chimera 2016	Statistical study. No splitting data
Hamano D; Aso dar Fitr an K; Barrat M; Meyer T	Injury prediction in volunte football players using the Functional Movement Screen™.	2016	J Sports Sci	34	14	10.1080/02640414.2016.1152390	Hamano 2016	Statistical study. No splitting data
Gribble PA; Terada M; Beard MQ; Kevin KB; Lapley AS; McCann RS; Pietrosimone BG; Thomas AC	Prediction of Lateral Ankle Sprains in Football Players Based on Clinical Tests and Body Mass Index.	2016	Am J Sports Med	44	2	10.1177/0363546515614585	Gribble 2016	Statistical study. No splitting data
Bardaxi SM; Maca JI; DeNoyelle JT; Miller SD; Jenk DT; Brooks GS	Functional movement screen normative values and validity in high school athletes: Can the FMS™ be used as a predictor of injury?	2015	Int J Sports Phys Ther	10	3		Bardaxi 2015	Statistical study. No splitting data
Garrison M; Westrick R; Johnson MR; Bunnerson J	Association between the functional movement screen and injury development in college athletes.	2015	Int J Sports Phys Ther	10	1		Garrison 2015	Statistical study. No splitting data
Kiesel KB; Butler RJ; Plisky PJ	Prediction of Injury by limited and asymmetrical functional movement patterns in american football players.	2014	J Sport Rehabil	23	2	10.1123/jsr.2013-0030	Kiesel 2014	Statistical study. No splitting data
McDonough A; Funk L	Can glenohumeral joint isokinetic strength and range of movement predict injury in professional rugby league.	2014	Phy s Ther Sport	15	2	10.1016/j.ptsp.2013.07.001	McDonough 2014	Statistical study. No splitting data
Lehr ME; Plisky PJ; Butler RJ; Fink ML; Kiesel KB; Underwood FB	Field-expedient screening and injury risk algorithm categories as predictors of noncontact lower extremity injury.	2013	Scand J Med Sci Sports	23	4	10.1111/sms.12 062	Lehr 2013	Statistical study. No splitting data
Mann KJ; Edwards S; Dankwart EJ; Hoff SP	A lower limb assessment tool for athletes at risk of developing patellar tendinopathy.	2013	Med Sci Sports Exerc	45	3	10.1249/MSS.0b013e31827 5e02	Mann 2013	Statistical study. No splitting data
Kennedy MD; Fisher B; Faubert-Kelly K; Lefebvre L; Vickery L; Molzan J; Parent E	Can pre-season fitness measures predict time to injury in varsity athletes? A retrospective case control study.	2012	Sports Med Arthrosc Rehabil Ther Technol	4	1	10.1186/1758-2555-4-26	Kennedy 201 2	Statistical study. No splitting data
Myer GD; Ford KR; Hunt JL; Hewett TE	An integrated approach to change the outcome part 2: neuromuscular screening methods to identify high ACL injury risk athletes.	2012	J Strength Cond Res	26	8	10.1519/JSC.0b013e318256d 16f	Myer 2012	Wrong outcomes
Gabbett TJ	The development and application of an injury prediction model for noncontact, soft-tissue injuries in elite collision sport athletes.	2010	J Strength Cond Res	24	10	10.1519/JSC.0b013 e3181 f1904	Gabbett 2010	Statistical study. No splitting data
Gribble PA; Nelson BT; Bandy WD	Predictive validity of an injury screening high school basketball players.	1997	Mid Sci Sports Exerc	29	10	10.1097/00005768-199710000-00001	Gribble 1997	Statistical study. No splitting data
Gamal DF; Wallar AJ; Bird YN	The New Zealand Rugby Injury and Performance Project II: Previous injury experience of a high-playing cohort.	1994	Br J Sports Med	28	4	10.1136/bjsm.28.4.229	Gamal 1994	Statistical study. No splitting data
Magee, L.; McCulloch, P.; Lambert, B.	Intrinsic Anthropometric Factors are Associated with Bone Stress Injuries in Collegiate Distance Runners: New Risk Metrics & Screening Tools?	2022	Orthopaedic Journal of Sports Medicine	10	7	10.1177/23259671211500685	Magee 2022	Wrong setting
Danj, F.; MacDonald, K.; Hunt, M.A.; Taunton, J.; Scott, A	Assessing Acute Chronic Workload Ratio Methodologies for the Prediction of Knee Pain in Mens Elite Volleyball	2022	Clinical Journal of Sport Medicine	32	3	10.1097/JSM.0000000000001035	Danj 2022	Wrong setting
Tahir, S.; Terk, S.; Tahereen, S.; Dominna, S.; Tojima, M.; Otomo, M.; Hiroka, S.; Tanaka, S.	Is Increased Kicking Leg Hip-to-on Muscle Tightness a Predictive Factor for Developing Spondylolysis in Adolescent Male Soccer Players?	2022	Clinical Journal of Sport Medicine	32	2	10.1097/JSM.0000000000000920	Tahir 2022	Statistical study. No splitting data
Tonanzu, U.; Ivanov, A.; Johnson, U.; Weiss, N.; Samuelson, M.; Skillgate, E.	The role of muscle of functional tests and psychological factors on prediction of injuries in adolescent female football player	2022	International Journal of Environment Research and Public Health	19	1	10.3390/ijerph19010143	Tonanzu 2022	Statistical study. No splitting data
Xue, M.; Liu, Y.; Cai, X.	Automated Detection Model Based on Deep Learning for Knee Joint Motion Injury due to Martial Arts	2022	Computational and Mathematical Methods in Medicine			10.1155/2022/2364 7 152	Xue 2022	Wrong outcomes
Ahdmad, T.A.; Tierney, A.C.; Cahalan, R.M.; Alandlds, N.S.; Clifford, A.M.	Injury risk profiles of amateur Irish women soccer players and players' opinions on risk factors and prevention strategies	2021	Phy sical Therapy in Sport	50		10.1016/j.ptsp.2021.05.008	Ahdmad 2021	Statistical study. No splitting data
Wanz, J.P.; Gruber, A.H.; Chaung, B.; Hennec, J.	Training and technique exclusion predict all reported running injuries: An international study	2021	Phy sical Therapy in Sport	48		10.1016/j.ptsp.2020.12.017	Wanz 2021	Statistical study. No splitting data
Hanner, T.; Wiggins, W.; Chaynton, J.; Herman, D.	Prediction of lower extremity overuse injuries in collegiate football players using outcomes-tive performance testing	2020	Clinical Journal of Sport Medicine	30	2	10.1097/JSM.0000000000000828	Hanner 2020	Wrong setting
Kanzy, S.J.; Palacios-Derflingher, L.; Shi, Q.; Whittaker, J.L.; Emery, C.A.	Association between Previous Injury and Risk Factors for Future Injury in Preprofessional Ballet and Contemporary Dancers	2019	Clinical Journal of Sport Medicine	29	3	10.1097/JSM.0000000000000513	Kanzy 2019	Statistical study. No splitting data
Roddy, J.; Murae, N.; Cormack, S.; Timmins, R.; Opie, D.	Predictive modelling of non-contact lower limb injuries in elite Australian footballers	2018	Journal of Science and Medicine in Sport	21		10.1016/j.jsam.2018.09.042	Roddy 2018	Wrong setting
Vasina Kirbiska, S.; Pullmanbian, K.; Sudbalez, S.; Ramanathan, S.; Martieza, M.; Ramanthan, K.; Bhanuvanthanm, T.	Does the Y-balance test predict lower extremity injury among volleyball players?	2018	Records: Journal of Pharmacy and Technology	11	4	10.5958/0974-360X.2018.00295.0	Vasa dKirbiska 2018	Statistical study. No splitting data
Szygowicz, M.; Mohalowska, M.; Walczak, T.; Owen, A.; Grabski, J.K.; Pyda, A.; Piontek, T.; Kotwicki, T.	Discussion about different cut-off values of conventional hamstring-to-quadriceps ratio used in hamstring injury prediction among professional male football players	2017	PLoS ONE	12	12	10.1371/journal.pone.0188974	Szygowicz 2017	Wrong outcomes
Schultz, A.B.; Tauffe, D.R.; Blackburn, M.; Logan, P.; White, D.; Drew, M.; Leskie, R.G.	Musculoskeletal screening as a predictor of seasonal injury in elite Olympic dans uniform	2016	Journal of Science and Medicine in Sport	19	11	10.1016/j.jsam.2016.02.011	Schultz 2016	Statistical study. No splitting data
Wilkerson, G.B.; Colston, M.A.; Baker, C.S.	A sport fitness index for assessment of sport-related injury risk	2016	Clinical Journal of Sport Medicine	26	5	10.1097/JSM.0000000000000250	Wilkerson 2016	Statistical study. No splitting data
Bergeron, B.; Mathis, B.; Nye, S.; Pace, K.B.E.; Vanoudis, S.; Vandeusen, S.M.P.; Stasi, F.F.	Can two-dimensional video analysis during single-leg drop vertical jump help identify non-contact knee injury risk? A one-year prospective study	2015	Clinical Biomechanics	30	8	10.1016/j.clinbiomech.2015.04.013	Qing mie 2015	Statistical study. No splitting data
Yu-an, C.; Edmond, S.; Deanh, J.	Dynamic standing balance is a predictor of lower extremity musculoskeletal injury in collegiate cross-country	2015	NASBA Journal	29	1	https://doi.org/10.1080/kaske.2015.supplement.001.8	Yuan 2015	Wrong setting
Arzani, M.G.; Thieschmann, T.W.; Smith, B.A.; Graham, D.; Sabelkic, J.; Anne, F.M.	The Functional Movement Screen as a predictor of injury in professional basketball players	2015	Current Orthopaedic Practice	26	6	10.1097/BCO.0000000000000296	Arzani 2015	Statistical study. No splitting data
Wilkerson, G.B.; Giles, JL.; Seibel, D.K.	Prediction of core and lower extremity strains and sprains in collegiate football players: a preliminary study.	2012	Journal of athletic training	47	3	https://doi.org/10.4085/1062-6050-47.3.15	Wilkerson 2012	Statistical study. No splitting data
Alkjarov, A.; Pauar-Ehrmais, J.; Bahor, J.	Understanding trends and risk factors of swimming-related injuries in varsity swimmers	2012	Clinical Kinesiology	66	2		Alkjarov 2012	Statistical study. No splitting data
Wilkerson, G.B.; Jenkins on, D.M.	Validation of an injury prediction model for college football players	2012	Journal of Science and Sport Medicine	22	2	10.1097/JSM.0b013e31824a01a	Wilkerson 2012	Wrong setting
Van Mechelen, M.; Kolkman, J.; Van Odiren, J.; Bloma-Zeinstra, S.M.A.; Koes, B.W.	Causes and predicting factors of lower extremity injuries during military training among rec uits	2007	Clinical Journal of Sport Medicine	17	1	10.1097/JSM.0b013e31803056e6	VanMechelen 2007	Statistical study. No splitting data
Gabbe, B.J.; Bennell, K.L.; Finch, C.F.	Why are older Australian football players at greater risk of hamstring injury?	2006	Journal of Science and Medicine in Sport	9	4	10.1016/j.jsam.2006.01.004	Gabbe 2006	Statistical study. No splitting data
Gabbe, B.J.; Finch, C.F.; Bennell, K.L.; Wajswelner, H.	Risk factors for hamstring injuries in community-level Australian football	2005	British Journal of Sports Medicine	39	2	10.1136/bjsm.2003.011197	Gabbe 2005	Statistical study. No splitting data
McGuine, T.A.; Greene, J.J.; Best, T.; Leverson, G.	Balance as a predictor of ankle injuries in high school basketball players.	2000	Clinical journal of sport medicine : official journal of the Canadian Academy of Sport Medicine	10	4		McGuine 2000	Statistical study. No splitting data
Bennell, K.; Tully, E.; Harvey, N.	Does the toe touch test predict hamstring injury in Australian Rules footballers?	1999	Australian Journal of Physiotherapy	45	2	10.1016/S0004-9514(14)60342-1	Bunnell 1999	Statistical study. No splitting data
Macan, C.	Prediction of injury in female elbull players.	1996	Clinical journal of sport medicine : official journal of the Canadian Academy of Sport Medicine	6	1	10.1097/00042752-199601000-00018	Macan 1996	Wrong setting
Song, Y. Sivasamy, G	Remote Sports Injury Monitoring using Wireless Sensor Networks	2022	Mobile Networks & Applications			10.1007/s11036-022-02020-2&a		Wrong outcomes
Huang, C.; Jiang, L.	Data mining-based sports injury prediction model based on embedded system and machine learning algorithm	2021	Microprocessors and Microsystems	81		10.1016/j.micpro.2020.103654	Huang 2021	Wrong setting
Song, HS.; Bin, XY.; Montenegro-Marin, CE; Kadiswaran orthy, S	Sitcup prediction and assessment of sports injuries using deep learning-based convolutional neural network	2021	Journal of Ambient Intelligence and Humanized Computing	12	3	10.1007/s12652-020-02025-6&4	Song 2021	Wrong study design
Wilkerson, GB; Gupta, A; Colston, MA	Mitigating Sports Injury Risk Using Internet of Things and Analytics Approaches	2018	Risk Analysis	38	7	10.1111/risa.12984	Wilkerson 2018	Statistical study. No splitting data
Colby, MJ; Dawson, B; Peeling, P; Heasman, J; Rogalski, B; Drew, MK; Stares, J; Zouhal, H; Lester, L	Multivariate modelling of subjective and objective monitoring data improves the detection of non-contact injury risk in elite Australian footballers	2017	Journal of Science and Medicine in Sport	20	12	10.1016/j.jsam.2017.05.010	Colby 2017	Statistical study. No splitting data
HSD, Nagla, A; Khalil, S; Mahmoud, A; Ghanem, A; Ghanem, M; Jones, P; Mosey, T; Humphrey, AS; El-Ana, A	Athlete-Customized Injury Prediction using Training Load Statistical Records and Machine Learning	2018	IEEE International Symposium on Signal Processing and Information Technology (ISSPIT)			10.1109/ISSPIT.2018.8642733	IEEE 2018	Wrong setting
Lisman, P.; Hildebrand, E; Nadelen, M; Leppert, K.	Association of Functional Movement Screen and Y-Balance Test Scores With Injury in High School Athletes	2021	Journal of Strength and Conditioning Research	35	7	10.1519/JSC.0000000000001062	Lisman 2021	Statistical study. No splitting data
Dyar, CS; Callison, R; Sanctuary, CE; Snodgrass, SJ	Functional Movement Screening and injury risk in elite adolescent rugby league players	2019	International Journal of Sports Science & Coaching	14	4	10.1177/1747954119853650	Dyar 2019	Statistical study. No splitting data
Stiffler, MR; Bell, DR; Sanfilippo, JL; Hetzel, SJ; Pickett, KA; Heidenscheit, BC	Star Excursion Balance Test Anterior Asymmetry Is Associated With Injury Status in Division I Collegiate Athletes	2017	Journal of Orthopaedic & Sports Physical Therapy	47	5	10.2519/jospt.2017.6974	Stiffler 2017	Statistical study. No splitting data
Galambos, SA; Terry, PC; Moyle, GM; Locke, SA	Psychological predictors of injury among elite athletes	2005	British Journal of Sports Medicine	39	6	10.1136/bjsm.2005.018440	Galambos 2005	Statistical study. No splitting data
Tabashiasi, SM; Danesharasi, H; Nikneshi, AA; Nia, HS	Functional Movement Screening Tests for the Prediction of Injuries in Volleyball: A Qualitative Study	2018	Annals of Applied Sport Science	6	4	https://dx.doi.org/10.29252/aassjournal.6.4.45	Tabashiasi 2018	Statistical study. No splitting data
Yang, G. Xu, X.	Sequence Video and Artificial Intelligence-assisted Basketball Injury Risk Early Warning Method	2022	Mobile Information Systems			10.1155/2022/2347738 145	Yang 2022	Wrong setting
Gupta, A; Wilkerson, GB; Sharda, R; Colston, MA	Who is More Injury-Prone? Prediction and Assessment of Injury Risk	2019	Decision Sciences	50	2	10.1111/dec.12333	Gupta 2019	Statistical study. No splitting data
Mostuoun, BB; Mitchell, CH; Johnson, AW; Fellingham, GW; Toland, JB; Myer, JW	Preseason Scans Cannot Predict Injury over Three Years of College Football	2020	Medicine & Science in Sports & Exercise	52	11	10.1249/MSS.0000000000002392	Mostuoun 2020	Statistical study. No splitting data
Shao, Z; Zhong, YY; Yu, ZX; Chu, XP	An Improved Neural Network Model for Early Detection of Joint Injuries in Tai Chi Sports	2022	Mobile Information Systems			10.1155/2022/8476 803	Shao 2022	Wrong outcomes
Kolodiaj, M. Jatror, T	Single Functional Movement Screen items as main predictors of injury risk in amateur male soccer players	2018	German Journal of Exercise and Sport Research	48	3	10.1007/s12662-018-0515-2	Kolodiaj 2018	Statistical study. No splitting data
Vallej, J.T; Lynagh, M; Tuna, B; Zadsaria, A; Townsley, A Glanson, C; Milanoa, S; Chalean, S	Functional Movement Screen Pain Location and Impact on Scoring Have Limited Value for Injury Risk Estimation in Junior Australian Football Players	2020	Journal of Orthopaedic & Sports Physical Therapy	50	2	10.2519/jospt.2020.9168	Fisher 2020	Statistical study. No splitting data
Jacobs, EI; Hardt, MI	Peak Torso and Lower Extremity Overuse Injury in Collegiate Track and Field and Cross Country Athletes	2022	Sports	10	3	10.3390/sports10030045	Lund kvi 2022	Statistical study. No splitting data
Stone, AD; Hiller, CE; Rae, K; Linklater, J; Mordlaz, J; Tirel, N; Nicholson, LL; Black, DA; Refshauge, KM	Predictive factors for ankle syndesmosis injury in football players: A prospective study	2014	Journal of Science and Medicine in Sport	17	6	10.1016/j.jsam.2013.12.009	Stone 2014	Statistical study. No splitting data
Kvorane, K; Flanagan, M; Bronar, J; Durall, C	The Accuracy of the Functional Movement Screen to Identify Individuals With an Elevated Risk of Musculoskeletal Injury	2014	Journal of Sport Rehabilitation	23	4	10.1123/jsr.2013-3002T	Knonva 2014	Wrong study design
Smith, PD; Hanlon, MP	Assessing the effectiveness of the functional movement screen in predicting noncontact injury amo ng soccer players	2017	Journal of Strength and Conditioning Research	31	12	10.1519/JSC.0000000000001757	Smith 2017	Statistical study. No splitting data
Slirk, M; Loka, D; Svantne, B; Bruns, D; Bartik, P; Vuthova, L	The risk prediction of posterior hamstring muscle injury to top athletes in the Karate kata discipline	2022	Journal of Martial Arts Anthropology	22	4	10.14589/do.22.4.3	Slirk 2022	Statistical study. No splitting data
Lucche, LE; Gerdsmith, TW; Rado, MJ	Y-Balance Test Performance Does Not Determine Non-Contact Lower Quadrant Injury in Collegiate Amateur Football Players	2020	Sports	8	3	10.3390/sports8030027	Lucche 2020	Statistical study. No splitting data
Chalmers, S; Debenedictis, T A; Zadsaria, A; Townsley, S; Glanson, C; Lynagh, M; Townsley, A Fuller, JT	Asymmetry during Functional Movement Screening and injury risk in junior football players: A replication study	2018	Scandinavian Journal of Medicine & Science in Sports	28	3	10.1111/sms.13021	Chalmers 201 8	Statistical study. No splitting data

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Authors	Title	Published Year	Journal	Volume	Issue	DOI	Study	Exclusion reason
Ajmi, DA; Rudzky, JD; Williams, MD; Mosier, N; Hlinsky, JT; Boonin, MN; Pitzul, T; Timmins, RG	Screening Hamstring Injury Risk Factors Multiple Times in a Season Does Not Improve the Identification of Future Injury Risk	2022	Medicine &Science in Sports & Exercise	54	2	10.1249/MSS.0000000000002782	Opaz 2022	Statistical study. No splitting data
Hewett, TE; Bowers, R; Ford, K; Myer, G	Multifactorial motion analysis for injury risk prediction: lessons learned from prospective longitudinal large cohort combined biomechanical - epidemiological studies	2015	Brazilian Journal of Physical Therapy	19	5	10.15 90/bjpt rbf20 14.0121	Hewett 201 5	Wrong outcomes
Olivier, B; Gray, J	Musculoskeletal prediction of non-contact injury in cricketers - Few and far between? A longitudinal cohort study	2018	Physical Therapy in Sport	34		10.10 16/j.ptsp.20 18.10.014	Olivier 201 8	Statistical study. No splitting data
Kolodziej, M; Nolte, K; Schmidt, M; Alt, T; Jaitner, T	Identification of Neuromuscular Performance Parameters as Risk Factors of Non-contact Injuries in Male Elite Youth Soccer Players: A Preliminary Study on 62 Players With 25 Non-contact Injuries	2021	Frontiers in Sports and Active Living	3		10.33 89/fspor.2021.615330	Kolodziej 2021	Statistical study. No splitting data
Mason, J; Wellmann, K; Groll, A; Braumann, KM; Jung, A; Hollander, K; Zech, A	Game Exposure, Player Characteristics, and Neuromuscular Performance Influence Injury Risk in Professional and Youth Field Hockey Players	2021	Orthopaedic Journal of Sports Medicine	9	4	10.11 77/2325 9671 21995167	Mason 202 1	Statistical study. No splitting data
Gaudet, S; Bagon, M; Tremblay, J	Cluster analysis using physical performance and self-report measures to identify shoulder injury in overhead female athletes	2019	Journal of Science and Medicine in Sport	22	3	10.10 16/j.jsma 2018.09.22 4	Gaudet 2019	Wrong setting
Cejudo, A; Cano-Díaz, A; de Baranda, PS	Asymmetry and Tightness of Lower Limb Muscles in Equestrian Athletes: Are They Predictors for Back Pain?	2020	Symmetry	12	10	10.33 90/sym1 2101 679	Cejudo 2020	Statistical study. No splitting data
Brumitt, J; Wilson, V; Ellis, N; Petersen, J; Zita, CI; Reyes, J	Posterior lower extremity functional limb scores are not associated with lower quadrant injury - A validation study with normative data on 395 division II athletes	2018	International Journal of Sports Physical Therapy	13	3	10.26 603/jspt20 180410	Brumitt 2018	Statistical study. No splitting data
Tomasi, G; Compere, T; Lyons, M; Nevill, AM; Watkinson, G	The Association Between Training Load Inflation and Injuries in Elite Soccer Players	2022	Journal of Strength and Conditioning Research	36	11	10.15 19/JSC.0000000000003914	Tomasi 2022	Statistical study. No splitting data
Lee, JW Y; 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	2018	Journal of Science and Medicine in Sport	21	8	10.10 16/j.jsma 2017.11.01 7	Lee 201 8	Statistical study. No splitting data
Delbiaggio, B; Radovanovic, S; Jovanovic, MZ; Obradovic, Z; Sukovic, S; Milic, B	A study on ski groups size and their relationship to the risk of injury	2022	Journal of Sports Engineering and Technology			10.11 77/1754337 1221118195		Wrong outcomes
Esteve, E; Casals, M; Suzi, M; Rathleff, MS; Clausen, MB; Vicens-Bordas, J; Holmich, P; Pitzul, T; Thorborg, K	Pain sources, pain scores and risk assessment of groin problems in male football players: a prospective follow-season study	2022	British Journal of Sports Medicine	56	9	10.11 36/bjsports-2020-1 02606	Esteve 2022	Statistical study. No splitting data
Markovic, G; Sarabon, N; Panic, J; Hadzic, V	Adductor Muscle Strength and Strength Asymmetry as Risk Factor for Groin Injuries among Professional Soccer Players: A Prospective Study	2020	International Journal of Environmental Research and Public Health	17	14	10.33 90/ijerph1 7144946	Markovic 2020	Statistical study. No splitting data
Swanevelder, S; Sevoy, N; Schwellnus, M; Jordaan, E	Predictors of multiple injuries in individual distance runners: A retrospective study of 75,401 entrants in 4 annual races-SAFER XX	2022	Journal of Sport and Health Science	11	3	10.10 16/j.jshs.20 21.11.002	Swanevelder 2022	Statistical study. No splitting data
Colston, MA; Wilkerson, GB; Dreyfus, H; Ross, R	Methods for Prediction of Core or Lower Extremity Injury Among High School Football Players as a Strategy for Longitudinal Reduction of Injury Risk	2018	International Journal of Athletic Therapy & Training	23	5	10.1123/ijatt.20 17-0085	Colston 201 8	Statistical study. No splitting data
IEEE, Kim, DY; Mendelapra, V; Bar, JM; Bodkin, S; Hostedter, N; Lach, J; Gong, JQ	Examining cross-validation strategies for predictive modeling of anterior cruciate ligament injury	2019	4TH IEEE/ACM International Conference on Connected Health: Applications, Systems and Engineering Technologies (CHASE)			10.11 09/CHASE48038.2019.0001 9	IEEE 2019	Wrong setting
IEEE, Pongjiyawate, AI; Ryoo, MS	Early Detection of Injuries in MLB Pitchers from Video	2019	IEEE CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)			10.11 09/CVPRW.2019.002 98	IEEE 2019	Wrong setting
Wilkerson, GB; Mokha, M	Neurocognitive Reaction Time Predicts Lower Extremity Sprains and Strains	2012	International Journal of Athletic Therapy & Training	17	6	10.1123/ijatt.17.6.4	Wilkerson 201 2	Statistical study. No splitting data
Davis, JJ; Grabyn, AH	Leg Stiffness, Joint Stiffness, and Running-Related Injury: Evidence From a Prospective Cohort Study	2021	Orthopaedic Journal of Sports Medicine	9	5	10.11 77/2325 9671 21101 11213	Davis 2021	Statistical study. No splitting data
Dabvandi, SM; Hosseinzadeh, M; Zuri, M; Bahrs, DG	Does ipsilateral and bilateral knee strength ratios predict lower extremity injuries of elite judokas: a prospective cohort study	2022	Research in Sports Medicine			10.1080/1543 8627.20 22.2126 777		Statistical study. No splitting data
Levanoni, IR; Dunn, KD; Sutherlin, MA; Dauty, A; Comins, S	Preseason Shoulder Disability Scores and the Ability to Identify Collegiate Swimmers Who Sustain Shoulder Injuries	2021	International Journal of Athletic Therapy & Training	26	6	10.1123/ijatt.2020-0111	Levanoni 2021	Statistical study. No splitting data
IEEE, Hatzandaki, C; Kodithuwakku, J; Manampuri, B; Bhatia, A; Silva, P	A Wearable System to Analyze the Human Arm for Predicting Injuries Due to Throwing	2019	41 ST Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)			10.11 09/EMBC.2019.88 57313	IEEE 2019	Statistical study. No splitting data
Lyon, SK; Padilla, BA; Tseng, KKW; Neffal, GI	Preoperative Injury Predictors Using The Functional Movement Screen In Division I Runners	2014	Medicine and Science in Sports and Exercise	46	5	10.12 49/01.mss.0000495341 .01578.55	Lyon 2014	Wrong setting
Whiteside, David; Martini, Douglas N.; Lepley, Adam S.; Zernicke, Ronald F.; Goulet, Grant C.	Predictors of Ulnar Collateral Ligament Reconstruction in Major League Baseball Pitchers	2016	The American Journal of sports medicine	44	9	10.11 77/0363 5465 1664 58	Whiteside 2016	Wrong outcomes
Abdo-Núñez, R.; Gutiérrez-Sánchez, A.; Pérez, M.; Iglesias, Yolanda-Santana, M.	Injury prediction in aerobic gymnastics based on anthropometric variables	2018	Science &Sports	33	4	https://doi.org/10.1016/j.scispo.2018.05.005	AbdoNúñez 2018	Statistical study. No splitting data
Cubvalus, Aaron F.; Sandoz, Zack; Fry, Andrew C.; Ryznyklo, Matthew R.; Magee, Lawrence M.	A simplified prediction model for lower extremity long bone stress injuries in male endurance running athletes	2020	Clinical Journal of Sport Medicine	30	5	10.1097/JSM.0000000000000661	Cubvalus 2020	Statistical study. No splitting data
Colby, Marcus J.; Dawson, Brian; Peeling, Peter; Heasman, Jarryd; Rogalski, Brent; Drew, Michael K.; Stares, Jordan	Improvement of prediction of noncontact injury in elite Australian footballers with repeated exposure to established high-risk workload scenarios	2018	International journal of sports physiology and performance	13	9	https://doi.org/10.1123/ijspp.2017-0686	Colby 2018	Statistical study. No splitting data
Feijen, Stef; Struyf, Thomas; Kuppens, Kevin; Tate, Angela; Struyf, Filip	Prediction of shoulder pain in youth competitive swimmers: the development and internal validation of a prognostic prediction model	2021	The American Journal of Sports Medicine	49	1	10.1177/0363 546520 96699 13	Feijen 2021	Statistical study. No splitting data
Ivarsson, Andreas; Johnson, Ulrika; Lindwall, Magnus; Gustafsson, Henrik; Altemyr, Mats	Psychosocial stress as a predictor of injury in elite junior soccer: a latent growth curve analysis	2014	Journal of Science and Medicine in Sport	17	4	https://doi.org/10.1016/j.jsma m.2013.10.243	Ivarsson 2014	Statistical study. No splitting data
Khayambashi, Khalil; Ghoddosi, Navid; Straub, Rachel K.; Powers, Christopher M.	Hip muscle strength predicts noncontact anterior cruciate ligament injury in male and female athletes: a prospective study	2016	The American Journal of sports medicine	44	2	https://doi.org/10.1177/0363 546515616116	Khayambashi 2016	Statistical study. No splitting data
McCann, Ryan S.; Kosik, Kyle B.; Tanaka, Masahiro; Bazett, Megan Q.; Bolognesi, Gretchen E.; Gribble, Phillip A.	Ankle lateral ankle sprain prediction in collegiate women's soccer players	2018	International Journal of Sports Physical Therapy	13	1	10.26 603/ijspt20 180013	McCann 2018	Statistical study. No splitting data
Portillo, Maria; Hines, Sherri M.; Sennett, Brian J.	Prediction of ACL injuries from vertical jump kinetics in Division 1 collegiate athletes	2021	International Journal of Sports Physical Therapy	16	1	https://doi.org/10.26603/001c.18310	Portillo 2021	Statistical study. No splitting data
Powers, Christopher M.; Ghoddosi, Navid; Straub, Rachel K.; Khayambashi, Khalil	Hip strength as a predictor of ankle sprains in male soccer players: a prospective study	2017	Journal of athletic training	52	11	https://doi.org/10.4085/1062-6050-52.11.18	Powers 2017	Statistical study. No splitting data
Shambaugh, J. PHILIP; Klein, Andrew; Herbert, John H.	Structural measures as predictors of injury basketball players.	1991	Medicine and science in sports and exercise	23	5		Shambaugh 1991	Statistical study. No splitting data
Starrick, Daniel B.; Vaida, Pamela M.; DiSarro, Michael J.; Gardner-Morse, Mack G.; Tourville, Timothy W.; Slauterbeck, James R.; Johnson, Robert J.; Shultz, Sandra J.; Bayuzick, Bruce D.	Combined anatomic factors predicting risk of anterior cruciate ligament injury for males and females	2015	The American Journal of sports medicine	43	4	https://doi.org/10.1177/0363 546514563574	Starrick 201 5	Statistical study. No splitting data
Tennonis, Maura; Cross, Chad L.; Cushman, Daniel M.; Mack, Travis G.; Petros, David J.; Willick, Stuart E.	Game injuries in relation to game schedules in the National Basketball Association	2017	Journal of science and medicine in sport	20	3	https://doi.org/10.1016/j.jsma m.2016.08.020	Tennonis 2017	Statistical study. No splitting data
Van Der Does, H. T. D.; Brink, M. S.; Benjaminse, Anne; Visscher, Chris; Lemmink, KAPM	Jump landing characteristics predict lower extremity injuries in indoor team sports	2016	International journal of sports medicine	37	3	10.1055/s-0035-1 598618	VanDerDoes 2016	Statistical study. No splitting data
Wisse, Brian William; Boone, Jonathan Keith; Matsuda, Carl Gino; McKeon, Patrick Owen; Uhl, Timothy Lee	Determination of the functional movement screen to predict musculoskeletal injury in intercollegiate athletes	2014	Athletic Training & Sports Health Care	6	4	https://doi.org/10.3928/19425936-20140715-01	Wisse 2014	Statistical study. No splitting data
Wilkerson, Gary B.; Colston, Marissa A.	Ankle taping and prophylaxis: a prospective test of traditional and new ankle taping methods	2015	Journal of athletic training	50	6	https://doi.org/10.4085/1062-6050-50.2.06	Wilkerson 201 5	Statistical study. No splitting data

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C Online supplemental: Table of the characteristics of the included studies of the scoping review

Author	Study design	Age (mean (SD))	Sample size	Sport	Level
G. Rodas 2019	Retrospective study	25 (6)	363	Soccer, futsal, basketball, handball and roller hockey	Professional
S. Jauhiainen 2022	Retrospective study	21 (4)	791	Soccer and handball	Elite
B. C. Luu 2020	Retrospective study	27	2322	Hockey	Professional
H. R. Thornton 2017	Prospective study	NS	25	Rugby	Professional
K. D. Peterson 2020	Retrospective study	NS	286	NCAA - team sports	D1
A. Cohan 2021	Retrospective study	NS	NS	Basketball	NBA
A. Hecksteden 2022	Prospective study	24.6 (3.5)	88	Soccer	Professional
J. Briand 2022	Prospective study	21 (2)	11	Short-track speed skating	International
J. McCullagh 2013	Prospective study	NS	39	Australian football league	Elite
J. D. Ruddy 2018	Prospective study	24 (3.5)	362	Australian football league	Elite
D. L. Carey 2018	Prospective study	NS	75	Australian football league	Professional
E. Vallance 2020	Prospective study	29.4 (5.8)	40	Soccer	French Ligue 2
L. Goggins 2022	Prospective study	18.2 (1.9)	17	Cricket	International
N. Rommers 2020	Prospective study	11.7 (1.7)	734	Soccer	Elite
A. Rossi 2018	Prospective study	24.7 (4.3)	18	Soccer	Elite
M. Mansouri 2022	Prospective study	20 (1.46)	74	American football	NCAA
A. Lyubovsky 2022	Prospective study	NS	101	American football	NCAA
A. López-Valenciano 2018	Prospective study	NS	132	Soccer and handball	Professional
A. Rossi 2021	Prospective study	26 (4)	26	Soccer	Professional
F. Ayala 2019	Prospective study	NS	96	Soccer	Professional
J. L. Oliver 2020	Prospective study	14.3 (2.1)	355	Soccer	Elite
S. Jauhiainen 2020	Prospective study	16 (+/-1.6)	314	Basketball and soccer	NS
J. Karuc 2021	Prospective study	NS	192	NS	NS
I. Ruiz-Pérez 2021	Prospective study	22.5 (5.4)	139	Futsal	Elite
S. Lovdal 2021	Prospective study	NS	77	Runners long and middle distances	national or international
M. Mandorino 2021	Prospective study	13.5 (0.3)	22	Soccer	Sub-elite
Y. Huang 2022	Prospective study	16.6 (1.3)	16	Basketball	National
C. Richter 2021	Retrospective study	NS	Train set : 218 Test set : 822	Train set : rugby and football Test set : Soccer and handball	Elite

NS: Not specified; NCAA : National Collegiate Athletic Association

Author	Type of data collection	Measurement Frequency	Period of the follow-up	Number of observations	Number of outcomes (injuries for monitoring/ injured for screening)
G. Rodas 2019	Screening	Once	10 seasons (2008-2018)	363	NS / 199
S. Jauhiainen 2022	Screening	Once	9 years (2007-2015)	791	60 / NS
B. C. Luu 2020	Monitoring	Game session	10 years (2007-2017)	NS	players (6673), goalies (309) / NS
H. R. Thornton 2017	Monitoring	Training and matches sessions	3 years (2013, 2014, 2015)	NS	156 / NS
K. D. Peterson 2020	Monitoring	Weekly	1 season (2017-2018)	286	52 / NS
A. Cohan 2021	Monitoring	Game session	10 years (2010-2020)	±125000	5000 / NS
A. Hecksteden 2022	Monitoring and screening	Monitoring: Daily Screening: Once	9 months (2019-2020)	17218	Acute non-contact and time-loss (51) / NS
J. Briand 2022	Monitoring	From daily to 3 times a week	2 seasons (2018-2020)	7370	NS / NS
J. McCullagh 2013	Monitoring and screening	Monitoring: Weekly Screening : Once	1 season (2010)	1210	163 / NS
J. D. Ruddy 2018	Screening	Once	2 seasons (2013, 2015)	2013 (186), 2015 (176)	NS / 2013 (27), 2015 (26)
D. L. Carey 2018	Monitoring	Training and competitions sessions	3 seasons (2014-2016)	2014-2015 (9203), 2016 (4664)	Non contact injury (388), non contact time loss (198), hamstring (49), non-contact lag (1601), non-contact time loss lag (784), hamstring lag (183) / NS
E. Vallance 2020	Monitoring and screening	Monitoring: Training and games sessions Screening: Once	1 season (2017-2018)	training session (245), matches (43)	142 / 33
L. Goggins 2022	Monitoring	Daily	17 months (2018-2019)	6027	50 / 16
N. Rommers 2020	Screening	Once	1 season (2017-2018)	734	NS / 368
A. Rossi 2018	Monitoring	Training session	2 seasons (2017-2018, 2018-2019)	NS	28
M. Mansouri 2022	Screening	Once	4-week pre-season practice period and 12 games	NS	64 / 41
A. Lyubovsky 2022	Monitoring	Daily	113 days (2019)	316	173 / NS
A. López-Valenciano 2018	Screening	Once	9 months (2013-2014)	120	32 / 29
A. Rossi 2021	Monitoring	Training session	23 weeks (2013-2014)	952	23 / 13
F. Ayala 2019	Screening	Once	9 months (2013-2014)	86	NS / 18
J. L. Oliver 2020	Screening	Once	10 months (2014-2015)	355	NS / 99
S. Jauhiainen 2020	Screening	Monitoring: Monthly Screening: Once	3 years (2011-2013)	314	57 / 78
J. Karuc 2021	Screening	Once	1 year (2015-2016)	192	NS / 49
I. Ruiz-Pérez 2021	Screening	Once	9 months (2015-2018)	139	31 / 31
S. Lovdal 2021	Monitoring	Daily and weekly	7 years (2012-2019)	Day approach (42183), week approach (42223)	Day approach (583 / NS), week approach (575 / NS)
M. Mandorino 2021	Monitoring and screening	Monitoring: Training and competition sessions (4 times a week) Screening: Once	1 season (2018-2019)	NS	Soft tissue injuries (40), muscle strain injuries (27) / NS
Y. Huang 2022	Monitoring	Daily, weekly and monthly	20 weeks	1813	27 / NS
C. Richter 2021	Screening	Once	NS	Train set (468), test set (4932)	Train set (156), test set (55) / train set (156), test set (55)

D Online supplemental: Risk of Bias assessment of the included studies using PROBAST

Study	ROB				Applicability			Overall	
	Participants	Predictors	Outcome	Analysis	Participants	Predictors	Outcome	ROB	Applicability
Ayala 2019 Int J Sports Med	+	?	-	-	+	+	+	-	+
Briand 2022 FSAL	?	?	-	-	+	+	+	-	+
Carey 2018 Int J Computer Sci Sport	?	?	?	-	+	+	+	-	+
Cohan 2021 J Sports Analytics	?	-	-	?	+	+	-	-	-
Goggins 2022 Int J Sports Med	+	?	?	-	+	+	+	-	+
Hecksteden 2022 Science Med Football	?	?	?	-	+	+	+	-	+
Huang 2022 Frontiers in Physiology	?	?	?	-	+	+	+	-	+
Jauhiainen 2022 Am J Sports Med	+	?	?	-	+	+	+	-	+
Jauhiainen 2020 Int J Sports Med	+	?	-	-	+	+	+	-	+
Karuc 2021 J Strength Cond Res	+	?	-	-	+	+	+	-	+
Lopez-Valenciano 2018 Med Sci Sports Exerc	+	?	?	-	+	+	+	-	+
Lovdal 2021 Int J Sports Physiol Perform	?	?	?	?	+	+	?	?	?
Luu 2020 Orthop J Sports Med	?	?	?	-	+	?	?	-	?
Lyubovsky 2022 Smart Health	?	-	?	-	+	+	+	-	+
Mandorino 2021 Sports (Basel)	+	+	?	-	+	+	+	-	+
Mansouri 2022 Sports Orthop Traumatol	?	?	?	-	+	+	?	-	?
McCullagh 2013 IJSHS	+	?	?	-	+	+	+	-	+
Oliver 2020 J Sci Med Sport	+	?	?	-	+	+	+	-	+
Peterson 2020 J Complex Networks	?	?	?	-	?	+	?	-	?
Richter 2021 Sports Biomech	+	-	-	?	+	+	?	-	?
Rodas 2019 Int J Sports Physiol Perform	+	?	?	-	+	+	+	-	+
Rommers 2020 Med Sci Sports Exerc	+	?	?	-	+	+	+	-	+
Rossi 2018 PLoS One	?	?	?	-	?	+	+	-	?
Rossi 2022 Sports Science for Health	+	?	?	-	+	+	+	-	+
Ruddy 2018 Med Sci Sports Exerc	+	-	?	-	+	+	+	-	+
Ruiz-Perez 2021 Frontiers in Physiology	+	?	?	-	+	+	+	-	+
Thornton 2016 Int J Sports Physiol Perform	?	?	?	-	+	+	+	-	+
Vallance 2020 MDPI Appl Sc	?	?	?	-	+	+	?	-	?

E Online supplemental: Table of the data extracted of the included studies of the scoping review

Author	Type of data collection	Time Management	Method validation	Cross-validation with fold number	Error / Imbv Sampling strategy	Ensemble method	Feature(s) number (trial)	Model Extracted	Model Categories	Accuracy	Specificity	Recall	Precision	ROC-AUC	F1-score
J. McCullagh 2013	Monitoring and screening	Time windows	Internal	CV	NU	NU	30	ANN	ANN	0.82	0.81	0.94	NS	NS	NS
K. C. Lau 2020	Monitoring	NS	External	CV	NU	NU	35 (players)	LR	LR	(mean) 0.95	NS	NS	NS	(mean) 0.94	(mean) 0.94
K. C. Lau 2020	Monitoring	NS	External	CV	NU	Bagging	35 (players)	RF	RF	(mean) 0.95	NS	NS	NS	(mean) 0.94	(mean) 0.94
K. C. Lau 2020	Monitoring	NS	External	CV	NU	NU	35 (players)	KNN	KNN	(mean) 0.70	NS	NS	NS	(mean) 0.75	(mean) 0.94
K. C. Lau 2020	Monitoring	NS	External	CV	NU	NU	35 (players)	NB	NB	(mean) 0.85	NS	NS	NS	(mean) 0.92	(mean) 0.78
K. C. Lau 2020	Monitoring	NS	External	CV	NU	Boosting	35 (players)	XGBoost	XGBoost	(mean) 0.95	NS	NS	NS	(mean) 0.95	(mean) 0.94
K. C. Lau 2020	Monitoring	NS	External	CV	NU	Bagging	35 (players)	Top 3 Ensemble	Top 3 Ensemble	(mean) 0.95	NS	NS	NS	(mean) 0.95	(mean) 0.94
K. C. Lau 2020	Monitoring	NS	External	CV	NU	NU	14 (goalies)	LR	LR	(mean) 0.97	NS	NS	NS	(mean) 0.95	(mean) 0.92
K. C. Lau 2020	Monitoring	NS	External	CV	NU	NU	14 (goalies)	RF	RF	(mean) 0.97	NS	NS	NS	(mean) 0.94	(mean) 0.92
K. C. Lau 2020	Monitoring	NS	External	CV	NU	NU	14 (goalies)	KNN	KNN	(mean) 0.81	NS	NS	NS	(mean) 0.82	(mean) 0.62
K. C. Lau 2020	Monitoring	NS	External	CV	NU	NU	14 (goalies)	NB	NB	(mean) 0.94	NS	NS	NS	(mean) 0.94	(mean) 0.87
K. C. Lau 2020	Monitoring	NS	External	CV	NU	Boosting	14 (goalies)	XGBoost	XGBoost	(mean) 0.97	NS	NS	NS	(mean) 0.96	(mean) 0.92
K. C. Lau 2020	Monitoring	NS	External	CV	NU	Bagging	14 (goalies)	Top 3 Ensemble	Top 3 Ensemble	(mean) 0.97	NS	NS	NS	(mean) 0.95	(mean) 0.95
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	NU	NU	58 (UPD HS)	GEE	GEE	NS	NS	NS	NS	(mean) 0.65	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	NU	NU	58 (UPD HS)	LR	LR	NS	NS	NS	NS	(mean) 0.72	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	NU	Bagging	58 (UPD HS)	RF	RF	NS	NS	NS	NS	(mean) 0.51	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	NU	NU	58 (UPD HS)	SVM	SVM	NS	NS	NS	NS	(mean) 0.53	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	NU	NU	58 (UPD NC)	GEE	GEE	NS	NS	NS	NS	(mean) 0.61	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	NU	NU	58 (UPD NC)	LR	LR	NS	NS	NS	NS	(mean) 0.61	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	NU	Bagging	58 (UPD NC)	RF	RF	NS	NS	NS	NS	(mean) 0.62	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	NU	NU	58 (UPD NC)	SVM	SVM	NS	NS	NS	NS	(mean) 0.55	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	NU	NU	58 (UPD NCTL)	GEE	GEE	NS	NS	NS	NS	(mean) 0.61	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	NU	NU	58 (UPD NCTL)	LR	LR	NS	NS	NS	NS	(mean) 0.60	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	NU	Bagging	58 (UPD NCTL)	RF	RF	NS	NS	NS	NS	(mean) 0.60	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	NU	NU	58 (UPD NCTL)	SVM	SVM	NS	NS	NS	NS	(mean) 0.56	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	NU	NU	58 (UPD HS lag)	GEE	GEE	NS	NS	NS	NS	(mean) 0.54	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	NU	NU	58 (UPD HS lag)	LR	LR	NS	NS	NS	NS	(mean) 0.55	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	NU	Bagging	58 (UPD HS lag)	RF	RF	NS	NS	NS	NS	(mean) 0.52	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	NU	NU	58 (UPD HS lag)	SVM	SVM	NS	NS	NS	NS	(mean) 0.52	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	NU	NU	58 (UPD NC lag)	GEE	GEE	NS	NS	NS	NS	(mean) 0.50	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	NU	NU	58 (UPD NC lag)	LR	LR	NS	NS	NS	NS	(mean) 0.55	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	NU	Bagging	58 (UPD NC lag)	RF	RF	NS	NS	NS	NS	(mean) 0.56	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	NU	NU	58 (UPD NC lag)	SVM	SVM	NS	NS	NS	NS	(mean) 0.55	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	NU	NU	58 (UPD NCTL lag)	GEE	GEE	NS	NS	NS	NS	(mean) 0.50	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	NU	NU	58 (UPD NCTL lag)	LR	LR	NS	NS	NS	NS	(mean) 0.54	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	NU	Bagging	58 (UPD NCTL lag)	RF	RF	NS	NS	NS	NS	(mean) 0.51	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	NU	NU	58 (UPD NCTL lag)	SVM	SVM	NS	NS	NS	NS	(mean) 0.51	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	NU	NU	14 (PCA HS)	GEE	GEE	NS	NS	NS	NS	(mean) 0.75	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	NU	NU	14 (PCA HS)	LR	LR	NS	NS	NS	NS	(mean) 0.75	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	NU	Bagging	14 (PCA HS)	RF	RF	NS	NS	NS	NS	(mean) 0.63	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	NU	NU	14 (PCA HS)	SVM	SVM	NS	NS	NS	NS	(mean) 0.60	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	NU	NU	14 (PCA NC)	GEE	GEE	NS	NS	NS	NS	(mean) 0.63	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	NU	NU	14 (PCA NC)	LR	LR	NS	NS	NS	NS	(mean) 0.63	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	NU	Bagging	14 (PCA NC)	RF	RF	NS	NS	NS	NS	(mean) 0.64	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	NU	NU	14 (PCA NC)	SVM	SVM	NS	NS	NS	NS	(mean) 0.57	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	NU	NU	14 (PCA NCTL)	GEE	GEE	NS	NS	NS	NS	(mean) 0.62	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	NU	NU	14 (PCA NCTL)	LR	LR	NS	NS	NS	NS	(mean) 0.63	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	NU	Bagging	14 (PCA NCTL)	RF	RF	NS	NS	NS	NS	(mean) 0.61	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	NU	NU	14 (PCA NCTL)	SVM	SVM	NS	NS	NS	NS	(mean) 0.57	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	RUS	NU	58 (Under HS)	GEE	GEE	NS	NS	NS	NS	(mean) 0.55	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	RUS	NU	58 (Under HS)	LR	LR	NS	NS	NS	NS	(mean) 0.63	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	RUS	Bagging	58 (Under HS)	RF	RF	NS	NS	NS	NS	(mean) 0.54	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	RUS	NU	58 (Under HS)	SVM	SVM	NS	NS	NS	NS	(mean) 0.62	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	RUS	NU	58 (Under NC)	GEE	GEE	NS	NS	NS	NS	(mean) 0.57	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	RUS	NU	58 (Under NC)	LR	LR	NS	NS	NS	NS	(mean) 0.61	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	RUS	Bagging	58 (Under NC)	RF	RF	NS	NS	NS	NS	(mean) 0.60	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	RUS	NU	58 (Under NC)	SVM	SVM	NS	NS	NS	NS	(mean) 0.64	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	RUS	NU	58 (Under NCTL)	GEE	GEE	NS	NS	NS	NS	(mean) 0.56	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	RUS	NU	58 (Under NCTL)	LR	LR	NS	NS	NS	NS	(mean) 0.61	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	RUS	Bagging	58 (Under NCTL)	RF	RF	NS	NS	NS	NS	(mean) 0.60	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	RUS	NU	58 (Under NCTL)	SVM	SVM	NS	NS	NS	NS	(mean) 0.63	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	SMOTE	NU	58 (Over HS)	GEE	GEE	NS	NS	NS	NS	(mean) 0.56	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	SMOTE	NU	58 (Over HS)	LR	LR	NS	NS	NS	NS	(mean) 0.69	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	SMOTE	Bagging	58 (Over HS)	RF	RF	NS	NS	NS	NS	(mean) 0.56	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	SMOTE	NU	58 (Over HS)	SVM	SVM	NS	NS	NS	NS	(mean) 0.67	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	SMOTE	NU	58 (Over NC)	GEE	GEE	NS	NS	NS	NS	(mean) 0.52	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	SMOTE	NU	58 (Over NC)	LR	LR	NS	NS	NS	NS	(mean) 0.61	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	SMOTE	Bagging	58 (Over NC)	RF	RF	NS	NS	NS	NS	(mean) 0.61	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	SMOTE	NU	58 (Over NC)	SVM	SVM	NS	NS	NS	NS	(mean) 0.61	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	SMOTE	NU	58 (Over NCTL)	GEE	GEE	NS	NS	NS	NS	(mean) 0.53	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	SMOTE	NU	58 (Over NCTL)	LR	LR	NS	NS	NS	NS	(mean) 0.60	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	SMOTE	Bagging	58 (Over NCTL)	RF	RF	NS	NS	NS	NS	(mean) 0.64	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	SMOTE	NU	58 (Over NCTL)	SVM	SVM	NS	NS	NS	NS	(mean) 0.62	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	SMOTE	NU	14 (PCA & Over HS)	GEE	GEE	NS	NS	NS	NS	(mean) 0.71	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	SMOTE	NU	14 (PCA & Over HS)	LR	LR	NS	NS	NS	NS	(mean) 0.72	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	SMOTE	Bagging	14 (PCA & Over HS)	RF	RF	NS	NS	NS	NS	(mean) 0.70	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	SMOTE	NU	14 (PCA & Over HS)	SVM	SVM	NS	NS	NS	NS	(mean) 0.60	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	SMOTE	NU	14 (PCA & Over NC)	GEE	GEE	NS	NS	NS	NS	(mean) 0.54	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	SMOTE	NU	14 (PCA & Over NC)	LR	LR	NS	NS	NS	NS	(mean) 0.62	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	SMOTE	Bagging	14 (PCA & Over NC)	RF	RF	NS	NS	NS	NS	(mean) 0.59	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	SMOTE	NU	14 (PCA & Over NC)	SVM	SVM	NS	NS	NS	NS	(mean) 0.61	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	SMOTE	NU	14 (PCA & Over NCTL)	GEE	GEE	NS	NS	NS	NS	(mean) 0.58	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	SMOTE	NU	14 (PCA & Over NCTL)	LR	LR	NS	NS	NS	NS	(mean) 0.61	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	SMOTE	Bagging	14 (PCA & Over NCTL)	RF	RF	NS	NS	NS	NS	(mean) 0.59	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	SMOTE	NU	14 (PCA & Over NCTL)	SVM	SVM	NS	NS	NS	NS	(mean) 0.61	NS
D. L. Casey 2018	Monitoring	Moving averages	External	CV	NU	NU	14 (PCA HS new player)	GEE	GEE	NS	NS	NS	NS	(mean) 0.75	NS
D. L. Casey 2018	Monitoring	Moving averages	External	CV	NU	NU	14 (PCA HS new player)	LR	LR	NS	NS	NS	NS	(mean) 0.76	NS
D. L. Casey 2018	Monitoring	Moving averages	External	CV	NU	Bagging	14 (PCA HS new player)	RF	RF	NS	NS	NS	NS	(mean) 0.54	NS
D. L. Casey 2018	Monitoring	Moving averages	External	CV	NU	NU	14 (PCA HS new player)	SVM	SVM	NS	NS	NS	NS	(mean) 0.55	NS
D. L. Casey 2018	Monitoring	Moving averages	External	CV	NU	NU	14 (PCA NC new player)	GEE	GEE	NS	NS	NS	NS	(mean) 0.63	NS
D. L. Casey 2018	Monitoring	Moving averages	External	CV	NU	NU	14 (PCA NC new player)	LR	LR	NS	NS	NS	NS	(mean) 0.63	NS
D. L. Casey 2018	Monitoring	Moving averages	External	CV	NU	Bagging	14 (PCA NC new player)	RF	RF	NS	NS	NS	NS	(mean) 0.61	NS
D. L. Casey 2018	Monitoring	Moving averages	External	CV	NU	NU	14 (PCA NC new player)	SVM	SVM	NS	NS	NS	NS	(mean) 0.57	NS
D. L. Casey 2018	Monitoring	Moving averages	External	CV	NU	NU	14 (PCA NCTL new player)	GEE	GEE	NS	NS	NS	NS	(mean) 0.66	NS
D. L. Casey 2018	Monitoring	Moving averages	External	CV	NU	NU	14 (PCA NCTL new player)	LR	LR	NS	NS	NS	NS	(mean) 0.66	NS
D. L. Casey 2018	Monitoring	Moving averages	External	CV	NU	Bagging	14 (PCA NCTL new player)	RF	RF	NS	NS	NS	NS	(mean) 0.59	NS
D. L. Casey 2018	Monitoring	Moving averages	External	CV	NU	NU	14 (PCA NCTL new player)	SVM	SVM	NS	NS	NS	NS	(mean) 0.59	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	NU	NU	14 (PCA HS returning	GEE	GEE	NS	NS	NS	NS	(mean) 0.70	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	NU	NU	14 (PCA HS returning	LR	LR	NS	NS	NS	NS	(mean) 0.71	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	NU	Bagging	14 (PCA HS returning	RF	RF	NS	NS	NS	NS	(mean) 0.85	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	NU	NU	14 (PCA HS returning	SVM	SVM	NS	NS	NS	NS	(mean) 0.75	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	NU	NU	14 (PCA NC returning	GEE	GEE	NS	NS	NS	NS	(mean) 0.63	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	NU	NU	14 (PCA NC returning	LR	LR	NS	NS	NS	NS	(mean) 0.63	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	NU	Bagging	14 (PCA NC returning	RF	RF	NS	NS	NS	NS	(mean) 0.64	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	NU	NU	14 (PCA NC returning	SVM	SVM	NS	NS	NS	NS	(mean) 0.56	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	NU	NU	14 (PCA NCTL returning	GEE	GEE	NS	NS	NS	NS	(mean) 0.58	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	NU	NU	14 (PCA NCTL returning	LR	LR	NS	NS	NS	NS	(mean) 0.60	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	NU	Bagging	14 (PCA NCTL returning	RF	RF	NS	NS	NS	NS	(mean) 0.63	NS
D. L. Casey 2018	Monitoring	Moving averages	NS	CV	NU	NU	14 (PCA NCTL returning	SVM	SVM	NS	NS	NS	NS	(mean) 0.47	NS
G. Rodas 2019	Screening	Net-applic	NS	NSCV	NU	NU	NS	SVM linear	SVM	0.52	0.40	0.62	NS	NS	NS
G. Rodas 2019	Screening	Net-applic	NS	NSCV	NU	NU	NS	SVM RBF	SVM	0.47	0.56	0.4	NS	NS	NS
G. Rodas 2019	Screening	Net-applic	NS	NSCV	NU	Bagging	NS	RF	RF	0.52	0.23	0.75	NS	NS	NS
K. D. Petersen 2020	Monitoring	Dynamic bayesian network	NS	Monaid CV	NU	NU	123	Riera	Riera	0.89	NS	0.80	0.73	NS	NS
K. D. Petersen 2020	Monitoring	Dynamic bayesian network	NS	CV	NU	NU	123	Arriva	Arriva	0.87	NS	0.77	0.66	NS	NS
K. D. Petersen 2020	Monitoring	Dynamic bayesian network	NS	CV	NU	NU	123	TVDBN-0	DBN	0.83	NS	0.67	0.61	NS	NS
K. D. Petersen 2020	Monitoring	Dynamic bayesian network	NS	CV	NU	NU	123	NaDBn	DBN	0.92	NS	0.65	0.62	NS	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	1 (Only injuries)	KNN	KNN	(mean) 0.73	NS	(mean) 0.76	(mean) 0.86	(mean) 0.86	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	1 (Only injuries)	LDA	LDA	(mean) 0.87	NS	(mean) 0.87	(mean) 0.87	(mean) 0.86	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	1 (Only injuries)	LR	LR	(mean) 0.87	NS	(mean) 0.87	(mean) 0.87	(mean) 0.86	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	1 (Only injuries)	Ridge	Ridge	(mean) 0.87	NS	(mean) 0.87	(mean) 0.87	(mean) 0.86	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	1 (Only injuries)	GNB	NB	(mean) 0.87	NS	(mean) 0.87	(mean) 0.87	(mean) 0.86	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	1 (Only injuries)	DT	DT	(mean) 0.87	NS	(mean) 0.87	(mean) 0.87	(mean) 0.86	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	Bagging	1 (Only injuries)	RF	RF	(mean) 0.87	NS	(mean) 0.87	(mean) 0.87	(mean) 0.86	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	1 (Only injuries)	SVM	SVM	(mean) 0.87	NS	(mean) 0.87	(mean) 0.87	(mean) 0.86	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	1 (Only injuries)	MLP	ANN	(mean) 0.87	NS	(mean) 0.87	(mean) 0.87	(mean) 0.86	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	Boosting	1 (Only injuries)	XGBoost	XGBoost	(mean) 0.87	NS	(mean) 0.87	(mean) 0.87	(mean) 0.86	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	5 (Personal features)	KNN	KNN	(mean) 0.84	NS	(mean) 0.84	(mean) 0.88	(mean) 0.87	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	5 (Personal features)	LDA	LDA	(mean) 0.87	NS	(mean) 0.87	(mean) 0.87	(mean) 0.86	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	5 (Personal features)	LR	LR	(mean) 0.87	NS	(mean) 0.87	(mean) 0.87	(mean) 0.86	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	5 (Personal features)	Ridge	Ridge	(mean) 0.87	NS	(mean) 0.87	(mean) 0.87	(mean) 0.86	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	5 (Personal features)	GNB	NB	(mean) 0.87	NS	(mean) 0.85	(mean) 0.85	(mean) 0.85	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	5 (Personal features)	DT	DT	(mean) 0.89	NS	(mean) 0.89	(mean) 0.89	(mean) 0.86	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	Bagging	5 (Personal features)	RF	RF	(mean) 0.89	NS	(mean) 0.89	(mean) 0.89	(mean) 0.88	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	5 (Personal features)	SVM	SVM	(mean) 0.89	NS	(mean) 0.89	(mean) 0.89	(mean) 0.86	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	5 (Personal features)	MLP	ANN	(mean) 0.87	NS	(mean) 0.87	(mean) 0.87	(mean) 0.86	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	Boosting	5 (Personal features)	XGBoost	XGBoost	(mean) 0.89	NS	(mean) 0.89	(mean) 0.88	(mean) 0.88	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	12 (GPS)	KNN	KNN	(mean) 0.94	NS	(mean) 0.93	(mean) 0.92	(mean) 0.90	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	12 (GPS)	LDA	LDA	(mean) 0.88	NS	(mean) 0.87	(mean) 0.87	(mean) 0.87	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	12 (GPS)	LR	LR	(mean) 0.86	NS	(mean) 0.86	(mean) 0.86	(mean) 0.86	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	12 (GPS)	Ridge	Ridge	(mean) 0.87	NS	(mean) 0.87	(mean) 0.87	(mean) 0.87	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	12 (GPS)	GNB	NB	(mean) 0.87	NS	(mean) 0.67	(mean) 0.87	(mean) 0.68	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	12 (GPS)	DT	DT	(mean) 0.91	NS	(mean) 0.91	(mean) 0.90	(mean) 0.88	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	Bagging	12 (GPS)	RF	RF	(mean) 0.93	NS	(mean) 0.93	(mean) 0.89	(mean) 0.90	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	12 (GPS)	SVM	SVM	(mean) 0.87	NS	(mean) 0.87	(mean) 0.89	(mean) 0.86	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	12 (GPS)	MLP	ANN	(mean) 0.87	NS	(mean) 0.83	(mean) 0.80	(mean) 0.82	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	Boosting	12 (GPS)	XGBoost	XGBoost	(mean) 0.92	NS	(mean) 0.93	(mean) 0.91	(mean) 0.92	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	10 (Questionnaires)	KNN	KNN	(mean) 0.92	NS	(mean) 0.92	(mean) 0.90	(mean) 0.89	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	10 (Questionnaires)	LDA	LDA	(mean) 0.87	NS	(mean) 0.87	(mean) 0.85	(mean) 0.86	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	10 (Questionnaires)	LR	LR	(mean) 0.87	NS	(mean) 0.87	(mean) 0.87	(mean) 0.86	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	10 (Questionnaires)	Ridge	Ridge	(mean) 0.87	NS	(mean) 0.87	(mean) 0.87	(mean) 0.86	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	10 (Questionnaires)	GNB	NB	(mean) 0.87	NS	(mean) 0.19	(mean) 0.87	(mean) 0.27	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	10 (Questionnaires)	DT	DT	(mean) 0.92	NS	(mean) 0.93	(mean) 0.92	(mean) 0.87	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	Bagging	10 (Questionnaires)	RF	RF	(mean) 0.94	NS	(mean) 0.94	(mean) 0.91	(mean) 0.91	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	10 (Questionnaires)	SVM	SVM	(mean) 0.89	NS	(mean) 0.89	(mean) 0.91	(mean) 0.86	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	10 (Questionnaires)	MLP	ANN	(mean) 0.87	NS	(mean) 0.87	(mean) 0.87	(mean) 0.86	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	Boosting	10 (Questionnaires)	XGBoost	XGBoost	(mean) 0.91	NS	(mean) 0.94	(mean) 0.91	(mean) 0.94	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	26 (All)	KNN	KNN	(mean) 0.93	NS	(mean) 0.93	(mean) 0.92	(mean) 0.90	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	26 (All)	LDA	LDA	(mean) 0.88	NS	(mean) 0.88	(mean) 0.88	(mean) 0.87	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	26 (All)	LR	LR	(mean) 0.86	NS	(mean) 0.86	(mean) 0.86	(mean) 0.86	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	26 (All)	Ridge	Ridge	(mean) 0.88	NS	(mean) 0.88	(mean) 0.88	(mean) 0.87	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	26 (All)	GNB	NB	(mean) 0.87	NS	(mean) 0.67	(mean) 0.87	(mean) 0.68	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	26 (All)	DT	DT	(mean) 0.91	NS	(mean) 0.92	(mean) 0.91	(mean) 0.89	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	Bagging	26 (All)	RF	RF	(mean) 0.93	NS	(mean) 0.93	(mean) 0.90	(mean) 0.91	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	26 (All)	SVM	SVM	(mean) 0.87	NS	(mean) 0.87	(mean) 0.90	(mean) 0.86	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	26 (All)	MLP	ANN	(mean) 0.87	NS	(mean) 0.82	(mean) 0.82	(mean) 0.83	NS

Author	Type of data collection	Time Management	Method validation	Crossvalidation with fold number	Over- / UnderSampling strategy	Ensemble method	Features number (trial)	Model Extracted	Model Categories	Accuracy	Specificity	Recall	Precision	ROC-AUC	F1 score
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	Boosting	28 (All)	XGBoost	XGBoost	(mean) 0.93	NS	(mean) 0.94	(mean) 0.92	(mean) 0.93	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	1 (Only injuries)	KNN	KNN	(mean) 0.57	NS	(mean) 0.59	(mean) 0.61	(mean) 0.66	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	1 (Only injuries)	LDA	LDA	(mean) 0.59	NS	(mean) 0.59	(mean) 0.59	(mean) 0.59	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	1 (Only injuries)	LR	LR	(mean) 0.59	NS	(mean) 0.59	(mean) 0.60	(mean) 0.59	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	1 (Only injuries)	Ridge	Ridge	(mean) 0.60	NS	(mean) 0.60	(mean) 0.60	(mean) 0.60	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	1 (Only injuries)	GNB	NB	(mean) 0.63	NS	(mean) 0.63	(mean) 0.63	(mean) 0.63	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	1 (Only injuries)	DT	DT	(mean) 0.68	NS	(mean) 0.68	(mean) 0.68	(mean) 0.68	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	Bagging	1 (Only injuries)	RF	RF	(mean) 0.68	NS	(mean) 0.68	(mean) 0.68	(mean) 0.68	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	1 (Only injuries)	SVM	SVM	(mean) 0.68	NS	(mean) 0.63	(mean) 0.63	(mean) 0.63	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	1 (Only injuries)	MLP	ANN	(mean) 0.68	NS	(mean) 0.68	(mean) 0.68	(mean) 0.68	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	Boosting	1 (Only injuries)	XGBoost	XGBoost	(mean) 0.68	NS	(mean) 0.68	(mean) 0.68	(mean) 0.68	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	5 (Personnal features)	KNN	KNN	(mean) 0.77	NS	(mean) 0.76	(mean) 0.77	(mean) 0.79	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	5 (Personnal features)	LDA	LDA	(mean) 0.78	NS	(mean) 0.64	(mean) 0.64	(mean) 0.63	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	5 (Personnal features)	LR	LR	(mean) 0.65	NS	(mean) 0.65	(mean) 0.65	(mean) 0.65	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	5 (Personnal features)	Ridge	Ridge	(mean) 0.65	NS	(mean) 0.66	(mean) 0.66	(mean) 0.66	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	5 (Personnal features)	GNB	NB	(mean) 0.65	NS	(mean) 0.51	(mean) 0.63	(mean) 0.64	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	5 (Personnal features)	DT	DT	(mean) 0.81	NS	(mean) 0.81	(mean) 0.80	(mean) 0.81	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	Bagging	5 (Personnal features)	RF	RF	(mean) 0.80	NS	(mean) 0.80	(mean) 0.80	(mean) 0.80	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	5 (Personnal features)	SVM	SVM	(mean) 0.80	NS	(mean) 0.65	(mean) 0.65	(mean) 0.65	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	5 (Personnal features)	MLP	ANN	(mean) 0.67	NS	(mean) 0.68	(mean) 0.70	(mean) 0.70	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	Boosting	5 (Personnal features)	XGBoost	XGBoost	(mean) 0.81	NS	(mean) 0.80	(mean) 0.80	(mean) 0.81	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	12 (GPS)	KNN	KNN	(mean) 0.89	NS	(mean) 0.89	(mean) 0.89	(mean) 0.85	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	12 (GPS)	LDA	LDA	(mean) 0.87	NS	(mean) 0.75	(mean) 0.74	(mean) 0.75	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	12 (GPS)	LR	LR	(mean) 0.77	NS	(mean) 0.67	(mean) 0.67	(mean) 0.67	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	12 (GPS)	Ridge	Ridge	(mean) 0.76	NS	(mean) 0.77	(mean) 0.76	(mean) 0.77	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	12 (GPS)	GNB	NB	(mean) 0.63	NS	(mean) 0.60	(mean) 0.63	(mean) 0.66	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	12 (GPS)	DT	DT	(mean) 0.93	NS	(mean) 0.92	(mean) 0.93	(mean) 0.91	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	Bagging	12 (GPS)	RF	RF	(mean) 0.97	NS	(mean) 0.96	(mean) 0.96	(mean) 0.96	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	12 (GPS)	SVM	SVM	(mean) 0.63	NS	(mean) 0.63	(mean) 0.63	(mean) 0.63	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	12 (GPS)	MLP	ANN	(mean) 0.71	NS	(mean) 0.71	(mean) 0.70	(mean) 0.73	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	Boosting	12 (GPS)	XGBoost	XGBoost	(mean) 0.97	NS	(mean) 0.97	(mean) 0.97	(mean) 0.97	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	10 (Questionnaires)	KNN	KNN	(mean) 0.89	NS	(mean) 0.89	(mean) 0.89	(mean) 0.87	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	10 (Questionnaires)	LDA	LDA	(mean) 0.79	NS	(mean) 0.51	(mean) 0.52	(mean) 0.51	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	10 (Questionnaires)	LR	LR	(mean) 0.67	NS	(mean) 0.67	(mean) 0.67	(mean) 0.67	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	10 (Questionnaires)	Ridge	Ridge	(mean) 0.67	NS	(mean) 0.68	(mean) 0.68	(mean) 0.69	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	10 (Questionnaires)	GNB	NB	(mean) 0.66	NS	(mean) 0.65	(mean) 0.63	(mean) 0.64	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	10 (Questionnaires)	DT	DT	(mean) 0.92	NS	(mean) 0.92	(mean) 0.92	(mean) 0.89	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	Bagging	10 (Questionnaires)	RF	RF	(mean) 0.97	NS	(mean) 0.97	(mean) 0.97	(mean) 0.96	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	10 (Questionnaires)	SVM	SVM	(mean) 0.79	NS	(mean) 0.71	(mean) 0.71	(mean) 0.71	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	10 (Questionnaires)	MLP	ANN	(mean) 0.77	NS	(mean) 0.76	(mean) 0.77	(mean) 0.77	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	Boosting	10 (Questionnaires)	XGBoost	XGBoost	(mean) 0.97	NS	(mean) 0.96	(mean) 0.96	(mean) 0.97	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	28 (All)	KNN	KNN	(mean) 0.89	NS	(mean) 0.89	(mean) 0.89	(mean) 0.85	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	28 (All)	LDA	LDA	(mean) 0.88	NS	(mean) 0.58	(mean) 0.57	(mean) 0.57	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	28 (All)	LR	LR	(mean) 0.67	NS	(mean) 0.67	(mean) 0.67	(mean) 0.67	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	28 (All)	Ridge	Ridge	(mean) 0.78	NS	(mean) 0.78	(mean) 0.78	(mean) 0.78	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	28 (All)	GNB	NB	(mean) 0.63	NS	(mean) 0.60	(mean) 0.63	(mean) 0.66	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	28 (All)	DT	DT	(mean) 0.93	NS	(mean) 0.92	(mean) 0.92	(mean) 0.91	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	Bagging	28 (All)	RF	RF	(mean) 0.97	NS	(mean) 0.97	(mean) 0.96	(mean) 0.63	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	28 (All)	SVM	SVM	(mean) 0.63	NS	(mean) 0.63	(mean) 0.63	(mean) 0.97	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	NU	28 (All)	MLP	ANN	(mean) 0.73	NS	(mean) 0.70	(mean) 0.71	(mean) 0.72	NS
E. Vallance 2020	Monitoring and screening	Time windows	NS	CV	NU	Boosting	28 (All)	XGBoost	XGBoost	(mean) 0.97	NS	(mean) 0.97	(mean) 0.97	(mean) 0.97	NS
L. Goggins 2022	Monitoring	Moving averages	Internal	CV	NU	NU	47 (Traditional)	DT	DT	NS	NS	NS	NS	(mean) 0.57	NS
L. Goggins 2022	Monitoring	Moving averages	Internal	CV	NU	NU	NS (Conditional)	DT	DT	NS	NS	NS	NS	(mean) 0.66	NS
L. Goggins 2022	Monitoring	Moving averages	Internal	CV	NU	Bagging	47 (Traditional)	RF	RF	NS	NS	NS	NS	(mean) 0.72	NS
L. Goggins 2022	Monitoring	Moving averages	Internal	CV	NU	Bagging	NS (Conditional)	RF	RF	NS	NS	NS	NS	(mean) 0.65	NS
N. Rommers 2020	Screening	Not-applic	Internal	CV	NU	Boosting	29	XGBoost	XGBoost	NS	NS	0.85	0.85	NS	0.85
A. Rossi 2018	Monitoring	Moving averages	Internal	SCV	ADASYN	NU	55	DT	DT	NS	(mean) 0.87	(mean) 0.80	(mean) 0.50	(mean) 0.76	(mean) 0.66
A. Rossi 2018	Monitoring	Moving averages	Internal	SCV	ADASYN	Bagging	55	RF	RF	NS	(mean) 0.90	(mean) 0.87	(mean) 0.41	(mean) 0.78	(mean) 0.65
A. Rossi 2018	Monitoring	Moving averages	Internal	SCV	ADASYN	NU	55	LR	LR	NS	(mean) 0.61	(mean) 0.18	(mean) 0.60	(mean) 0.50	(mean) 0.31
A. Rossi 2018	Monitoring	Moving averages	Internal	SCV	ADASYN	NU	1 (Assign injury if positive)	Dummy classifier	Dummy classifier	NS	(mean) 0.77	(mean) 0.04	(mean) 0.43	(mean) 0.60	(mean) 0.07
A. Rossi 2018	Monitoring	Moving averages	Internal	SCV	ADASYN	NU	0 (Assign injury class)	Dummy classifier	Dummy classifier	NS	(mean) 0.00	(mean) 1.00	(mean) 0.02	(mean) 0.50	(mean) 0.04
A. Rossi 2018	Monitoring	Moving averages	Internal	SCV	ADASYN	NU	0 (Assign non-injury class)	Dummy classifier	Dummy classifier	NS	(mean) 1.00	(mean) 0.00	(mean) 0.00	(mean) 0.50	(mean) 0.00
A. Rossi 2018	Monitoring	Moving averages	Internal	SCV	ADASYN	NU	0 (Random assignment)	Dummy classifier	Dummy classifier	NS	(mean) 0.98	(mean) 0.05	(mean) 0.06	(mean) 0.51	(mean) 0.05
A. Cohen 2021	Monitoring	Time2vec	NS	SCV	NU	NU	16	METIC	METIC	0.93	NS	0.20	0.01	0.80	0.02
A. Cohen 2021	Monitoring	Time2vec	NS	SCV	Over-Sampling	NU	16	OnR Ridge	Ridge	0.96	NS	0,07	0,00	0,52	0,00
A. Cohen 2021	Monitoring	Time2vec	NS	SCV	Over-Sampling	NU	16	OnR LR	LR	0.99	NS	0,00	0,00	0,50	0,00
A. Cohen 2021	Monitoring	Time2vec	NS	SCV	Over-Sampling	Bagging	16	Extra Trees	Extra Trees	0.99	NS	0,00	0,00	0,50	0,00
A. Cohen 2021	Monitoring	Time2vec	NS	SCV	NU	NU	16 (Assign no-injury class)	Dummy classifier	Dummy classifier	0.99	NS	0,00	0,00	0,50	0,00
A. Cohen 2021	Monitoring	Time2vec	NS	SCV	NU	NU	16	OnR Gaussian NB	NB	0.99	NS	0,00	0,00	0,50	0,00
A. Cohen 2021	Monitoring	Time2vec	NS	SCV	NU	NU	16	Lasso	Lasso	0.99	NS	0,00	0,00	0,50	0,00
A. Cohen 2021	Monitoring	Time2vec	NS	SCV	NU	NU	16	OnR Ridge	Ridge	0.99	NS	0,00	0,00	0,50	0,00
A. Cohen 2021	Monitoring	Time2vec	NS	SCV	Over-Sampling	Boosting	16	OnR XGBoost	XGBoost	0.99	NS	0,00	0,00	0,49	0,00
A. Cohen 2021	Monitoring	Time2vec	NS	SCV	NU	Bagging	16	Extra Trees	Extra Trees	0.99	NS	0,00	0,00	0,49	0,00
A. Cohen 2021	Monitoring	Time2vec	NS	SCV	NU	Boosting	16	OnR XGBoost	XGBoost	0.99	NS	0,00	0,00	0,48	0,00
A. Cohen 2021	Monitoring	Time2vec	NS	SCV	NU	Bagging	16	RF	RF	0.99	NS	0,00	0,00	0,48	0,00
A. Cohen 2021	Monitoring	Time2vec	NS	SCV	NU	NU	16	OnR LR	LR	0.99	NS	0,00	0,00	0,45	0,00
A. Cohen 2021	Monitoring	Time2vec	NS	SCV	Over-Sampling	NU	16	OnR Bernouilli NB	NB	0.82	NS	0,12	0,00	0,45	0,00
A. Cohen 2021	Monitoring	Time2vec	NS	SCV	NU	NU	16	OnR Bernouilli	NB	0.80	NS	0,10	0,00	0,39	0,00
M. Mansouri 2022	Screening	Not-applic	Internal	NU	NU	Boosting	24	XGBoost	XGBoost	0.70	NS	NS	NS	NS	NS
M. Mansouri 2022	Screening	Not-applic	Internal	NU	NU	NU	24	MLP	ANN	0.80	NS	NS	NS	NS	NS
A. Lyubovsky 2022	Monitoring	NS	Internal	NU	NU	NU	12 (Player Stats)	Voting	Voting	NS	NS	(mean) 0.73	(mean) 0.29	(mean) 0.63	(mean) 0.40
A. Lyubovsky 2022	Monitoring	NS	Internal	NU	NU	NU	12 (Player Stats)	LR	LR	NS	NS	(mean) 0.77	(mean) 0.33	(mean) 0.79	(mean) 0.46
A. Lyubovsky 2022	Monitoring	NS	Internal	NU	NU	NU	12 (Player Stats)	SVM	SVM	NS	NS	(mean) 0.77	(mean) 0.28	(mean) 0.69	(mean) 0.39
A. Lyubovsky 2022	Monitoring	NS	Internal	NU	NU	NU	12 (Player Stats)	KNN	KNN	NS	NS	(mean) 0.06	(mean) 0.18	(mean) 0.62	(mean) 0.09
A. Lyubovsky 2022	Monitoring	NS	Internal	NU	NU	NU	12 (Player Stats)	DT	DT	NS	NS	(mean) 0.62	(mean) 0.29	(mean) 0.65	(mean) 0.36
A. Lyubovsky 2022	Monitoring	NS	Internal	NU	NU	Bagging	12 (Player Stats)	RF	RF	NS	NS	(mean) 0.16	(mean) 0.24	(mean) 0.71	(mean) 0.19
A. Lyubovsky 2022	Monitoring	NS	Internal	NU	NU	NU	177 (Surveys)	Voting	Voting	NS	NS	(mean) 0.69	(mean) 0.26	(mean) 0.59	(mean) 0.35
A. Lyubovsky 2022	Monitoring	NS	Internal	NU	NU	NU	177 (Surveys)	LR	LR	NS	NS	(mean) 0.74	(mean) 0.29	(mean) 0.66	(mean) 0.39
A. Lyubovsky 2022	Monitoring	NS	Internal	NU	NU	NU	177 (Surveys)	SVM	SVM	NS	NS	(mean) 0.74	(mean) 0.26	(mean) 0.62	(mean) 0.36
A. Lyubovsky 2022	Monitoring	NS	Internal	NU	NU	NU	177 (Surveys)	KNN	KNN	NS	NS	(mean) 0.12	(mean) 0.20	(mean) 0.61	(mean) 0.14
A. Lyubovsky 2022	Monitoring	NS	Internal	NU	NU	NU	177 (Surveys)	DT	DT	NS	NS	(mean) 0.46	(mean) 0.25	(mean) 0.57	(mean) 0.29
A. Lyubovsky 2022	Monitoring	NS	Internal	NU	NU	Bagging	177 (Surveys)	RF	RF	NS	NS	(mean) 0.08	(mean) 0.01	(mean) 0.66	(mean) 0.08
A. Lyubovsky 2022	Monitoring	NS	Internal	NU	NU	NU	446 (GPS)	Voting	Voting	NS	NS	(mean) 0.54	(mean) 0.20	(mean) 0.47	(mean) 0.26
A. Lyubovsky 2022	Monitoring	NS	Internal	NU	NU	NU	446 (GPS)	LR	LR	NS	NS	(mean) 0.57	(mean) 0.19	(mean) 0.42	(mean) 0.27
A. Lyubovsky 2022	Monitoring	NS	Internal	NU	NU	NU	446 (GPS)	SVM	SVM	NS	NS	(mean) 0.66	(mean) 0.20	(mean) 0.46	(mean) 0.30
A. Lyubovsky 2022	Monitoring	NS	Internal	NU	NU	NU	446 (GPS)	KNN	KNN	NS	NS	(mean) 0.07	(mean) 0.20	(mean) 0.47	(mean) 0.09
A. Lyubovsky 2022	Monitoring	NS	Internal	NU	NU	NU	446 (GPS)	DT	DT	NS	NS	(mean) 0.38	(mean) 0.19	(mean) 0.45	(mean) 0.23
A. Lyubovsky 2022	Monitoring	NS	Internal	NU	NU	Bagging	446 (GPS)	RF	RF	NS	NS	(mean) 0.02	(mean) 0.03	(mean) 0.43	(mean) 0.02
A. Lyubovsky 2022	Monitoring	NS	Internal	NU	NU	NU	50 (Trainind load)	Voting	Voting	NS	NS	(mean) 0.57	(mean) 0.15	(mean) 0.51	(mean) 0.19
A. Lyubovsky 2022	Monitoring	NS	Internal	NU	NU	NU	50 (Trainind load)	LR	LR	NS	NS	(mean) 0.65	(mean) 0.16	(mean) 0.52	(mean) 0.20
A. Lyubovsky 2022	Monitoring	NS	Internal	NU	NU	NU	50 (Trainind load)	SVM	SVM	NS	NS	(mean) 0.77	(mean) 0.17	(mean) 0.52	(mean) 0.25
A. Lyubovsky 2022	Monitoring	NS	Internal	NU	NU	NU	50 (Trainind load)	KNN	KNN	NS	NS	(mean) 0.00	(mean) 0.00	(mean) 0.49	(mean) 0.00
A. Lyubovsky 2022	Monitoring	NS	Internal	NU	NU	NU	50 (Trainind load)	DT	DT	NS	NS	(mean) 0.65	(mean) 0.20	(mean) 0.58	(mean) 0.26
A. Lyubovsky 2022	Monitoring	NS	Internal	NU	NU	Bagging	50 (Trainind load)	RF	RF	NS	NS	(mean) 0.10	(mean) 0.10	(mean) 0.50	(mean) 0.10
H. R. Thornton 2016	Monitoring	Moving averages	NS	NU	NU	Bagging	5 (Hit-up forwards)	RF	RF	NS	NS	NS	NS	(mean) 0.65	NS
H. R. Thornton 2016	Monitoring	Moving averages	NS	NU	NU	Bagging	5 (wide-running forwards)	RF	RF	NS	NS	NS	NS	(mean) 0.64	NS
H. R. Thornton 2016	Monitoring	Moving averages	NS	NU	NU	Bagging	5 (Adjustables)	RF	RF	NS	NS	NS	NS	(mean) 0.74	NS
H. R. Thornton 2016	Monitoring	Moving averages	NS	NU	NU	Bagging	5 (Outside backs)	RF	RF	NS	NS	NS	NS	(mean) 0.64	NS
A. López-Valenciano 2018	Screening	Not-applic	NS	CV	NU	NU	151	J48	DT	NS	(mean) 0.79	(mean) 0.17	NS	(mean) 0.42	NS
A. López-Valenciano 2018	Screening	Not-applic	NS	CV	NU	NU	151	Simple Cart	DT	NS	(mean) 0.95	(mean) 0.03	NS	(mean) 0.46	NS
A. López-Valenciano 2018	Screening	Not-applic	NS	CV	NU	NU	151	ADTree	DT	NS	(mean) 0.88	(mean) 0.21	NS	(mean) 0.62	NS
A. López-Valenciano 2018	Screening	Not-applic	NS	CV	NU	NU	151	Rtree	DT	NS	(mean) 0.66	(mean) 0.52	NS	(mean) 0.61	NS
A. López-Valenciano 2018	Screening	Not-applic	NS	CV	SMOTE	NU	151	J48	DT	NS	(mean) 0.78	(mean) 0.31	NS	(mean) 0.45	NS
A. López-Valenciano 2018	Screening	Not-applic	NS	CV	SMOTE	NU	151	Simple Cart	DT	NS	(mean) 0.71	(mean) 0.35	NS	(mean) 0.49	NS
A. López-Valenciano 2018	Screening	Not-applic	NS	CV	SMOTE	NU	151	ADTree	DT	NS	(mean) 0.77	(mean) 0.31	NS	(mean) 0.61	NS
A. López-Valenciano 2018	Screening	Not-applic	NS	CV	SMOTE	NU	151	Rtree	DT	NS	(mean) 0.71	(mean) 0.35	NS	(mean) 0.52	NS
A. López-Valenciano 2018	Screening	Not-applic	NS	CV	ROS	NU	151	J48	DT	NS	(mean) 0.73	(mean) 0.44	NS	(mean) 0.58	NS
A. López-Valenciano 2018	Screening	Not-applic	NS	CV	ROS	NU	151	Simple Cart	DT	NS	(mean) 0.74	(mean) 0.48	NS	(mean) 0.62	NS
A. López-Valenciano 2018	Screening	Not-applic	NS	CV	ROS	NU	151	ADTree	DT	NS	(mean) 0.85	(mean) 0.48	NS	(mean) 0.71	NS
A. López-Valenciano 2018	Screening	Not-applic	NS	CV	ROS	NU	151	Rtree	DT	NS	(mean) 0.82	(mean) 0.55	NS	(mean) 0.71	NS
A. López-Valenciano 2018	Screening	Not-applic	NS	CV	RUS	NU	151	J48	DT	NS	(mean) 0.65	(mean) 0.55	NS	(mean) 0.61	NS
A. López-Valenciano 2018	Screening	Not-applic	NS	CV	RUS	NU	151	Simple Cart	DT	NS	(mean) 0.93	(mean) 0.14	NS	(mean) 0.57	NS
A. López-Valenciano 2018	Screening	Not-applic	NS	CV	RUS	NU	151	ADTree	DT	NS	(mean) 0.70	(mean) 0.62	NS	(mean) 0.66	NS
A. López-Valenciano 2018	Screening	Not-applic	NS	CV	RUS	NU	151	Rtree	DT	NS	(mean) 0.62	(mean) 0.48	NS	(mean) 0.56	NS
A. López-Valenciano 2018	Screening	Not-applic	NS	CV	NU	AdaBoost	151	J48	DT	NS	(mean) 0.90	(mean) 0.14	NS	(mean) 0.58	NS
A. López-Valenciano 2018	Screening	Not-applic	NS	CV	NU	AdaBoost	151	Simple Cart	DT	NS	(mean) 0.84	(mean) 0.38	NS	(mean) 0.61	NS
A. López-Valenciano 2018	Screening	Not-applic	NS	CV	NU	AdaBoost	151	ADTree	DT	NS	(mean) 0.93	(mean) 0.24	NS	(mean) 0.69	NS
A. López-Valenciano 2018	Screening	Not-applic	NS	CV	NU	AdaBoost	151	Rtree	DT	NS	(mean) 0.99	(mean) 0.10	NS	(mean) 0.59	NS
A. López-Valenciano 2018	Screening	Not-applic	NS	CV	NU	AdaBoost	151	J48	DT	NS	(mean) 0.91	(mean) 0.00	NS	(mean) 0.56	NS
A. López-Valenciano 2018	Screening	Not-applic	NS	CV	NU	AdaBoost	151	Simple Cart	DT	NS	(mean) 0.85	(mean) 0.21	NS	(mean) 0.55	NS
A. López-Valenciano 2018	Screening	Not-applic	NS	CV	NU	AdaBoost	151	ADTree	DT	NS	(mean) 0.90	(mean) 0.28	NS	(mean) 0.70	NS
A. López-Valenciano 2018	Screening	Not-applic	NS	CV	NU	AdaBoost	151	Rtree	DT	NS	(mean) 0.86	(mean) 0.21	NS	(mean) 0.52	NS
A. López-Valenciano 2018	Screening	Not-applic	NS	CV	NU	Bagging	151	J48	DT	NS	(mean) 0.93	(mean) 0.07	NS	(mean) 0.54	NS
A. López-Valenciano 2018	Screening	Not-applic	NS	CV	NU	Bagging	151	Simple Cart	DT	NS	(mean) 0.98	(mean) 0.03	NS	(mean) 0.67	NS
A. López-Valenciano 2018	Screening	Not-applic	NS	CV	NU	Bagging	151	ADTree	DT	NS	(mean) 0.99	(mean) 0.10	NS	(mean) 0.72	NS
A. López-Valenciano 2018	Screening	Not-applic	NS	CV	NU	Bagging	151	Rtree	DT	NS	(mean) 0.91	(mean) 0.24	NS	(mean) 0.66	NS
A. López-Valenciano 2018	Screening	Not-applic	NS	CV	SMOTE	Bagging	151	J48	DT	NS	(mean) 0.77	(mean) 0.24	NS	(mean) 0.49	NS
A. López-Valenciano 2018	Screening	Not-applic	NS	CV	SMOTE	Bagging	151	Simple Cart	DT	NS	(mean) 0.86	(mean) 0.41	NS	(mean) 0.69	NS
A. López-Valenciano 2018	Screening	Not-applic	NS	CV	SMOTE	Bagging	151	ADTree	DT	NS	(mean) 0.86	(mean) 0.28	NS	(mean) 0.65	NS
A. López-Valenciano 2018	Screening	Not-applic	NS	CV	RUS	Bagging	151	J48	DT	NS	(mean) 0.76	(mean) 0.38	NS	(mean) 0.61	NS
A. López-Valenciano 2018	Screening	Not-applic	NS	CV	RUS	Bagging	151	Simple Cart	DT	NS	(mean) 0.78	(mean) 0.52	NS	(mean) 0.65	NS
A. López-Valenciano 2018	Screening	Not-applic	NS	CV	RUS	Bagging	151	ADTree	DT	NS	(mean) 0.92	(mean) 0.31	NS	(mean) 0.70	NS
A. López-Valenciano 2018	Screening	Not-applic	NS	CV	RUS	Bagging	151	Rtree	DT	NS	(mean) 0.85	(mean) 0.48	NS	(mean) 0.72	NS
A. López-Valenciano 2018	Screening	Not-applic	NS	CV	ROS	Bagging	151	J48	DT	NS	(mean) 0.92	(mean) 0.14	NS	(mean) 0.58	NS
A. López-Valenciano 2018	Screening	Not-applic	NS	CV	ROS	Bagging	151	Simple Cart	DT	NS	(mean) 0.93	(mean) 0.14	NS	(mean) 0.72	NS
A. López-Valenciano 2018	Screening	Not-applic	NS	CV	ROS	Bagging	151	ADTree	DT	NS	(mean) 0.97	(mean) 0.10	NS	(mean) 0.76	NS
A. López-Valenciano 2018	Screening	Not-applic	NS	CV	ROS	Bagging	151	Rtree	DT	NS	(mean) 0.89	(mean) 0.14	NS	(mean) 0.63	NS
A. López-Valenciano 2018	Screening	Not-applic	NS	CV	RUS	Bagging	151	J48	DT	NS	(mean) 0.85	(mean) 0.28	NS	(mean) 0.67	NS
A. López-Valenciano 2018	Screening	Not-applic	NS	CV	RUS	Bagging	151	Simple Cart	DT	NS	(mean) 0.88	(mean) 0.31	NS	(mean) 0.71	NS
A. López-Valenciano 2018	Screening	Not-applic	NS	CV	RUS	Bagging	151	ADTree	DT	NS	(mean) 0.74	(mean) 0.41	NS	(mean) 0.62	NS
A. López-Valenciano 2018	Screening	Not-applic	NS	CV	RUS	Bagging	151	Rtree	DT	NS	(mean) 0.82	(mean) 0.28	NS	(mean) 0.57	NS
A. López-Valenciano 2018	Screening	Not-applic	NS	CV	SMOTE	Bagging	151	J48	DT	NS	(mean) 0.97	(mean) 0.14	NS	(mean) 0.56	NS
A. López-Valenciano 2018	Screening	Not-applic	NS	CV	SMOTE	Bagging	151	Simple Cart	DT	NS	(mean) 0.97	(mean) 0.10	NS	(mean) 0.64	NS
A. López-Valenciano 2018	Screening	Not-applic	NS	CV	SMOTE	Bagging	151	ADTree	DT	NS	(mean) 0.97	(mean) 0.21	NS	(mean) 0.73	NS
A. López-Valenciano 2018	Screening	Not-applic	NS	CV	SMOTE	Bagging	151	Rtree	DT	NS	(mean) 0.93	(mean) 0.24	NS	(mean) 0.55	NS
A. López-Valenciano 2018	Screening	Not-applic	NS	CV	NU	NU	151 (MetaCost-Sensitive)	J48	DT	NS	(mean) 0.62	(mean) 0.41	NS	(mean) 0.47	NS
A. López-Valenciano 2018	Screening	Not-applic	NS	CV	NU	NU	151 (MetaCost-Sensitive)	Simple Cart	DT	NS	(mean) 0.90	(mean) 0.17	NS	(mean) 0.58	NS
A. López-Valenciano 2018	Screening	Not-applic	NS	CV	NU	NU	151 (MetaCost-Sensitive)	ADTree	DT	NS	(mean) 0.41	(mean) 0.76	NS	(mean) 0.66	NS
A. López-Valenciano 2018	Screening	Not-applic	NS	CV	NU	NU	151 (MetaCost-Sensitive)	Rtree	DT	NS	(mean) 0.64	(mean) 0.48	NS	(mean) 0.56	NS
A. López-Valenciano 2018	Screening	Not-applic	NS	CV	NU	NU	151 (Cost-Sensitive)	J48	DT	NS	(mean) 0.57	(mean) 0.52	NS	(mean) 0.53	NS
A. López-Valenciano 2018	Screening	Not-applic	NS	CV	NU	NU	151 (Cost-Sensitive)	Simple Cart	DT	NS	(mean) 0.53	(mean) 0.44	NS	(mean) 0.54	NS
A. López-Valenciano 2018	Screening	Not-applic	NS	CV	NU	NU	151 (Cost-Sensitive)	ADTree	DT	NS	(mean) 0.70	(mean) 0.52	NS	(mean) 0.64	NS
A. López-Valenciano 2018	Screening	Not-applic

Author	Type of data collection	Time_Management	Method validation	Cross-validation with fold number	Over- / Under-Sampling strategy	Ensemble_method	Features number (trial)	Model Extracted	Model Categories	Accuracy	Specificity	Recall	Precision	ROC-AUC	F1 score
A. López-Valenciano 2018	Screening	Not-applic	NS	CV	SMOTE	Bagging	151 (Cost-Sensitive)	ADTree	DT	NS	(mean) 0.79	(mean) 0.66	NS	(mean) 0.75	NS
A. López-Valenciano 2018	Screening	Not-applic	NS	CV	SMOTE	Bagging	151 (Cost-Sensitive)	Rtree	DT	NS	(mean) 0.87	(mean) 0.07	NS	(mean) 0.54	NS
A. López-Valenciano 2018	Screening	Not-applic	NS	CV	ROS	Bagging	151 (Cost-Sensitive)	J48	DT	NS	(mean) 0.73	(mean) 0.41	NS	(mean) 0.51	NS
A. López-Valenciano 2018	Screening	Not-applic	NS	CV	ROS	Bagging	151 (Cost-Sensitive)	Simple Cart	DT	NS	(mean) 0.64	(mean) 0.55	NS	(mean) 0.61	NS
A. López-Valenciano 2018	Screening	Not-applic	NS	CV	ROS	Bagging	151 (Cost-Sensitive)	ADTree	DT	NS	(mean) 0.71	(mean) 0.62	NS	(mean) 0.74	NS
A. López-Valenciano 2018	Screening	Not-applic	NS	CV	ROS	Bagging	151 (Cost-Sensitive)	Rtree	DT	NS	(mean) 0.97	(mean) 0.14	NS	(mean) 0.55	NS
A. López-Valenciano 2018	Screening	Not-applic	NS	CV	RUS	Bagging	151 (Cost-Sensitive)	J48	DT	NS	(mean) 0.67	(mean) 0.41	NS	(mean) 0.55	NS
A. López-Valenciano 2018	Screening	Not-applic	NS	CV	RUS	Bagging	151 (Cost-Sensitive)	Simple Cart	DT	NS	(mean) 0.69	(mean) 0.52	NS	(mean) 0.65	NS
A. López-Valenciano 2018	Screening	Not-applic	NS	CV	RUS	Bagging	151 (Cost-Sensitive)	ADTree	DT	NS	(mean) 0.68	(mean) 0.59	NS	(mean) 0.74	NS
A. López-Valenciano 2018	Screening	Not-applic	NS	CV	RUS	Bagging	151 (Cost-Sensitive)	Rtree	DT	NS	(mean) 0.82	(mean) 0.38	NS	(mean) 0.63	NS
A. Rossi 2021	Monitoring	Moving averages	Internal	RFECV	ADASYN	NU	52 (High)	DT	DT	NS	(mean) 0.81	(mean) 0.68	(mean) 0.19	NS	(mean) 0.30
A. Rossi 2021	Monitoring	Moving averages	Internal	RFECV	ADASYN	Boosting	52 (High)	XGBoost	XGBoost	NS	(mean) 0.94	(mean) 0.42	(mean) 0.33	NS	(mean) 0.37
A. Rossi 2021	Monitoring	Moving averages	Internal	RFECV	ADASYN	NU	0 (High)	Dummy classifier	Dummy classifier	NS	(mean) 0.50	(mean) 0.37	(mean) 0.05	NS	(mean) 0.08
A. Rossi 2021	Monitoring	Moving averages	Internal	RFECV	ADASYN	NU	52 (Low)	DT	DT	NS	(mean) 0.92	(mean) 0.73	(mean) 0.44	NS	(mean) 0.55
A. Rossi 2021	Monitoring	Moving averages	Internal	RFECV	ADASYN	Boosting	52 (Low)	XGBoost	XGBoost	NS	(mean) 0.95	(mean) 0.80	(mean) 0.56	NS	(mean) 0.66
A. Rossi 2021	Monitoring	Moving averages	Internal	RFECV	ADASYN	NU	0 (Low)	Dummy classifier	Dummy classifier	NS	(mean) 0.52	(mean) 0.70	(mean) 0.11	NS	(mean) 0.18
A. Rossi 2021	Monitoring	Moving averages	Internal	RFECV	ADASYN	NU	52 (Endorse)	DT	DT	NS	(mean) 0.87	(mean) 0.71	(mean) 0.30	NS	(mean) 0.42
A. Rossi 2021	Monitoring	Moving averages	Internal	RFECV	ADASYN	Boosting	52 (Endorse)	XGBoost	XGBoost	NS	(mean) 0.94	(mean) 0.65	(mean) 0.48	NS	(mean) 0.56
A. Rossi 2021	Monitoring	Moving averages	Internal	RFECV	ADASYN	NU	0 (Endorse)	Dummy classifier	Dummy classifier	NS	(mean) 0.51	(mean) 0.57	(mean) 0.08	NS	(mean) 0.14
A. Rossi 2021	Monitoring	Moving averages	Internal	RFECV	ADASYN	NU	52 (Blood groupe as	DT	DT	NS	(mean) 0.84	(mean) 0.68	(mean) 0.20	NS	(mean) 0.31
A. Rossi 2021	Monitoring	Moving averages	Internal	RFECV	ADASYN	Boosting	52 (Blood groupe as variable)	XGBoost	XGBoost	NS	(mean) 0.98	(mean) 0.65	(mean) 0.58	NS	(mean) 0.61
A. Rossi 2021	Monitoring	Moving averages	Internal	RFECV	ADASYN	NU	0 (Blood groupe as variable)	Dummy classifier	Dummy classifier	NS	(mean) 0.49	(mean) 0.45	(mean) 0.05	NS	(mean) 0.09
A. Rossi 2021	Monitoring	Moving averages	Internal	RFECV	ADASYN	NU	52 (No-Split)	DT	DT	NS	(mean) 0.78	(mean) 0.63	(mean) 0.14	NS	(mean) 0.23
A. Rossi 2021	Monitoring	Moving averages	Internal	RFECV	ADASYN	Boosting	52 (No-Split)	XGBoost	XGBoost	NS	(mean) 0.95	(mean) 0.61	(mean) 0.40	NS	(mean) 0.48
A. Rossi 2021	Monitoring	Moving averages	Internal	RFECV	ADASYN	NU	0 (No-Split)	Dummy classifier	Dummy classifier	NS	(mean) 0.49	(mean) 0.45	(mean) 0.05	NS	(mean) 0.09
A. Rossi 2021	Monitoring	Moving averages	Internal	RFECV	ADASYN	NU	52 (Blood groupe as	DT	DT	NS	(mean) 0.91	(mean) 0.34	(mean) 0.20	NS	(mean) 0.25
A. Rossi 2021	Monitoring	Moving averages	Internal	RFECV	ADASYN	Boosting	52 (Blood groupe as variable)	XGBoost	XGBoost	NS	(mean) 0.94	(mean) 0.42	(mean) 0.32	NS	(mean) 0.36
A. Rossi 2021	Monitoring	Moving averages	Internal	RFECV	ADASYN	NU	0 (Blood groupe as variable)	Dummy classifier	Dummy classifier	NS	(mean) 0.94	(mean) 0.07	(mean) 0.07	NS	(mean) 0.07
A. Rossi 2021	Monitoring	Moving averages	Internal	RFECV	ADASYN	NU	52 (No-Split)	DT	DT	NS	(mean) 0.90	(mean) 0.35	(mean) 0.19	NS	(mean) 0.25
A. Rossi 2021	Monitoring	Moving averages	Internal	RFECV	ADASYN	Boosting	52 (No-Split)	XGBoost	XGBoost	NS	(mean) 0.93	(mean) 0.39	(mean) 0.27	NS	(mean) 0.32
A. Rossi 2021	Monitoring	Moving averages	Internal	RFECV	ADASYN	NU	0 (No-Split)	Dummy classifier	Dummy classifier	NS	(mean) 0.94	(mean) 0.07	(mean) 0.08	NS	(mean) 0.07
F. Ayala 2019	Screening	Not-applic	Internal	SCV	NU	NU	66 (Cost-Sensitive)	J48	DT	NS	(mean) 0.78	(mean) 0.17	NS	(mean) 0.47	NS
F. Ayala 2019	Screening	Not-applic	Internal	SCV	NU	NU	66 (Cost-Sensitive)	ADTree	DT	NS	(mean) 0.81	(mean) 0.33	NS	(mean) 0.68	NS
F. Ayala 2019	Screening	Not-applic	Internal	SCV	NU	NU	66 (Cost-Sensitive)	Simple cart	DT	NS	(mean) 0.69	(mean) 0.78	NS	(mean) 0.76	NS
F. Ayala 2019	Screening	Not-applic	Internal	SCV	SMOTE	NU	66 (Cost-Sensitive)	J48	DT	NS	(mean) 0.77	(mean) 0.33	NS	(mean) 0.55	NS
F. Ayala 2019	Screening	Not-applic	Internal	SCV	SMOTE	NU	66 (Cost-Sensitive)	ADTree	DT	NS	(mean) 0.79	(mean) 0.50	NS	(mean) 0.76	NS
F. Ayala 2019	Screening	Not-applic	Internal	SCV	SMOTE	NU	66 (Cost-Sensitive)	Simple cart	DT	NS	(mean) 0.69	(mean) 0.50	NS	(mean) 0.60	NS
F. Ayala 2019	Screening	Not-applic	Internal	SCV	SMOTE	Boosting	66 (Cost-Sensitive)	J48	DT	NS	(mean) 0.90	(mean) 0.33	NS	(mean) 0.67	NS
F. Ayala 2019	Screening	Not-applic	Internal	SCV	SMOTE	Boosting	66 (Cost-Sensitive)	ADTree	DT	NS	(mean) 0.84	(mean) 0.78	NS	(mean) 0.84	NS
F. Ayala 2019	Screening	Not-applic	Internal	SCV	SMOTE	Boosting	66 (Cost-Sensitive)	Simple cart	DT	NS	(mean) 0.79	(mean) 0.50	NS	(mean) 0.66	NS
F. Ayala 2019	Screening	Not-applic	Internal	SCV	RUS	Boosting	66 (Cost-Sensitive)	J48	DT	NS	(mean) 0.66	(mean) 0.67	NS	(mean) 0.72	NS
F. Ayala 2019	Screening	Not-applic	Internal	SCV	RUS	Boosting	66 (Cost-Sensitive)	ADTree	DT	NS	(mean) 0.63	(mean) 0.78	NS	(mean) 0.75	NS
F. Ayala 2019	Screening	Not-applic	Internal	SCV	RUS	Boosting	66 (Cost-Sensitive)	Simple cart	DT	NS	(mean) 0.57	(mean) 0.78	NS	(mean) 0.70	NS
F. Ayala 2019	Screening	Not-applic	Internal	SCV	NS	Bagging	66 (Cost-Sensitive)	J48	DT	NS	(mean) 0.81	(mean) 0.3	NS	(mean) 0.61	NS
F. Ayala 2019	Screening	Not-applic	Internal	SCV	NS	Bagging	66 (Cost-Sensitive)	ADTree	DT	NS	(mean) 0.82	(mean) 0.56	NS	(mean) 0.81	NS
F. Ayala 2019	Screening	Not-applic	Internal	SCV	NS	Bagging	66 (Cost-Sensitive)	Simple cart	DT	NS	(mean) 0.75	(mean) 0.72	NS	(mean) 0.73	NS
F. Ayala 2019	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	66 (Cost-Sensitive)	J48	DT	NS	(mean) 0.75	(mean) 0.33	NS	(mean) 0.58	NS
F. Ayala 2019	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	66 (Cost-Sensitive)	ADTree	DT	NS	(mean) 0.82	(mean) 0.67	NS	(mean) 0.85	NS
F. Ayala 2019	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	66 (Cost-Sensitive)	Simple cart	DT	NS	(mean) 0.71	(mean) 0.61	NS	(mean) 0.72	NS
J. L. Oliver 2020	Screening	Not-applic	Internal	SCV	NU	AdaBoost	20	J48 con	DT	NS	(mean) 0.85	(mean) 0.23	NS	(mean) 0.55	NS
J. L. Oliver 2020	Screening	Not-applic	Internal	SCV	NU	AdaBoost	20	ADTree	DT	NS	(mean) 0.79	(mean) 0.31	NS	(mean) 0.57	NS
J. L. Oliver 2020	Screening	Not-applic	Internal	SCV	NU	AdaBoost	20	REPTree	DT	NS	(mean) 0.77	(mean) 0.29	NS	(mean) 0.56	NS
J. L. Oliver 2020	Screening	Not-applic	Internal	SCV	NU	AdaBoost	20	J48 con	DT	NS	(mean) 0.83	(mean) 0.32	NS	(mean) 0.59	NS
J. L. Oliver 2020	Screening	Not-applic	Internal	SCV	NU	AdaBoost	20	ADTree	DT	NS	(mean) 0.72	(mean) 0.36	NS	(mean) 0.55	NS
J. L. Oliver 2020	Screening	Not-applic	Internal	SCV	NU	AdaBoost	20	REPTree	DT	NS	(mean) 0.79	(mean) 0.29	NS	(mean) 0.59	NS
J. L. Oliver 2020	Screening	Not-applic	Internal	SCV	NU	Bagging	20	J48 con	DT	NS	(mean) 0.91	(mean) 0.27	NS	(mean) 0.63	NS
J. L. Oliver 2020	Screening	Not-applic	Internal	SCV	NU	Bagging	20	ADTree	DT	NS	(mean) 0.73	(mean) 0.47	NS	(mean) 0.63	NS
J. L. Oliver 2020	Screening	Not-applic	Internal	SCV	NU	Bagging	20	REPTree	DT	NS	(mean) 0.94	(mean) 0.09	NS	(mean) 0.56	NS
J. L. Oliver 2020	Screening	Not-applic	Internal	SCV	SMOTE	AdaBoost	20	J48 con	DT	NS	(mean) 0.72	(mean) 0.43	NS	(mean) 0.62	NS
J. L. Oliver 2020	Screening	Not-applic	Internal	SCV	SMOTE	AdaBoost	20	ADTree	DT	NS	(mean) 0.76	(mean) 0.34	NS	(mean) 0.58	NS
J. L. Oliver 2020	Screening	Not-applic	Internal	SCV	SMOTE	AdaBoost	20	REPTree	DT	NS	(mean) 0.75	(mean) 0.37	NS	(mean) 0.59	NS
J. L. Oliver 2020	Screening	Not-applic	Internal	SCV	ROS	AdaBoost	20	J48 con	DT	NS	(mean) 0.84	(mean) 0.27	NS	(mean) 0.60	NS
J. L. Oliver 2020	Screening	Not-applic	Internal	SCV	ROS	AdaBoost	20	ADTree	DT	NS	(mean) 0.76	(mean) 0.32	NS	(mean) 0.59	NS
J. L. Oliver 2020	Screening	Not-applic	Internal	SCV	ROS	AdaBoost	20	REPTree	DT	NS	(mean) 0.75	(mean) 0.32	NS	(mean) 0.60	NS
J. L. Oliver 2020	Screening	Not-applic	Internal	SCV	RUS	AdaBoost	20	J48 con	DT	NS	(mean) 0.76	(mean) 0.48	NS	(mean) 0.64	NS
J. L. Oliver 2020	Screening	Not-applic	Internal	SCV	RUS	AdaBoost	20	ADTree	DT	NS	(mean) 0.77	(mean) 0.40	NS	(mean) 0.64	NS
J. L. Oliver 2020	Screening	Not-applic	Internal	SCV	RUS	AdaBoost	20	REPTree	DT	NS	(mean) 0.96	(mean) 0.10	NS	(mean) 0.58	NS
J. L. Oliver 2020	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	20	J48 con	DT	NS	(mean) 0.85	(mean) 0.35	NS	(mean) 0.66	NS
J. L. Oliver 2020	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	20	ADTree	DT	NS	(mean) 0.80	(mean) 0.43	NS	(mean) 0.67	NS
J. L. Oliver 2020	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	20	REPTree	DT	NS	(mean) 0.87	(mean) 0.24	NS	(mean) 0.64	NS
J. L. Oliver 2020	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	20	J48 con	DT	NS	(mean) 0.81	(mean) 0.42	NS	(mean) 0.66	NS
J. L. Oliver 2020	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	20	ADTree	DT	NS	(mean) 0.73	(mean) 0.53	NS	(mean) 0.65	NS
J. L. Oliver 2020	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	20	REPTree	DT	NS	(mean) 0.83	(mean) 0.30	NS	(mean) 0.63	NS
J. L. Oliver 2020	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	20	J48 con	DT	NS	(mean) 0.80	(mean) 0.42	NS	(mean) 0.63	NS
J. L. Oliver 2020	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	20	ADTree	DT	NS	(mean) 0.84	(mean) 0.39	NS	(mean) 0.66	NS
J. L. Oliver 2020	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	20	REPTree	DT	NS	(mean) 0.87	(mean) 0.29	NS	(mean) 0.61	NS
J. L. Oliver 2020	Screening	Not-applic	Internal	SCV	NU	NU	20	J48 con	DT	NS	(mean) 0.84	(mean) 0.30	NS	(mean) 0.61	NS
J. L. Oliver 2020	Screening	Not-applic	Internal	SCV	NU	NU	20	ADTree	DT	NS	(mean) 0.55	(mean) 0.67	NS	(mean) 0.63	NS
J. L. Oliver 2020	Screening	Not-applic	Internal	SCV	NU	NU	20	REPTree	DT	NS	(mean) 0.90	(mean) 0.07	NS	(mean) 0.49	NS
J. L. Oliver 2020	Screening	Not-applic	Internal	SCV	SMOTE	NU	20	J48 con	DT	NS	(mean) 0.75	(mean) 0.46	NS	(mean) 0.60	NS
J. L. Oliver 2020	Screening	Not-applic	Internal	SCV	SMOTE	NU	20	ADTree	DT	NS	(mean) 0.68	(mean) 0.37	NS	(mean) 0.57	NS
J. L. Oliver 2020	Screening	Not-applic	Internal	SCV	SMOTE	NU	20	REPTree	DT	NS	(mean) 0.70	(mean) 0.43	NS	(mean) 0.55	NS
J. L. Oliver 2020	Screening	Not-applic	Internal	SCV	SMOTE	NU	20	J48 con	DT	NS	(mean) 0.80	(mean) 0.41	NS	(mean) 0.60	NS
J. L. Oliver 2020	Screening	Not-applic	Internal	SCV	SMOTE	NU	20	ADTree	DT	NS	(mean) 0.63	(mean) 0.42	NS	(mean) 0.58	NS
J. L. Oliver 2020	Screening	Not-applic	Internal	SCV	SMOTE	NU	20	REPTree	DT	NS	(mean) 0.77	(mean) 0.40	NS	(mean) 0.57	NS
J. L. Oliver 2020	Screening	Not-applic	Internal	SCV	ROS	NU	20	J48 con	DT	NS	(mean) 0.78	(mean) 0.36	NS	(mean) 0.62	NS
J. L. Oliver 2020	Screening	Not-applic	Internal	SCV	ROS	NU	20	ADTree	DT	NS	(mean) 0.69	(mean) 0.50	NS	(mean) 0.58	NS
J. L. Oliver 2020	Screening	Not-applic	Internal	SCV	ROS	NU	20	REPTree	DT	NS	(mean) 0.79	(mean) 0.38	NS	(mean) 0.61	NS
J. L. Oliver 2020	Screening	Not-applic	Internal	SCV	RUS	NU	20	J48 con	DT	NS	(mean) 0.77	(mean) 0.41	NS	(mean) 0.64	NS
J. L. Oliver 2020	Screening	Not-applic	Internal	SCV	RUS	NU	20	ADTree	DT	NS	(mean) 0.52	(mean) 0.64	NS	(mean) 0.62	NS
J. L. Oliver 2020	Screening	Not-applic	Internal	SCV	RUS	NU	20	REPTree	DT	NS	(mean) 0.79	(mean) 0.40	NS	(mean) 0.61	NS
J. L. Oliver 2020	Screening	Not-applic	Internal	SCV	NU	NU	20 (Meta Cost-Sensitive)	J48 con	DT	NS	(mean) 0.65	(mean) 0.60	NS	(mean) 0.64	NS
J. L. Oliver 2020	Screening	Not-applic	Internal	SCV	NU	NU	20 (Meta Cost-Sensitive)	ADTree	DT	NS	(mean) 0.72	(mean) 0.58	NS	(mean) 0.64	NS
J. L. Oliver 2020	Screening	Not-applic	Internal	SCV	NU	NU	20 (Meta Cost-Sensitive)	REPTree	DT	NS	(mean) 0.61	(mean) 0.60	NS	(mean) 0.60	NS
J. L. Oliver 2020	Screening	Not-applic	Internal	SCV	NU	NU	20 (Cost-Sensitive)	J48 con	DT	NS	(mean) 0.73	(mean) 0.47	NS	(mean) 0.61	NS
J. L. Oliver 2020	Screening	Not-applic	Internal	SCV	NU	NU	20 (Cost-Sensitive)	ADTree	DT	NS	(mean) 0.55	(mean) 0.67	NS	(mean) 0.63	NS
J. L. Oliver 2020	Screening	Not-applic	Internal	SCV	NU	NU	20 (Cost-Sensitive)	REPTree	DT	NS	(mean) 0.72	(mean) 0.34	NS	(mean) 0.52	NS
J. L. Oliver 2020	Screening	Not-applic	Internal	SCV	NU	AdaBoost	20 (Cost-Sensitive)	J48 con	DT	NS	(mean) 0.77	(mean) 0.37	NS	(mean) 0.61	NS
J. L. Oliver 2020	Screening	Not-applic	Internal	SCV	NU	AdaBoost	20 (Cost-Sensitive)	ADTree	DT	NS	(mean) 0.73	(mean) 0.43	NS	(mean) 0.61	NS
J. L. Oliver 2020	Screening	Not-applic	Internal	SCV	NU	AdaBoost	20 (Cost-Sensitive)	REPTree	DT	NS	(mean) 0.80	(mean) 0.30	NS	(mean) 0.59	NS
J. L. Oliver 2020	Screening	Not-applic	Internal	SCV	NU	AdaBoost	20 (Cost-Sensitive)	J48 con	DT	NS	(mean) 0.86	(mean) 0.30	NS	(mean) 0.64	NS
J. L. Oliver 2020	Screening	Not-applic	Internal	SCV	NU	AdaBoost	20 (Cost-Sensitive)	ADTree	DT	NS	(mean) 0.81	(mean) 0.29	NS	(mean) 0.62	NS
J. L. Oliver 2020	Screening	Not-applic	Internal	SCV	NU	AdaBoost	20 (Cost-Sensitive)	REPTree	DT	NS	(mean) 0.71	(mean) 0.31	NS	(mean) 0.49	NS
J. L. Oliver 2020	Screening	Not-applic	Internal	SCV	NU	Bagging	20 (Cost-Sensitive)	J48 con	DT	NS	(mean) 0.76	(mean) 0.50	NS	(mean) 0.64	NS
J. L. Oliver 2020	Screening	Not-applic	Internal	SCV	NU	Bagging	20 (Cost-Sensitive)	ADTree	DT	NS	(mean) 0.74	(mean) 0.56	NS	(mean) 0.66	NS
J. L. Oliver 2020	Screening	Not-applic	Internal	SCV	NU	Bagging	20 (Cost-Sensitive)	REPTree	DT	NS	(mean) 0.79	(mean) 0.36	NS	(mean) 0.65	NS
S. Jodvaisiene 2020	Screening	NS	NS	SCV	NU	Bagging	54	RF	RF	NS	NS	NS	NS	(mean) 0.63	NS
S. Jodvaisiene 2020	Screening	Not-applic	NS	SCV	NU	NU	54	L1-LR	LR	NS	NS	NS	NS	(mean) 0.65	NS
J. Kaniz 2021	Screening	Not-applic	Internal	NCV	NU	NU	7	LR	LR	NS	(mean) 0.65	(mean) 0.59	NS	(mean) 0.62	NS
J. Kaniz 2021	Screening	Not-applic	Internal	NCV	NU	NU	7	LDA	LDA	NS	(mean) 0.60	(mean) 0.43	NS	(mean) 0.44	NS
J. Kaniz 2021	Screening	Not-applic	Internal	NCV	NU	NU	7	NB	NB	NS	(mean) 0.71	(mean) 0.41	NS	(mean) 0.54	NS
J. Kaniz 2021	Screening	Not-applic	Internal	NCV	NU	NU	7	kNN	KNN	NS	(mean) 0.66	(mean) 0.53	NS	(mean) 0.57	NS
E. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	8	C4.5	DT	NS	NS	NS	NS	(mean) 0.48	NS
E. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	8	ADTree	DT	NS	NS	NS	NS	(mean) 0.58	NS
E. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	8	SVM	SVM	NS	NS	NS	NS	(mean) 0.49	NS
E. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	8	KNN	KNN	NS	NS	NS	NS	(mean) 0.5	NS
E. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	8	RF	RF	NS	NS	NS	NS	(mean) 0.49	NS
E. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	NU	8	C4.5	DT	NS	NS	NS	NS	(mean) 0.47	NS
E. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	NU	8	ADTree	DT	NS	NS	NS	NS	(mean) 0.56	NS
E. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	NU	8	SVM	SVM	NS	NS	NS	NS	(mean) 0.49	NS
E. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	NU	8	KNN	KNN	NS	NS	NS	NS	(mean) 0.49	NS
E. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	NU	8	RF	RF	NS	NS	NS	NS	(mean) 0.52	NS
E. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ROS	NU	8	C4.5	DT	NS	NS	NS	NS	(mean) 0.45	NS
E. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ROS	NU	8	ADTree	DT	NS	NS	NS	NS	(mean) 0.57	NS
E. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ROS	NU	8	SVM	SVM	NS	NS	NS	NS	(mean) 0.5	NS
E. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ROS	NU	8	KNN	KNN	NS	NS	NS	NS	(mean) 0.49	NS
E. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ROS	NU	8	RF	RF	NS	NS	NS	NS	(mean) 0.5	NS
E. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	NU	8	C4.5	DT	NS	NS	NS	NS	(mean) 0.5	NS
E. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	NU	8	ADTree	DT	NS	NS	NS	NS	(mean) 0.57	NS
E. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	NU	8	SVM	SVM	NS	NS	NS	NS	(mean) 0.51	NS
E. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	NU	8	KNN	KNN	NS	NS	NS	NS	(mean) 0.52	NS
E. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	NU	8	RF	RF	NS	NS	NS	NS	(mean) 0.49	NS
E. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ENN	NU	8	C4.5	DT	NS	NS	NS	NS	(mean) 0.5	NS
E. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ENN	NU	8	ADTree	DT	NS	NS	NS	NS	(mean) 0.56	NS
E. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ENN	NU	8	SVM	SVM	NS	NS	NS	NS	(mean) 0.49	NS
E. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ENN	NU	8	KNN	KNN	NS	NS	NS	NS	(mean) 0.51	NS
E. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ENN	NU	8	RF	RF	NS	NS	NS	NS	(mean) 0.5	NS
E. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	8	C4.5	DT	NS	NS	NS	NS	(mean) 0.44	NS
E. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	8	ADTree	DT	NS	NS	NS	NS	(mean) 0.47	NS
E. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	8	SVM	SVM	NS	NS	NS	NS	(mean) 0.5	NS
E. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	8	KNN	KNN	NS	NS	NS	NS	(mean) 0.48	NS
E. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	8	C4.5	DT	NS	NS	NS	NS	(mean) 0.45	NS
E. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	8	ADTree	DT	NS	NS	NS	NS	(mean) 0.48	NS
E. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	8	SVM	SVM	NS	NS	NS	NS	(mean) 0.51	NS
E. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	8	KNN	KNN	NS	NS	NS	NS	(mean) 0.47	NS
E. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	Bagging	8	C4.5	DT	NS	NS	NS	NS	(mean) 0.5	NS
E. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	Bagging	8	ADTree	DT	NS	NS	NS	NS	(mean) 0.58	NS
E. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	Bagging	8	SVM	SVM	NS	NS	NS	NS	(mean) 0.51	NS
E. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	Bagging	8	KNN	KNN	NS	NS	NS	NS	(mean) 0.5	NS
E. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Boosting	8	C4.5	DT	NS	NS	NS	NS	(mean) 0.48	NS
E. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Boosting	8	ADTree	DT	NS	NS	NS	NS	(mean) 0.51	NS
E. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Boosting	8	SVM	SVM	NS	NS	NS	NS	(mean) 0.51	NS
E. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Boosting	8	KNN	KNN	NS	NS	NS	NS	(mean) 0.48	NS
E. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	Boosting	8	C4.5	DT	NS	NS	NS	NS	(mean) 0.46	NS
E. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	Boosting	8	ADTree	DT	NS	NS	NS	NS	(mean) 0.49	NS
E. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	Boosting	8	SVM	SVM	NS	NS	NS	NS	(mean) 0.49	NS
E. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	Boosting	8	KNN	KNN	NS	NS	NS	NS	(mean) 0.46	NS
E. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	8	C4.5	DT	NS	NS	NS	NS	(mean) 0.49	NS
E. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	8	ADTree	DT	NS	NS	NS	NS	(mean) 0.57	NS
E. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	8	SVM	SVM	NS	NS	NS	NS	(mean) 0.55	NS
E. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	8	KNN	KNN	NS	NS	NS	NS	(mean) 0.48	NS
E. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	8	C4.5	DT	NS	NS	NS	NS	(mean) 0.53	NS
E. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	8	ADTree	DT	NS	NS	NS	NS	(mean) 0.58	NS
E. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	8	SVM	SVM	NS	NS	NS	NS	(mean) 0.57	NS
E. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	8	KNN	KNN	NS	NS	NS	NS	(mean) 0.53	NS

Author	Type of data collection	Time Management	Method validation	Cross-validation with fold number	Over- / Under-Sampling strategy	Ensemble method	Features number (trial)	Model Extracted	Model Categories	Accuracy	Specificity	Recall	Precision	ROC-AUC	F1 score
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	8	C4.5	DT	NS	NS	NS	NS	(mean) 0.53	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	8	ADTree	DT	NS	NS	NS	NS	(mean) 0.58	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	8	SVM	SVM	NS	NS	NS	NS	(mean) 0.55	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	8	KNN	KNN	NS	NS	NS	NS	(mean) 0.52	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	8 (Meta Cost-Sensitive)	C4.5	DT	NS	NS	NS	NS	(mean) 0.5	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	8 (Meta Cost-Sensitive)	ADTree	DT	NS	NS	NS	NS	(mean) 0.56	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	8 (Meta Cost-Sensitive)	SVM	SVM	NS	NS	NS	NS	(mean) 0.49	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	8 (Meta Cost-Sensitive)	KNN	KNN	NS	NS	NS	NS	(mean) 0.51	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	8 (Cost-Sensitive)	C4.5	DT	NS	NS	NS	NS	(mean) 0.48	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	8 (Cost-Sensitive)	ADTree	DT	NS	NS	NS	NS	(mean) 0.57	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	8 (Cost-Sensitive)	SVM	SVM	NS	NS	NS	NS	(mean) 0.47	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	8 (Cost-Sensitive)	KNN	KNN	NS	NS	NS	NS	(mean) 0.51	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	8 (Cost-Sensitive)	C4.5	DT	NS	NS	NS	NS	(mean) 0.52	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	8 (Cost-Sensitive)	ADTree	DT	NS	NS	NS	NS	(mean) 0.57	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	8 (Cost-Sensitive)	SVM	SVM	NS	NS	NS	NS	(mean) 0.56	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	8 (Cost-Sensitive)	KNN	KNN	NS	NS	NS	NS	(mean) 0.49	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	8 (Cost-Sensitive)	C4.5	DT	NS	NS	NS	NS	(mean) 0.54	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	8 (Cost-Sensitive)	ADTree	DT	NS	NS	NS	NS	(mean) 0.58	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	8 (Cost-Sensitive)	SVM	SVM	NS	NS	NS	NS	(mean) 0.58	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	8 (Cost-Sensitive)	KNN	KNN	NS	NS	NS	NS	(mean) 0.53	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	8 (Cost-Sensitive)	C4.5	DT	NS	NS	NS	NS	(mean) 0.55	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	8 (Cost-Sensitive)	ADTree	DT	NS	NS	NS	NS	(mean) 0.58	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	8 (Cost-Sensitive)	SVM	SVM	NS	NS	NS	NS	(mean) 0.55	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	8 (Cost-Sensitive)	KNN	KNN	NS	NS	NS	NS	(mean) 0.52	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	1	C4.5	DT	NS	NS	NS	NS	(mean) 0.5	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	1	ADTree	DT	NS	NS	NS	NS	(mean) 0.46	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	1	SVM	SVM	NS	NS	NS	NS	(mean) 0.5	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	1	KNN	KNN	NS	NS	NS	NS	(mean) 0.46	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	1	RF	RF	NS	NS	NS	NS	(mean) 0.45	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	NU	1	C4.5	DT	NS	NS	NS	NS	(mean) 0.41	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	NU	1	ADTree	DT	NS	NS	NS	NS	(mean) 0.41	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	NU	1	SVM	SVM	NS	NS	NS	NS	(mean) 0.45	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	NU	1	KNN	KNN	NS	NS	NS	NS	(mean) 0.41	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	NU	1	RF	RF	NS	NS	NS	NS	(mean) 0.41	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ROS	NU	1	C4.5	DT	NS	NS	NS	NS	(mean) 0.48	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ROS	NU	1	ADTree	DT	NS	NS	NS	NS	(mean) 0.45	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ROS	NU	1	SVM	SVM	NS	NS	NS	NS	(mean) 0.49	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ROS	NU	1	KNN	KNN	NS	NS	NS	NS	(mean) 0.46	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ROS	NU	1	RF	RF	NS	NS	NS	NS	(mean) 0.44	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	NU	1	C4.5	DT	NS	NS	NS	NS	(mean) 0.49	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	NU	1	ADTree	DT	NS	NS	NS	NS	(mean) 0.46	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	NU	1	SVM	SVM	NS	NS	NS	NS	(mean) 0.49	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	NU	1	KNN	KNN	NS	NS	NS	NS	(mean) 0.46	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	NU	1	RF	RF	NS	NS	NS	NS	(mean) 0.46	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ENN	NU	1	C4.5	DT	NS	NS	NS	NS	(mean) 0.5	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ENN	NU	1	ADTree	DT	NS	NS	NS	NS	(mean) 0.47	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ENN	NU	1	SVM	SVM	NS	NS	NS	NS	(mean) 0.5	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ENN	NU	1	KNN	KNN	NS	NS	NS	NS	(mean) 0.47	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ENN	NU	1	RF	RF	NS	NS	NS	NS	(mean) 0.46	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	1	C4.5	DT	NS	NS	NS	NS	(mean) 0.45	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	1	ADTree	DT	NS	NS	NS	NS	(mean) 0.46	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	1	SVM	SVM	NS	NS	NS	NS	(mean) 0.47	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	1	KNN	KNN	NS	NS	NS	NS	(mean) 0.46	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	1	C4.5	DT	NS	NS	NS	NS	(mean) 0.45	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	1	ADTree	DT	NS	NS	NS	NS	(mean) 0.46	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	1	SVM	SVM	NS	NS	NS	NS	(mean) 0.46	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	1	KNN	KNN	NS	NS	NS	NS	(mean) 0.46	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	Bagging	1	C4.5	DT	NS	NS	NS	NS	(mean) 0.49	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	Bagging	1	ADTree	DT	NS	NS	NS	NS	(mean) 0.43	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	Bagging	1	SVM	SVM	NS	NS	NS	NS	(mean) 0.52	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	Bagging	1	KNN	KNN	NS	NS	NS	NS	(mean) 0.46	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Boosting	1	C4.5	DT	NS	NS	NS	NS	(mean) 0.42	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Boosting	1	ADTree	DT	NS	NS	NS	NS	(mean) 0.42	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Boosting	1	SVM	SVM	NS	NS	NS	NS	(mean) 0.44	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Boosting	1	KNN	KNN	NS	NS	NS	NS	(mean) 0.42	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	Boosting	1	C4.5	DT	NS	NS	NS	NS	(mean) 0.46	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	Boosting	1	ADTree	DT	NS	NS	NS	NS	(mean) 0.46	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	Boosting	1	SVM	SVM	NS	NS	NS	NS	(mean) 0.46	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	Boosting	1	KNN	KNN	NS	NS	NS	NS	(mean) 0.47	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	1	C4.5	DT	NS	NS	NS	NS	(mean) 0.42	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	1	ADTree	DT	NS	NS	NS	NS	(mean) 0.41	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	1	SVM	SVM	NS	NS	NS	NS	(mean) 0.41	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	1	KNN	KNN	NS	NS	NS	NS	(mean) 0.42	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	1	C4.5	DT	NS	NS	NS	NS	(mean) 0.48	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	1	ADTree	DT	NS	NS	NS	NS	(mean) 0.44	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	1	SVM	SVM	NS	NS	NS	NS	(mean) 0.51	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	1	KNN	KNN	NS	NS	NS	NS	(mean) 0.45	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	1	C4.5	DT	NS	NS	NS	NS	(mean) 0.38	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	1	ADTree	DT	NS	NS	NS	NS	(mean) 0.38	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	1	SVM	SVM	NS	NS	NS	NS	(mean) 0.41	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	1	KNN	KNN	NS	NS	NS	NS	(mean) 0.38	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	1 (Meta Cost-Sensitive)	C4.5	DT	NS	NS	NS	NS	(mean) 0.5	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	1 (Meta Cost-Sensitive)	ADTree	DT	NS	NS	NS	NS	(mean) 0.5	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	1 (Meta Cost-Sensitive)	SVM	SVM	NS	NS	NS	NS	(mean) 0.5	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	1 (Meta Cost-Sensitive)	KNN	KNN	NS	NS	NS	NS	(mean) 0.58	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	1 (Cost-Sensitive)	C4.5	DT	NS	NS	NS	NS	(mean) 0.5	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	1 (Cost-Sensitive)	ADTree	DT	NS	NS	NS	NS	(mean) 0.46	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	1 (Cost-Sensitive)	SVM	SVM	NS	NS	NS	NS	(mean) 0.48	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	1 (Cost-Sensitive)	KNN	KNN	NS	NS	NS	NS	(mean) 0.46	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	1 (Cost-Sensitive)	C4.5	DT	NS	NS	NS	NS	(mean) 0.42	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	1 (Cost-Sensitive)	ADTree	DT	NS	NS	NS	NS	(mean) 0.41	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	1 (Cost-Sensitive)	SVM	SVM	NS	NS	NS	NS	(mean) 0.43	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	1 (Cost-Sensitive)	KNN	KNN	NS	NS	NS	NS	(mean) 0.42	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	1 (Cost-Sensitive)	C4.5	DT	NS	NS	NS	NS	(mean) 0.43	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	1 (Cost-Sensitive)	ADTree	DT	NS	NS	NS	NS	(mean) 0.44	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	1 (Cost-Sensitive)	SVM	SVM	NS	NS	NS	NS	(mean) 0.43	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	1 (Cost-Sensitive)	KNN	KNN	NS	NS	NS	NS	(mean) 0.43	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	1 (Cost-Sensitive)	C4.5	DT	NS	NS	NS	NS	(mean) 0.37	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	1 (Cost-Sensitive)	ADTree	DT	NS	NS	NS	NS	(mean) 0.37	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	1 (Cost-Sensitive)	SVM	SVM	NS	NS	NS	NS	(mean) 0.37	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	1 (Cost-Sensitive)	KNN	KNN	NS	NS	NS	NS	(mean) 0.37	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	3	C4.5	DT	NS	NS	NS	NS	(mean) 0.5	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	3	ADTree	DT	NS	NS	NS	NS	(mean) 0.56	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	3	SVM	SVM	NS	NS	NS	NS	(mean) 0.5	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	3	KNN	KNN	NS	NS	NS	NS	(mean) 0.64	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	3	RF	RF	NS	NS	NS	NS	(mean) 0.63	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	NU	3	C4.5	DT	NS	NS	NS	NS	(mean) 0.54	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	NU	3	ADTree	DT	NS	NS	NS	NS	(mean) 0.54	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	NU	3	SVM	SVM	NS	NS	NS	NS	(mean) 0.51	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	NU	3	KNN	KNN	NS	NS	NS	NS	(mean) 0.61	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	NU	3	RF	RF	NS	NS	NS	NS	(mean) 0.6	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ROS	NU	3	C4.5	DT	NS	NS	NS	NS	(mean) 0.54	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ROS	NU	3	ADTree	DT	NS	NS	NS	NS	(mean) 0.57	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ROS	NU	3	SVM	SVM	NS	NS	NS	NS	(mean) 0.53	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ROS	NU	3	KNN	KNN	NS	NS	NS	NS	(mean) 0.64	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ROS	NU	3	RF	RF	NS	NS	NS	NS	(mean) 0.63	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	NU	3	C4.5	DT	NS	NS	NS	NS	(mean) 0.49	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	NU	3	ADTree	DT	NS	NS	NS	NS	(mean) 0.56	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	NU	3	SVM	SVM	NS	NS	NS	NS	(mean) 0.53	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	NU	3	KNN	KNN	NS	NS	NS	NS	(mean) 0.6	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	NU	3	RF	RF	NS	NS	NS	NS	(mean) 0.59	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ENN	NU	3	C4.5	DT	NS	NS	NS	NS	(mean) 0.5	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ENN	NU	3	ADTree	DT	NS	NS	NS	NS	(mean) 0.55	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ENN	NU	3	SVM	SVM	NS	NS	NS	NS	(mean) 0.5	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ENN	NU	3	KNN	KNN	NS	NS	NS	NS	(mean) 0.62	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ENN	NU	3	RF	RF	NS	NS	NS	NS	(mean) 0.62	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	3	C4.5	DT	NS	NS	NS	NS	(mean) 0.58	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	3	ADTree	DT	NS	NS	NS	NS	(mean) 0.62	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	3	SVM	SVM	NS	NS	NS	NS	(mean) 0.52	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	3	KNN	KNN	NS	NS	NS	NS	(mean) 0.63	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	3	C4.5	DT	NS	NS	NS	NS	(mean) 0.56	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	3	ADTree	DT	NS	NS	NS	NS	(mean) 0.62	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	3	SVM	SVM	NS	NS	NS	NS	(mean) 0.56	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	3	KNN	KNN	NS	NS	NS	NS	(mean) 0.63	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	Bagging	3	C4.5	DT	NS	NS	NS	NS	(mean) 0.51	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	Bagging	3	ADTree	DT	NS	NS	NS	NS	(mean) 0.58	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	Bagging	3	SVM	SVM	NS	NS	NS	NS	(mean) 0.53	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	Bagging	3	KNN	KNN	NS	NS	NS	NS	(mean) 0.64	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Boosting	3	C4.5	DT	NS	NS	NS	NS	(mean) 0.6	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Boosting	3	ADTree	DT	NS	NS	NS	NS	(mean) 0.59	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Boosting	3	SVM	SVM	NS	NS	NS	NS	(mean) 0.57	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Boosting	3	KNN	KNN	NS	NS	NS	NS	(mean) 0.62	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	Boosting	3	C4.5	DT	NS	NS	NS	NS	(mean) 0.59	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	Boosting	3	ADTree	DT	NS	NS	NS	NS	(mean) 0.61	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	Boosting	3	SVM	SVM	NS	NS	NS	NS	(mean) 0.57	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	Boosting	3	KNN	KNN	NS	NS	NS	NS	(mean) 0.62	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	3	C4.5	DT	NS	NS	NS	NS	(mean) 0.61	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	3	ADTree	DT	NS	NS	NS	NS	(mean) 0.58	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	3	SVM	SVM	NS	NS	NS	NS	(mean) 0.59	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	3	KNN	KNN	NS	NS	NS	NS	(mean) 0.64	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	3	C4.5	DT	NS	NS	NS	NS	(mean) 0.56	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	3	ADTree	DT	NS	NS	NS	NS	(mean) 0.58	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	3	SVM	SVM	NS	NS	NS	NS	(mean) 0.57	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	3	KNN	KNN	NS	NS	NS	NS	(mean) 0.62	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	3	C4.5	DT	NS	NS	NS	NS	(mean) 0.59	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	3	ADTree	DT	NS	NS	NS	NS	(mean) 0.58	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	3	SVM	SVM	NS	NS	NS	NS	(mean) 0.57	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	3	KNN	KNN	NS	NS	NS	NS	(mean) 0.62	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	3 (Meta Cost-Sensitive)	C4.5	DT	NS	NS	NS	NS	(mean) 0.5	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	3 (Meta Cost-Sensitive)	ADTree	DT	NS	NS	NS	NS	(mean) 0.56	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	3 (Meta Cost-Sensitive)	SVM	SVM	NS	NS	NS	NS	(mean) 0.51	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	3 (Meta Cost-Sensitive)	KNN	KNN	NS	NS	NS	NS	(mean) 0.56	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	3 (Cost-Sensitive)	C4.5	DT	NS	NS	NS	NS	(mean) 0.5	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	3 (Cost-Sensitive)	ADTree	DT	NS	NS	NS	NS	(mean) 0.56	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	3 (Cost-Sensitive)	SVM	SVM	NS	NS	NS	NS	(mean) 0.52	NS

Author	Type of data collection	Time_Management	Method validation	Cross-validation with fold number	Over- / Under-Sampling strategy	Ensemble_method	Features number (trial)	Model Extracted	Model Categories	Accuracy	Specificity	Recall	Precision	ROC-AUC	F1 score
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	3 (Cost-Sensitive)	KNN	KNN	NS	NS	NS	NS	(mean) 0.64	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	3 (Cost-Sensitive)	C4.5	DT	NS	NS	NS	NS	(mean) 0.59	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	3 (Cost-Sensitive)	ADTree	DT	NS	NS	NS	NS	(mean) 0.58	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	3 (Cost-Sensitive)	SVM	SVM	NS	NS	NS	NS	(mean) 0.58	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	3 (Cost-Sensitive)	KNN	KNN	NS	NS	NS	NS	(mean) 0.64	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	3 (Cost-Sensitive)	C4.5	DT	NS	NS	NS	NS	(mean) 0.56	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	3 (Cost-Sensitive)	ADTree	DT	NS	NS	NS	NS	(mean) 0.58	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	3 (Cost-Sensitive)	SVM	SVM	NS	NS	NS	NS	(mean) 0.57	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	3 (Cost-Sensitive)	KNN	KNN	NS	NS	NS	NS	(mean) 0.62	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	3 (Cost-Sensitive)	C4.5	DT	NS	NS	NS	NS	(mean) 0.58	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	3 (Cost-Sensitive)	ADTree	DT	NS	NS	NS	NS	(mean) 0.58	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	3 (Cost-Sensitive)	SVM	SVM	NS	NS	NS	NS	(mean) 0.57	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	3 (Cost-Sensitive)	KNN	KNN	NS	NS	NS	NS	(mean) 0.62	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	5	C4.5	DT	NS	NS	NS	NS	(mean) 0.5	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	5	ADTree	DT	NS	NS	NS	NS	(mean) 0.44	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	5	SVM	SVM	NS	NS	NS	NS	(mean) 0.49	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	5	KNN	KNN	NS	NS	NS	NS	(mean) 0.46	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	5	RF	RF	NS	NS	NS	NS	(mean) 0.38	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	NU	5	C4.5	DT	NS	NS	NS	NS	(mean) 0.46	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	NU	5	ADTree	DT	NS	NS	NS	NS	(mean) 0.47	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	NU	5	SVM	SVM	NS	NS	NS	NS	(mean) 0.49	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	NU	5	KNN	KNN	NS	NS	NS	NS	(mean) 0.45	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	NU	5	RF	RF	NS	NS	NS	NS	(mean) 0.42	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ROS	NU	5	C4.5	DT	NS	NS	NS	NS	(mean) 0.42	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ROS	NU	5	ADTree	DT	NS	NS	NS	NS	(mean) 0.44	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ROS	NU	5	SVM	SVM	NS	NS	NS	NS	(mean) 0.45	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ROS	NU	5	KNN	KNN	NS	NS	NS	NS	(mean) 0.46	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ROS	NU	5	RF	RF	NS	NS	NS	NS	(mean) 0.38	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	NU	5	C4.5	DT	NS	NS	NS	NS	(mean) 0.49	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	NU	5	ADTree	DT	NS	NS	NS	NS	(mean) 0.45	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	NU	5	SVM	SVM	NS	NS	NS	NS	(mean) 0.45	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	NU	5	KNN	KNN	NS	NS	NS	NS	(mean) 0.47	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	NU	5	RF	RF	NS	NS	NS	NS	(mean) 0.41	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ENN	NU	5	C4.5	DT	NS	NS	NS	NS	(mean) 0.5	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ENN	NU	5	ADTree	DT	NS	NS	NS	NS	(mean) 0.45	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ENN	NU	5	SVM	SVM	NS	NS	NS	NS	(mean) 0.49	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ENN	NU	5	KNN	KNN	NS	NS	NS	NS	(mean) 0.48	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ENN	NU	5	RF	RF	NS	NS	NS	NS	(mean) 0.4	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	5	C4.5	DT	NS	NS	NS	NS	(mean) 0.42	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	5	ADTree	DT	NS	NS	NS	NS	(mean) 0.46	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	5	SVM	SVM	NS	NS	NS	NS	(mean) 0.46	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	5	KNN	KNN	NS	NS	NS	NS	(mean) 0.49	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	5	C4.5	DT	NS	NS	NS	NS	(mean) 0.43	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	5	ADTree	DT	NS	NS	NS	NS	(mean) 0.45	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	5	SVM	SVM	NS	NS	NS	NS	(mean) 0.44	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	5	KNN	KNN	NS	NS	NS	NS	(mean) 0.41	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	Bagging	5	C4.5	DT	NS	NS	NS	NS	(mean) 0.46	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	Bagging	5	ADTree	DT	NS	NS	NS	NS	(mean) 0.43	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	Bagging	5	SVM	SVM	NS	NS	NS	NS	(mean) 0.41	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	Bagging	5	KNN	KNN	NS	NS	NS	NS	(mean) 0.47	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Boosting	5	C4.5	DT	NS	NS	NS	NS	(mean) 0.45	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Boosting	5	ADTree	DT	NS	NS	NS	NS	(mean) 0.45	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Boosting	5	SVM	SVM	NS	NS	NS	NS	(mean) 0.45	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Boosting	5	KNN	KNN	NS	NS	NS	NS	(mean) 0.47	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	Boosting	5	C4.5	DT	NS	NS	NS	NS	(mean) 0.43	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	Boosting	5	ADTree	DT	NS	NS	NS	NS	(mean) 0.44	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	Boosting	5	SVM	SVM	NS	NS	NS	NS	(mean) 0.44	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	Boosting	5	KNN	KNN	NS	NS	NS	NS	(mean) 0.46	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	5	C4.5	DT	NS	NS	NS	NS	(mean) 0.42	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	5	ADTree	DT	NS	NS	NS	NS	(mean) 0.43	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	5	SVM	SVM	NS	NS	NS	NS	(mean) 0.44	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	5	KNN	KNN	NS	NS	NS	NS	(mean) 0.46	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	5	C4.5	DT	NS	NS	NS	NS	(mean) 0.43	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	5	ADTree	DT	NS	NS	NS	NS	(mean) 0.43	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	5	SVM	SVM	NS	NS	NS	NS	(mean) 0.41	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	5	KNN	KNN	NS	NS	NS	NS	(mean) 0.47	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	5	C4.5	DT	NS	NS	NS	NS	(mean) 0.44	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	5	ADTree	DT	NS	NS	NS	NS	(mean) 0.46	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	5	SVM	SVM	NS	NS	NS	NS	(mean) 0.46	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	5	KNN	KNN	NS	NS	NS	NS	(mean) 0.45	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	5 (Meta Cost-Sensitive)	C4.5	DT	NS	NS	NS	NS	(mean) 0.5	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	5 (Meta Cost-Sensitive)	ADTree	DT	NS	NS	NS	NS	(mean) 0.42	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	5 (Meta Cost-Sensitive)	SVM	SVM	NS	NS	NS	NS	(mean) 0.48	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	5 (Meta Cost-Sensitive)	KNN	KNN	NS	NS	NS	NS	(mean) 0.47	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	5 (Cost-Sensitive)	C4.5	DT	NS	NS	NS	NS	(mean) 0.5	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	5 (Cost-Sensitive)	ADTree	DT	NS	NS	NS	NS	(mean) 0.43	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	5 (Cost-Sensitive)	SVM	SVM	NS	NS	NS	NS	(mean) 0.46	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	5 (Cost-Sensitive)	KNN	KNN	NS	NS	NS	NS	(mean) 0.46	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	5 (Cost-Sensitive)	C4.5	DT	NS	NS	NS	NS	(mean) 0.43	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	5 (Cost-Sensitive)	ADTree	DT	NS	NS	NS	NS	(mean) 0.44	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	5 (Cost-Sensitive)	SVM	SVM	NS	NS	NS	NS	(mean) 0.43	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	5 (Cost-Sensitive)	KNN	KNN	NS	NS	NS	NS	(mean) 0.46	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	5 (Cost-Sensitive)	C4.5	DT	NS	NS	NS	NS	(mean) 0.44	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	5 (Cost-Sensitive)	ADTree	DT	NS	NS	NS	NS	(mean) 0.43	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	5 (Cost-Sensitive)	SVM	SVM	NS	NS	NS	NS	(mean) 0.43	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	5 (Cost-Sensitive)	KNN	KNN	NS	NS	NS	NS	(mean) 0.47	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	5 (Cost-Sensitive)	C4.5	DT	NS	NS	NS	NS	(mean) 0.45	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	5 (Cost-Sensitive)	ADTree	DT	NS	NS	NS	NS	(mean) 0.46	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	5 (Cost-Sensitive)	SVM	SVM	NS	NS	NS	NS	(mean) 0.45	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	5 (Cost-Sensitive)	KNN	KNN	NS	NS	NS	NS	(mean) 0.44	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	2	C4.5	DT	NS	NS	NS	NS	(mean) 0.5	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	2	ADTree	DT	NS	NS	NS	NS	(mean) 0.6	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	2	SVM	SVM	NS	NS	NS	NS	(mean) 0.5	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	2	KNN	KNN	NS	NS	NS	NS	(mean) 0.6	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	2	RF	RF	NS	NS	NS	NS	(mean) 0.6	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	NU	2	C4.5	DT	NS	NS	NS	NS	(mean) 0.57	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	NU	2	ADTree	DT	NS	NS	NS	NS	(mean) 0.56	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	NU	2	SVM	SVM	NS	NS	NS	NS	(mean) 0.52	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	NU	2	KNN	KNN	NS	NS	NS	NS	(mean) 0.55	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	NU	2	RF	RF	NS	NS	NS	NS	(mean) 0.56	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ROS	NU	2	C4.5	DT	NS	NS	NS	NS	(mean) 0.55	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ROS	NU	2	ADTree	DT	NS	NS	NS	NS	(mean) 0.6	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ROS	NU	2	SVM	SVM	NS	NS	NS	NS	(mean) 0.53	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ROS	NU	2	KNN	KNN	NS	NS	NS	NS	(mean) 0.59	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ROS	NU	2	RF	RF	NS	NS	NS	NS	(mean) 0.6	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	NU	2	C4.5	DT	NS	NS	NS	NS	(mean) 0.52	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	NU	2	ADTree	DT	NS	NS	NS	NS	(mean) 0.58	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	NU	2	SVM	SVM	NS	NS	NS	NS	(mean) 0.53	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	NU	2	KNN	KNN	NS	NS	NS	NS	(mean) 0.58	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	NU	2	RF	RF	NS	NS	NS	NS	(mean) 0.59	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ENN	NU	2	C4.5	DT	NS	NS	NS	NS	(mean) 0.5	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ENN	NU	2	ADTree	DT	NS	NS	NS	NS	(mean) 0.59	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ENN	NU	2	SVM	SVM	NS	NS	NS	NS	(mean) 0.5	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ENN	NU	2	KNN	KNN	NS	NS	NS	NS	(mean) 0.59	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ENN	NU	2	RF	RF	NS	NS	NS	NS	(mean) 0.59	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	2	C4.5	DT	NS	NS	NS	NS	(mean) 0.6	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	2	ADTree	DT	NS	NS	NS	NS	(mean) 0.6	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	2	SVM	SVM	NS	NS	NS	NS	(mean) 0.53	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	2	KNN	KNN	NS	NS	NS	NS	(mean) 0.6	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	2	C4.5	DT	NS	NS	NS	NS	(mean) 0.6	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	2	ADTree	DT	NS	NS	NS	NS	(mean) 0.6	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	2	SVM	SVM	NS	NS	NS	NS	(mean) 0.61	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	2	KNN	KNN	NS	NS	NS	NS	(mean) 0.6	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	Bagging	2	C4.5	DT	NS	NS	NS	NS	(mean) 0.58	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	Bagging	2	ADTree	DT	NS	NS	NS	NS	(mean) 0.6	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	Bagging	2	SVM	SVM	NS	NS	NS	NS	(mean) 0.54	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	Bagging	2	KNN	KNN	NS	NS	NS	NS	(mean) 0.6	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	2	C4.5	DT	NS	NS	NS	NS	(mean) 0.56	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	2	ADTree	DT	NS	NS	NS	NS	(mean) 0.55	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	2	SVM	SVM	NS	NS	NS	NS	(mean) 0.56	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	2	KNN	KNN	NS	NS	NS	NS	(mean) 0.54	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	Bagging	2	C4.5	DT	NS	NS	NS	NS	(mean) 0.58	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	Bagging	2	ADTree	DT	NS	NS	NS	NS	(mean) 0.59	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	Bagging	2	SVM	SVM	NS	NS	NS	NS	(mean) 0.58	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	Bagging	2	KNN	KNN	NS	NS	NS	NS	(mean) 0.59	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	2	C4.5	DT	NS	NS	NS	NS	(mean) 0.59	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	2	ADTree	DT	NS	NS	NS	NS	(mean) 0.6	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	2	SVM	SVM	NS	NS	NS	NS	(mean) 0.6	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	2	KNN	KNN	NS	NS	NS	NS	(mean) 0.6	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	2	C4.5	DT	NS	NS	NS	NS	(mean) 0.61	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	2	ADTree	DT	NS	NS	NS	NS	(mean) 0.6	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	2	SVM	SVM	NS	NS	NS	NS	(mean) 0.6	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	2	KNN	KNN	NS	NS	NS	NS	(mean) 0.59	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	2	C4.5	DT	NS	NS	NS	NS	(mean) 0.57	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	2	ADTree	DT	NS	NS	NS	NS	(mean) 0.58	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	2	SVM	SVM	NS	NS	NS	NS	(mean) 0.61	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	2	KNN	KNN	NS	NS	NS	NS	(mean) 0.57	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	2 (Meta Cost-Sensitive)	C4.5	DT	NS	NS	NS	NS	(mean) 0.5	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	2 (Meta Cost-Sensitive)	ADTree	DT	NS	NS	NS	NS	(mean) 0.52	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	2 (Meta Cost-Sensitive)	SVM	SVM	NS	NS	NS	NS	(mean) 0.5	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	2 (Meta Cost-Sensitive)	KNN	KNN	NS	NS	NS	NS	(mean) 0.48	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	2 (Cost-Sensitive)	C4.5	DT	NS	NS	NS	NS	(mean) 0.5	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	2 (Cost-Sensitive)	ADTree	DT	NS	NS	NS	NS	(mean) 0.6	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	2 (Cost-Sensitive)	SVM	SVM	NS	NS	NS	NS	(mean) 0.53	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	2 (Cost-Sensitive)	KNN	KNN	NS	NS	NS	NS	(mean) 0.6	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	2 (Cost-Sensitive)	C4.5	DT	NS	NS	NS	NS	(mean) 0.59	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	2 (Cost-Sensitive)	ADTree	DT	NS	NS	NS	NS	(mean) 0.6	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	2 (Cost-Sensitive)	SVM	SVM	NS	NS	NS	NS	(mean) 0.6	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	2 (Cost-Sensitive)	KNN	KNN	NS	NS	NS	NS	(mean) 0.6	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	2 (Cost-Sensitive)	C4.5	DT	NS	NS	NS	NS	(mean) 0.61	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	2 (Cost-Sensitive)	ADTree	DT	NS	NS	NS	NS	(mean) 0.6	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	2 (Cost-Sensitive)	SVM	SVM	NS	NS	NS	NS	(mean) 0.6	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	2 (Cost-Sensitive)	KNN	KNN	NS	NS	NS	NS	(mean) 0.59	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	2 (Cost-Sensitive)	C4.5	DT	NS	NS	NS	NS	(mean) 0.56	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	2 (Cost-Sensitive)	ADTree	DT	NS	NS	NS	NS	(mean) 0.57	NS

Author	Type of data collection	Time Management	Method validation	Cross-validation with fold number	Over- / Under-Sampling strategy	Ensemble method	Features number (trial)	Model Extracted	Model Categories	Accuracy	Specificity	Recall	Precision	ROC-AUC	F1 score
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	2 (Cost-Sensitive)	SVM	SVM	NS	NS	NS	NS	(mean) 0.6	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	2 (Cost-Sensitive)	KNN	KNN	NS	NS	NS	NS	(mean) 0.56	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	27	C4.5	DT	NS	NS	NS	NS	(mean) 0.63	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	27	ADTree	DT	NS	NS	NS	NS	(mean) 0.75	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	27	SVM	SVM	NS	NS	NS	NS	(mean) 0.57	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	27	KNN	KNN	NS	NS	NS	NS	(mean) 0.59	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	27	RF	RF	NS	NS	NS	NS	(mean) 0.69	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	NU	27	C4.5	DT	NS	NS	NS	NS	(mean) 0.61	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	NU	27	ADTree	DT	NS	NS	NS	NS	(mean) 0.71	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	NU	27	SVM	SVM	NS	NS	NS	NS	(mean) 0.56	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	NU	27	KNN	KNN	NS	NS	NS	NS	(mean) 0.6	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	NU	27	RF	RF	NS	NS	NS	NS	(mean) 0.68	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ROS	NU	27	C4.5	DT	NS	NS	NS	NS	(mean) 0.62	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ROS	NU	27	ADTree	DT	NS	NS	NS	NS	(mean) 0.75	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ROS	NU	27	SVM	SVM	NS	NS	NS	NS	(mean) 0.57	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ROS	NU	27	KNN	KNN	NS	NS	NS	NS	(mean) 0.59	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ROS	NU	27	RF	RF	NS	NS	NS	NS	(mean) 0.71	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	NU	27	C4.5	DT	NS	NS	NS	NS	(mean) 0.64	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	NU	27	ADTree	DT	NS	NS	NS	NS	(mean) 0.69	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	NU	27	SVM	SVM	NS	NS	NS	NS	(mean) 0.6	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	NU	27	KNN	KNN	NS	NS	NS	NS	(mean) 0.62	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	NU	27	RF	RF	NS	NS	NS	NS	(mean) 0.69	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ENN	NU	27	C4.5	DT	NS	NS	NS	NS	(mean) 0.6	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ENN	NU	27	ADTree	DT	NS	NS	NS	NS	(mean) 0.7	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ENN	NU	27	SVM	SVM	NS	NS	NS	NS	(mean) 0.56	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ENN	NU	27	KNN	KNN	NS	NS	NS	NS	(mean) 0.6	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ENN	NU	27	RF	RF	NS	NS	NS	NS	(mean) 0.67	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	27	C4.5	DT	NS	NS	NS	NS	(mean) 0.6	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	27	ADTree	DT	NS	NS	NS	NS	(mean) 0.75	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	27	SVM	SVM	NS	NS	NS	NS	(mean) 0.58	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	27	KNN	KNN	NS	NS	NS	NS	(mean) 0.53	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	27	C4.5	DT	NS	NS	NS	NS	(mean) 0.61	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	27	ADTree	DT	NS	NS	NS	NS	(mean) 0.73	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	27	SVM	SVM	NS	NS	NS	NS	(mean) 0.58	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	27	KNN	KNN	NS	NS	NS	NS	(mean) 0.56	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	Bagging	27	C4.5	DT	NS	NS	NS	NS	(mean) 0.74	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	Bagging	27	ADTree	DT	NS	NS	NS	NS	(mean) 0.76	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	Bagging	27	SVM	SVM	NS	NS	NS	NS	(mean) 0.68	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	Bagging	27	KNN	KNN	NS	NS	NS	NS	(mean) 0.61	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Boosting	27	C4.5	DT	NS	NS	NS	NS	(mean) 0.65	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Boosting	27	ADTree	DT	NS	NS	NS	NS	(mean) 0.67	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Boosting	27	SVM	SVM	NS	NS	NS	NS	(mean) 0.57	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Boosting	27	KNN	KNN	NS	NS	NS	NS	(mean) 0.58	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	Boosting	27	C4.5	DT	NS	NS	NS	NS	(mean) 0.67	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	Boosting	27	ADTree	DT	NS	NS	NS	NS	(mean) 0.68	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	Boosting	27	SVM	SVM	NS	NS	NS	NS	(mean) 0.62	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	Boosting	27	KNN	KNN	NS	NS	NS	NS	(mean) 0.63	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	27	C4.5	DT	NS	NS	NS	NS	(mean) 0.76	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	27	ADTree	DT	NS	NS	NS	NS	(mean) 0.76	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	27	SVM	SVM	NS	NS	NS	NS	(mean) 0.68	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	27	KNN	KNN	NS	NS	NS	NS	(mean) 0.61	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	27	C4.5	DT	NS	NS	NS	NS	(mean) 0.76	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	27	ADTree	DT	NS	NS	NS	NS	(mean) 0.74	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	27	SVM	SVM	NS	NS	NS	NS	(mean) 0.69	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	27	KNN	KNN	NS	NS	NS	NS	(mean) 0.65	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	27	C4.5	DT	NS	NS	NS	NS	(mean) 0.74	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	27	ADTree	DT	NS	NS	NS	NS	(mean) 0.74	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	27	SVM	SVM	NS	NS	NS	NS	(mean) 0.68	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	27	KNN	KNN	NS	NS	NS	NS	(mean) 0.63	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	27 (Meta Cost-Sensitive)	C4.5	DT	NS	NS	NS	NS	(mean) 0.62	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	27 (Meta Cost-Sensitive)	ADTree	DT	NS	NS	NS	NS	(mean) 0.73	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	27 (Meta Cost-Sensitive)	SVM	SVM	NS	NS	NS	NS	(mean) 0.56	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	27 (Meta Cost-Sensitive)	KNN	KNN	NS	NS	NS	NS	(mean) 0.61	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	27 (Cost-Sensitive)	C4.5	DT	NS	NS	NS	NS	(mean) 0.64	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	27 (Cost-Sensitive)	ADTree	DT	NS	NS	NS	NS	(mean) 0.76	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	27 (Cost-Sensitive)	SVM	SVM	NS	NS	NS	NS	(mean) 0.57	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	27 (Cost-Sensitive)	KNN	KNN	NS	NS	NS	NS	(mean) 0.5	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	27 (Cost-Sensitive)	C4.5	DT	NS	NS	NS	NS	(mean) 0.75	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	27 (Cost-Sensitive)	ADTree	DT	NS	NS	NS	NS	(mean) 0.76	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	27 (Cost-Sensitive)	SVM	SVM	NS	NS	NS	NS	(mean) 0.68	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	27 (Cost-Sensitive)	KNN	KNN	NS	NS	NS	NS	(mean) 0.61	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	27 (Cost-Sensitive)	C4.5	DT	NS	NS	NS	NS	(mean) 0.76	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	27 (Cost-Sensitive)	ADTree	DT	NS	NS	NS	NS	(mean) 0.74	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	27 (Cost-Sensitive)	SVM	SVM	NS	NS	NS	NS	(mean) 0.69	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	27 (Cost-Sensitive)	KNN	KNN	NS	NS	NS	NS	(mean) 0.64	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	27 (Cost-Sensitive)	C4.5	DT	NS	NS	NS	NS	(mean) 0.73	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	27 (Cost-Sensitive)	ADTree	DT	NS	NS	NS	NS	(mean) 0.74	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	27 (Cost-Sensitive)	SVM	SVM	NS	NS	NS	NS	(mean) 0.68	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	27 (Cost-Sensitive)	KNN	KNN	NS	NS	NS	NS	(mean) 0.63	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	8	C4.5	DT	NS	NS	NS	NS	(mean) 0.52	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	8	ADTree	DT	NS	NS	NS	NS	(mean) 0.51	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	8	SVM	SVM	NS	NS	NS	NS	(mean) 0.49	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	8	KNN	KNN	NS	NS	NS	NS	(mean) 0.61	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	8	RF	RF	NS	NS	NS	NS	(mean) 0.57	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	NU	8	C4.5	DT	NS	NS	NS	NS	(mean) 0.56	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	NU	8	ADTree	DT	NS	NS	NS	NS	(mean) 0.53	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	NU	8	SVM	SVM	NS	NS	NS	NS	(mean) 0.48	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	NU	8	KNN	KNN	NS	NS	NS	NS	(mean) 0.61	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	NU	8	RF	RF	NS	NS	NS	NS	(mean) 0.56	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ROS	NU	8	C4.5	DT	NS	NS	NS	NS	(mean) 0.53	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ROS	NU	8	ADTree	DT	NS	NS	NS	NS	(mean) 0.52	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ROS	NU	8	SVM	SVM	NS	NS	NS	NS	(mean) 0.5	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ROS	NU	8	KNN	KNN	NS	NS	NS	NS	(mean) 0.62	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ROS	NU	8	RF	RF	NS	NS	NS	NS	(mean) 0.57	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	NU	8	C4.5	DT	NS	NS	NS	NS	(mean) 0.54	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	NU	8	ADTree	DT	NS	NS	NS	NS	(mean) 0.52	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	NU	8	SVM	SVM	NS	NS	NS	NS	(mean) 0.5	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	NU	8	KNN	KNN	NS	NS	NS	NS	(mean) 0.56	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	NU	8	RF	RF	NS	NS	NS	NS	(mean) 0.56	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ENN	NU	8	C4.5	DT	NS	NS	NS	NS	(mean) 0.51	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ENN	NU	8	ADTree	DT	NS	NS	NS	NS	(mean) 0.51	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ENN	NU	8	SVM	SVM	NS	NS	NS	NS	(mean) 0.49	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ENN	NU	8	KNN	KNN	NS	NS	NS	NS	(mean) 0.59	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ENN	NU	8	RF	RF	NS	NS	NS	NS	(mean) 0.56	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	8	C4.5	DT	NS	NS	NS	NS	(mean) 0.58	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	8	ADTree	DT	NS	NS	NS	NS	(mean) 0.52	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	8	SVM	SVM	NS	NS	NS	NS	(mean) 0.53	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	8	KNN	KNN	NS	NS	NS	NS	(mean) 0.6	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	8	C4.5	DT	NS	NS	NS	NS	(mean) 0.57	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	8	ADTree	DT	NS	NS	NS	NS	(mean) 0.53	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	8	SVM	SVM	NS	NS	NS	NS	(mean) 0.52	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	8	KNN	KNN	NS	NS	NS	NS	(mean) 0.56	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	Bagging	8	C4.5	DT	NS	NS	NS	NS	(mean) 0.5	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	Bagging	8	ADTree	DT	NS	NS	NS	NS	(mean) 0.53	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	Bagging	8	SVM	SVM	NS	NS	NS	NS	(mean) 0.5	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	Bagging	8	KNN	KNN	NS	NS	NS	NS	(mean) 0.64	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Boosting	8	C4.5	DT	NS	NS	NS	NS	(mean) 0.54	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Boosting	8	ADTree	DT	NS	NS	NS	NS	(mean) 0.5	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Boosting	8	SVM	SVM	NS	NS	NS	NS	(mean) 0.52	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Boosting	8	KNN	KNN	NS	NS	NS	NS	(mean) 0.61	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	Boosting	8	C4.5	DT	NS	NS	NS	NS	(mean) 0.54	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	Boosting	8	ADTree	DT	NS	NS	NS	NS	(mean) 0.53	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	Boosting	8	SVM	SVM	NS	NS	NS	NS	(mean) 0.52	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	Boosting	8	KNN	KNN	NS	NS	NS	NS	(mean) 0.57	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	8	C4.5	DT	NS	NS	NS	NS	(mean) 0.57	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	8	ADTree	DT	NS	NS	NS	NS	(mean) 0.54	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	8	SVM	SVM	NS	NS	NS	NS	(mean) 0.51	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	8	KNN	KNN	NS	NS	NS	NS	(mean) 0.64	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	8	C4.5	DT	NS	NS	NS	NS	(mean) 0.54	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	8	ADTree	DT	NS	NS	NS	NS	(mean) 0.54	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	8	SVM	SVM	NS	NS	NS	NS	(mean) 0.5	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	8	KNN	KNN	NS	NS	NS	NS	(mean) 0.61	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	8	C4.5	DT	NS	NS	NS	NS	(mean) 0.56	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	8	ADTree	DT	NS	NS	NS	NS	(mean) 0.53	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	8	SVM	SVM	NS	NS	NS	NS	(mean) 0.51	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	8	KNN	KNN	NS	NS	NS	NS	(mean) 0.63	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	8 (Meta Cost-Sensitive)	C4.5	DT	NS	NS	NS	NS	(mean) 0.5	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	8 (Meta Cost-Sensitive)	ADTree	DT	NS	NS	NS	NS	(mean) 0.5	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	8 (Meta Cost-Sensitive)	SVM	SVM	NS	NS	NS	NS	(mean) 0.49	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	8 (Meta Cost-Sensitive)	KNN	KNN	NS	NS	NS	NS	(mean) 0.59	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	8 (Cost-Sensitive)	C4.5	DT	NS	NS	NS	NS	(mean) 0.52	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	8 (Cost-Sensitive)	ADTree	DT	NS	NS	NS	NS	(mean) 0.51	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	8 (Cost-Sensitive)	SVM	SVM	NS	NS	NS	NS	(mean) 0.49	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	8 (Cost-Sensitive)	KNN	KNN	NS	NS	NS	NS	(mean) 0.61	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	8 (Cost-Sensitive)	C4.5	DT	NS	NS	NS	NS	(mean) 0.57	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	8 (Cost-Sensitive)	ADTree	DT	NS	NS	NS	NS	(mean) 0.54	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	8 (Cost-Sensitive)	SVM	SVM	NS	NS	NS	NS	(mean) 0.52	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	8 (Cost-Sensitive)	KNN	KNN	NS	NS	NS	NS	(mean) 0.64	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	8 (Cost-Sensitive)	C4.5	DT	NS	NS	NS	NS	(mean) 0.55	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	8 (Cost-Sensitive)	ADTree	DT	NS	NS	NS	NS	(mean) 0.53	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	8 (Cost-Sensitive)	SVM	SVM	NS	NS	NS	NS	(mean) 0.53	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	8 (Cost-Sensitive)	KNN	KNN	NS	NS	NS	NS	(mean) 0.61	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	8 (Cost-Sensitive)	C4.5	DT	NS	NS	NS	NS	(mean) 0.57	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	8 (Cost-Sensitive)	ADTree	DT	NS	NS	NS	NS	(mean) 0.53	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	8 (Cost-Sensitive)	SVM	SVM	NS	NS	NS	NS	(mean) 0.52	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	8 (Cost-Sensitive)	KNN	KNN	NS	NS	NS	NS	(mean) 0.63	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	11	C4.5	DT	NS	NS	NS	NS	(mean) 0.61	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	11	ADTree	DT	NS	NS	NS	NS	(mean) 0.64	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	11	SVM	SVM	NS	NS	NS	NS	(mean) 0.53	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	11	KNN	KNN	NS	NS	NS	NS	(mean) 0.59	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	11	RF	RF	NS	NS	NS	NS	(mean) 0.56	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	NU	11	C4.5	DT	NS	NS	NS	NS	(mean) 0.63	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	NU	11	ADTree	DT	NS	NS	NS	NS	(mean) 0.65	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	NU	11	SVM	SVM	NS	NS	NS	NS	(mean) 0.62	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	NU	11	KNN	KNN	NS	NS	NS	NS	(mean) 0.59	NS

Author	Type of data collection	Time_Management	Method validation	Cross-validation with fold number	Over- / Under-Sampling strategy	Ensemble_method	Features number (trial)	Model Extracted	Model Categories	Accuracy	Specificity	Recall	Precision	ROC-AUC	F1 score
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	NU	11	RF	RF	NS	NS	NS	NS	(mean) 0.57	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ROS	NU	11	C4.5	DT	NS	NS	NS	NS	(mean) 0.59	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ROS	NU	11	ADTree	DT	NS	NS	NS	NS	(mean) 0.64	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ROS	NU	11	SVM	SVM	NS	NS	NS	NS	(mean) 0.61	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ROS	NU	11	KNN	KNN	NS	NS	NS	NS	(mean) 0.56	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ROS	NU	11	RF	RF	NS	NS	NS	NS	(mean) 0.56	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	NU	11	C4.5	DT	NS	NS	NS	NS	(mean) 0.62	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	NU	11	ADTree	DT	NS	NS	NS	NS	(mean) 0.62	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	NU	11	SVM	SVM	NS	NS	NS	NS	(mean) 0.6	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	NU	11	KNN	KNN	NS	NS	NS	NS	(mean) 0.6	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	NU	11	RF	RF	NS	NS	NS	NS	(mean) 0.61	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ENN	NU	11	ADTree	DT	NS	NS	NS	NS	(mean) 0.64	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ENN	NU	11	SVM	SVM	NS	NS	NS	NS	(mean) 0.53	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ENN	NU	11	KNN	KNN	NS	NS	NS	NS	(mean) 0.58	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ENN	NU	11	RF	RF	NS	NS	NS	NS	(mean) 0.58	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	11	C4.5	DT	NS	NS	NS	NS	(mean) 0.62	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	11	ADTree	DT	NS	NS	NS	NS	(mean) 0.61	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	11	SVM	SVM	NS	NS	NS	NS	(mean) 0.58	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	11	KNN	KNN	NS	NS	NS	NS	(mean) 0.54	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	11	C4.5	DT	NS	NS	NS	NS	(mean) 0.63	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	11	ADTree	DT	NS	NS	NS	NS	(mean) 0.67	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	11	SVM	SVM	NS	NS	NS	NS	(mean) 0.61	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	11	KNN	KNN	NS	NS	NS	NS	(mean) 0.56	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	Bagging	11	C4.5	DT	NS	NS	NS	NS	(mean) 0.62	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	Bagging	11	ADTree	DT	NS	NS	NS	NS	(mean) 0.68	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	Bagging	11	SVM	SVM	NS	NS	NS	NS	(mean) 0.58	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	Bagging	11	KNN	KNN	NS	NS	NS	NS	(mean) 0.59	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Boosting	11	C4.5	DT	NS	NS	NS	NS	(mean) 0.58	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Boosting	11	ADTree	DT	NS	NS	NS	NS	(mean) 0.57	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Boosting	11	SVM	SVM	NS	NS	NS	NS	(mean) 0.66	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Boosting	11	KNN	KNN	NS	NS	NS	NS	(mean) 0.57	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	Boosting	11	C4.5	DT	NS	NS	NS	NS	(mean) 0.59	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	Boosting	11	ADTree	DT	NS	NS	NS	NS	(mean) 0.61	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	Boosting	11	SVM	SVM	NS	NS	NS	NS	(mean) 0.6	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	Boosting	11	KNN	KNN	NS	NS	NS	NS	(mean) 0.59	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	11	C4.5	DT	NS	NS	NS	NS	(mean) 0.64	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	11	ADTree	DT	NS	NS	NS	NS	(mean) 0.67	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	11	SVM	SVM	NS	NS	NS	NS	(mean) 0.63	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	11	KNN	KNN	NS	NS	NS	NS	(mean) 0.59	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	11	C4.5	DT	NS	NS	NS	NS	(mean) 0.68	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	11	ADTree	DT	NS	NS	NS	NS	(mean) 0.68	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	11	SVM	SVM	NS	NS	NS	NS	(mean) 0.64	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	11	KNN	KNN	NS	NS	NS	NS	(mean) 0.62	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	11	C4.5	DT	NS	NS	NS	NS	(mean) 0.64	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	11	ADTree	DT	NS	NS	NS	NS	(mean) 0.67	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	11	SVM	SVM	NS	NS	NS	NS	(mean) 0.63	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	11	KNN	KNN	NS	NS	NS	NS	(mean) 0.59	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	11 (Meta Cost-Sensitive)	C4.5	DT	NS	NS	NS	NS	(mean) 0.57	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	11 (Meta Cost-Sensitive)	ADTree	DT	NS	NS	NS	NS	(mean) 0.66	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	11 (Meta Cost-Sensitive)	SVM	SVM	NS	NS	NS	NS	(mean) 0.54	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	11 (Meta Cost-Sensitive)	KNN	KNN	NS	NS	NS	NS	(mean) 0.59	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	11 (Cost-Sensitive)	C4.5	DT	NS	NS	NS	NS	(mean) 0.59	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	11 (Cost-Sensitive)	ADTree	DT	NS	NS	NS	NS	(mean) 0.64	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	11 (Cost-Sensitive)	SVM	SVM	NS	NS	NS	NS	(mean) 0.54	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	11 (Cost-Sensitive)	KNN	KNN	NS	NS	NS	NS	(mean) 0.59	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	11 (Cost-Sensitive)	C4.5	DT	NS	NS	NS	NS	(mean) 0.66	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	11 (Cost-Sensitive)	ADTree	DT	NS	NS	NS	NS	(mean) 0.67	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	11 (Cost-Sensitive)	SVM	SVM	NS	NS	NS	NS	(mean) 0.65	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	11 (Cost-Sensitive)	KNN	KNN	NS	NS	NS	NS	(mean) 0.58	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	11 (Cost-Sensitive)	C4.5	DT	NS	NS	NS	NS	(mean) 0.7	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	11 (Cost-Sensitive)	ADTree	DT	NS	NS	NS	NS	(mean) 0.68	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	11 (Cost-Sensitive)	SVM	SVM	NS	NS	NS	NS	(mean) 0.66	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	11 (Cost-Sensitive)	KNN	KNN	NS	NS	NS	NS	(mean) 0.61	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	11 (Cost-Sensitive)	C4.5	DT	NS	NS	NS	NS	(mean) 0.66	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	11 (Cost-Sensitive)	ADTree	DT	NS	NS	NS	NS	(mean) 0.67	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	11 (Cost-Sensitive)	SVM	SVM	NS	NS	NS	NS	(mean) 0.64	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	11 (Cost-Sensitive)	KNN	KNN	NS	NS	NS	NS	(mean) 0.59	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	19	C4.5	DT	NS	NS	NS	NS	(mean) 0.46	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	19	ADTree	DT	NS	NS	NS	NS	(mean) 0.51	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	19	SVM	SVM	NS	NS	NS	NS	(mean) 0.52	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	19	KNN	KNN	NS	NS	NS	NS	(mean) 0.5	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	19	RF	RF	NS	NS	NS	NS	(mean) 0.44	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	NU	19	C4.5	DT	NS	NS	NS	NS	(mean) 0.51	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	NU	19	ADTree	DT	NS	NS	NS	NS	(mean) 0.53	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	NU	19	SVM	SVM	NS	NS	NS	NS	(mean) 0.52	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	NU	19	KNN	KNN	NS	NS	NS	NS	(mean) 0.46	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	NU	19	RF	RF	NS	NS	NS	NS	(mean) 0.45	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ROS	NU	19	C4.5	DT	NS	NS	NS	NS	(mean) 0.45	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ROS	NU	19	ADTree	DT	NS	NS	NS	NS	(mean) 0.51	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ROS	NU	19	SVM	SVM	NS	NS	NS	NS	(mean) 0.53	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ROS	NU	19	KNN	KNN	NS	NS	NS	NS	(mean) 0.49	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ROS	NU	19	RF	RF	NS	NS	NS	NS	(mean) 0.45	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	NU	19	C4.5	DT	NS	NS	NS	NS	(mean) 0.48	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	NU	19	ADTree	DT	NS	NS	NS	NS	(mean) 0.52	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	NU	19	SVM	SVM	NS	NS	NS	NS	(mean) 0.53	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	NU	19	KNN	KNN	NS	NS	NS	NS	(mean) 0.52	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	NU	19	RF	RF	NS	NS	NS	NS	(mean) 0.47	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ENN	NU	19	C4.5	DT	NS	NS	NS	NS	(mean) 0.47	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ENN	NU	19	ADTree	DT	NS	NS	NS	NS	(mean) 0.51	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ENN	NU	19	SVM	SVM	NS	NS	NS	NS	(mean) 0.52	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ENN	NU	19	KNN	KNN	NS	NS	NS	NS	(mean) 0.5	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ENN	NU	19	RF	RF	NS	NS	NS	NS	(mean) 0.47	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	19	ADTree	DT	NS	NS	NS	NS	(mean) 0.51	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	19	SVM	SVM	NS	NS	NS	NS	(mean) 0.52	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	19	KNN	KNN	NS	NS	NS	NS	(mean) 0.49	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	19	C4.5	DT	NS	NS	NS	NS	(mean) 0.48	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	19	ADTree	DT	NS	NS	NS	NS	(mean) 0.5	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	19	SVM	SVM	NS	NS	NS	NS	(mean) 0.53	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	19	KNN	KNN	NS	NS	NS	NS	(mean) 0.48	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	Bagging	19	C4.5	DT	NS	NS	NS	NS	(mean) 0.49	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	Bagging	19	ADTree	DT	NS	NS	NS	NS	(mean) 0.52	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	Bagging	19	SVM	SVM	NS	NS	NS	NS	(mean) 0.55	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	Bagging	19	KNN	KNN	NS	NS	NS	NS	(mean) 0.5	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Boosting	19	C4.5	DT	NS	NS	NS	NS	(mean) 0.5	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Boosting	19	ADTree	DT	NS	NS	NS	NS	(mean) 0.51	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Boosting	19	KNN	KNN	NS	NS	NS	NS	(mean) 0.47	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	Boosting	19	C4.5	DT	NS	NS	NS	NS	(mean) 0.5	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	Boosting	19	ADTree	DT	NS	NS	NS	NS	(mean) 0.51	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	Boosting	19	SVM	SVM	NS	NS	NS	NS	(mean) 0.53	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	Boosting	19	KNN	KNN	NS	NS	NS	NS	(mean) 0.52	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	19	C4.5	DT	NS	NS	NS	NS	(mean) 0.47	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	19	ADTree	DT	NS	NS	NS	NS	(mean) 0.52	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	19	SVM	SVM	NS	NS	NS	NS	(mean) 0.55	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	19	KNN	KNN	NS	NS	NS	NS	(mean) 0.49	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	19	C4.5	DT	NS	NS	NS	NS	(mean) 0.51	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	19	ADTree	DT	NS	NS	NS	NS	(mean) 0.53	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	19	SVM	SVM	NS	NS	NS	NS	(mean) 0.56	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	19	KNN	KNN	NS	NS	NS	NS	(mean) 0.52	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	19	C4.5	DT	NS	NS	NS	NS	(mean) 0.54	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	19	ADTree	DT	NS	NS	NS	NS	(mean) 0.53	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	19	SVM	SVM	NS	NS	NS	NS	(mean) 0.54	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	19	KNN	KNN	NS	NS	NS	NS	(mean) 0.5	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	19 (Meta Cost-Sensitive)	C4.5	DT	NS	NS	NS	NS	(mean) 0.47	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	19 (Meta Cost-Sensitive)	ADTree	DT	NS	NS	NS	NS	(mean) 0.5	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	19 (Meta Cost-Sensitive)	SVM	SVM	NS	NS	NS	NS	(mean) 0.53	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	19 (Meta Cost-Sensitive)	KNN	KNN	NS	NS	NS	NS	(mean) 0.48	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	19 (Cost-Sensitive)	C4.5	DT	NS	NS	NS	NS	(mean) 0.45	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	19 (Cost-Sensitive)	ADTree	DT	NS	NS	NS	NS	(mean) 0.51	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	19 (Cost-Sensitive)	SVM	SVM	NS	NS	NS	NS	(mean) 0.53	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	19 (Cost-Sensitive)	KNN	KNN	NS	NS	NS	NS	(mean) 0.5	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	19 (Cost-Sensitive)	C4.5	DT	NS	NS	NS	NS	(mean) 0.48	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	19 (Cost-Sensitive)	ADTree	DT	NS	NS	NS	NS	(mean) 0.52	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	19 (Cost-Sensitive)	SVM	SVM	NS	NS	NS	NS	(mean) 0.55	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	19 (Cost-Sensitive)	KNN	KNN	NS	NS	NS	NS	(mean) 0.49	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	19 (Cost-Sensitive)	C4.5	DT	NS	NS	NS	NS	(mean) 0.52	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	19 (Cost-Sensitive)	ADTree	DT	NS	NS	NS	NS	(mean) 0.53	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	19 (Cost-Sensitive)	SVM	SVM	NS	NS	NS	NS	(mean) 0.56	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	19 (Cost-Sensitive)	KNN	KNN	NS	NS	NS	NS	(mean) 0.52	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	19 (Cost-Sensitive)	C4.5	DT	NS	NS	NS	NS	(mean) 0.54	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	19 (Cost-Sensitive)	ADTree	DT	NS	NS	NS	NS	(mean) 0.53	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	19 (Cost-Sensitive)	SVM	SVM	NS	NS	NS	NS	(mean) 0.55	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	19 (Cost-Sensitive)	KNN	KNN	NS	NS	NS	NS	(mean) 0.5	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	46	C4.5	DT	NS	NS	NS	NS	(mean) 0.6	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	46	ADTree	DT	NS	NS	NS	NS	(mean) 0.76	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	46	SVM	SVM	NS	NS	NS	NS	(mean) 0.56	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	46	KNN	KNN	NS	NS	NS	NS	(mean) 0.75	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	46	RF	RF	NS	NS	NS	NS	(mean) 0.74	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	NU	46	C4.5	DT	NS	NS	NS	NS	(mean) 0.72	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	NU	46	ADTree	DT	NS	NS	NS	NS	(mean) 0.75	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	NU	46	SVM	SVM	NS	NS	NS	NS	(mean) 0.69	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	NU	46	KNN	KNN	NS	NS	NS	NS	(mean) 0.74	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	NU	46	RF	RF	NS	NS	NS	NS	(mean) 0.74	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ROS	NU	46	C4.5	DT	NS	NS	NS	NS	(mean) 0.7	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ROS	NU	46	ADTree	DT	NS	NS	NS	NS	(mean) 0.76	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ROS	NU	46	SVM	SVM	NS	NS	NS	NS	(mean) 0.69	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ROS	NU	46	KNN	KNN	NS	NS	NS	NS	(mean) 0.75	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ROS	NU	46	RF	RF	NS	NS	NS	NS	(mean) 0.75	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	NU	46	C4.5	DT	NS	NS	NS	NS	(mean) 0.68	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	NU	46	ADTree	DT	NS	NS	NS	NS	(mean) 0.75	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	NU	46	SVM	SVM	NS	NS	NS	NS	(mean) 0.68	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	NU	46	KNN	KNN	NS	NS	NS	NS	(mean) 0.75	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	NU	46	RF	RF	NS	NS	NS	NS	(mean) 0.74	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ENN	NU	46	C4.5	DT	NS	NS	NS	NS	(mean) 0.58	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ENN	NU	46	ADTree	DT	NS	NS	NS	NS	(mean) 0.76	NS
L Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ENN	NU	46	SVM	SVM	NS	NS	NS	NS	(mean) 0.56	NS

Author	Type of data collection	Time_Management	Method validation	Cross-validation with fold number	Over- / Under-Sampling strategy	Ensemble_method	Features number (trial)	Model Extracted	Model Categories	Accuracy	Specificity	Recall	Precision	ROC-AUC	F1 score
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ENN	NU	46	KNN	KNN	NS	NS	NS	NS	(mean) 0.75	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ENN	NU	46	RF	RF	NS	NS	NS	NS	(mean) 0.74	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	46	C4.5	DT	NS	NS	NS	NS	(mean) 0.76	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	46	ADTree	DT	NS	NS	NS	NS	(mean) 0.76	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	46	SVM	SVM	NS	NS	NS	NS	(mean) 0.78	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	46	KNN	KNN	NS	NS	NS	NS	(mean) 0.74	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	46	C4.5	DT	NS	NS	NS	NS	(mean) 0.76	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	46	ADTree	DT	NS	NS	NS	NS	(mean) 0.75	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	46	SVM	SVM	NS	NS	NS	NS	(mean) 0.76	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	46	KNN	KNN	NS	NS	NS	NS	(mean) 0.75	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	Bagging	46	C4.5	DT	NS	NS	NS	NS	(mean) 0.73	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	Bagging	46	ADTree	DT	NS	NS	NS	NS	(mean) 0.76	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	Bagging	46	SVM	SVM	NS	NS	NS	NS	(mean) 0.66	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	Bagging	46	KNN	KNN	NS	NS	NS	NS	(mean) 0.76	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	46	C4.5	DT	NS	NS	NS	NS	(mean) 0.74	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	46	ADTree	DT	NS	NS	NS	NS	(mean) 0.75	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	46	SVM	SVM	NS	NS	NS	NS	(mean) 0.75	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	46	KNN	KNN	NS	NS	NS	NS	(mean) 0.74	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	Bagging	46	C4.5	DT	NS	NS	NS	NS	(mean) 0.75	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	Bagging	46	ADTree	DT	NS	NS	NS	NS	(mean) 0.76	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	Bagging	46	SVM	SVM	NS	NS	NS	NS	(mean) 0.76	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	Bagging	46	KNN	KNN	NS	NS	NS	NS	(mean) 0.75	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	46	C4.5	DT	NS	NS	NS	NS	(mean) 0.75	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	46	ADTree	DT	NS	NS	NS	NS	(mean) 0.77	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	46	SVM	SVM	NS	NS	NS	NS	(mean) 0.75	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	46	KNN	KNN	NS	NS	NS	NS	(mean) 0.76	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	46	C4.5	DT	NS	NS	NS	NS	(mean) 0.75	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	46	ADTree	DT	NS	NS	NS	NS	(mean) 0.76	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	46	SVM	SVM	NS	NS	NS	NS	(mean) 0.75	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	46	KNN	KNN	NS	NS	NS	NS	(mean) 0.76	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	46	C4.5	DT	NS	NS	NS	NS	(mean) 0.77	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	46	ADTree	DT	NS	NS	NS	NS	(mean) 0.78	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	46	SVM	SVM	NS	NS	NS	NS	(mean) 0.77	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	46	KNN	KNN	NS	NS	NS	NS	(mean) 0.77	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	46 (Meta Cost-Sensitive)	C4.5	DT	NS	NS	NS	NS	(mean) 0.54	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	46 (Meta Cost-Sensitive)	ADTree	DT	NS	NS	NS	NS	(mean) 0.72	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	46 (Meta Cost-Sensitive)	SVM	SVM	NS	NS	NS	NS	(mean) 0.5	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	46 (Meta Cost-Sensitive)	KNN	KNN	NS	NS	NS	NS	(mean) 0.52	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	46 (Cost-Sensitive)	C4.5	DT	NS	NS	NS	NS	(mean) 0.64	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	46 (Cost-Sensitive)	ADTree	DT	NS	NS	NS	NS	(mean) 0.76	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	46 (Cost-Sensitive)	SVM	SVM	NS	NS	NS	NS	(mean) 0.5	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	46 (Cost-Sensitive)	KNN	KNN	NS	NS	NS	NS	(mean) 0.75	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	46 (Cost-Sensitive)	C4.5	DT	NS	NS	NS	NS	(mean) 0.76	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	46 (Cost-Sensitive)	ADTree	DT	NS	NS	NS	NS	(mean) 0.77	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	46 (Cost-Sensitive)	SVM	SVM	NS	NS	NS	NS	(mean) 0.76	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	46 (Cost-Sensitive)	KNN	KNN	NS	NS	NS	NS	(mean) 0.76	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	46 (Cost-Sensitive)	C4.5	DT	NS	NS	NS	NS	(mean) 0.75	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	46 (Cost-Sensitive)	ADTree	DT	NS	NS	NS	NS	(mean) 0.76	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	46 (Cost-Sensitive)	SVM	SVM	NS	NS	NS	NS	(mean) 0.77	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	46 (Cost-Sensitive)	KNN	KNN	NS	NS	NS	NS	(mean) 0.76	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	46 (Cost-Sensitive)	C4.5	DT	NS	NS	NS	NS	(mean) 0.77	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	46 (Cost-Sensitive)	ADTree	DT	NS	NS	NS	NS	(mean) 0.78	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	46 (Cost-Sensitive)	SVM	SVM	NS	NS	NS	NS	(mean) 0.77	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	46 (Cost-Sensitive)	KNN	KNN	NS	NS	NS	NS	(mean) 0.77	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	65	C4.5	DT	NS	NS	NS	NS	(mean) 0.64	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	65	ADTree	DT	NS	NS	NS	NS	(mean) 0.74	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	65	SVM	SVM	NS	NS	NS	NS	(mean) 0.57	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	65	KNN	KNN	NS	NS	NS	NS	(mean) 0.7	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	65	RF	RF	NS	NS	NS	NS	(mean) 0.71	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	NU	65	C4.5	DT	NS	NS	NS	NS	(mean) 0.71	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	NU	65	ADTree	DT	NS	NS	NS	NS	(mean) 0.74	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	NU	65	SVM	SVM	NS	NS	NS	NS	(mean) 0.65	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	NU	65	KNN	KNN	NS	NS	NS	NS	(mean) 0.7	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	NU	65	RF	RF	NS	NS	NS	NS	(mean) 0.71	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ROS	NU	65	C4.5	DT	NS	NS	NS	NS	(mean) 0.69	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ROS	NU	65	ADTree	DT	NS	NS	NS	NS	(mean) 0.74	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ROS	NU	65	SVM	SVM	NS	NS	NS	NS	(mean) 0.66	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ROS	NU	65	KNN	KNN	NS	NS	NS	NS	(mean) 0.7	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ROS	NU	65	RF	RF	NS	NS	NS	NS	(mean) 0.71	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	NU	65	C4.5	DT	NS	NS	NS	NS	(mean) 0.66	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	NU	65	ADTree	DT	NS	NS	NS	NS	(mean) 0.72	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	NU	65	SVM	SVM	NS	NS	NS	NS	(mean) 0.65	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	NU	65	KNN	KNN	NS	NS	NS	NS	(mean) 0.7	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	NU	65	RF	RF	NS	NS	NS	NS	(mean) 0.71	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ENN	NU	65	C4.5	DT	NS	NS	NS	NS	(mean) 0.64	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ENN	NU	65	ADTree	DT	NS	NS	NS	NS	(mean) 0.73	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ENN	NU	65	SVM	SVM	NS	NS	NS	NS	(mean) 0.57	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ENN	NU	65	KNN	KNN	NS	NS	NS	NS	(mean) 0.7	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	ENN	NU	65	RF	RF	NS	NS	NS	NS	(mean) 0.71	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	65	C4.5	DT	NS	NS	NS	NS	(mean) 0.75	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	65	ADTree	DT	NS	NS	NS	NS	(mean) 0.77	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	65	SVM	SVM	NS	NS	NS	NS	(mean) 0.72	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	65	KNN	KNN	NS	NS	NS	NS	(mean) 0.69	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	65	C4.5	DT	NS	NS	NS	NS	(mean) 0.75	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	65	ADTree	DT	NS	NS	NS	NS	(mean) 0.74	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	65	SVM	SVM	NS	NS	NS	NS	(mean) 0.8	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	AdaBoost	65	KNN	KNN	NS	NS	NS	NS	(mean) 0.69	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	Bagging	65	C4.5	DT	NS	NS	NS	NS	(mean) 0.74	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	Bagging	65	ADTree	DT	NS	NS	NS	NS	(mean) 0.74	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	Bagging	65	SVM	SVM	NS	NS	NS	NS	(mean) 0.69	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	Bagging	65	KNN	KNN	NS	NS	NS	NS	(mean) 0.72	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	65	C4.5	DT	NS	NS	NS	NS	(mean) 0.72	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	65	ADTree	DT	NS	NS	NS	NS	(mean) 0.75	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	65	SVM	SVM	NS	NS	NS	NS	(mean) 0.74	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	65	KNN	KNN	NS	NS	NS	NS	(mean) 0.71	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	Bagging	65	C4.5	DT	NS	NS	NS	NS	(mean) 0.74	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	Bagging	65	ADTree	DT	NS	NS	NS	NS	(mean) 0.75	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	Bagging	65	SVM	SVM	NS	NS	NS	NS	(mean) 0.75	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	RUS	Bagging	65	KNN	KNN	NS	NS	NS	NS	(mean) 0.71	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	65	C4.5	DT	NS	NS	NS	NS	(mean) 0.74	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	65	ADTree	DT	NS	NS	NS	NS	(mean) 0.74	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	65	SVM	SVM	NS	NS	NS	NS	(mean) 0.74	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	65	KNN	KNN	NS	NS	NS	NS	(mean) 0.72	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	65	C4.5	DT	NS	NS	NS	NS	(mean) 0.74	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	65	ADTree	DT	NS	NS	NS	NS	(mean) 0.74	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	65	SVM	SVM	NS	NS	NS	NS	(mean) 0.74	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	65	KNN	KNN	NS	NS	NS	NS	(mean) 0.72	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	65	C4.5	DT	NS	NS	NS	NS	(mean) 0.75	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	65	ADTree	DT	NS	NS	NS	NS	(mean) 0.75	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	65	SVM	SVM	NS	NS	NS	NS	(mean) 0.75	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	65	KNN	KNN	NS	NS	NS	NS	(mean) 0.72	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	65 (Meta Cost-Sensitive)	C4.5	DT	NS	NS	NS	NS	(mean) 0.57	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	65 (Meta Cost-Sensitive)	ADTree	DT	NS	NS	NS	NS	(mean) 0.7	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	65 (Meta Cost-Sensitive)	SVM	SVM	NS	NS	NS	NS	(mean) 0.5	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	65 (Meta Cost-Sensitive)	KNN	KNN	NS	NS	NS	NS	(mean) 0.6	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	65 (Cost-Sensitive)	C4.5	DT	NS	NS	NS	NS	(mean) 0.69	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	65 (Cost-Sensitive)	ADTree	DT	NS	NS	NS	NS	(mean) 0.74	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	65 (Cost-Sensitive)	SVM	SVM	NS	NS	NS	NS	(mean) 0.5	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	NU	NU	65 (Cost-Sensitive)	KNN	KNN	NS	NS	NS	NS	(mean) 0.71	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	65 (Cost-Sensitive)	C4.5	DT	NS	NS	NS	NS	(mean) 0.75	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	65 (Cost-Sensitive)	ADTree	DT	NS	NS	NS	NS	(mean) 0.74	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	65 (Cost-Sensitive)	SVM	SVM	NS	NS	NS	NS	(mean) 0.75	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Over-Sampling	Bagging	65 (Cost-Sensitive)	KNN	KNN	NS	NS	NS	NS	(mean) 0.72	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	65 (Cost-Sensitive)	C4.5	DT	NS	NS	NS	NS	(mean) 0.75	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	65 (Cost-Sensitive)	ADTree	DT	NS	NS	NS	NS	(mean) 0.74	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	65 (Cost-Sensitive)	SVM	SVM	NS	NS	NS	NS	(mean) 0.75	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	Under-Sampling	Bagging	65 (Cost-Sensitive)	KNN	KNN	NS	NS	NS	NS	(mean) 0.72	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	65 (Cost-Sensitive)	C4.5	DT	NS	NS	NS	NS	(mean) 0.76	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	65 (Cost-Sensitive)	ADTree	DT	NS	NS	NS	NS	(mean) 0.75	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	65 (Cost-Sensitive)	SVM	SVM	NS	NS	NS	NS	(mean) 0.75	NS
L. Ruiz-Pérez 2021	Screening	Not-applic	Internal	SCV	SMOTE	Bagging	65 (Cost-Sensitive)	KNN	KNN	NS	NS	NS	NS	(mean) 0.72	NS
S. Lovdal 2021	Monitoring	Time windows	External	NU	NU	Bagging	70 (Day approach)	XGBoost	XGBoost	NS	(mean) 0.74	(mean) 0.58	NS	(mean) 0.72	NS
S. Lovdal 2021	Monitoring	Time windows	External	NU	NU	Bagging	69 (Week approach)	XGBoost	XGBoost	NS	(mean) 0.75	(mean) 0.50	NS	(mean) 0.68	NS
C. Richter 2021	Screening	Not-applic	External	NU	SMOTE	NU	3	NS	NS	NS	0,53	0,58	NS	0,57	NS
C. Richter 2021	Screening	Not-applic	External	NU	SMOTE	NU	3	NS	NS	NS	0,53	0,56	NS	0,59	NS
M. Mendonino 2021	Monitoring and screening	NS	NS	SCV	SMOTE	NU	15	LR	LR	NS	(mean) 0.97	(mean) 0.05	(mean) 0.04	(mean) 0.63	NS
M. Mendonino 2021	Monitoring and screening	NS	NS	SCV	SMOTE	Bagging	15	RF	RF	NS	(mean) 0.97	(mean) 0.03	(mean) 0.03	(mean) 0.58	NS
M. Mendonino 2021	Monitoring and screening	NS	NS	SCV	SMOTE	NU	15	SVM	SVM	NS	(mean) 0.98	(mean) 0.02	(mean) 0.04	(mean) 0.55	NS
M. Mendonino 2021	Monitoring and screening	NS	NS	SCV	SMOTE	NU	15 (lag)	LR	LR	NS	(mean) 0.95	(mean) 0.20	(mean) 0.04	(mean) 0.55	NS
M. Mendonino 2021	Monitoring and screening	NS	NS	SCV	SMOTE	Bagging	15 (lag)	RF	RF	NS	(mean) 0.95	(mean) 0.39	(mean) 0.10	(mean) 0.66	NS
M. Mendonino 2021	Monitoring and screening	NS	NS	SCV	SMOTE	NU	15 (lag)	SVM	SVM	NS	(mean) 0.97	(mean) 0.29	(mean) 0.12	(mean) 0.71	NS
A. Hecksteden 2022	Monitoring and screening	NS	Internal	LOOCV	ROS	Boosting	13	Gradient boosting	XGBoost	NS	NS	NS	NS	0,62	NS
A. Heckstеden 2022	Monitoring and screening	NS	Internal	LOOCV	ROS	Boosting	13 (Round Robin, 2)	Gradient boosting	XGBoost	NS	NS	NS	NS	0,62	NS
A. Heckstеden 2022	Monitoring and screening	NS	Internal	LOOCV	ROS	Boosting	13 (Round Robin, 3)	Gradient boosting	XGBoost	NS	NS	NS	NS	0,69	NS
A. Heckstеden 2022	Monitoring and screening	NS	Internal	LOOCV	ROS	Boosting	13 (Round Robin, 4)	Gradient boosting	XGBoost	NS	NS	NS	NS	0,68	NS
A. Heckstеden 2022	Monitoring and screening	NS	Internal	LOOCV	ROS	Boosting	13 (Leaky folds, 1)	Gradient boosting	XGBoost	NS	NS	NS	NS	0,59	NS
A. Heckstеden 2022	Monitoring and screening	NS	Internal	LOOCV	ROS	Boosting	13 (Leaky folds, 2)	Gradient boosting	XGBoost	NS	NS	NS	NS	0,64	NS
A. Heckstеden 2022	Monitoring and screening	NS	Internal	LOOCV	ROS	Boosting	13 (Leaky folds, 3)	Gradient boosting	XGBoost	NS	NS	NS	NS	0,57	NS
A. Heckstеden 2022	Monitoring and screening	NS	Internal	LOOCV	NU	Boosting	13 (noRos)	Gradient boosting	XGBoost	NS	NS	NS	NS	0,48	NS
A. Heckstеden 2022	Monitoring and screening	NS	Internal	LOOCV	ROS	Boosting	2 (Monitoring only)	Gradient boosting	XGBoost	NS	NS	NS	NS	0,56	NS
A. Heckstеden 2022	Monitoring and screening	NS	Internal	LOOCV	ROS	Boosting	5 (Monitoring + screening)	Gradient boosting	XGBoost	NS	NS	NS	NS	0,52	NS
J. Briand 2022	Monitoring	Moving averages	Internal	NU	Weighting	Bagging	1014 (1 days)	RF	RF	NS	(mean) 0.72	(mean) 0.70	NS	NS	NS
J. Briand 2022	Monitoring	Moving averages	Internal	NU	Weighting	Bagging	1014 (2 days)	RF	RF	NS	(mean) 0.77	(mean) 0.50	NS	NS	NS
J. Briand 2022	Monitoring	Moving averages	Internal	NU	Weighting	Bagging	1014 (3 days)	RF	RF	NS	(mean) 0.81	(mean) 0.40	NS	NS	NS
J. Briand 2022	Monitoring	Moving averages	Internal	NU	Weighting	Bagging	1014 (4 days)	RF	RF	NS	(mean) 0.85	(mean) 0.27	NS	NS	NS
J. Briand 2022	Monitoring	Moving averages	Internal	NU	Weighting	Bagging	1014 (5 days)	RF	RF	NS	(mean) 0.81	(mean) 0.26	NS	NS	NS
J. Briand 2022	Monitoring	Moving averages	Internal	NU	Weighting	Bagging	1014 (6 days)	RF	RF	NS	(mean) 0.86	(mean) 0.18	NS	NS	NS
J. Briand 2022	Monitoring	Moving averages	Internal	NU	Weighting	Bagging	1014 (7 days)	RF	RF	NS	(mean) 0.87	(mean) 0.14	NS	NS	NS
J. Briand 2022	Monitoring	Moving averages	Internal	NU	Weighting	Bagging	182 (1 day)	RF	RF	NS	(mean) 0.73	(mean) 0.24	NS	NS	NS
J. Briand 2022	Monitoring	Moving averages	Internal	NU	Weighting	Bagging	182 (2 days)	RF	RF	NS	(mean) 0.76	(mean) 0.20	NS	NS	NS
J. Briand 2022	Monitoring	Moving averages	Internal	NU	Weighting	Bagging	182 (3 days)	RF	RF	NS	(mean) 0.78	(mean) 0.20	NS	NS	NS
J. Briand 2022	Monitoring	Moving averages	Internal	NU	Weighting	Bagging	182 (4 days)	RF	RF	NS	(mean) 0.75	(mean) 0.23	NS	NS	NS
J. Briand 2022	Monitoring	Moving averages	Internal	NU	Weighting	Bagging	182 (5 days)	RF	RF	NS	(mean) 0.72	(mean) 0.27	NS	NS	NS
J. Briand 2022	Monitoring	Moving averages	Internal	NU	Weighting	Bagging	182 (6 days)	RF	RF	NS	(mean) 0.73	(mean) 0.27	NS	NS	NS
J. Briand 2022	Monitoring	Moving averages	Internal	NU	Weighting	Bagging	182 (7 days)	RF	RF	NS	(mean) 0.73	(mean) 0.23	NS	NS	NS

Author	Type of data collection	Time Management	Method validation	Cross-validation with fold number	Over / Under-Sampling strategy	Ensemble method	Features number (trial)	Model Extracted	Model Categories	Accuracy	Specificity	Recall	Precision	ROC-AUC	F1 score
S. Jauhiainen 2022	Screening	Not-applic	Internal	CV	NU	NU	283	LR	LR	NS	NS	NS	NS	(mean) 0.61	NS
S. Jauhiainen 2022	Screening	Not-applic	Internal	CV	NU	NU	283	RF	RF	NS	NS	NS	NS	(mean) 0.57	NS
S. Jauhiainen 2022	Screening	Not-applic	Internal	CV	NU	NU	283	SVM linear	SVM	NS	NS	NS	NS	(mean) 0.63	NS
S. Jauhiainen 2022	Screening	Not-applic	Internal	CV	NU	NU	283	SVM non-linear	SVM	NS	NS	NS	NS	(mean) 0.61	NS
S. Jauhiainen 2022	Screening	Not-applic	Internal	CV	SMOTE	NU	283	LR	LR	NS	NS	NS	NS	(mean) 0.60	NS
S. Jauhiainen 2022	Screening	Not-applic	Internal	CV	SMOTE	NU	283	RF	RF	NS	NS	NS	NS	(mean) 0.56	NS
S. Jauhiainen 2022	Screening	Not-applic	Internal	CV	SMOTE	NU	283	SVM linear	SVM	NS	NS	NS	NS	(mean) 0.58	NS
S. Jauhiainen 2022	Screening	Not-applic	Internal	CV	SMOTE	NU	283	SVM non-linear	SVM	NS	NS	NS	NS	(mean) 0.59	NS
S. Jauhiainen 2022	Screening	Not-applic	Internal	CV	Under-Sampling	NU	283	LR	LR	NS	NS	NS	NS	(mean) 0.57	NS
S. Jauhiainen 2022	Screening	Not-applic	Internal	CV	Under-Sampling	NU	283	RF	RF	NS	NS	NS	NS	(mean) 0.50	NS
S. Jauhiainen 2022	Screening	Not-applic	Internal	CV	Under-Sampling	NU	283	SVM linear	SVM	NS	NS	NS	NS	(mean) 0.57	NS
S. Jauhiainen 2022	Screening	Not-applic	Internal	CV	Under-Sampling	NU	283	SVM non-linear	SVM	NS	NS	NS	NS	(mean) 0.58	NS
S. Jauhiainen 2022	Screening	Not-applic	Internal	CV	NU	NU	283 (Weighted)	LR	LR	NS	NS	NS	NS	(mean) 0.61	NS
S. Jauhiainen 2022	Screening	Not-applic	Internal	CV	NU	NU	283 (Weighted)	RF	RF	NS	NS	NS	NS	(mean) 0.58	NS
S. Jauhiainen 2022	Screening	Not-applic	Internal	CV	NU	NU	283 (Weighted)	SVM linear	SVM	NS	NS	NS	NS	(mean) 0.59	NS
S. Jauhiainen 2022	Screening	Not-applic	Internal	CV	NU	NU	283 (Weighted)	SVM non-linear	SVM	NS	NS	NS	NS	(mean) 0.60	NS
Y. Huang 2022	Monitoring	Moving averages	NS	SCV	SMOTE	NU	18	Dummy classifier	Dummy classifier	NS	NS	(mean) 0.35	(mean) 0.87	NS	NS
Y. Huang 2022	Monitoring	Moving averages	NS	SCV	SMOTE	NU	18	LR	LR	NS	NS	(mean) 0.56	(mean) 0.89	NS	NS
Y. Huang 2022	Monitoring	Moving averages	NS	SCV	SMOTE	NU	18	SVM	SVM	NS	NS	(mean) 0.90	(mean) 0.92	NS	NS
Y. Huang 2022	Monitoring	Moving averages	NS	SCV	SMOTE	NU	18	KNN	KNN	NS	NS	(mean) 0.80	(mean) 0.90	NS	NS
Y. Huang 2022	Monitoring	Moving averages	NS	SCV	SMOTE	NU	18	NB	NB	NS	NS	(mean) 0.62	(mean) 0.90	NS	NS
Y. Huang 2022	Monitoring	Moving averages	NS	SCV	SMOTE	NU	18	DT	DT	NS	NS	(mean) 0.82	(mean) 0.90	NS	NS
Y. Huang 2022	Monitoring	Moving averages	NS	SCV	SMOTE	Bagging	18	RF	RF	NS	NS	(mean) 0.92	(mean) 0.92	NS	NS
Y. Huang 2022	Monitoring	Moving averages	NS	SCV	SMOTE	Boosting	18	XGBoost	XGBoost	NS	NS	(mean) 0.88	(mean) 0.91	NS	NS
Y. Huang 2022	Monitoring	Moving averages	NS	SCV	SMOTE	Stacking	18	dFusionModel (RF)	RF	NS	NS	(mean) 0.99	(mean) 0.99	NS	NS
Y. Huang 2022	Monitoring	Moving averages	NS	SCV	SMOTE	NU	18 (Perceived well-being)	XGBoost	XGBoost	NS	NS	(mean) 0.81	(mean) 0.87	NS	NS
Y. Huang 2022	Monitoring	Moving averages	NS	SCV	SMOTE	NU	18 (Training load)	XGBoost	XGBoost	NS	NS	(mean) 0.74	(mean) 0.88	NS	NS
Y. Huang 2022	Monitoring	Moving averages	NS	SCV	SMOTE	NU	18 (Physiological response)	XGBoost	XGBoost	NS	NS	(mean) 0.73	(mean) 0.86	NS	NS
Y. Huang 2022	Monitoring	Moving averages	NS	SCV	SMOTE	NU	18 (Physical performance)	XGBoost	XGBoost	NS	NS	(mean) 0.84	(mean) 0.86	NS	NS
Y. Huang 2022	Monitoring	Moving averages	NS	SCV	SMOTE	NU	18 (all)	wFusionModel (RF)	RF	NS	NS	(mean) 0.97	(mean) 0.98	NS	NS
J. D. Ruddy 2018	Screening	Not-applic	NS	CV	SMOTE	NU	3, 8 (2013)	NB	NB	NS	NS	NS	NS	(median) 0.60	NS
J. D. Ruddy 2018	Screening	Not-applic	NS	CV	SMOTE	NU	3, 8 (2013-2015)	NB	NB	NS	NS	NS	NS	(median) 0.54	NS
J. D. Ruddy 2018	Screening	Not-applic	NS	CV	SMOTE	Bagging	3 (2013)	NB	NB	NS	NS	NS	NS	(median) 0.59	NS
J. D. Ruddy 2018	Screening	Not-applic	NS	CV	SMOTE	Bagging	3 (2013)	LR	LR	NS	NS	NS	NS	(median) 0.59	NS
J. D. Ruddy 2018	Screening	Not-applic	NS	CV	SMOTE	Bagging	3 (2013)	RF	RF	NS	NS	NS	NS	(median) 0.59	NS
J. D. Ruddy 2018	Screening	Not-applic	NS	CV	SMOTE	Bagging	3 (2013)	SVM	SVM	NS	NS	NS	NS	(median) 0.59	NS
J. D. Ruddy 2018	Screening	Not-applic	NS	CV	SMOTE	Bagging	3 (2013)	ANN	ANN	NS	NS	NS	NS	(median) 0.59	NS
J. D. Ruddy 2018	Screening	Not-applic	NS	CV	SMOTE	Bagging	8 (2013)	NB	NB	NS	NS	NS	NS	(median) 0.57	NS
J. D. Ruddy 2018	Screening	Not-applic	NS	CV	SMOTE	Bagging	8 (2013)	LR	LR	NS	NS	NS	NS	(median) 0.57	NS
J. D. Ruddy 2018	Screening	Not-applic	NS	CV	SMOTE	Bagging	8 (2013)	RF	RF	NS	NS	NS	NS	(median) 0.57	NS
J. D. Ruddy 2018	Screening	Not-applic	NS	CV	SMOTE	Bagging	8 (2013)	SVM	SVM	NS	NS	NS	NS	(median) 0.57	NS
J. D. Ruddy 2018	Screening	Not-applic	NS	CV	SMOTE	Bagging	8 (2013)	ANN	ANN	NS	NS	NS	NS	(median) 0.57	NS
J. D. Ruddy 2018	Screening	Not-applic	NS	CV	SMOTE	Bagging	3, 8 (2013)	NB	NB	NS	NS	NS	NS	(median) 0.58	NS
J. D. Ruddy 2018	Screening	Not-applic	NS	CV	SMOTE	Bagging	3, 8 (2013)	LR	LR	NS	NS	NS	NS	(median) 0.58	NS
J. D. Ruddy 2018	Screening	Not-applic	NS	CV	SMOTE	Bagging	3, 8 (2013)	RF	RF	NS	NS	NS	NS	(median) 0.58	NS
J. D. Ruddy 2018	Screening	Not-applic	NS	CV	SMOTE	Bagging	3, 8 (2013)	SVM	SVM	NS	NS	NS	NS	(median) 0.58	NS
J. D. Ruddy 2018	Screening	Not-applic	NS	CV	SMOTE	Bagging	3, 8 (2013)	ANN	ANN	NS	NS	NS	NS	(median) 0.58	NS
J. D. Ruddy 2018	Screening	Not-applic	NS	CV	NU	Bagging	3, 8 (2013)	NB	NB	NS	NS	NS	NS	(median) 0.59	NS
J. D. Ruddy 2018	Screening	Not-applic	NS	CV	NU	Bagging	3, 8 (2013)	LR	LR	NS	NS	NS	NS	(median) 0.59	NS
J. D. Ruddy 2018	Screening	Not-applic	NS	CV	NU	Bagging	3, 8 (2013)	RF	RF	NS	NS	NS	NS	(median) 0.59	NS
J. D. Ruddy 2018	Screening	Not-applic	NS	CV	NU	Bagging	3, 8 (2013)	SVM	SVM	NS	NS	NS	NS	(median) 0.59	NS
J. D. Ruddy 2018	Screening	Not-applic	NS	CV	NU	Bagging	3, 8 (2013)	ANN	ANN	NS	NS	NS	NS	(median) 0.59	NS
J. D. Ruddy 2018	Screening	Not-applic	NS	CV	SMOTE	Bagging	3 (2015)	NB	NB	NS	NS	NS	NS	(median) 0.57	NS
J. D. Ruddy 2018	Screening	Not-applic	NS	CV	SMOTE	Bagging	3 (2015)	LR	LR	NS	NS	NS	NS	(median) 0.57	NS
J. D. Ruddy 2018	Screening	Not-applic	NS	CV	SMOTE	Bagging	3 (2015)	RF	RF	NS	NS	NS	NS	(median) 0.57	NS
J. D. Ruddy 2018	Screening	Not-applic	NS	CV	SMOTE	Bagging	3 (2015)	SVM	SVM	NS	NS	NS	NS	(median) 0.57	NS
J. D. Ruddy 2018	Screening	Not-applic	NS	CV	SMOTE	Bagging	3 (2015)	ANN	ANN	NS	NS	NS	NS	(median) 0.57	NS
J. D. Ruddy 2018	Screening	Not-applic	NS	CV	SMOTE	Bagging	8 (2015)	NB	NB	NS	NS	NS	NS	(median) 0.57	NS
J. D. Ruddy 2018	Screening	Not-applic	NS	CV	SMOTE	Bagging	8 (2015)	LR	LR	NS	NS	NS	NS	(median) 0.57	NS
J. D. Ruddy 2018	Screening	Not-applic	NS	CV	SMOTE	Bagging	8 (2015)	RF	RF	NS	NS	NS	NS	(median) 0.57	NS
J. D. Ruddy 2018	Screening	Not-applic	NS	CV	SMOTE	Bagging	8 (2015)	SVM	SVM	NS	NS	NS	NS	(median) 0.57	NS
J. D. Ruddy 2018	Screening	Not-applic	NS	CV	SMOTE	Bagging	8 (2015)	ANN	ANN	NS	NS	NS	NS	(median) 0.57	NS
J. D. Ruddy 2018	Screening	Not-applic	NS	CV	SMOTE	Bagging	3, 8 (2015)	NB	NB	NS	NS	NS	NS	(median) 0.57	NS
J. D. Ruddy 2018	Screening	Not-applic	NS	CV	SMOTE	Bagging	3, 8 (2015)	LR	LR	NS	NS	NS	NS	(median) 0.57	NS
J. D. Ruddy 2018	Screening	Not-applic	NS	CV	SMOTE	Bagging	3, 8 (2015)	RF	RF	NS	NS	NS	NS	(median) 0.57	NS
J. D. Ruddy 2018	Screening	Not-applic	NS	CV	SMOTE	Bagging	3, 8 (2015)	SVM	SVM	NS	NS	NS	NS	(median) 0.57	NS
J. D. Ruddy 2018	Screening	Not-applic	NS	CV	SMOTE	Bagging	3, 8 (2015)	ANN	ANN	NS	NS	NS	NS	(median) 0.57	NS
J. D. Ruddy 2018	Screening	Not-applic	NS	CV	NU	Bagging	3, 8 (2015)	NB	NB	NS	NS	NS	NS	(median) 0.57	NS
J. D. Ruddy 2018	Screening	Not-applic	NS	CV	NU	Bagging	3, 8 (2015)	LR	LR	NS	NS	NS	NS	(median) 0.57	NS
J. D. Ruddy 2018	Screening	Not-applic	NS	CV	NU	Bagging	3, 8 (2015)	RF	RF	NS	NS	NS	NS	(median) 0.57	NS
J. D. Ruddy 2018	Screening	Not-applic	NS	CV	NU	Bagging	3, 8 (2015)	SVM	SVM	NS	NS	NS	NS	(median) 0.57	NS
J. D. Ruddy 2018	Screening	Not-applic	NS	CV	NU	Bagging	3, 8 (2015)	ANN	ANN	NS	NS	NS	NS	(median) 0.57	NS
J. D. Ruddy 2018	Screening	Not-applic	NS	CV	SMOTE	Bagging	3 (2013-2015)	NB	NB	NS	NS	NS	NS	(median) 0.53	NS
J. D. Ruddy 2018	Screening	Not-applic	NS	CV	SMOTE	Bagging	3 (2013-2015)	LR	LR	NS	NS	NS	NS	(median) 0.53	NS
J. D. Ruddy 2018	Screening	Not-applic	NS	CV	SMOTE	Bagging	3 (2013-2015)	RF	RF	NS	NS	NS	NS	(median) 0.53	NS
J. D. Ruddy 2018	Screening	Not-applic	NS	CV	SMOTE	Bagging	3 (2013-2015)	SVM	SVM	NS	NS	NS	NS	(median) 0.53	NS
J. D. Ruddy 2018	Screening	Not-applic	NS	CV	SMOTE	Bagging	3 (2013-2015)	ANN	ANN	NS	NS	NS	NS	(median) 0.53	NS
J. D. Ruddy 2018	Screening	Not-applic	NS	CV	SMOTE	Bagging	8 (2013-2015)	NB	NB	NS	NS	NS	NS	(median) 0.52	NS
J. D. Ruddy 2018	Screening	Not-applic	NS	CV	SMOTE	Bagging	8 (2013-2015)	LR	LR	NS	NS	NS	NS	(median) 0.52	NS
J. D. Ruddy 2018	Screening	Not-applic	NS	CV	SMOTE	Bagging	8 (2013-2015)	RF	RF	NS	NS	NS	NS	(median) 0.52	NS
J. D. Ruddy 2018	Screening	Not-applic	NS	CV	SMOTE	Bagging	8 (2013-2015)	SVM	SVM	NS	NS	NS	NS	(median) 0.52	NS
J. D. Ruddy 2018	Screening	Not-applic	NS	CV	SMOTE	Bagging	8 (2013-2015)	ANN	ANN	NS	NS	NS	NS	(median) 0.52	NS
J. D. Ruddy 2018	Screening	Not-applic	NS	CV	SMOTE	Bagging	3, 8 (2013-2015)	NB	NB	NS	NS	NS	NS	(median) 0.53	NS
J. D. Ruddy 2018	Screening	Not-applic	NS	CV	SMOTE	Bagging	3, 8 (2013-2015)	LR	LR	NS	NS	NS	NS	(median) 0.53	NS
J. D. Ruddy 2018	Screening	Not-applic	NS	CV	SMOTE	Bagging	3, 8 (2013-2015)	RF	RF	NS	NS	NS	NS	(median) 0.53	NS
J. D. Ruddy 2018	Screening	Not-applic	NS	CV	SMOTE	Bagging	3, 8 (2013-2015)	SVM	SVM	NS	NS	NS	NS	(median) 0.53	NS
J. D. Ruddy 2018	Screening	Not-applic	NS	CV	SMOTE	Bagging	3, 8 (2013-2015)	ANN	ANN	NS	NS	NS	NS	(median) 0.53	NS
J. D. Ruddy 2018	Screening	Not-applic	NS	CV	SMOTE	Bagging	3, 8 (2013-2015)	NB	NB	NS	NS	NS	NS	(median) 0.52	NS
J. D. Ruddy 2018	Screening	Not-applic	NS	CV	NU	Bagging	3, 8 (2013-2015)	LR	LR	NS	NS	NS	NS	(median) 0.52	NS
J. D. Ruddy 2018	Screening	Not-applic	NS	CV	NU	Bagging	3, 8 (2013-2015)	RF	RF	NS	NS	NS	NS	(median) 0.52	NS
J. D. Ruddy 2018	Screening	Not-applic	NS	CV	NU	Bagging	3, 8 (2013-2015)	SVM	SVM	NS	NS	NS	NS	(median) 0.52	NS
J. D. Ruddy 2018	Screening	Not-applic	NS	CV	NU	Bagging	3, 8 (2013-2015)	ANN	ANN	NS	NS	NS	NS	(median) 0.52	NS
J. D. Ruddy 2018	Screening	Not-applic	NS	CV	SMOTE	NU	3, 8 (2015)	RF	RF	NS	NS	NS	NS	(median) 0.58	NS
J. D. Ruddy 2018	Screening	Not-applic	NS	CV	SMOTE	NU	3, 8 (2015)	NB	NB	NS	NS	NS	NS	(median) 0.58	NS

ADTree, alternating decision tree; ANN, artificial neural network; CV, cross-validation; DT, decision tree; ENN, wilson's edited nearest neighbor rule; EWMA, exponantial weighted moving average; GEE, generalized estimating equations; GNB, gaussian naïve bayes; GPS, global positioning system; HS, hamstring; KNN, k-nearest neighbors; LDA, Linear discriminant analysis; LOOCV, leave one-out with cross-validation; LR, logistic regression; METIC, multiple bidirectional encoder transformers for injury classification; MLP, multi-layer perceptron; NB, Naïve Bayes; NC, non-contact; NCTL, non-contact time loss; NSCV, nested stratified cross-validation; NS, not-specified; NU, not-used; NsDbn, non-stationary dynamic bayesian network; OvR, one-vs-the-rest; PCA, principal component analysis; PCA, principal component analysis; REPTree, reduces error pruning tree; RF, random forest; RFECV, recursive feature elimination with cross-validation; ROS, random over-sampling; RUS, random under-sampling; Rtree, random tree; SCV, stratified cross-validation; SMOTE, synthetic minority over-sampling technique; SVM, support vector machine; TVDBN, time-varying dynamic bayesian network; UPD, un-processed data

4.1.2 Scoping review: key findings

1. Our systematic search included 28 studies, including 99 different methods and 106 different models describing the current machine learning techniques used to develop prediction models for sports injuries.

2. The different machine learning techniques to develop prediction machine learning models for sports injuries used two main data collections approaches: screening and monitoring.

3. The main difference between screening and monitoring over the development of predictive machine learning models was the time dependency that arose from the use of a monitoring approach.

4. This time dependency should be notably taken into account by ordering the data chronologically when dealing with validation procedure and the management of imbalance class problems.

5. In the monitoring and screening approaches, the ROC-AUC score was the most frequent reported performance metric for machine learning models.

6. Consideration should be given to representing and standardising the range of model capabilities through different performance metrics for machine learning models.

Our systematic search was conducted on 07 December 2022. We submitted the manuscript, and after three rejections we considered improvement and also we are considering updating this search to include the latest articles that have been published in the meantime, as well as incorporating the last risk of bias tool (PROBAST-AI, (Collins et al., 2021)) and transparent reporting for systematic review of multivariable prediction models for individual prognosis or diagnosis (TRIPOD-SRMA, (Snell et al., 2023)) before resubmission.

4.2 IPredict-AI: Protocol

4.2.1 Context

- Based on the information presented in the Section 4.1, there is currenlty a gap in the management of time-dependency when dealing with validation procedure and the management of imbalance class problem as well as the standardisation of report of perforamnce metrics for machine learning models.
- Based on the information presented in the Section 2.3, developing and evaluating injury prevention strategies is important in athletics.
- Injury prevention strategies in general and specifically in athletics should be improved to overcome the challenges of developing, implementing and analysing measures and to better address the complexity and multifactorial nature of injuries.
- Using digital health as an injury prevention strategy could be promising notably by the use of health status feedback.
- The development of injury prevention strategies using machine learning to provide individualised injury risk estimation feedback could therefore be a relevant injury risk reduction approach to reduce the occurrence of sports injuries in the specific context of athletics.

OBJECTIVE 2

In this context, our objective was to develop and assess the effectiveness of an injury prevention strategy using prediction models developed using machine learning in order to reduce the occurrence of sports injuries in the specific context of athletics.

PUBLISHED

Open access Protocol

BMJ Open

Relationship between a daily injury risk estimation feedback (I-REF) based on machine learning techniques and actual injury risk in athletics (track and field): protocol for a prospective cohort study over an athletics season

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ABSTRACT

Introduction Two-thirds of athletes (65%) have at least one injury complaint leading to participation restriction (ICPR) in athletics (track and field) during one season. The emerging practice of medicine and public health supported by electronic processes and communication in sports medicine represents an opportunity for developing new injury risk reduction strategies. Modelling and predicting the risk of injury in real-time through artificial intelligence using machine learning techniques might represent an innovative injury risk reduction strategy. Thus, the primary aim of this study will be to analyse the relationship between the level of **I**njury **R**isk **E**stimation **F**eedback (I-REF) use (average score of athletes' self-declared level of I-REF consideration for their athletics activity) and the ICPR burden during an athletics season.

Method and analysis We will conduct a prospective cohort study, called **I**njury **Predict**ion with **A**rtificial **I**ntelligence (IPredict-AI), over one 38-week athletics season (from September 2022 to July 2023) involving competitive athletics athletes licensed with the **F**rench **F**ederation of **A**thletics. All athletes will be asked to complete daily questionnaires on their athletics activity, their psychological state, their sleep, the level of I-REF use and any ICPR. I-REF will present a daily estimation of the ICPR risk ranging from 0% (no risk for injury) to 100% (maximal risk for injury) for the following day. All athletes will be free to see I-REF and to adapt their athletics activity according to I-REF. The primary outcome will be the ICPR burden over the follow-up (over an athletics season), defined as the number of days lost from training and/or competition due to ICPR per 1000 hours of athletics activity. The relationship between ICPR burden and the level of I-REF use will be explored by using linear regression models.

Ethics and dissemination This prospective cohort study was reviewed and approved by the Saint-Etienne University Hospital Ethical Committee (Institutional Review Board: IORG0007394, IRBN1062022/CHUSTE). Results of the study will be disseminated in peer-reviewed journals and in international scientific congresses, as well as to the included participants.

STRENGTHS AND LIMITATIONS OF THIS STUDY

⇒ This study will assess the interest and efficacy of daily monitoring of physical, psychological and contextual variables combined with artificial intelligence in reducing sports injury risk.
⇒ This is the first study in athletics, and in other sports, using a machine learning model to predict injury in a real-time athletics field context.
⇒ This study will use an online tool (web application) to collect data based on daily assessment.
⇒ This study requires daily participation and may therefore be a limiting factor for athletes' involvement.
⇒ As this is an exploratory study, the sample size is unknown, and consequently, the amount of data collected may be limited for the purposes of developing a machine learning model.

INTRODUCTION

Athletics (track and field) activity leads to a risk of injury.[1–4] Indeed, epidemiological studies showed that about two-thirds of athletes presented at least one injury during an athletics season.[1 2 5 6] Specifically, in a French one-season athletics study, 65% of athletes reported at least one injury complaint leading to participation restriction (ICPR).[6] Another way to quantify the impact of injuries is the injury burden, defined as the number of sports activity days lost due to injury per 1000 hours of activity.[7] Regarding athletics activity, a previous study showed an ICPR burden equal to 285.6±619.6 days per 1000 hours of athletics activity.[6] Injuries negatively

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affect athletes' training, performance, career and health. Therefore, reducing the risk of injury is fundamental to promoting healthy and sustainable athletics activity.

Injury risk reduction interventions in athletics, as in other sports, can vary because of the multifactorial nature of injuries. These interventions can target the athletes' physical or psychological condition, training, equipment, rules, lifestyle, medical organisation or sports organisation.[3 8] The emerging practice of medicine and public health supported by electronic processes and communication (e-Health) in sports medicine[9] represents an opportunity to develop new injury risk reduction strategies. Providing athletes with individualised health status feedback[10] could be one of these opportunities and could involve more domains in a bio-psycho-social approach. Artificial intelligence (AI) approaches using machine learning (ML) techniques make it possible to provide more in-depth feedback provided to athletes, by individualising their health status, and especially by taking into account individual multifactorial data that are used by the predictive models.[11–13] ML is a field of AI consisting of the development of algorithms that can automatically learn from data to make decisions.[12] In sports medicine, supervised ML algorithms are often used to direct the model's prediction towards a defined goal or target phenomenon (eg, injury events).[12 14] ML models have the potential to act as an automated data analysts that are able to provide insight into the athlete's condition.[15] Therefore, ML models may help the clinical decision-making process for sports scientists, team physicians and athletic trainers when the data acquired from different sources (eg, wearable sensors and even questionnaires from smartphones) are transformed into accurate decisions regarding the health, safety and performance of athletes.[15] Indeed, ML methods can be used to identify athletes at high risk of injury and can help detect the most important injury risk factors.[12] Consequently, ML techniques could also provide individualised injury risk estimations for athletes.

A recent systematic review of the methodology and performance of existing musculoskeletal injury prediction models in sports found that 98% of these models have a high risk of bias.[16] The main reasons for this finding were the inappropriate and incomplete evaluation procedure of the models[16] and the lack of transparency when reporting the models (ie, full equations or complete code not appropriately described).[17] This can be considered a poor methodology and lead to a lack of generalisation. ML predictive model analysis is principally made retrospectively at the end of the sports season.[18–25] Such retrospective developments could lead to difficulties in reusing the models with new data sets or for performing external validations in different contexts (eg, environmental differences, professional vs amateur athletes; geographical, club vs national sports federations; or temporal situations, the same population at different period vs different populations at different periods). In a real sports medicine context, using geographical or domain data to externally validate the predictive model could be highly challenging (eg, collaboration, environmental constraints). Thus, the quality and nature of each new observation will influence model performance, making it more complex to compare modelling procedures or validate predictions.[26] On the contrary, using temporal input data to provide a real-time prediction could help close the gap between the injury risk reduction programmes and athletics activity, strengthening the model validation process without the need for study replication.[27] As most athletes now have access to digital tools (smartphones, computers), there is an opportunity to implement real-time semi-automated data acquisition through online software (eg, web or smartphone application). Such real-time semi-automated data acquisition can be an opportunity to develop real-time ML approaches. In addition, both techniques, ML and real-time semi-automated data acquisition make it possible to individualise injury risk estimation by using adaptative tree-based questionnaires (eg, individualised questions based on prior answers) and personal features such as the data related to injury risk estimation at a given time. To sum up, providing an individual **I**njury complaint leading to participation restriction **R**isk **E**stimation **F**eedback (I-REF) based on ML could be a relevant injury risk reduction approach.

Study hypothesis and objectives

Hypothesis

We hypothesise that providing a daily individual I-REF presented to each athlete will be related to a reduced ICPR burden during an athletics season.

Primary goal

The primary aim of this study will be to analyse the relationship between the level of I-REF use (calculated as the average score of the athletes' self-declared level of consideration of the I-REF for their athletics activity) and the ICPR burden during an athletics season (ie, 34-week follow-up).

Secondary goal

The secondary aims of this study will be to analyse the association between the level of I-REF use and:

- The percentage of athletes with at least one ICPR during an athletics season.
- The time to the first ICPR during an athletics season.
- The number of ICPR per 1000 hours of athletics activity during an athletics season.

The tertiary objectives will be to analyse the association between the frequency of I-REF view (calculated as the ratio between the total number of days that an athlete checks their I-REF and the number of days that the I-REF is generated) and:

- The ICPR burden during an athletics season.
- The percentage of athletes with at least one ICPR during an athletics season.
- The time to the first ICPR during an athletics season.
- The number of ICPR per 1000 hours of athletics activity during an athletics season.

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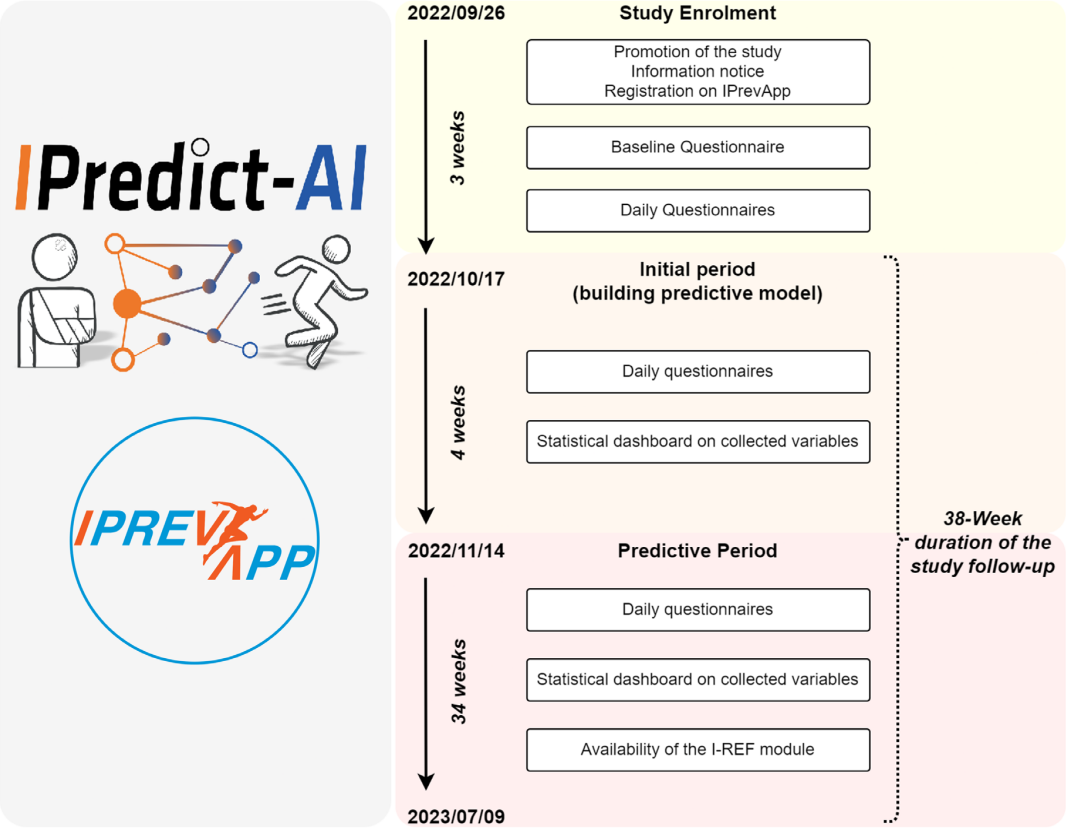


Figure 1 Study design overview. IPredict-AI, Injury Prediction with Artificial Intelligence; IPrevApp, Injury Prevention Application; I-REF, Injury Risk Estimation Feedback.

METHODS AND ANALYSIS

Study design and overall procedure

We will conduct a prospective cohort study, called **I**njury **Predict**ion with **A**rtificial **I**ntelligence (IPredict-AI), over one athletics season (38 weeks), from September 2022 to July 2023 (figure 1). This study will involve competing athletics athletes licensed with the **F**rench **F**ederation of **A**thletics (FFA). This study protocol is reported according to the **ST**rengthening the **R**eporting of **OB**servational studies in **E**pidemiology (STROBE) items[28] and following the **S**tandard **P**rotocol **I**tems: **R**ecommendations for **I**nterventional **T**rials-**A**rtificial **I**ntelligence (SPIRIT-AI).[26]

Patient and public involvement

Participants and the public were involved in the design and development of the study protocol.

Materials

The inclusion procedure and data collection will be carried out online on a mobile and computer website application (IPrevApp, https://iprevapp.emse.fr) hosted on a local host server AlmaLinux V.8.6 (Sky Tiger) with a database (MariaDB V.10.1.48). A virtual Python environment (through an open-source Python V.3.10.2)[29] is implemented to perform the ML analysis using the open-source scikit-learn libraries V.1.1.2,[30] on high-performance computing hardware (2 CPU Intel Xeon Gold 6132, 14-core, 2.6 GHz). All statistical analyses regarding the primary and secondary aims will be carried out using the Statistical Software R.[31]

Population recruitment and inclusion/exclusion criteria

At the beginning of the 2022–2023 athletics season, the FFA will disseminate information about the IPredict-AI study through their website, social media and by email to all athletes licensed at the FFA for competition. These emails will include an invitation to participate in this study at an individual level, as well as a description of the study purpose and procedure, the participation right, a letter of information and a link to register on the website application. Once the athlete will be registered, the athlete's account will open automatically and will offer access to the IPredict-AI study. The inclusion period will be 3 weeks from 26 September 2022 to 17 October 2022.

The inclusion of athletes will be based on the following criteria: athletes must be licensed at the FFA for competition (sprints, hurdles, jumps, throws, combined events

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and endurance disciplines), without any counterindications for competitive athletics activity attested by the licence at the FFA, be aged between 15 and 60, have daily access to a digital device (smartphone, computer, tablet) with a network connection (public or private). We will not exclude athletes based on their baseline injury status or history.[6]

Injury definition

Following Edouard *et al*,[6] we chose the term 'injury complaint' since it refers to self-reported information without medical diagnosis.[32] Here, an injury is defined as: 'a pain, physical complaint or musculoskeletal lesion sustained by an athlete regardless of whether it received medical attention or its consequences with respect to impairments in connection with competition or training'.[33] Athletes reporting an injury complaint will be asked to provide the following information: the circumstance of injury occurrence (training, competition, not related to athletics activity), mode of onset (sudden or gradual),[33] injury location[33] and consequence on athletic participation classified into four categories: (1) full participation with no discomfort, (2) full participation with discomfort, (3) reduced participation due to injury complaint and (4) full absence due to injury complaint.[6 34] Injury complaints will be differentiated between those related to athletics activity and those outside of athletics activity. For the study outcome, we will restrict the analysis to injury complaints related to athletics activity (training and competition). The term 'injury complaint leading to participation restriction' (ICPR) corresponds to the last two categories (c and d).

Data collection

All data will be collected through questionnaires on the website application. To minimise filling errors, we will use only close-ended questions (slider, single-choice, multiple-choice, drop-down list). To avoid missing values during the filling process of a new observation, all questions in the questionnaires will be mandatory.

After being included in the study, athletes will have to fulfil a baseline questionnaire that contains their demographic characteristics (age, weight, height, sex, primary athletics discipline) and their history of injuries and illnesses during the previous athletics season (2021/2022) (table 1).

During the athletics season and throughout the study (from the end of the inclusion to the end of the study follow-up, ie, 38 weeks), the daily follow-up will consist of two questionnaires: one in the morning and one in the evening. These questionnaires will collect parameters related to the athletics activity (eg, volume, intensity, types), athletes' psychological state (eg, anxiety, stress, self-regulation, emotions), sleep, injuries, illnesses and, only for the 34 last weeks, the level of I-REF use and the frequency of I-REF view. All these parameters are shown in table 1. The daily questionnaires will take between 0.5 and 5 min to be filled out and will be displayed automatically in the website application. They will be accessible during the whole day from 3:00 a.m. to 24 hours. Every night at 3:00, the answers will be reset for the next day.

In this study, missing data will necessarily result from athletes not responding to questions. When omissions occur, no imputation strategy will be used, the questionnaire will be considered incomplete. In addition, some questions and thus variables (eg, competition, training session, stress event) will depend on responses to other questions. Sometimes there will be no response to a certain question and thus no value for a related variable, but this cannot be considered a missing observation. These variables will take a predefined default value within their initial response range (eg, if the athlete replies that he/she did not go to training, the database will record 0 hours of training). The variables which cannot take a default value will be replaced by a constant one (eg, '−1'), which reflects the absence of a daily life event.

The response proportion to the questionnaire will be calculated at the individual athlete's level and expressed as the number of responses obtained in the questionnaires divided by the total number of expected responses.[6] Several strategies will be used to promote regular participation and maintain high response rates throughout the study. First, in order to help athletes to integrate the questionnaires into their daily lives, a calendar file in universal '.ics' format will be made available to athletes directly from the website application and will contain all IPredict-AI study reminders for easy addition into a personal calendar. In addition, automatic reminders will be generated if an athlete has not yet completed a questionnaire before the questionnaire closing time. Furthermore, social media, emails and newsletters within the website application will be used to disseminate information regarding the study (eg, tips and tricks regarding the use of the website application, and key details), thus promoting the use of the study's daily questionnaires throughout the study period. Participating athletes will have access to a visual dashboard on the platform displaying their personal data for the collected variables over time, allowing an individualised real-time summary of the athlete's answers.

Daily individualised feedback on ICPR risk estimation (I-REF)

The daily feedback on individual athlete ICPR risk estimation (ie, I-REF) will be calculated by a dynamic model (ie, predictive model) using the collected data. More precisely, the feedback presented by the website application will reflect the athlete's probability of ICPR and will be called I-REF (figure 2). The I-REF value will range between 0% (no risk of injury) and 100% (maximal risk of injury) for the following day (figure 2A). The I-REF value will be displayed on the website application together with the receiver operator characteristic area under the curve (ROC-AUC), which measures the ability of the predictive classifier model to distinguish between the two classes of injury/non-injury (figure 2B). This ROC-AUC ranges from 0 (bad performance of the predictive model) to 1 (perfect performance of the predictive model). The

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Table 1 Summary of data collected during the IPredict-AI study

Questionnaires details					Machine learning model	
Questionnaire	Occurrence	Theme	Variables	Period (figure 1.)	Input features X	Output data Y
Collected variables						
Registration	Unique	Demographic	Age	SE	X	
Baseline	Unique	Demographic	Sex	SE, IP, PP	X	
Baseline	Unique	Demographic	Weight	SE, IP, PP	X	
Baseline	Unique	Demographic	Height	SE, IP, PP	X	
Baseline	Unique	Athletics activity	Number of years of athletics activity	SE, IP, PP	X	
Baseline	Unique	Athletics activity	Main athletics discipline	SE, IP, PP	X	
Baseline	Unique	Athletics activity	Mean hours of athletics per week	SE, IP, PP	X	
Baseline	Unique	Athletics activity	Mean hours of sports per week, outside athletics	SE, IP, PP	X	
Baseline	Unique	Injury	Injury(ies) last season	SE, IP, PP	X	
Baseline	Unique	Illness	Illness(es) last season	SE, IP, PP	X	
Morning	Daily	Sleep details	Time to fall asleep (Ts)	SE, IP, PP		
Morning	Daily	Sleep details	Time to wake up (Tw)	SE, IP, PP		
Morning	Daily	Sleep details	Quality	SE, IP, PP	X	
Morning	Daily	State of fitness	Fatigue	SE, IP, PP	X	
Morning	Daily	State of fitness	Pain	SE, IP, PP	X	
Morning	Daily	Anxiety	Concern	SE, IP, PP		
Morning	Daily	Anxiety	Tension	SE, IP, PP		
Morning	Daily	Anxiety	Confidence	SE, IP, PP		
Morning	Daily	Training	Event	SE, IP, PP		
Morning	Daily	Motivation to train	Intrinsic (i)	SE, IP, PP		
Morning	Daily	Motivation to train	Introjected (ii)	SE, IP, PP		
Morning	Daily	Motivation to train	Extrinsic (iii)	SE, IP, PP		
Morning	Daily	Motivation to train	Amotivation (iv)	SE, IP, PP		
Evening	Daily	Training session	Number (n)	SE, IP, PP		
Evening	Daily	Training session (n)	Duration (D_{train_i})	SE, IP, PP		
Evening	Daily	Training session (n)	Intensity (I_{train_i})	SE, IP, PP		
Evening	Daily	Training session (n)	Type of training	SE, IP, PP		
Evening	Daily	Training session (n)	Number of sprints	SE, IP, PP		
Evening	Daily	Training self-efficacy	Performance assessment (TSE_1)	SE, IP, PP		
Evening	Daily	Training self-efficacy	Performance belief assessment (TSE_2)	SE, IP, PP		
Evening	Daily	Competition session	Event	SE, IP, PP		
Evening	Daily	Competition session	Duration (D_{comp})	SE, IP, PP		
Evening	Daily	Competition session	Intensity (I_{comp})	SE, IP, PP		
Evening	Daily	Competition self-efficacy	Performance assessment (CSE_1)	SE, IP, PP		
Evening	Daily	Competition self-efficacy	Performance belief assessment (CSE_2)	SE, IP, PP		
Evening	Daily	I-REF	I-REF level of use	PP		
Evening	Daily	State of fitness	Fatigue	SE, IP, PP	X	
Evening	Daily	State of fitness	Pain	SE, IP, PP	X	
Evening	Daily	Emotions	Positive emotion	SE, IP, PP	X	
Evening	Daily	Emotions	Negative emotion	SE, IP, PP	X	

Continued

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Table 1 Continued

Questionnaires details					Machine learning model	
Questionnaire	Occurrence	Theme	Variables	Period (figure 1.)	Input features X	Output data Y
Evening	Daily	Stress	Event	SE, IP, PP		
Evening	Daily	Stress	Perceived demands ($P_{demands}$)	SE, IP, PP		
Evening	Daily	Stress	Perceived ressources ($P_{ressources}$)	SE, IP, PP		
Evening	Daily	Illness	Event	SE, IP, PP	X	
Evening	Daily	Illness	Detail(s)	SE, IP, PP		
Evening	Daily	Injury	Event	SE, IP, PP		
Evening	Daily	New injury	Event	SE, IP, PP		X
Evening	Daily	New injury	Place of appearance	SE, IP, PP		
Evening	Daily	New injury	Mode of onset	SE, IP, PP		
Evening	Daily	New injury	Mechanism of occurrence	SE, IP, PP		
Evening	Daily	New injury	Body laterality	SE, IP, PP		
Evening	Daily	New injury	Body locality	SE, IP, PP		
Evening	Daily	New injury	Impact of new injury on the training	SE, IP, PP		
Evening	Daily	Injury tracking	Tracking of past injury(ies)	SE, IP, PP	X	
Evening	Daily	Injury tracking	Impact of past injury(ies) on training	SE, IP, PP		
Processed variables						
Morning	Daily	Night duration	$Score = Ts - Tw$	SE, IP, PP	X	
Morning	Daily	Anxiety	$Score = \frac{Concern + Tension}{2} - Confidence$	SE, IP, PP	X	
Morning	Daily	Motivation to train	$Score = 2i + 1ii + (-1iii) + (-2iv)$	SE, IP, PP	X	
Evening	Daily	Training workload (T_w)	$Score = \sum_{i=1}^{n} (D_{train_i} * I_{train_i})$	SE, IP, PP		
Evening	Daily	Training self-efficacy	$Score = \frac{TSE_1 + TSE_2}{2}$	SE, IP, PP	X	
Evening	Daily	Competition workload (C_w)	$Score = D_{comp} * I_{comp}$	SE, IP, PP		
Evening	Daily	Overall daily workload	$Score = T_w + C_w$	SE, IP, PP	X	
Evening	Daily	Competition self-efficacy	$Score = \frac{CSE_1 + CSE_2}{2}$	SE, IP, PP	X	
Evening	Daily	Stress	$Score = -P_{demands} + P_{ressources}$	SE, IP, PP	X	

IP, initial period; IPredict-AI, Injury Prediction with Artificial Intelligence; I-REF, Injury complaint leading to participation restriction Risk Estimation Feedback; PP, predictive period; SE, study enrolment.

I-REF value will be estimated individually based on the athlete's features (table 1). In order to mitigate overestimation in ROC-AUC score estimation, we will adhere to the practice of nested cross-validation, which serves to reduce bias in small data sets.[35] Specifically, 200 iterations of nested cross-validation will be conducted to calculate each ROC-AUC score. This will involve the random selection of 75% of the data as the outer training set for hyper-parameters tuning, while the remaining 25% will be reserved for validation, serving as the outer test set. Then, for the inner cross-validation, half of the 75% selected for hyper-parameters tuning, that is, 50% (inner train set), will be used for predicting the remaining 50% (inner test set). To evaluate the performance of each model on the outer test set, we will conduct validation by retaining the best model from the inner cross-validations. This process will be repeated four times for each of the 200 iterations to obtain the best model for each outer test set.

The development of I-REF will be made using tree-based ensemble classifier machine learning techniques. Tree-based models are among the most popular ML predictive models in sports medicine.[12 16] Compared with deep learning models such as neural networks, they are more accurate for data sets where features (like ours) are individually meaningful and not strongly related via a temporal or spatial structure (as in the image or speech recognition). Besides accuracy, explainability is another essential aspect of ML models in healthcare.

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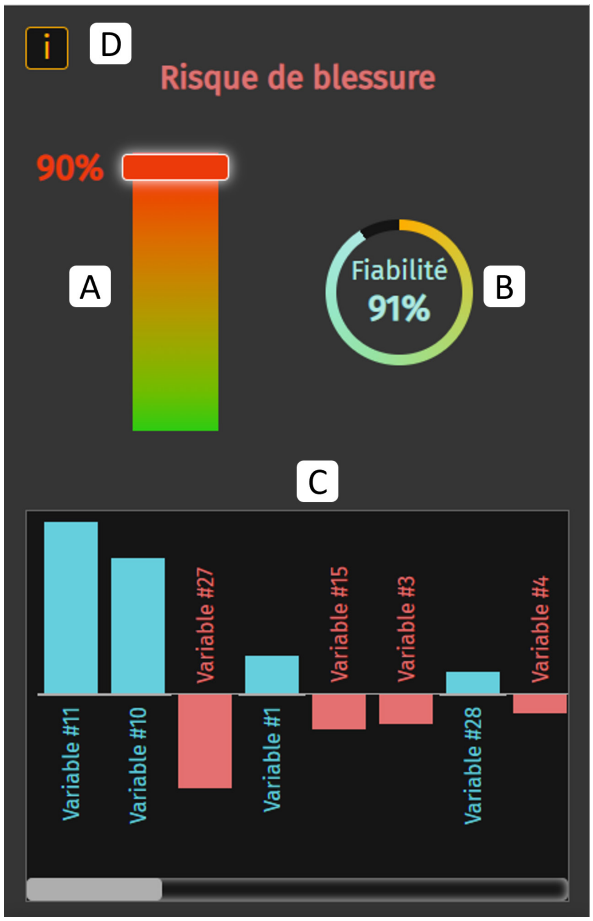


Figure 2 I-REF Module on smartphone. (A) Individual predicted class probability. (B) Ability of the predictive classifier model to distinguish between the two classes injury/non-injury. (C) Individual amount of contribution of each X to predict the Y value, where each variable will be displayed (eg, Variable #12) and will be ordered based on their absolute value influence. Blue variables decrease the risk of injury; red variables increase it. (D) Link for users to a simple explanation of A, B and C. 'Risque de blessure' means 'injury risk', 'Fiabilité' corresponds to the receiver operator characteristic area under the curve and means 'trustability', and 'Variable' means 'variable'.

The often-denounced black box effect of ML models is partly resolved by models that have good explainability.[35 36] Recent research conducted by Lundberg *et al*[37] has provided a tailor-made method for decision trees, hereby strengthening their use. Baseline and daily questionnaires data will be used as input features (*X*) (table 1). The output parameter (*Y*) will be the new injury event (ie, ICPR, as a binary outcome). Our modelling process aims to establish a binary classification based on *X* from the day of starting data collection to the day of the last model training in order to obtain a predicted classification value of *Y* (ie, 0: not injured, 1: injured) for the following day. Then, we will estimate the predicted class probabilities ranging between 0 and 100 of this binary classification, which will represent the risk of injury. Finally, to individualise the procedure we will use a recent local interpretable explanation method for ML tree algorithms[37] based on classic game-theory additive Shapley values[38] to extract the amount of contribution of each *X* to predict its *Y* value (figure 2C,D).[39]

When algorithms are intended to help real-time clinical decision-making as conditions evolve, then these algorithms should make dynamic predictions using new data as it becomes available.[40] However, there is no standardised method to set the period between each model training (ie, the time span between each retraining of the model) in connection with model performance when predictions are made in a real-time context.[40] A possibility to solve this could be to evaluate model performance metrics at several predetermined, discrete time points, achieving continued monitoring of the predictive performance of the model.[27 40 41] We will train the first version of our model within the first 4 weeks of data collection (figure 1), and we will retrain the model each week.

Athletes will be able to check the I-REF value for the first time after 4 weeks of data collection (figure 1). All athletes will be free to consult their own I-REF value, or not, and they will also be free to adapt or not their athletics activity based on it, or not. They will not receive any practical individualised recommendations regarding the risk of ICPR, so the management of this risk will be their own responsibility.

The level of I-REF use by athletes will be assessed by calculating the average score of the self-declared level of consideration that athletes give to I-REF for their athletics activity days. The frequency of I-REF viewing will be calculated as the ratio between the total number of days that athletes check their I-REF divided by the number of days that an I-REF is generated. For the frequency of I-REF viewing, we will consider that an athlete checked the I-REF when he/she enters the I-REF module in the application. This variable will be monitored automatically.

Strategies to limit the bias

We will develop strategies to limit filing errors and missing values (see the 'data collection' section). Strategies will also be implemented to limit bias in the predictive ML model and in the ROC-AUC score estimation (see the 'Daily individualized feedback on ICPR risk estimation (I-REF)' section). In order to limit the bias implied by the non-randomisation, the key variables, that have been shown to be associated with injury risk: sex, age and history of ICPR during the previous season, will be included in the analyses as independent variables. Consequently, there will be no stratification as these key variables will be already included in the analyses.

Sample size

As this study is an exploratory hypothesis-generating research project formal sample calculation is not necessary.

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Study outcomes

The primary outcome will be the ICPR burden, defined as the number of athletics activity days lost due to ICPR per 1000 hours of exposure,[6 7] over the period of follow-up with the presentation of I-REF to the athletes (ie, 34 weeks). The secondary outcomes will be (i) the percentage of athletes who will present at least one ICPR during the follow-up, (ii) the time, in hours of athletics activity, to the first ICPR[6] and (iii) the number of ICPR per 1000 hours of exposure during the follow-up. All these variables will be gathered from the daily questionnaires in the website application. The follow-up window will be 34 weeks, starting when the first I-REF is calculated and provided to athletes, and finishing at the end of the follow-up (figure 1).

Statistical methods

We will perform the statistical analyses using a well-known software, namely R (V.3.6.3 (2020-02-29, Copyright 2020 The Foundation for Statistical Computing (Comprehensive R Archive Network, http://www.R-project.org)) and the R library 'survival').[31]

For the primary outcome, we will use a linear regression model where the dependent variable will be the ICPR burden and the independent variables will be the level of use of I-REF, sex, age and history of ICPR during the previous season. Using this model, we will explore the relationship between the ICPR burden and the level of use of I-REF by calculating the model coefficient for the variable 'level of use of I-REF' and its 95% CI.

For the secondary outcome (i), we will adjust a logistic regression model where the dependent variable will be the occurrence (or non-occurrence) of at least one ICPR over the season. We will calculate the OR with 95% CI as a measure of association. For the secondary outcome (ii), we will use survival analysis. First, non-athletics-related ICPR will be analysed as competing risks (using R package 'cmprsk') to explore whether there were significant differences between the athletes who showed higher and lower use of I-REF in terms of the cumulative incidence of ICPR occurred during athletics and outside of athletics. Second, we will adjust a Cox proportional hazards model where the dependent variable will be the time to the first ICPR. We will calculate the HR with 95% CI as a measure of association. Participants will be considered as right-censored (ie, will have incomplete data on the study outcomes at the right side of the follow-up period) if they stop completing the questionnaires, if they have an ICPR that occurred outside of athletics activity or if they have not had an injury at the end of the follow-up. For the secondary outcome (iii), we will use a linear regression model where the dependent variable will be the number of ICPR per 1000 hours of exposure during the follow-up. For all these analyses of secondary outcomes, we will include as independent variables the ones mentioned above in relation to the primary outcome analysis.

Except for the analysis of secondary outcome (ii), which has been explained above, these analyses will be performed on athletes with 100% of the data (complete case analysis). We will also consider performing sensitivity analyses based on consideration of 'best-case' and 'worst-case' scenarios.

Ethics and dissemination

This prospective cohort study was reviewed and approved by the Saint-Etienne University Hospital Ethical Committee (Institutional Review Board: IORG0007394, IRBN1062022/CHUSTE). Participants' study information will not be released outside of the study without the written permission of the participants. During the study, participants will give their personal information and complete study questionnaires through a secured individual account on a website application. The database will be hosted on the physical server of Mines Saint-Etienne secured by a private network and individual professional access (login, password). Only P-ED, PE, LN, and the engineer who developed the application will have access to the database before, during and after the trial. Any extraction from this database will necessarily involve the anonymisation of the subjects. The raw database will not be made available online.

The results of the study will be communicated through articles in peer-reviewed journals following the STROBE items[26] to produce the manuscripts, and in international scientific congresses. Individuals who have contributed to the design and implementation of the protocol will be eligible to be included in publications as coauthors. The results of the study will also be part of the doctoral thesis of P-ED. In addition, the participants of this study will be informed about the results of the study. Dissemination of the results to the end-users, with the aim of knowledge translation will also be made.

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Contributors PE and LN initiated the study design. P-ED, LN, DB, KH and PE conceived the study. DB provided methodological advice regarding the study design and statistical analysis. P-ED, LN, AR, JC, KH and PE conceived the daily questionnaires. P-ED, LN and CL conceived the machine learning analyses. P-ED, LN, DB, AR, CL, AB, JC, KH and PE contributed to the refinement of the study protocol, the writing of the paper and approved the final manuscript.

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Competing interests None declared.

Patient and public involvement Patients and/or the public were involved in the design, or conduct, or reporting, or dissemination plans of this research. Refer to the Methods section for further details.

Patient consent for publication Not applicable.

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4.3 IPredict-AI: Results

4.3.1 Context

- As shown in the Section 4.1 the majority of prognostic studies using machine learning to predict the injury was made retrospectively without assessing and interacting with athletes.
- In a context of sports medicine and athletics, they are no data on the implementation of a system using machine learning pipeline that can interact with athletes and act as an injury prevention strategy.
- In Section 4.2, we presented the protocol we developed to answer the first part of the PhD objective 2 (Section 3.2).
- In this Section 4.3, we therefore present the results.

OBJECTIVE 2

In this context, our objective was to develop and assess the effectiveness of an injury prevention strategy using prediction models developed using machine learning in order to reduce the occurrence of sports injuries in the specific context of athletics.

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Association between the use of daily injury risk estimation feedback (I-REF) based on machine learning techniques and injuries in athletics (track and field): results of a prospective cohort study over an athletics season

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ABSTRACT

Objective To analyse the association between the level of use of injury risk estimation feedback (I-REF) provided to athletes and the injury burden during an athletics season.

Method We conducted a prospective cohort study over a 38-week follow-up period on athletes competing at the French Federation of Athletics. Athletes completed daily questionnaires on their athletics activity, psychological state, sleep, self-reported level of I-REF use, and injuries. I-REF provided a daily estimation of the injury risk for the next day, ranging from 0% (no risk of injury) to 100% (maximum risk of injury). The primary outcome was the injury burden during the follow-up, defined as the number of days with injury per 1000 hours of athletics activity. A negative binomial regression model was used to analyse the association between self-reported I-REF use and the injury burden.

Results Of the 897 athletes who met the inclusion criteria, 112 (38% women) were included in the analysis. The mean daily response rate of the follow-up was 37%±30%. The primary analysis found no significant association between the self-reported I-REF use and the injury burden (n=112, e^{β}: 0.992, 95% CI: 0.977 to 1.007; p=0.308). However, when considering athletes' daily response rate in secondary analysis, for a response rate of at least 9%, we observed a significant association between the self-reported level of I-REF use and the injury burden (n=76, e^{β}: 0.981, 95% CI: 0.965 to 0.998; p=0.027).

Conclusions Daily injury risk estimation feedback using machine learning was not associated with reducing injury burden.

WHAT IS ALREADY KNOWN ON THIS TOPIC

⇒ Athletics (track and field) activity is associated with injury occurrences, with about two-thirds of athletes suffering at least one injury during an athletics season.

⇒ The prognostic modelling of sports injuries using machine learning could be used to reduce injury-related epidemiological outcomes.

⇒ No studies investigate the potential effectiveness of injury prognostic modelling to reduce 'the injury burden' in specific sports settings.

INTRODUCTION

Track and field (athletics) activity is associated with injury occurrences.[1] Developing injury prevention strategies is therefore essential to limit the impact of athletic injuries on health and sports participation.[1 2] Among these strategies, the emerging practice of e-health in sports medicine represents a unique opportunity.[2 3] In particular, artificial intelligence approaches using machine learning (ML) techniques could tackle the complexity of injury aetiology through multifactorial data, making it possible to provide athletes with individualised injury risk estimation feedback.[2 4 5] These approaches can help athletes be aware of their injury risk and adapt their behaviour to mitigate it.[6] However, in sports medicine studies,[4 7–9] ML was until now only used to develop models predicting injuries with maximal predictive performance, but it has not linked the prediction to a potential preventive effect. Today, as most athletes have access to digital tools (eg, smartphones, smartwatches, computers), implementing a monitoring system for injury prevention through online software (eg, websites or smartphone applications) is easier than some decades ago. Therefore, we developed a real-time injury prognostic model using ML that

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WHAT THIS STUDY ADDS

⇒ Daily injury risk estimation feedback based on prognostic modelling using machine learning was viewed about two-thirds of the times in a sample of competitive athletics athletes. It was, in turn, used one-third of the time.

⇒ When the analysis was performed on all athletes included in the study, using injury risk estimation feedback based on injury prognostic modelling using a machine was not associated with an injury burden reduction.

⇒ When the analysis was performed on those athletes with a minimum response rate of 9%, we observed that a 10-point increase in the self-reported level of injury risk estimation feedback use (scale 0–100) was linked with a 19% (95% CI: 2 to 35) decrease in injury burden.

HOW THIS STUDY MIGHT AFFECT RESEARCH, PRACTICE OR POLICY

⇒ Although our primary analysis did not report any significant association between the use of an injury risk estimation feedback based on injury prognostic modelling and injury burden, the significant association reported in the secondary analysis taking into account the athletes' daily response rate suggests the interest of continuing investigations on injury prediction modelling using machine learning as a strategy to reduce injury-related epidemiological outcomes.

⇒ Randomised controlled trials should be performed to assess the efficacy of using injury prognostic modelling via machine learning to reduce the injury-related epidemiological outcomes.

⇒ Developing a prognostic model using a machine learning algorithm can promote the creating of a semi-autonomous and real-time injury monitoring system.

provided athletes with individualised injury risk estimation feedback (I-REF) and investigated how athletes' self-reported use of this estimation or simply access to this estimation was associated with a change in different injury-related epidemiological outcomes (burden, prevalence, time to first injury, incidence).[2] Given the challenge of describing the injury problem in proportions, rates or severity,[10] there is a need to dress the whole picture.[11] Regarding the I-REF, as no previous study has ever explored the potential use of injury prediction with ML for injury prevention, there is a need to explore this before investigating the exact mechanisms through which injury prediction may lead to prevention.

In this context, the primary aim of this study was to analyse the association between the self-reported level of I-REF use and the injury burden, defined as the number of days with injury per 1000 hours of athletics exposure during an athletics season in competing athletes. The secondary aims were to analyse the association between the self-reported level of I-REF use and (i) injury prevalence, defined as the percentage of athletes with at least one injury during an athletics season, (ii) time to the first injury, and (iii) injury incidence, defined as the number of injuries per 1000 hours of athletics exposure during an athletics season. The tertiary aims were to analyse the association between the frequency of I-REF view and (i) injury burden, (ii) injury prevalence, (iii) time to the first injury, and (iv) injury incidence, all during an athletics season.

METHODS

Study design and setting

We conducted the prospective cohort study 'Injury Prediction with Artificial Intelligence' (IPredict-AI) over 38 weeks, from 17 October 2022 to 09 July 2023, on competing track and field athletes licensed with the French Federation of Athletics (FFA). We used a website application (IPrevApp, https://iprevapp.emse.fr) to collect the data and provide athletes with the I-REF. The study follow-up was divided into an initial period (4 weeks) and a predictive period (34 weeks) during which athletes had access to the I-REF (figure 1).[2]

This study was reviewed and approved by the Saint-Etienne University Hospital Ethical Committee (Institutional Review Board: IORG0007394, IRBN1062022/CHUSTE). The present article was written according to the STrengthening the Reporting of OBservational studies in Epidemiology (STROBE)[12] and the extension for Sport Injury and Illness Surveillance (SIIS).[10] The study protocol was published a priori.[2]

Patient and public involvement

There was no patient or public involvement.

Equity, diversity, and inclusion statement

All FFA-licensed athletes were eligible and could be included in this study without restrictions based on gender, race/ethnicity/culture, socioeconomic level, or marginalised group representation.

The research team consisted of three junior and seven senior researchers from different disciplines (sports medicine, sports science, sports epidemiology, physical medicine and rehabilitation, statistics, and methodology of research) and five different countries in Europe (France, Germany, Greece, Luxembourg and Spain).

Participants

Potential study participants were FFA-licensed athletes competing at the beginning of the 2022–2023 season. The inclusion criteria were athletes competing in sprints, hurdles, jumps, throws, combined events, middle distance, long distance, road running and race-walking disciplines without medical restrictions that would prevent participation in competitive athletics, as confirmed by the FFA license, for those aged between 15 and 60 with daily access to an internet connection via a digital device. More details can be found in the study protocol.[2]

Injury definition

In this study, the *injury* was defined as an injury complaint self-reported by an athlete related to athletics activity (training and competition) that leads to reduced participation or full absence in athletics (ie, injury complaint leading to participation restriction).[2 13]

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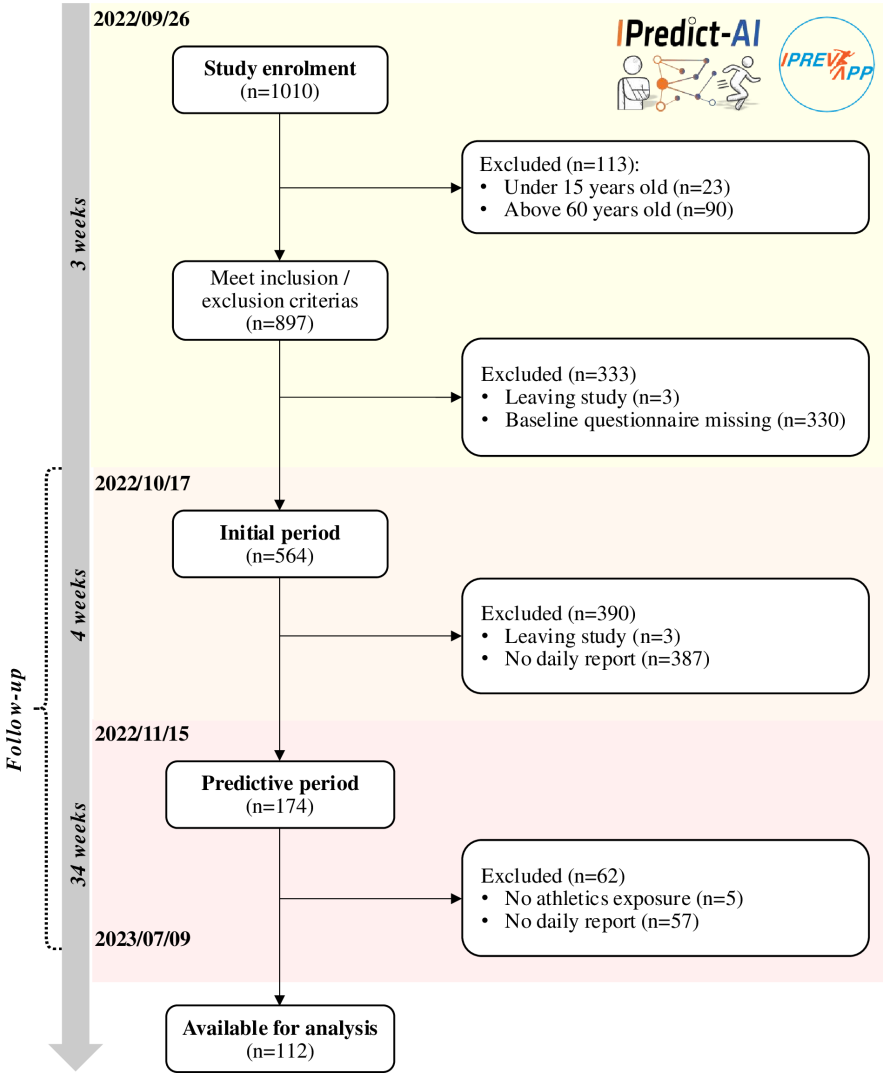


Figure 1 Flowchart of the IPredict-AI study.

Collected variables

All data were collected using online questionnaires in a secured individual session via a website application.[2] Before starting the study, athletes were asked to complete a baseline questionnaire. Throughout the 38-week follow-up period, all included athletes were asked to respond to two daily questionnaires: one in the morning and one in the evening.[2] As detailed in the protocol,[2] these two daily questionnaires allowed to accurately capture the athletes' daily routine and reduce a potential recall bias.[2] Several strategies were used to promote the integration of the questionnaires into the athletes' daily routine: calendar files, automatic reminders, social network publications, personalised real-time dashboards and a delayed answer possibility.[2] We collected different variables via (i) the baseline questionnaire: age, weight, height, sex, primary athletics discipline, injury and illnesses history during the preceding (2021/2022) athletics season; (ii) the morning daily questionnaire: sleep (duration, quality), state of fitness (fatigue, pain) and psychological aspects (anxiety, motivation to train); and (iii) the evening daily questionnaire: training and competition activities, psychological aspects (stress, emotions, self-efficacy), state of fitness, any illness and any injury.[2] During the predictive period, the evening daily questionnaire also asked athletes to rate on a scale from 0 ('not at all') to 100 ('totally') how much they perceived to have used the I-REF to adapt their athletics activities (ie, self-reported level of I-REF use).[2] More information about the variables collected can be found in the protocol.[2]

Daily individualised feedback on injury risk estimation (I-REF)

During the predictive period, after submitting the two daily questionnaires, athletes had daily access to a dedicated page of the IPrevApp containing their individualised I-REF for the following day.[2] This I-REF corresponded to the athlete's probability of having an

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injury for the following day and ranged from 0% ('no risk of injury') to 100% ('maximal risk of injury').[2] This value was calculated using a tree-based ensemble classifier, namely a random forest. The first version of the random forest model was trained using the data collected from the initial period, and then updated versions were retrained each week during the predictive period.[2] The athletes also had access to the model receiver operator characteristic area under the curve (ROC-AUC) metric, which measures the model's ability to distinguish between the two classes of injury/non-injury.[2] The ROC-AUC value lies between 0 (indicating bad discrimination performance) and 100 (indicating perfect discrimination performance), and the contribution of each collected variable to the I-REF value in the ML model.[2] This information could allow the athletes to interpret the model's prediction confidence. The athletes also had access to information about how each data point influenced their score positively or negatively. This way, they could have a first indication of the aspects of their current lifestyle that could influence their injury risk.[2] In total, 26 variables from the morning, evening and baseline questionnaires were used as input data in the machine-learning model.[2] An I-REF for the following day was only generated when athletes completed both the morning and evening questionnaires for the present day. This I-REF was considered to be viewed when the athletes accessed the I-REF within the allowed period.[2] For the analysis, each athlete's self-reported level of I-REF use was calculated as the individual mean of the daily athlete's self-reported level of I-REF use for all I-REF values generated and viewed over the predictive period. To assess the influence of I-REF independently of consideration by the athletes, the frequency of I-REF view for each athlete was calculated as the ratio between the total number of days that an athlete viewed their I-REF and the number of days that the I-REF was generated.[2]

Outcomes

The outcomes were calculated based on the data from the evening questionnaire over the predictive period. The primary outcome was the injury burden, defined as the number of days with injury per 1000 hours of athletics exposure (training and competition)[2 10] because it encompasses both the incidence and severity of the injuries.[10 11] The secondary outcomes were (i) the injury prevalence, defined as the percentage of athletes with at least one injury, (ii) the time (in hours of athletics exposure) to the first injury, and (iii) the injury incidence, defined as the number of injuries per 1000 hours of athletics exposure.[2]

Sample size

Due to this project's observational design and exploratory nature, we performed no formal sample size calculation.[2]

Statistical analysis

We first conducted a descriptive analysis using counts and percentages (n (%)) for categorical variables and means and SDs for continuous variables. We calculated the individual response rate to the daily questionnaires (only morning, only evening, both morning and evening) as the number of questionnaires completed divided by the number of expected questionnaires during the initial and the predictive period.[2]

For the analysis of the primary outcome, we used a negative binomial regression model in which the dependent variable was the number of days with injury, the covariates were the self-reported level of I-REF use, sex, age, history of injury during the previous season,[13] and the offset was the athletics exposure (online supplemental appendix B). We examined this model for overdispersion and checked that it provided a better fit than other models for count variables (online supplemental appendix A). We calculated the exponential of the β coefficient (ie, e^{β}) for the covariate self-reported level of I-REF use, as well as its 95% CI and the p value of the corresponding test (with significance level α set at 0.05). With this notation, $e^{\beta}>1$ represents an increased risk, $e^{\beta}=1$ has no effect (null hypothesis) and $e^{\beta}<1$ is a decreased risk. For this analysis, we included all athletes who provided at least one evening questionnaire regardless of their response rate. In addition, we performed iterations of this analysis for all possible minimum response rate thresholds ranging from 0% to 100%.[14] Specifically, for a given minimum response rate threshold, all athletes with a response rate equal to or above this threshold were included in the analysis.[14]

For the secondary outcome (i), we used a logistic regression model with the prevalence as the dependent variable; the OR and its 95% CI were calculated as a measure of association. For the secondary outcome (ii), we performed a survival analysis by adjusting a Cox proportional hazards model where the dependent variable was the time to the first injury. Here, we calculated the HR and its 95% CI as a measure of association. Finally, for the secondary outcome (iii), we used a negative binomial regression model in which the dependent variable was the injury incidence. For all secondary outcomes, we used sex, age and injury history during the previous season as additional covariates.

For the analysis of the primary and secondary outcomes except the secondary outcome (ii), the robustness of all analyses was tested based on the consideration of 'best-case' and 'worst- case' scenarios, where we imputed the data corresponding to the missing days (ie, athletes who did not respond to the evening questionnaire) (online supplemental appendix B). In the best-case scenario, we assumed that athletes did not experience an injury and had a maximum self-reported level of I-REF use (Online supplemental appendix A). In the worst-case scenario, we assumed that athletes experienced an injury and had a maximum self-reported level of I- REF use (Online supplemental appendix A). For both scenarios, we

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imputed each athlete's mean individual reported exposure (online supplemental appendix B).

Descriptive analyses were performed on Python (v3.12.2) using Pandas (v2.2.1), NumPy (v1.26.4) and SciPy (v.1.13) packages.[15–18] The statistical outcome analyses were performed on R Statistical Software (v4.4.0).[19] Time-to-event analyses were performed using the R Package 'Survival' (v3.6.4).[20]

Deviations from the protocol

- We extended the time frame for completing the daily questionnaires (ie, morning and evening) from 24 to 72 hours to give the athletes more flexibility. If the questionnaires were completed with delay (ie, after the next day), we checked the chronological order of these questionnaires to ensure accuracy and minimise recall bias.
- A descriptive analysis of athletes' characteristics, athletics exposure, injury, self-reported level of I-REF use, and frequency of I-REF view was not foreseen originally and has been added.
- As no athlete reached 100% of the response rate, we did not perform the complete case analysis that was originally planned. Instead, we included all athletes in the analysis regardless of their response rate. In addition, we conducted analyses for different minimum response rate thresholds to limit potential bias on the epidemiological outcomes that could be caused by neglecting individual response rates.[14]
- We opted for a negative binomial rather than a regular linear regression model for the analysis of the primary outcome because (i) our data were overdispersed (online supplemental appendix A), (ii) it is suitable for event rate data (ie, events per unit time) such as the injury burden,[21] and (iii) it was the best-fitting model among a set of candidates to fit our data (online supplemental appendix A).
- At the end of the follow-up, each athlete received an individual dashboard summarising the data collected during the predictive period.

RESULTS

Participants

During the 3 weeks of enrolment, 1010 athletes registered on the website application, and 897 (88.8%) athletes met the inclusion criteria (figure 1). Among these, 564 (62.9%) athletes began the initial period, and 174 (19.4% of all included athletes and 30.9% of those who began the initial period) started the predictive period of the follow-up (figure 1). Finally, 112 (12.5% of all included athletes and 19.9% of those who began the initial period) athletes with at least one response in the predictive period were included in the analysis (figure 1). Their baseline characteristics are presented in table 1.

Responses to the daily questionnaires

During the initial period (28 days), the 112 athletes completed 2784 (88.8%) morning questionnaires, 2805 (89.4%) evening questionnaires and 2721 (86.8%) daily combination of morning and evening on the same day. The mean average daily response rate over the initial period was 83.8±27.7% (figure 2). During the predictive period (237 days), the 112 athletes completed 8635 (32.5%) morning questionnaires, 8665 (32.6%) evening questionnaires and 8274 (31.2%) daily combinations of both morning and evening questionnaires on the same day. The average daily response rate over the predictive period was 31.2%±31.6% (figure 2). No athletes reported 100% of the requested daily questionnaires (online supplemental appendix C). Times of completion were presented in the online supplemental appendix D.

Injuries leading to participation restriction

During the predictive period, 42 athletes reported 66 injuries and 379 days with injury. The total exposure was 6699 hours of athletics activities. The observed prevalence was 37.5% (95% CI: 28.6 to 46.4) of athletes injured at least once, and the mean injury incidence was 14.7±34.1 (95% CI: 9.01 to 21.46) injuries per 1000 hours of athletics exposure. The mean injury burden was 71.5±212.7 (95% CI: 36.9 to 113.72) days with injury per 1000 hours of athletics exposure.

Injury risk estimation feedback (I-REF)

During the predictive period, the mean of individual athletes' self-reported level of I-REF use was 36.1%±32.1%, and the mean of the individual athlete's frequency of I-REF view was 57.2%±31.5%. Regarding the ROC-AUC metric,[2] the mean over the predictive period was 0.63±0.02. The weekly evolution of ML metrics is provided in online supplemental appendix E.

Analyses

The analysis of the primary outcome, which includes all 112 athletes regardless of their response rate, showed no significant association between the self-reported level of I-REF use and the injury burden (e^{β}: 0.992, 95% CI: 0.977 to 1.007; p=0.308) (figure 3 and table 2). However, when we repeated this analysis for different minimum response rate thresholds, we found that a higher level of self-reported level of I-REF use was associated with lower injury burden for athletes with a response rate over the predictive period of at least 9% (n=76, e^{β}: 0.981, 95% CI: 0.965 to 0.998; p=0.027) (figure 3 and table 2). The sensitivity analysis showed a significant decrease in the injury burden in the best-case scenario (e^{β}: 0.919, 95% CI: 0.885 to 0.954; p=1.240^{-5}) and a significant increase in the worst-case scenario (e^{β}: 1.054, 95% CI: 1.041 to 1.067; p=3.594^{-16}) (table 2).

For the analyses of the secondary outcomes, when including all 112 athletes regardless of their response rate, none of the analyses reported a significant association between the self-reported level of I-REF use and the injury-related epidemiological outcomes (ie, prevalence, time to the first injury, incidence) (table 2). However, when we repeated this analysis for different minimum response rate thresholds, we found that a higher level of

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Table 1 Athletes' baseline characteristics: Data are presented as mean and SD for continuous variables and numbers and percentages (%) for ordinal or categorical variables

	All included athletes	Men included athletes	Women included athletes
	Mean (SD) or n (%)	Mean (SD) or n (%)	Mean (SD) or n (%)
N	112 (100%)	70 (62%)	42 (38%)
Age (years)	34 (15)	35 (15)	32 (14)
Height (cm)	176 (8)	180 (6)	168 (6)
Body mass (kg)	67 (11)	72 (9)	59 (8)
Endurance disciplines	59 (53%)	38 (54%)	21 (50%)
800 m	2 (2%)	–	2 (5%)
1500 m	–	–	–
3000 m steeplechase	1 (1%)	1 (1%)	–
5000 m	2 (2%)	1 (1%)	1 (2%)
10 000 m	6 (5%)	2 (3%)	4 (10%)
Road running (10k, half-marathon, marathon)	31 (28%)	19 (27%)	12 (29%)
Cross-country	1 (1%)	1 (1%)	–
Race walks	–	–	–
Trail	16 (14%)	14 (20%)	2 (5%)
Explosive disciplines	53 (47%)	32 (46%)	21 (50%)
100 m	9 (8%)	5 (7%)	4 (10%)
200 m	3 (3%)	1 (1%)	2 (5%)
400 m	3 (3%)	2 (3%)	1 (2%)
100 m hurdles	–	–	–
110 m hurdles	2 (2%)	2 (3%)	–
400 m hurdles	7 (6%)	5 (7%)	2 (5%)
Discus throw	1 (1%)	–	1 (2%)
Hammer throw	1 (1%)	–	1 (2%)
Javelin throw	–	–	–
Shot put	–	–	–
High jump	2 (2%)	1 (1%)	1 (2%)
Pole vault	4 (3%)	3 (4%)	1 (2%)
Long jump	5 (4%)	3 (4%)	2 (5%)
Triple jump	4 (3%)	–	4 (10%)
Decathlon	10 (9%)	10 (14%)	–
Heptathlon	2 (2%)	–	2 (5%)
Number of years of athletics	13 (11)	13 (12)	13 (11)
Weekly athletics training (hours)	7 (3)	7 (3)	8 (4)
Weekly training out of athletics (hours)	3 (3)	3 (3)	3 (3)
History of at least one injury (2021/2022)	74 (66%)	50 (68%)	26 (60%)
History of at least one illness (2021/2022)	23 (20%)	13 (18%)	10 (23%)

self-reported level of I- REF use was associated with lower injury incidence for athletes with a response rate over the predictive period of at least 9% (n=76, e^{β}: 0.989, 95% CI: 0.978 to 0.999; p=0.046) (online supplemental appendix F).

The tertiary analyses are presented in table 2 and online supplemental appendix F.

DISCUSSION

We found that, when including all athletes in the analysis of the primary outcome regardless of their response rate, there was no association between the self-reported level of I-REF use and the injury burden. However, when including athletes with a minimum response rate of 9%, the analysis revealed a significant association between the

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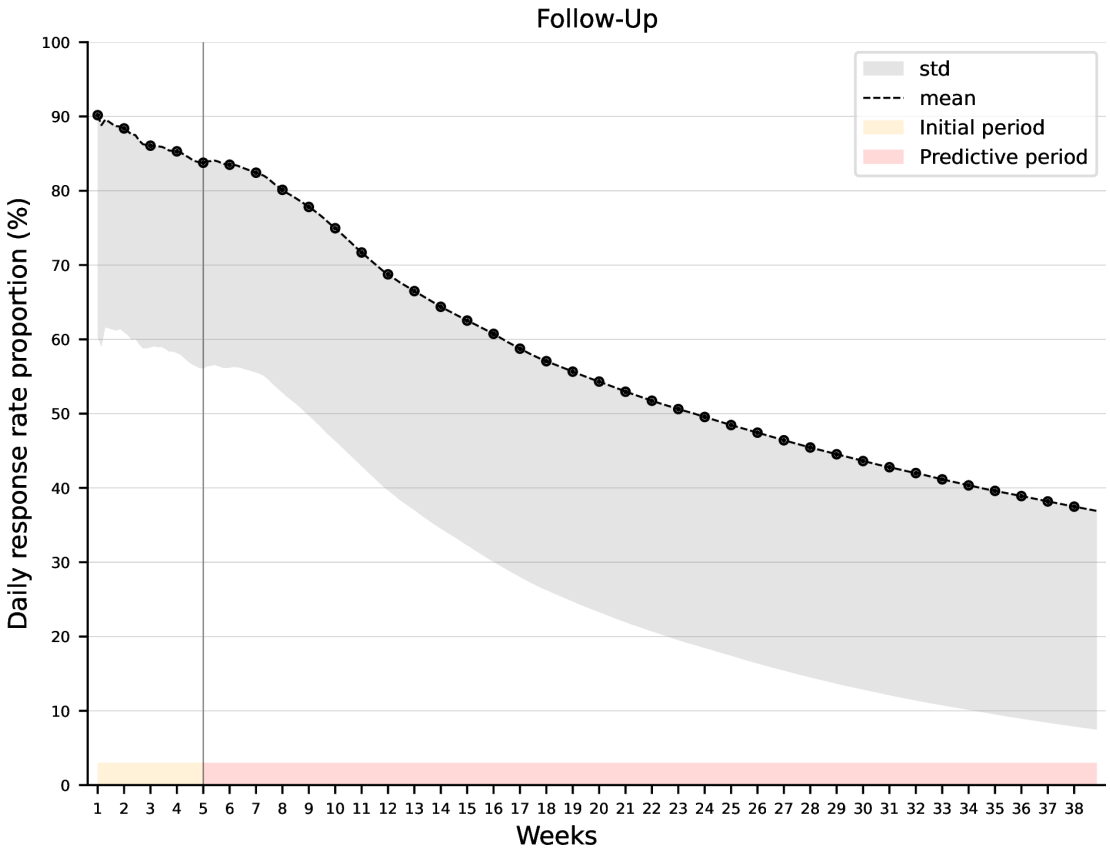


Figure 2 The mean daily response rate proportion (n=112) over the 38 weeks of the follow-up. The mean daily response rate was 90.2±29.9 on the first day of the initial period. It decreased steadily during the entire study period until a mean daily response rate of 36.9±29.4 on the last day of the predictive period.

self-reported level of I-REF use and the injury burden, with the injury burden decreasing by 19% (95% CI: 2 to 35) for every 10-point increase in the self-reported level of I-REF use. We reported similar results for the injury incidence but not for the injury prevalence and the time to the first injury.

Interest in using an injury risk estimation feedback (I-REF) to reduce injury-related epidemiological outcome

Current studies on injury prognostic modelling using ML in sports medicine have been focused on developing accurate prognostic models.[4 7 8] Our study took a step forward and was the first to analyse the potential clinical interest of providing athletes with feedback based on ML injury prognostic models. The primary outcome analysis showed that using the I-REF was associated with a lower injury burden, when setting a minimum response rate, accounting for bias due to heterogeneity of missing information over the study sample and study period (figure 3).[14] The tertiary analysis found no association between the I-REF frequency of view and epidemiological outcomes. This could mean that sole access to unsupervised online feedback (ie, viewing I- REF) was insufficient to achieve significant association with injury risk reduction.

Response proportion to the daily questionnaire

Our study's average daily response rate over the predictive period was around 30%, which is lower than previous epidemiological studies in athletics that used regular prospective data collection (values between 20% and 91%).[13 22–24] This response rate could, in the first place, be due to the use of a twice-daily questionnaire compared with the weekly or bi-weekly questionnaires used in previous studies.[13 23] Specifically, our study design included 14 times more questionnaires than a weekly one. An obvious disadvantage of increasing the data collection frequency (eg, weekly to daily) is the potential decrease of the individual athlete response rates[13 22 25] as in the present study. Our 30% response rate can also be attributed to the length of the follow-up period, since the response proportions decreased over time (figure 2).[13 26] Generally, regular athletes' self-reported online questionnaires reduce recall bias for calculating epidemiological outcomes.[14] Therefore, more streamlined efforts should be made to promote a higher daily response rate.[2] For instance, this can be done by (i) educating end-users about the benefits of monitoring their states over time and providing scientific evidence of improved health and performance through this monitoring,[13] (ii) reducing

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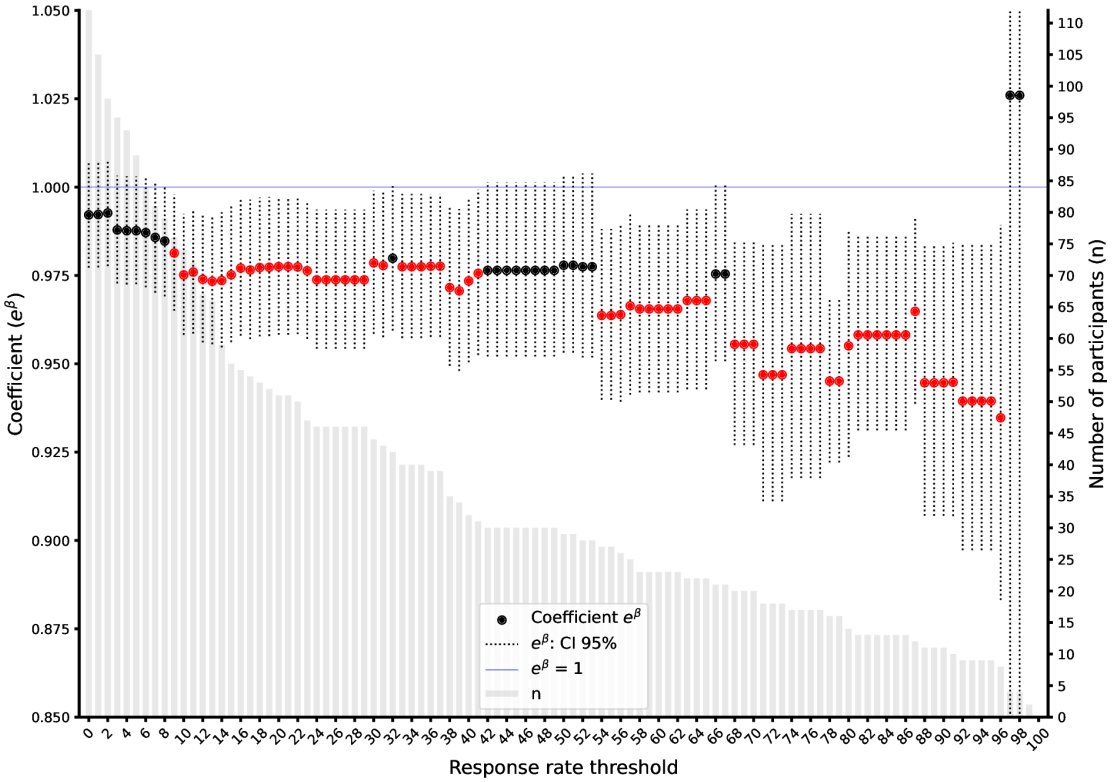


Figure 3 Response rate threshold analysis including one negative binomial regression model per each minimum response rate threshold (x-axis). For a minimum response rate threshold, the analysis was performed for all athletes whose response rate was equal to or above that threshold. The circular dots represent the estimate (e^{β}) for the covariate 'self-reported level of I-REF use' (left y-axis). Vertical dashed lines around the estimates represent 95% CI. The red colour indicates a statistically significant result (p<0.05). Vertical grey bars represent the number of athletes in each response rate threshold (right y-axis). The horizontal blue line represents the null hypothesis (e^{β} =1). I-REF, injury risk estimation feedback.

the load of the data collection by moving from twice-daily to once-daily questionnaire, and/or (iii) increasing the motivation of athletes to use the website application through a gamification approach with virtual incentives like leaderboards, awards, quests or leagues inside the website application.[27]

Adherence to the I-REF

The self-reported level of I-REF use by athletes to adapt their athletics practice was around 36%. Previous unsupervised randomised controlled trials in individual sports also reported low compliance with the proposed interventions, with <10% of athletes reporting high level of compliance.[13 28] Given all this, maximising the level of compliance is a big challenge when implementing unsupervised injury prevention strategies in individual sports.[13 28 29] In addition, in the specific context of injury prognostic models using ML as an intervention to prevent injury, individual beliefs and behaviours can play an important role in compliance. Indeed, a high inter-individual variability has been reported regarding the perceived stress level induced by the feedback provided via injury prognostic models using ML.[30] In this context, potential strategies to maximise the use of an injury prognostic model using ML feedback could be (i) to provide text advice based on the individual data collected, (ii) to provide deeper educational content on how artificial intelligence works, or (iii) to increase the motivation of athletes with a study game-based approach by using virtual ranking and with awards inside the website application.

Strengths and limitations

This is the first study to analyse the association between the level of I-REF use and injury-related epidemiological outcomes in a real-world setting. Also, athletes were provided with feedback on the model's performance and how different variables may influence the injury-related epidemiological outcome. The study protocol was published a priori.[2]

However, we must acknowledge some limitations. This study was not a randomised controlled trial. The intervention's effect size is relatively small, and the results may have occurred by chance, which could be illustrated by the large variability in the sensitivity analysis. The study was conducted online without supervision, which may have led to athletes not properly understanding the study requirements (eg, data collection, I-REF interpretation).

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Table 2 Results of the analyses (primary, secondary and tertiary analyses) of the Injury Prediction with Artificial Intelligence (IPredict-AI) study including 112 competing track and field athletes during the 34 weeks of the predictive period

			Coefficient				
Analysis	Outcome	Covariate	Type	Value	95% CI lower	95% CI upper	P value
Primary main scenario	Injury burden	Self-reported level of I-REF use	e^{β}	0.992	0.997	1.007	0.308
Primary best scenario	Injury burden	Self-reported level of I-REF use	e^{β}	0.919	0.885	0.954	1.240^{-5}
Primary worst scenario	Injury burden	Self-reported level of I-REF use	e^{β}	1.054	1.041	1.067	3.594^{-16}
Secondary main scenario	Injury prevalence	Self-reported level of I-REF use	OR	1	0.987	1.013	0.997
Secondary best scenario	Injury prevalence	Self-reported level of I-REF use	OR	0.947	0.912	0.983	0.004
Secondary main scenario	Time to the first injury	Self-reported level of I-REF use	HR	1.004	0.989	1.020	0.576
Secondary main scenario	Injury incidence	Self-reported level of I-REF use	e^{β}	0.992	0.982	1.002	0.126
Secondary best scenario	Injury incidence	Self-reported level of I-REF use	e^{β}	0.956	0.936	0.977	3.783^{-5}
Secondary worst scenario	Injury incidence	Self-reported level of I-REF use	e^{β}	1.053	1.040	1.066	2.231^{-17}
Tertiary main scenario	Injury burden	Frequency of I-REF view	e^{β}	0.990	0.973	1.007	0.242
Tertiary best scenario	Injury burden	Frequency of I-REF view	e^{β}	0.964	0.946	0.982	1.564^{-4}
Tertiary worst scenario	Injury burden	Frequency of I-REF view	e^{β}	1.001	0.994	1.007	0.817
Tertiary main scenario	Injury prevalence	Frequency of I-REF view	OR	1.001	0.988	1.014	0.930
Tertiary best scenario	Injury prevalence	Frequency of I-REF view	OR	0.993	0.978	1.007	0.327
Tertiary main scenario	Time to the first injury	Frequency of I-REF view	HR	0.994	0.974	1.016	0.597
Tertiary main scenario	Injury incidence	Frequency of I-REF view	$e\beta$	0.993	0.980	1.006	0.285
Tertiary best scenario	Injury incidence	Frequency of I-REF view	$e\beta$	0.983	0.971	0.995	0.005
Tertiary worst scenario	Injury incidence	Frequency of I-REF view	$e\beta$	1.001	0.995	1.007	0.804

injury, injury complaint leading to participation restriction; I-REF, injury risk estimation feedback.

We did not analyse how athletes adjusted their behaviour when considering the I-REF values. Indeed, depending on these values, athletes could have either reduced their athletic training as a preventive measure in case of high risk of injury or increased their athletic training in case of low risk. The fact that we encouraged the website application through personalised real-time dashboards displaying the collected data could have influenced the association between the self-reported level of I-REF use and the injury burden. Athletes could have modified their behaviour (eg, increase or decrease their athletics exposure) based on the data collected and reported (eg, fatigue, pain, sleep quality) without considering the I-REF. This study may have involved only a subgroup of athletes who used digital technologies.[3] Access to digital technologies could have induced financial costs and a socioeconomic bias in the studied sample.

Practical implications

Injury prognostic models using ML could be considered one of the new potential strategies for injury prevention. This strategy could help deal with the complexity of injury aetiology and could be valuable for decision-making on the load management by athletes, health professionals and coaches in the field.

Our research also has some methodological implications. First, developing an injury prognostic model using ML can promote the creation of monitoring systems based on new technologies, such as our daily data collection approach. This could, in turn, help expand the possibilities of epidemiological surveillance by tracking injuries and their impact on training over time. This may be highly relevant for health professionals and coaches. However, analysing epidemiological outcomes using a daily monitoring approach is challenging and inevitably leads to missing data due to the large number of questionnaires to be completed. Therefore, using a complete case analysis in studies with that monitoring system seems unrealistic and inappropriate. Further research should consider analysis strategies that are better adapted to this context.[14]

Finally, improving our understanding of how athletes deal with the feedback provided by an injury prognostic model using ML is essential. This could be achieved by developing strategies to quantitatively or qualitatively assess athletes' behavioural change, which can help better isolate the effects of the feedback.

CONCLUSIONS

The use of real-time injury risk estimation feedback, based on prognostic modelling using ML, was not associated with an injury burden reduction. However, when the response rate was considered, the analysis revealed a significant association with a reduction in injury burden for athletes with a minimum response rate of 9%.

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Therefore, this approach could be considered as an additional injury prevention approach, while further research is mandated to determine its efficacy and mechanism of action.

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Contributors PE and LN initiated the study design. PED, LN, DB, KH and PE conceptualised the study. PED carried out the data collection and processing. DB, PE, CL and PED carried out the statistical analysis. All authors contributed to the refinement of the article, writing of the article and approval of the final manuscript. PED is the guarantor of the manuscript.

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Competing interests None declared. PE is an Associate Editor for the British Journal of Sports Medicine, the BMJ Open Sport & Exercise Medicine, and the Scandinavian Journal of Medicine & Science in Sports. KH is the head team physician of the German Athletics Federation, Editor of the German Journal of Sports Medicine and an Associate Editor for the BMJ Open Sport & Exercise Medicine. CL is Associate Editor for the Journal of Quantitative Analysis in Sports.

Patient and public involvement Patients and/or the public were not involved in the design, or conduct, or reporting, or dissemination plans of this research.

Patient consent for publication Not applicable.

Ethics approval This prospective cohort study was reviewed and approved by the Ethics Committee of Saint-Etienne University Hospital (Institutional Review Board: IORG0007394, IRBN1062022/CHUSTE). All athletes were informed about the study aim and procedure, that their data is used for research, and their rights to refuse to use their data for research. The Ethical Committee required no signed informed consent. The study data of the participants will not be published outside the study without their written consent. During the study, participants had access to their data and completed the study questionnaires via a secure individual account on a website application. The database was hosted on the physical server of Mines Saint-Etienne and was secured by a private network with individual professional access (login, password). Only PED, PE, LN and the engineer who developed the application had access to the database before, during and after the study. Each extraction from this database included the anonymisation of the participants.

Provenance and peer review Not commissioned; externally peer reviewed.

Data availability statement Data are available upon reasonable request. The analysis script is available in an open access repository through https://github.com/PEDandrieux/IPredict-AI_Results_Protocol. The data are available on request. Requests for data sharing by appropriate researchers and institutions will be considered on a case-by-case basis. Interested parties should contact the corresponding author Pierre-Eddy Dandrieux (pierre.eddy.dandrieux@univ-st-etienne.fr).

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A Online supplemental: negative binomial regression model for assessing the primary outcome.

Dispersion analysis

When analysing the injury burden data of athletes, situations with unequal dispersion can be observed. We define the dispersion index, i.e. DI, as the ratio between the expectation $E(X)$ and the variance $V(X)$ of a random variable X:

$$DI = \frac{E(X)}{V(X)}. \tag{1}$$

If $DI < 1$, we are in the situation of over-dispersion, the variance being larger than the expectation. When $DI > 1$, the variance is less than the average, which corresponds to underdispersion. The last situation, in which $DI = 1$, leads to equidisperion and is typically modelled by a Poisson distribution.

We analysed the injury burden of athletes over the period and found that the empirical mean 71.5 is lower than the empirical variance 45233.92. This leads to a dispersion index $DI = 0.002$, which indicates overdispersion. Therefore, a Poisson distribution may not be the most appropriate to model the injury burden.

Distribution comparison

To assess the goodness of fit of the different distributions we have considered to model the injury burden, we have provided the associated Akaike information criterion (AIC), which is an estimator of the prediction error (i.e. a lower AIC means a lower prediction error) and thus of the relative quality of the statistical models for a given data set:

Distribution	AIC
Gaussian	1369.05
Poisson	1143.08
Poisson zero-inflated	920.05
Conway-Maxwell-Poisson	415.03
Negative binomial zero-inflated	354.75
Negative binomial	352.84

Negative binomial model

We decided to use a negative binomial distribution for the Analysis of the primary outcome because our data were overdispersed and the AIC was minimised when using the negative

binomial distribution.

The dependent variable (μ in equation (2)) is the number of days with injury (i.e., the numerator of the injury burden). Since the injury burden was time loss, the denominator, i.e. the athletics exposure, was shifted to the right side of the equation by multiplication and appears as offset term in Equation (2) after the typical logarithmic transformation ($\log(exposure)$). The covariate of interest is the I-REF level of use ($\beta_1 X_1$) and we used as further covariates sex (X_2), age (X_3) and history of injury during the previous season (X_4), leading to

$$\log(\mu) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \log(exposure). \quad (2)$$

In this equation, $\beta_0, \ldots, \beta_4$ are the parameters to be estimated.

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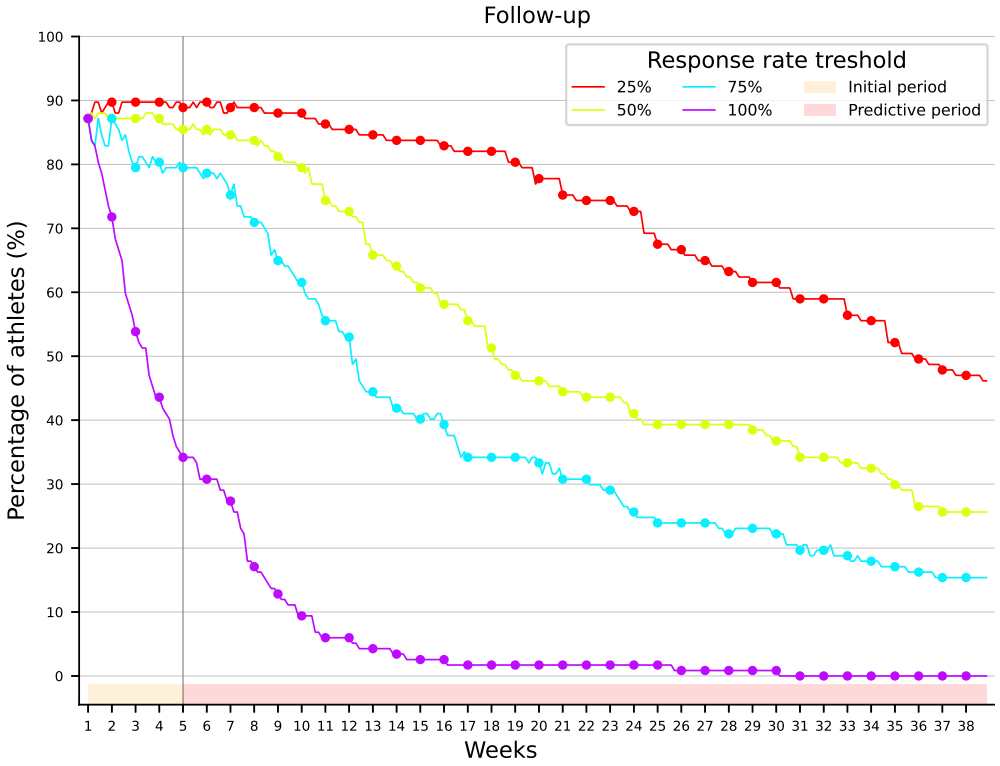
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B Online supplemental: Sensitivity analyses

Table 1: Configurations of the sensitivity analyses considering a ”best-case” and a ”worst-case” scenario over the different analysis and for different minimum response rate thresholds. For prevalence, we only performed a best-case scenario analysis, as all athletes had the same prevalence in the worst-case scenario (i.e., season prevalence equal to 1) because there was at least one missing day for each. This fact leads to a model convergence problem.

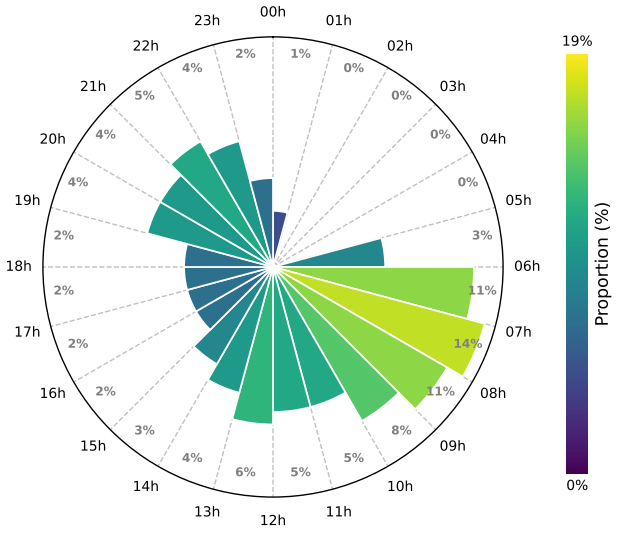
Outcomes scenarios			Imputation strategy (injury/exposure/covariate) for each outcome		
Analysis	Scenario	Outcome	Number of day with ICPR	Athletics exposure	Self-reported level of I-REF use
Primary analysis	best-case scenario	injury burden	0	individual mean	100
Primary analysis	worst-case scenario	injury burden	1	individual mean	100
Analysis	Scenario	Outcome	Number of ICPR	Athletics exposure	Self-reported level of I-REF use
Secondary analysis	best-case scenario	injury prevalence	0	not applicable	100
Analysis	Scenario	Outcome	Number of ICPR	Athletics exposure	Self-reported level of I-REF use
Secondary analysis	best-case scenario	injury incidence	0	individual mean	100
Secondary analysis	worst-case scenario	injury incidence	1	individual mean	100
Analysis	Scenario	Outcome	Number of day with ICPR	Athletics exposure	Frequency of I-REF view
Tertiary analysis	best-case scenario	injury burden	0	individual mean	1
Tertiary analysis	worst-case scenario	injury burden	1	individual mean	1
Analysis	Scenario	Outcome	Number of ICPR	Athletics exposure	Frequency of I-REF view
Tertiary analysis	best-case scenario	injury prevalence	0	not applicable	1
Analysis	Scenario	Outcome	Number of ICPR	Athletics exposure	Frequency of I-REF view
Tertiary analysis	best-case scenario	injury incidence	0	individual mean	1
Tertiary analysis	worst-case scenario	injury incidence	1	individual mean	1

C Online supplemental: Evolution over time of the percentage of athletes (n=112) with a minimum daily response rate ranging from 25% to 100% over the follow-up.

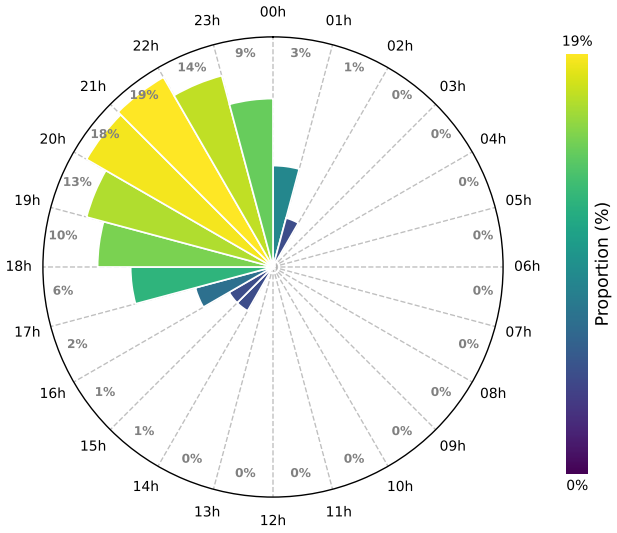


D Online supplemental: Times of completion.

The times of completion of the morning (a) and evening (b) questionnaires over the follow-up. During the follow-up, the mean ± std hours of completion of morning questionnaires were 12h43m ± 02h44m, and evening questionnaires were filled at 19h07m ± 02h42m.

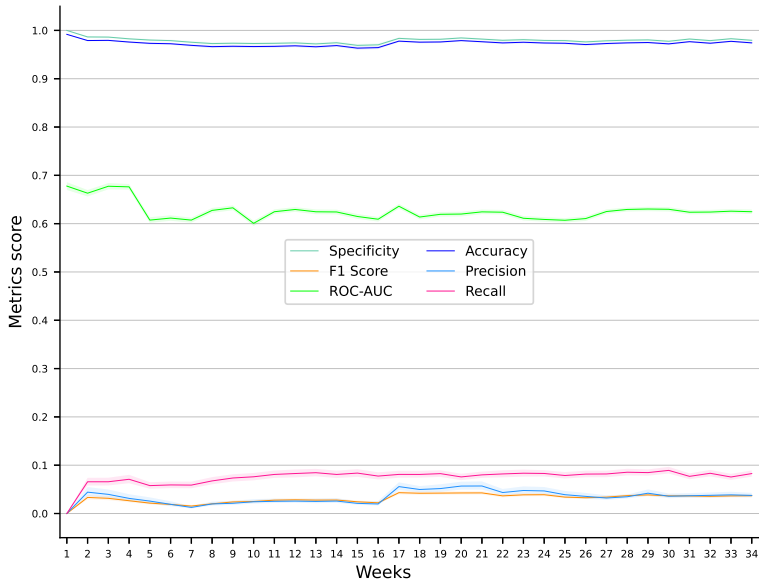


(a) Times of completion details of the morning questionnaire during the follow-up (n=112).

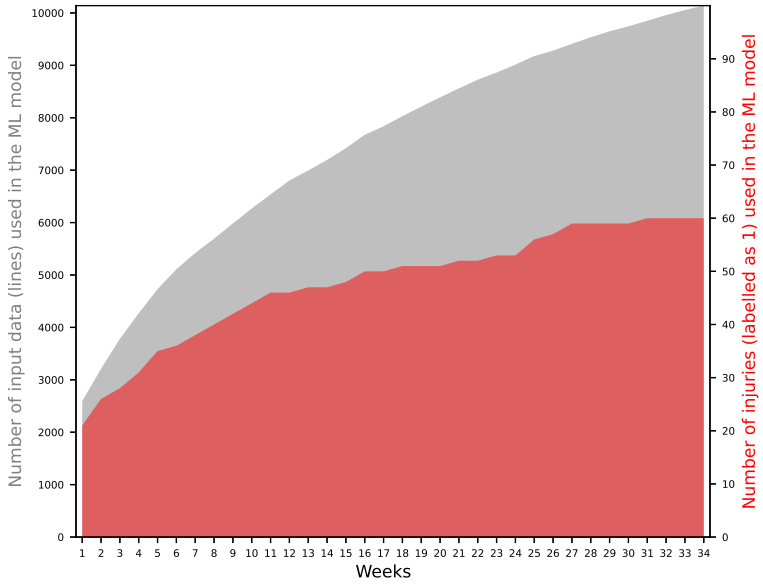


(b) Times of completion details of the evening questionnaire during the follow-up (n=112).

E Online supplemental: Machine learning metrics and number of datas used over the predictive period.



(a) Weekly machine learning metrics scores of the random forest model. The shaded area represents 95%CI.



(b) Weekly total number of input data (i.e., number of lines, in grey), and total number of injuries (i.e., the injury labelled as 1, in red) used in the machine learning model.

The confusion matrix is a contingency table, that allows for the visualisation of the performance of an algorithm:

		Actual classes	
		Injury	No-injury
Predicted classes	Injury	True positive (TP)	False positive (FP)
	No-injury	False negative (FN)	True negative (TN)

Several metrics are derived from the confusion matrix to evaluate machine learning classification performance:

- The precision represents the proportion of positive samples that were correctly classified to the total number of positive predicted samples (equation (3)). The goal is to determine how many real injuries are detected from all the predictions.

$$Precision = \frac{TP}{TP+FP} \tag{3}$$

- The recall represents the positive correctly classified samples to the total number of positive samples (equation (4)). The goal is to determine how many injuries are correctly predicted among all the injury occurrences.

$$Recall = \frac{TP}{TP+FN} \tag{4}$$

- The specificity represents the ratio of the correctly classified negative samples to the total number of negative samples (equation (5)). The goal is to determine how many of the uninjured are correctly predicted among all the non-injury occurrences.

$$Specificity = \frac{TN}{FP+TN} \tag{5}$$

- The accuracy represents the ratio between the correctly classified samples to the total number of samples (equation (6)). The goal is to determine the number of accurate

predictions made for both the injured and the uninjured.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{6}$$

- The F_1 score represents the harmonic mean of precision and recall (equation (7)). The goal is to determine if the model can predict injuries, both within the injuries and throughout all predictions.

$$F_1 = \frac{2*TP}{2*TP+FP+FN} \tag{7}$$

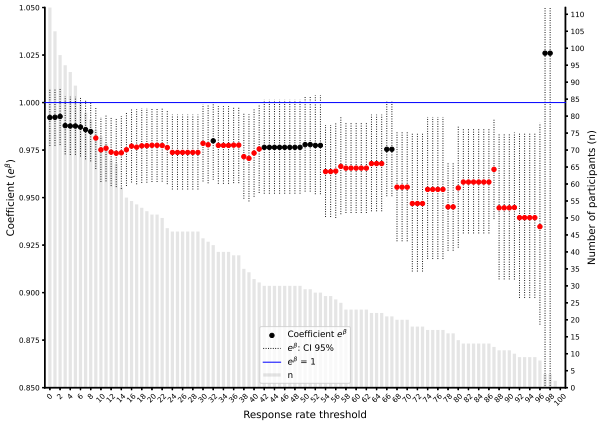
- The area under the curve (AUC) metric is based on the two-dimensional receiver operating characteristics (ROC) curve in which the recall represents the y-axis and the False positive rate (equation (8)) represents the x-axis. It is used to make a balance between the benefits, i.e., recall, and costs, i.e., false positive rates. The AUC score can be calculated by adding the areas of trapezoids of the ROC measures.

$$False\ positive\ rate\ (FPR) = 1 - Specificity \tag{8}$$

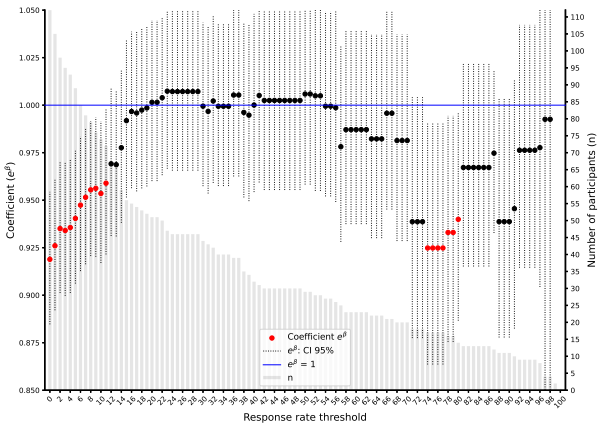
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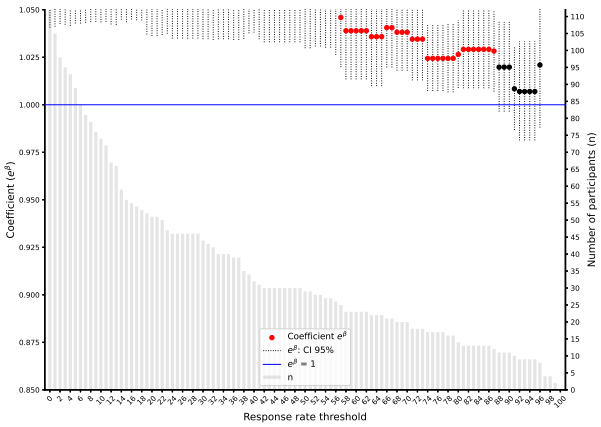
F Online supplemental: Results of the minimum response rate thresholds analysis (primary, secondary and tertiary).



(a) Main scenario analysis

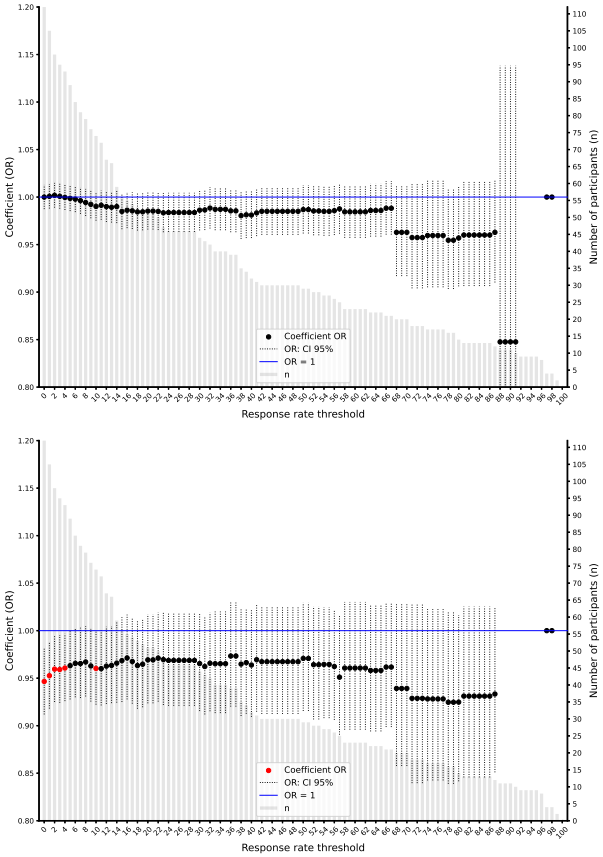


(b) Best scenario analysis



(c) Worst scenario analysis

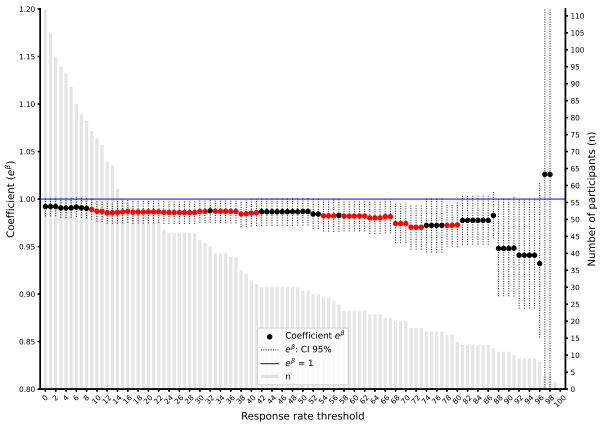
Figure 1: Analysis of the primary outcome; Outcome: injury burden; Covariate: self-reported level of I-REF use



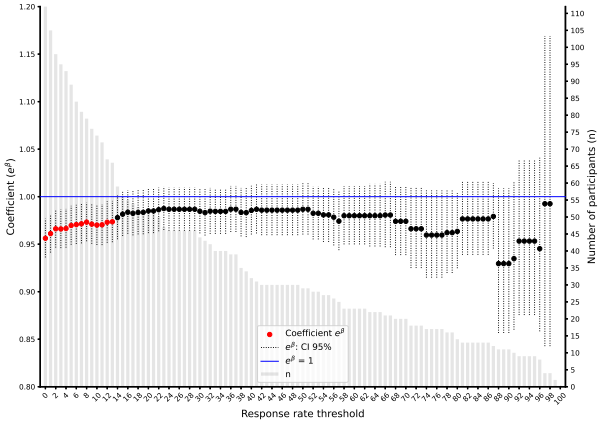
(a) Main scenario analysis

(b) Best scenario analysis

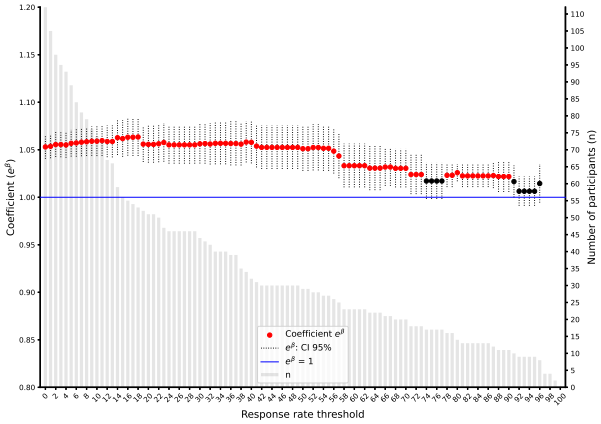
Figure 2: Secondary analysis; Outcome: injury prevalence; Covariate: self-reported level of I-REF use



(a) Main scenario analysis

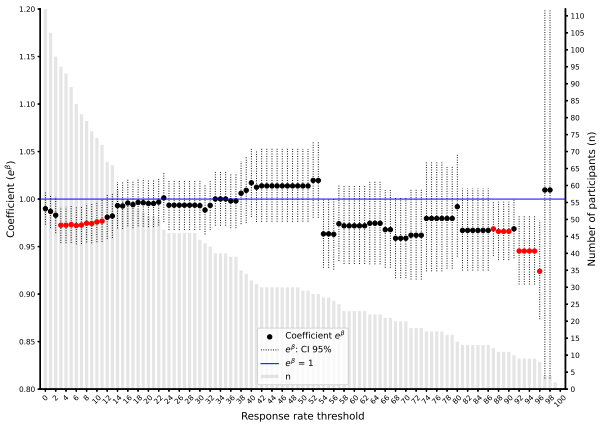


(b) Best scenario analysis

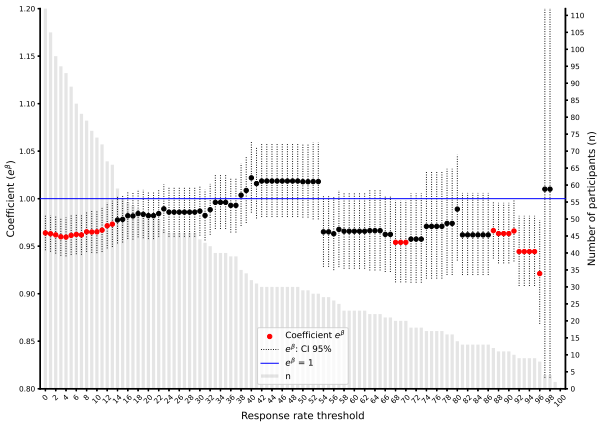


(c) Worst scenario analysis

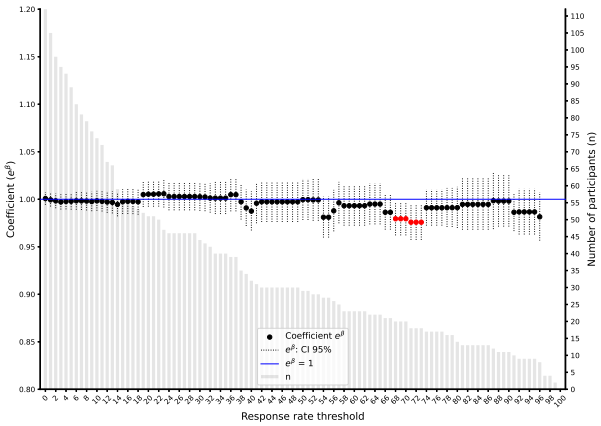
Figure 3: Secondary analysis; Outcome: injury incidence; Covariate: self-reported level of I-REF use



(a) Main scenario analysis

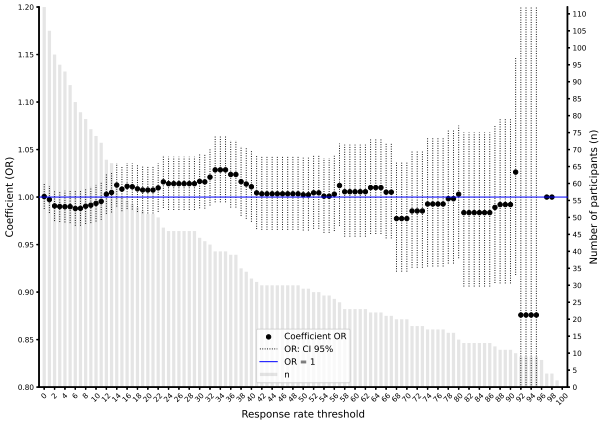


(b) Best scenario analysis

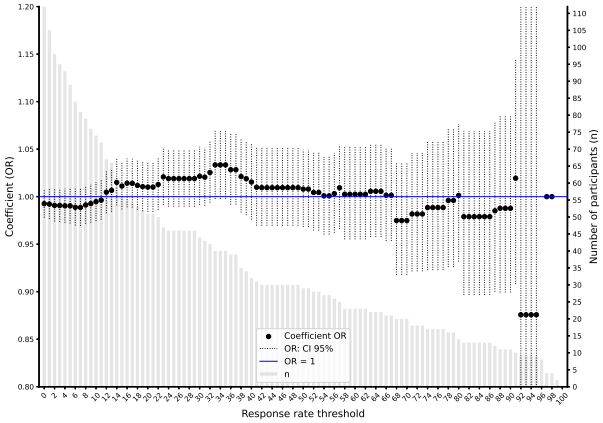


(c) Worst scenario analysis

Figure 4: Tertiary analysis; Outcome: injury burden; Covariate: frequency of I-REF view

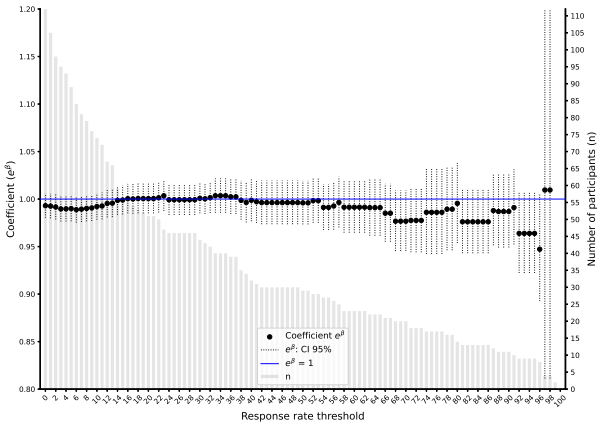


(a) Main scenario analysis

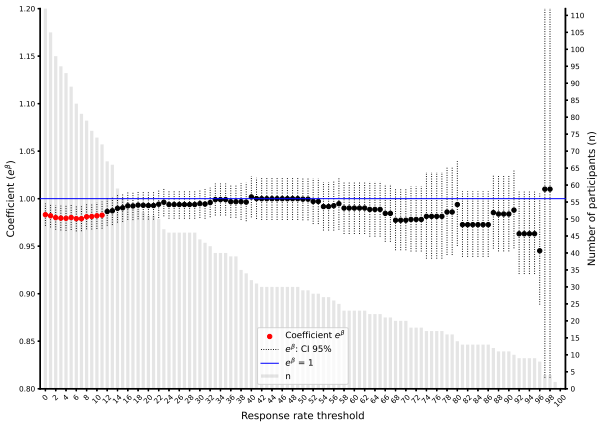


(b) Best scenario analysis

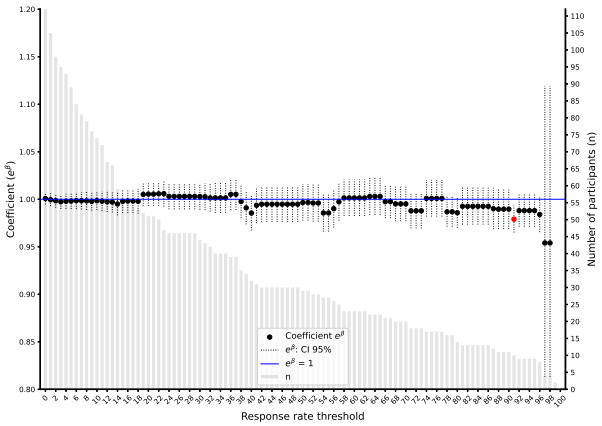
Figure 5: Tertiary analysis; Outcome: injury prevalence; Covariate: self-reported level of I-REF use



(a) Main scenario analysis



(b) Best scenario analysis



(c) Worst scenario analysis

Figure 6: Tertiary analysis; Outcome: injury incidence; Covariate: frequency of I-REF view

4.3.2 IPredict-AI: key findings

1. The I-REF frequency of view was performed on average half of the time and, one out of ten athletes reached an I-REF view frequency of 100%.

2. The use of the daily injury risk estimation feedback (I-REF) by athletes to adapt their athletics practice was around 30%.

3. In the primary analysis, in which all athletes were included regardless of their response rate, we observed no association between the level of I-REF use and the number of days with ICPR.

4. However, when athletes with a minimum response rate of 9% were included, the analysis revealed a significant association between the level of I-REF use and the number of days with ICPR for athletes, with the number of days with ICPR decreasing by 20% for every 10 points increase in the level of I-REF use.

4.4 Injury prediction perception

4.4.1 Context

- As shown in the Paragraph 2.1.3.3.2, studies investigating the use of online technologies as an injury risk reduction measured through health status feedback is limited and with mixed results.
- As shown in the Section 2.3.7.4, improving the adoption of injury prevention strategies could be performed by a better understanding of perceptions and beliefs related to injury risk reduction and the factors associated with adherence or non–adherence to injury prevention strategies.
- In addition, individualisation of the injury risk reduction approach and its implementation could help to improve adherence to injury risk reduction approaches
- As shown in the Section 4.3, an injury risk estimation feedback developed from predictive machine learning models was used about half of the time of his availability.
- Thus, better understanding the perception of athletics stakeholders regarding the use of machine learning as an injury prevention strategy through injury prediction is of importance to improve its implementation for future work.

OBJECTIVE 3

In this context our aim was to explore perceptions and beliefs of elite athletics (track and field) athletes, coaches, and health professionals, towards the use of injury prediction as an injury prevention strategy.

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Original Research

Perceptions and beliefs on sports injury prediction as an injury risk reduction strategy: An online survey on elite athletics (track and field) athletes, coaches, and health professionals

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ABSTRACT

Objectives: To explore perceptions and beliefs of elite athletics (track and field) athletes, coaches, and health professionals, towards the use of injury prediction as an injury risk reduction strategy.
Design: Cross-sectional study.
Method: During the 2022 European Athletics Championships in Munich, registered athletes, coaches, and health professionals were asked to complete an online questionnaire on their perceptions and beliefs of injury prediction use as an injury risk reduction strategy. The perceived level of interest, intent to use, help, potential stress (psychological impact) and dissemination were assessed by a score from 0 to 100.
Results: We collected 54 responses from 17 countries. Elite athletics stakeholders expressed a perceived level of interest, intent to use, and help of injury prediction of (mean ± SD) 85 ± 16, 84 ± 16, and 85 ± 15, respectively. The perceived level of potential stress was 41 ± 33 (range from 0 to 100), with an important inter-individual variability in each elite athletics stakeholder's category.
Conclusions: This was the first study investigating the perceptions and beliefs of elite athletics stakeholders regarding the use of injury prediction as an injury risk reduction strategy. Regardless of the stakeholders, there was a high perceived level of interest, intent to use and help reported in this potential strategy.

1. Introduction

Injury is a centrepiece for elite athletics (track and field) athletes and their teams, as it negatively affects athletes' performance, career and health (Edouard et al., 2015, 2020). In order to reduce injury risk, it is fundamental to develop efficient and well-accepted injury risk reduction strategies (van Mechelen et al., 1992).

Injury risk reduction strategies can target different domains (e.g., physical conditions, techniques, lifestyle, equipment) (Edouard et al., 2015). Identification of risk factors within these domains can also be part of the injury risk reduction approach to identify athletes at higher risk of injuries and to orient the approach (van Mechelen et al., 1992; Bahr, 2005). However, sports injuries are a complex phenomenon resulting from the interaction of multiple risk factors and inciting events across various domains (Bittencourt et al., 2016; Fonseca et al., 2020). Understanding the relative influence of these factors is challenging due to the complexity of the interactions involved. Recently, predictive modelling using artificial intelligence through machine learning techniques has been used in sports medicine attempting to address this complex task by predicting the injury based on the learning of emerging patterns from various parameters (Van Eetvelde et al., 2021). In the prognostic sports medicine field, the use of machine learning techniques frequently aims to predict the classification of an event, such as an injury "yes" or "no", and to report the probability of that classification (i.e.,

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injury risk), with the goal to identify athletes at higher injury risk (Van Eetvelde et al., 2021). As a result, the development of artificial intelligence and machine learning techniques may enable measuring an athlete's own risk of injury occurrence based on data collected at the beginning of the season (Jauhiainen et al., 2022; Rommers et al., 2020) or over the season (e.g., workload or psychological variables) (Briand et al., 2022; Rahlf et al., 2022; Rossi et al., 2018). Machine learning techniques can also be used to further investigate the relative importance of individual risk factors in sports injuries (Rommers et al., 2020; Van Eetvelde et al., 2021). In the near future, elite athletes, coaches, or health professionals could have the possibility to have access to the injury risk prediction provided by predictive algorithms to manage training and injury risk, in addition to other injury risk reduction strategies.

Today, further research is necessary to develop efficient predictive algorithms and assess their effectiveness as an injury risk reduction strategy (Bullock et al., 2022; Dandrieux et al., 2023). However, before such innovative potential injury risk measures are available, it is relevant to explore how injury risk prediction will be received by the end users and whether injury risk prediction will be expected to be used by them. It is also important to understand how stakeholders will use this predictive information to align research and related development with stakeholders' expectations in order to optimize their development by matching their expectations and/or practice to maximize their use and adherence. Indeed, few studies have been published on the perceptions of sports stakeholders regarding injury prevention strategies (McCall et al., 2015; O'Brien and Finch, 2016; Räisänen et al., 2021), and no in athletics (track and field). Existing research tends to focus on specific stakeholder groups without conducting individual analyses for each stakeholder simultaneously (McCall et al., 2015; O'Brien and Finch, 2016; Räisänen et al., 2021). In this context, the primary aim of this study was to explore the perceptions and beliefs of elite athletics (track and field) athletes, coaches, and health professionals towards the use of injury prediction as an injury risk reduction strategy. The secondary aim was to explore differences in perceptions and beliefs between elite athletics stakeholders.

2. Methods

We took the opportunity of the European Athletics championships (15th to August 21, 2022, Munich, Germany) to conduct a cross-sectional study through an online questionnaire of elite athletics athletes, coaches, and health professionals. All data were collected anonymously so that no individual participant could be directly identified. The study was reviewed and approved by the Saint-Etienne University Hospital Ethical Committee (Institutional Review Board: IORG0007394; IRBN792022/CHUSTE). The aim and procedure of the study were explained to all participants, and they were informed that their data would be used for research purposes. It was also made clear to them that they had the right to refuse to have their data used for research purposes. The Ethical Committee did not require signed informed consent for the use of the athletes' data.

There was no patient or public involvement in this study. However, this study raised the patient/public involvement needed for future studies regarding injury risk prediction as an injury risk reduction strategy. A summary of the study results will be disseminated to the public.

One month prior to the 2022 European Athletics Championships in Munich, all registered athletes, coaches, and health professionals were informed about the study via email by the study team. This email was sent to the European Athletics, who were requested to forward it to their national member sports federations, with the task of informing the participating athletes, coaches, and health professionals about the study.

During the 2022 European Athletics Championships in Munich, which took place from August 15th to 21st, registered athletes, coaches and health professionals were informed about the current study and were asked to complete an Injury PREDiction perceptions Questionnaire (IPREDQ) regarding perceptions of injury risk prediction (i.e., the use of machine learning to build prognostic algorithm able to forecast an estimation of the risk of injury based on regular data collection) as an injury risk reduction strategy for elite athletics stakeholders using the following approaches: (i) a flyer given to each athlete, coach, and health professionals with their accreditation, (ii) posters displayed in various locations at the Championships (such as hotels, medical centres, training areas, warm-up areas, accreditation centres), (iii) emails sent by their national federations, (iv) volunteers at different venues throughout the Championships who informed athletes about the study, expressed interest in their participation, and provided information on how to participate. Thus, elite athletics athletes, coaches, and health professionals registered at the 2022 European Athletics championships were invited to complete the IPREDQ (Supplementary material S1).

The IPREDQ was developed by a team of researchers (n = 6) with backgrounds in sports medicine, sports science, epidemiology, biostatistics, data science, and athletics coaching. IPREDQ was designed to gather relevant information directly from the targeted population through a self-report assessment with the aim of providing an understanding of their perceptions of sports injury prediction through injury risk prediction. Authors formulated questions related (i) to the degree of interest in the sports injury prediction, (ii) to the intent to use (i.e., if they would use it in their work and/or practice), (iii) to the help in the field induced by this approach, (iv) to the stress related by such information (i.e., potential emotional or psychological impact that may result from increased stress during practice), (Van Custem et al., 2017) and (v) to the dissemination (i.e., gauge perceptions of the targeted population on how well it aligns with their needs and how it can be applied in their respective roles as athletes, coaches or health professionals) (Supplementary material S1). The IPREDQ was designed with the intention of being concise in order to maximize the number of responses, and with a focus on being easy to understand and clear. In this study, an adaptation of the visual analogue scale methodology was employed as it is a widely used tool to measure attitudes, opinions, or perceptions in the field of research (Sung & Wu, 2018). Subjects were asked to evaluate their level of perceptions and beliefs by assigning a numerical score on a scale from 0 indicating "not at all" to 100 indicating "totally". The assessment was conducted using a digital tool, which featured an untranslated continuous sliding scale, with only the endpoints (i.e., not at all, totally) of the scale visible to the participants. From an initial position of the slider set at the midpoint of the sliding scale, participants were required to adjust the slider to their desired position prior to confirming their score. IPREDQ development followed an iterative process of revisions and feedback between the 6 researchers through electronic communication until a state of consistency was reached. Upon completion of the final round of revisions, all contributing experts were requested to confirm their agreement with the final version of the IPREDQ. The IPREDQ was created in English and was available online only using a QR code to access the website application containing IPREDQ (IPrevApp, https://iprevapp.emse.fr). Athletes, coaches, and health professionals were instructed to complete the questionnaire during the championships period from 15th to August 21, independently, with the option to seek assistance from volunteers at various venues if necessary.

Statistical analyses were conducted utilizing Python version 3.10.2, as provided by the Python Software Foundation (https://www.python.org/) (Rossum & Drake, 2010). Data were processed using the pandas package version 1.5.1 (https://pandas.pydata.org/) (McKinney et al., 2010; team T pandas development, 2020). The SciPy package version 1.9.3 was used for conducting statistical analyses (https://scipy.org/) (Virtanen et al., 2020).

Descriptive analyses were performed for continuous variables and categorical variables, including the calculation of means, standard deviations (SDs), median, minimum, maximum and quantity (n) and proportion (%), respectively. Inter-individual variability was assessed through the dispersion of values, including standard deviations,

minimum, and maximum values.

To determine whether there were any significant statistical differences in the values between athletes, coaches, and health professionals, firstly normality of distribution and homogeneity of variance were verified using the Shapiro-Wilk test and Bartlett's test, respectively. If these assumptions were met, a one-way ANOVA (parametric) analysis was performed, followed by a Bonferroni pairwise comparison test. If the assumptions were not met, a Kruskal-Wallis (non-parametric) test was used, followed by a Mann-Whitney pairwise comparison test. The threshold for statistical significance was set at a p-value of less than 0.05.

3. Results

Among the total of 2410 elite athletics stakeholders (1540 athletes, 705 coaches, 165 health professionals) from 52 countries registered at the 2022 European Athletics Championships, 54 (2.2%) completed the IPREDQ and were included in the present study: 20 athletes (1.3%), 12 coaches (1.7%), 22 health professionals (13.3%), from 17 countries (32.7%). The characteristics of these stakeholders are presented in Table 1.

Regarding the perceptions and beliefs of elite athletics (track and field) athletes, coaches, and health professionals towards the use of injury prediction, all responders expressed a perceived level of interest, intent to use, and help of sports injury prediction as an injury risk reduction strategy, with an overall mean score above 80 out of maximum 100 (Table 2 and Fig. 1). Potential stress induced by injury prediction was 41 ± 33, and there was an important inter-individual variability (i.e., average of standard deviation between stakeholders equal to 30) (Table 2 and Fig. 1). Concerning the dissemination of injury prediction, the mean perceived level of relevance for use reported by stakeholders ranged from 80 to 100 (Table 2 and Fig. 1).

Regarding the exploration of differences in perceptions and beliefs between elite athletics stakeholders, as the data did not meet the assumptions of normality and equal variance, non-parametric Kruskal-Wallis tests were employed to determine if there were any significant differences in the median perceptions of interest, intent to use, and help among elite athletics stakeholders. Tests revealed that median perceptions of interest ($p = 0.027$) and help ($p = 0.014$) were significantly different between athletes, coaches, and health professionals (Table 1, Fig. 1). Post-hoc analysis using Mann-Whitney U tests showed that the median interest for health professionals (median = 99) was significantly higher compared to athletes (median = 73), $p = 0.013$ (Table 1, Fig. 1). Additionally, median perceptions of the help for health professionals (median = 90) and coaches (median = 99) were significantly higher compared to athletes (median = 75), $p = 0.019$ (Table 1, Fig. 1). No statistically significant differences were found in perceptions of the stress and dissemination (for athletes, coaches, and health professionals) of sports injury prediction risk reduction measures among athletes, coaches, or health professionals (Table 1, Fig. 1).

Table 1
Characteristics of the included participants. *The statistics for the ages of men medical team members were calculated using 21 and 17 responses in total due to one missing value encountered.

Total potential participants (n)	All	Athletes	Coaches	Health professionals
	2410	1540	705	165
Number of survey respondent (n (%))	54 (2.2)	20 (1.3)	12 (1.7)	22 (13.3)*
Age in years (mean (SD))	40.7 (14.6)	26.1 (4.5)	54.5 (9.0)	46.8 (11)
Men potential participants (n (%))	**1537 (64)**	**805 (52.3)**	**617 (88.1)**	**115 (70.6)**
Number of survey respondent (n (%))	40 (2.6)	11 (1.4)	11 (1.8)	18 (15.7)*
Age in years (mean (SD))	43 (13.9)	26.8 (4.0)	53.9 (9.2)	46.4 (11.1)
Women potential participants (n (%))	**866 (36)**	**735 (47.7)**	**83 (11.9)**	**48 (29.4)**
Number of survey respondent (n (%))	14 (1.6)	9 (1.2)	1 (1.2)	4 (8.3)
Age in years (mean (SD))	34.4 (15)	25.2 (5.1)	61 (0.0)	48.5 (12.3)

Table 2
Results from the injury prediction perceptions questionnaires according to stakeholders. # Significantly different at a p-value of less than 0.05 when compared to the Athlete group.

Injury PREDiction Perceptions Questionnaire	All mean (SD) *median (min-max)*	Athletes mean (SD) *median (min-max)*	Coaches mean (SD) *median (min-max)*	Health Professionals mean (SD) *median (min-max)*
Would you be interested to have such information? (Interest)	85 (16) 87 (48–100)	77 (18) 73 (48–100)	85 (12) 83 (69–100)	91 (12) 99 (53–100)#
Would you use such information? (Intent to use)	84 (16) 85 (41–100)	79 (18) 79 (41–100)	83 (14) 85 (50–100)	89 (14) 95 (52–100)
Would this information help you to manage your injury risk, manage your training, manage your athlete? (Help)	85 (15) 88 (51–100)	78 (16) 75 (51–100)	93 (10) 99 (68–100)#	88 (13) 90 (54–100)#
Would this information disturb/stress you for your practice? (Stress)	41 (33) 32 (0–100)	51 (33) 54 (0–100)	36 (36) 25 (0–100)	34 (31) 22 (0–89)
Do you think that such "injury risk estimation" would be relevant to help practice/ management for athletes? (Dissemination)	85 (15) 87 (48–100)	80 (18) 79 (48–100)	89 (14) 96 (65–100)	87 (14) 91 (53–100)
Do you think that such "injury risk estimation" would be relevant to help practice/ management for coaches? (Dissemination)	83 (19) 88 (29–100)	78 (23) 82 (29–100)	89 (14) 98 (68–100)	85 (16) 90 (54–100)
Do you think that such "injury risk estimation" would be relevant to help practice/ management for medical teams? (Dissemination)	85 (18) 96 (26–100)	79 (20) 79 (26–100)	89 (16) 100 (60–100)	88 (17) 96 (50–100)

4. Discussion

The main findings of the present study were that (i) there was a high perceived level of interest, intent to use, help and dissemination, regardless of stakeholders, and with higher scores for coaches and health professionals regarding sports injury prediction and (ii) the potential stress induced by the injury risk prediction seems to be more nuanced, affected by individual factors and appears to be of greater significance for athletes compared to coaches and health professionals. This study represents the first investigation of the perceptions and beliefs of stakeholders, in athletics and elite sports, regarding the use of injury prediction as an injury risk reduction strategy.

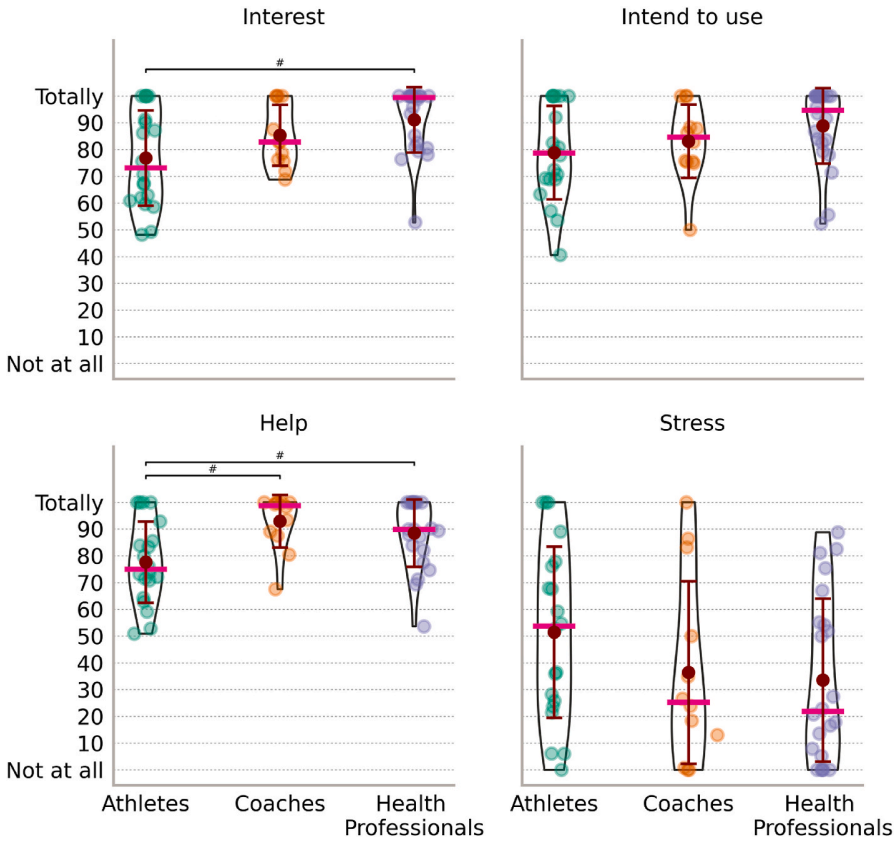


Fig. 1. Comparisons of answers between elite athletics stakeholders regarding their perceived level of interest, intent to use, help and stress induced by sports injury prediction approaches. Individuals are represented by single points. The probability density curve is shown by black lines. Means and SDs are represented through red points and lines. Medians are represented using a pink horizontal line. #$p < 0.05$ compared to "Athletes" using a non-parametric test. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Injury risk prediction represents a future innovative potential strategy for injury risk reduction. Although further research is necessary to develop efficient predictive algorithms, (Dandrieux et al., 2023) it is also of interest to explore whether such an injury risk reduction strategy would be accepted and used by the end users. Therefore, we performed this exploratory study. Our present results reported that this potential innovative injury risk reduction strategy would be well accepted by the end users. Indeed, athletes, coaches and health professionals who participated in this study, predominantly declared a high perceived level of interest, and intent to use, help and disseminate injury prediction as an injury risk reduction strategy. These results support the interest to continue working in this field and develop efficient injury risk prediction models.

Regarding the potential stress induction, there is a more mitigating result with a higher score (i.e., higher median) for athletes. We also observed an important variability with these stress values ranging from 0 to 100 for athletes and coaches and from 0 to 89 for health professionals with SDs higher than 30 for all stakeholders. This highlights the fact that individual reactions to a predicted event, such as injury, will vary between individuals. Regardless of the prediction models' efficacy in predicting injuries that could be influenced by several factors in the data collection and processing stages, the feedback provided can still have significant consequences. Thus, the uncertainty associated with the injury prediction feedback may result in varying behaviour among stakeholders in their practice. This information is fundamental in advancing the development and implementation of this type of preventive measure. Specifically, the implementation of injury prediction can be optimized by understanding and modelling the status of the athletes within their environment and interactions with stakeholders (Navarro et al., 2022), as well as incorporating individualized information regarding the perceived efficacy of proposed injury risk reduction strategies.

Regarding the exploration of differences in perceptions and beliefs between elite athletics stakeholders, we observed a higher mean perceived level of interest, intent to use, and help for health professionals and coaches compared to athletes. This could be explained by the fact that health professionals and coaches may be more concerned about injury risk prediction as it is a part of their job and could facilitate it (i.e., quality of work, time saving). On the contrary, athletes could see injury prediction strategy as a time-consuming task (e.g., data collection, understanding the tool) in their daily work and consequently were less concerned. But this could be also considered surprising to see this lower perceived level of interest by athletes as they are the first people concerned. Or the higher scores for health professionals and coaches could just be due to the fact that they have been more informed about injury prediction and asked to participate in this study. Indeed, the participation rate in this study was higher for health professionals (10%) and coaches (2%) compared to athletes (1%).

It is important to mention some limitations in this study. First, the sample size of participants could be considered small compared to the eligible population (2.2%), but in absolute value ($n = 54$) this was comparable to other studies on perceptions of injury prevention, where sample sizes typically range from 18 to 50 (McCall et al., 2015; O'Brien and Finch, 2016; Räisänen et al., 2021). Numerous and various strategies to disseminate information about the study and the IPREDQ (such as emails to athletes through federations, information through medical and coaching staffs, posters, flyers, and social media, and volunteers on-site to present the study to the athletes) and encourage the targeted

population to participate in this study. Possible explanations for the low participation could be that: included elite athletics stakeholders were focused on the championships, and the IPREDQ was available only in English. Additionally, the 2022 European Athletics Championships was included in the Munich 2022 European Championships, which is a continental event, every four years, gathering the same period and location of the European Championships of several sports (http://www.munich2022.com/en): athletics, beach volleyball, canoe sprint, cycling, gymnastics, rowing, sport climbing, table tennis and triathlon. As an important event with many communications and events happening simultaneously which could have diluted the present study among the masses. Second, there could have been some bias in the data collection, as some questions could have been misunderstood, because for instance of the language (i.e., only English), the terms used (e.g., misunderstanding of terms), the self-reported and not supervised approach, and we did not use a validated questionnaire; instead, we developed a questionnaire specifically tailored to address the objectives of this study. Third, potential recruitment bias may have arisen with a vested and/or dedicated interest in research from stakeholders, resulting in responses skewed toward a higher level of interest, intent to use or help. Fourth, no thresholds were established to address the discussion regarding inter-individual variability answers. Thus, the results of this study should be interpreted with caution given the small sample size that could limit their generability.

As practical implications, the present results highlight the fact that injury risk prediction as an injury risk reduction strategy could be well-accepted by elite athletics stakeholders. As such, this encourages researchers to continue work to develop efficient injury risk prediction models. This development is challenging due to the complex characteristics of each injury context (Bittencourt et al., 2016). Nevertheless, our present results underscore the importance of simultaneously pursuing the implementation of these preventive measures to ensure their practical use. To be achieved, the general population's expectations must align with the injury risk reduction strategies (Edouard et al., 2022). And, this study demonstrates a tendency towards increased stress with high inter-individual variability to consider in the implementation of preventive measures to ensure their use. Thus, the IPREDQ questionnaire could be used as a screening tool to determine the perceived level of acceptance of injury risk prediction as an injury risk reduction strategy and the level of potential stress associated with implementing injury prediction within a population.

5. Conclusion

In conclusion, the present study was the first investigation of the perceptions and beliefs of elite athletics athletes, coaches, and health professionals regarding the use of injury prediction as an injury risk reduction strategy. Regardless of the stakeholder group (athletes, coaches, health professionals), there was a high perceived level of interest, intent to use, help and dissemination regarding injury prediction as an injury risk reduction strategy with higher scores among coaches and health professionals. Potential stress induced by injury prediction seems to be more nuanced and affected by individual factors and appears to be of greater significance for athletes compared to coaches and health professionals. Our results are relevant for the development of injury prediction as an injury risk reduction strategy as they provide insights into how elite athletics stakeholders may respond to this preventive measure. This is an important step for properly defining implementation strategies and may have implications for future research and practice in the use of sports clinical prediction modelling as an injury risk reduction strategy in elite athletics.

Data availability statement

Data are available upon reasonable request. Requests for data sharing from appropriate researchers and entities will be considered on a case-by-case basis. Interested parties should contact the corresponding author Pierre-Eddy Dandrieux (pierre.eddy.dandrieux@univ-st-etienne.fr).

Ethics

The study was reviewed and approved by the Saint-Etienne University Hospital Ethical Committee (Institutional Review Board: IORG0007394, IRBN792022/CHUSTE).

CRediT authorship contribution statement

Pierre-Eddy Dandrieux: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Resources, Supervision, Validation, Writing – original draft, Writing – review & editing. **Laurent Navarro:** Conceptualization, Supervision, Visualization, Writing – review & editing. **Joris Chapon:** Conceptualization, Data curation, Investigation, Resources, Writing – review & editing. **Jeanne Tondut:** Formal analysis, Visualization, Writing – review & editing. **Michael Zyskowski:** Investigation, Methodology, Supervision, Writing – review & editing, Project administration. **Karsten Hollander:** Conceptualization, Methodology, Supervision, Validation, Writing – review & editing. **Pascal Edouard:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing.

Declaration of competing interest

No conflict of interest. PE is Associate Editor for the BJSM and the BMJ Open Sports and Exercise Medicine. KH is Editor for the German Journal of Sports Medicine, and Associate Editor for the BMJ Open Sports and Exercise Medicine.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ptsp.2024.01.007.

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Supplementary material S1:

The injury prediction perceptions questionnaire (IPREDQ) for the 2022 European Championships in Munich (Germany).

Dear athletes, coaches, manager teams, medical teams,
The development of artificial intelligence and machine learning makes it possible to estimate for an athlete his/her own risk of injury occurrence based on data collected from athletes. For example, the athlete is performing regular physical tests and/or completing regularly (daily or weekly) some questionnaires. These data are first used to develop a predictive algorithm. Then, the athlete continues to perform such tests and complete such questionnaire, and the predictive algorithm is able to forecast an estimation of the risk of injury that can occur in the coming days associated with details of which data influenced negatively or positively the injury risk score for each athlete and how much confidence we can have in the prediction (like for the weather). In summary, in the coming years/months, an athlete, coach, health professional, would have, in addition to other information useful to manage training and injury risk, the injury risk estimation provided by the predictive algorithm.

1. Interest
Would you be interested to have such information? (a scale from not at all-0 to totally-100)
2. Intent to use
Would you use such information? (a scale from not at all-0 to totally-100)
3. Help
Would this information help you to manage your injury risk, manage your training, manage your athlete? (a scale from not at all-0 to totally-100)
4. Stress
Would this information disturb/stress you for your practice? (a scale from not at all-0 to totally-100)
5. Dissemination
Do you think that such "injury risk estimation" would be relevant to help practice/management for:
-athletes (a scale from not at all-0 to totally-100)
-coaches (a scale from not at all-0 to totally-100)
-medical teams (a scale from not at all-0 to totally-100)
-management teams (a scale from not at all-0 to totally-100)

4.4.2 Injury prediction perception: key findings

1. There was a high perceived level of interest, intent to use, help and dissemination, regardless of stakeholders, and with higher scores for coaches and health professionals regarding sports injury prediction

2. The potential stress induced by the injury risk prediction seems to be more nuanced, affected by individual factors and appears to be of greater significance for athletes compared to coaches and health professionals.

Chapter 5

GENERAL DISCUSSION

The general problematic of this PhD manuscript was to investigate the use of artificial intelligence and in particular machine learning in the context of injury prevention in sports, and specifically in athletics (track and field). To respond to this general problem, we have defined three objectives (Section 3.2) and our personal contributions have led to the following results:

1. The scoping review (Section 4.1) included 28 studies, including 99 methods and 106 different models describing the current machine learning techniques used to develop prediction models for sports injuries. Two data collection approaches have been found, namely monitoring or screening, which lead to specific implications in the management of the machine learning process with methodological implications.

2. An individual injury risk estimation feedback (Sections 4.2 and 4.3) based on prognostic modelling using machine learning could be considered as an additional injury prevention approach, while further research is mandated to determine its efficacy and mechanism of action.

3. Among elite athletics stakeholders (athletes, coaches and health professionals) the potentials perceived help, interest and intent to use of sports injury prediction as an injury prevention strategy were high, while potential psychological consequences such as stress appear to be of greater concern to athletes compared to coaches and health professionals (Section 4.4).

These results, all together, allow to open a discussion, that also takes into account the limitations of our works, and is divided into three parts.

5.1 Global challenges

5.1.1 Towards study methodology improvement

In the Section 4.1, our results showed that 97% of the included studies were evaluated as high risk of bias assessed according to the latest available guidelines for prediction models (Wolff et al., 2019). One explanation for this reported poor quality of study methodology may be the recent interest in injury prediction using machine learning models that has emerged in the literature since the 2010s (Section 4.1), coupled with very recent emergence of guidelines for predictive modelling using machine learning in healthcare that are currently being produced (Collins et al., 2021) which may explain the non-standardised and poor quality reporting of the included studies. Indeed, the first guidance on reporting clinical prediction models with machine learning was published a few months ago with the Transparent Reporting of a multivariable prediction model for Individual Prognosis Or Diagnosis with Artificial Intelligence (TRIPOD+AI, Figure 31) (Collins et al., 2024b). The authors of the included studies therefore had no access to reporting guidelines specifically targeting predictive modelling and artificial intelligence that would help them to improve the quality of the study reports. Indeed, methodological concerns about study design and analysis (e.g. small sample size, overfitting), incomplete reporting (leading to difficulties in fully evaluating studies using predictive models) and no clear link to clinical decision making should be consider (Collins et al., 2024a; Riley et al., 2024a,b; Efthimiou et al., 2024). In order to consider these methodological points, several guidelines on predictive modelling in healthcare have recently been published to improve the quality of conducting, developing, analysing and reporting study using predictive modelling in healthcare such as:

- A three part series on evaluating a performance of a clinical prediction model (Collins et al., 2024a; Riley et al., 2024a,b).
- A step by step guide on how to develop a prediction model (Figure 30) (Efthimiou et al., 2024).
- Reporting guidelines (under development) for conducting systematic reviews and meta-analyses that address the studies using artificial intelligence and machine learning models in prognosis or diagnosis (Cacciamani et al., 2023; Snell et al., 2023).



Figure 30: Thirteen proposed steps for developing a clinical prediction model, from (Efthimiou et al., 2024).

TRIPOD+AI

Version: 11-January-2024

Section/Topic	Item	Development / evaluation[1]	Checklist item	Reported on page
TITLE				
Title	1	D;E	Identify the study as developing or evaluating the performance of a multivariable prediction model, the target population, and the outcome to be predicted	
ABSTRACT				
Abstract	2	D;E	See TRIPOD+AI for Abstracts checklist	
INTRODUCTION				
Background	3a	D;E	Explain the healthcare context (including whether diagnostic or prognostic) and rationale for developing or evaluating the prediction model, including references to existing models	
	3b	D;E	Describe the target population and the intended purpose of the prediction model in the context of the care pathway, including its intended users (e.g., healthcare professionals, patients, public)	
	3c	D;E	Describe any known health inequalities between sociodemographic groups	
Objectives	4	D;E	Specify the study objectives, including whether the study describes the development or validation of a prediction model (or both)	
METHODS				
Data	5a	D;E	Describe the sources of data separately for the development and evaluation datasets (e.g., randomised trial, cohort, routine care or registry data), the rationale for using these data, and representativeness of the data	
	5b	D;E	Specify the dates of the collected participant data, including start and end of participant accrual; and, if applicable, end of follow-up	
Participants	6a	D;E	Specify key elements of the study setting (e.g., primary care, secondary care, general population) including the number and location of centres	
	6b	D;E	Describe the eligibility criteria for study participants	
	6c	D;E	Give details of any treatments received, and how they were handled during model development or evaluation, if relevant	
Data preparation	7	D;E	Describe any data pre-processing and quality checking, including whether this was similar across relevant sociodemographic groups	
Outcome	8a	D;E	Clearly define the outcome that is being predicted and the time horizon, including how and when assessed, the rationale for choosing this outcome, and whether the method of outcome assessment is consistent across sociodemographic groups	
	8b	D;E	If outcome assessment requires subjective interpretation, describe the qualifications and demographic characteristics of the outcome assessors	
	8c	D;E	Report any actions to blind assessment of the outcome to be predicted	
Predictors	9a	D	Describe the choice of initial predictors (e.g., literature, previous models, all available predictors) and any pre-selection of predictors before model building	
	9b	D;E	Clearly define all predictors, including how and when they were measured (and any actions to blind assessment of predictors for the outcome and other predictors)	
	9c	D;E	If predictor measurement requires subjective interpretation, describe the qualifications and demographic characteristics of the predictor assessors	
Sample size	10	D;E	Explain how the study size was arrived at (separately for development and evaluation), and justify that the study size was sufficient to answer the research question. Include details of any sample size calculation	
Missing data	11	D;E	Describe how missing data were handled. Provide reasons for omitting any data	
Analytical methods	12a	D	Describe how the data were used (e.g., for development and evaluation of model performance) in the analysis, including whether the data were partitioned, considering any sample size requirements	
	12b	D	Depending on the type of model, describe how predictors were handled in the analyses (functional form, rescaling, transformation, or any standardisation).	
	12c	D	Specify the type of model, rationale[2], all model-building steps, including any hyperparameter tuning, and method for internal validation	
	12d	D;E	Describe if and how any heterogeneity in estimates of model parameter values and model performance was handled and quantified across clusters (e.g., hospitals, countries). See TRIPOD-Cluster for additional considerations[3]	
	12e	D;E	Specify all measures and plots used (and their rationale) to evaluate model performance (e.g., discrimination, calibration, clinical utility) and, if relevant, to compare multiple models	
	12f	E	Describe any model updating (e.g., recalibration) arising from the model evaluation, either overall or for particular sociodemographic groups or settings	
	12g	E	For model evaluation, describe how the model predictions were calculated (e.g., formula, code, object, application programming interface)	
Class imbalance	13	D;E	If class imbalance methods were used, state why and how this was done, and any subsequent methods to recalibrate the model or the model predictions	
Fairness	14	D;E	Describe any approaches that were used to address model fairness and their rationale	
Model output	15	D	Specify the output of the prediction model (e.g., probabilities, classification). Provide details and rationale for any classification and how the thresholds were identified	

[1] D=items relevant only to the development of a prediction model; E=items relating solely to the evaluation of a prediction model; D;E=items applicable to both the development and evaluation of a prediction model

[2] Separately for all model building approaches.

[3] TRIPOD-Cluster is a checklist of reporting recommendations for studies developing or validating models that explicitly account for clustering or explore heterogeneity in model performance (eg, at different hospitals or centres). Debray et al, BMJ 2023; 380: e071018 [DOI: 10.1136/bmj-2022-071018]

Page 1 of 2

Figure 31: Checklists of the Transparent Reporting of a multivariable prediction model for Individual Prognosis Or Diagnosis with Artificial Intelligence (TRIPOD+AI) (Collins et al., 2024b).

Training versus evaluation	16	D;E	Identify any differences between the development and evaluation data in healthcare setting, eligibility criteria, outcome, and predictors	
Ethical approval	17	D;E	Name the institutional research board or ethics committee that approved the study and describe the participant-informed consent or the ethics committee waiver of informed consent	
OPEN SCIENCE				
Funding	18a	D;E	Give the source of funding and the role of the funders for the present study	
Conflicts of interest	18b	D;E	Declare any conflicts of interest and financial disclosures for all authors	
Protocol	18c	D;E	Indicate where the study protocol can be accessed or state that a protocol was not prepared	
Registration	18d	D;E	Provide registration information for the study, including register name and registration number, or state that the study was not registered	
Data sharing	18e	D;E	Provide details of the availability of the study data	
Code sharing	18f	D;E	Provide details of the availability of the analytical code[4]	
PATIENT & PUBLIC INVOLVEMENT				
Patient & Public Involvement	19	D;E	Provide details of any patient and public involvement during the design, conduct, reporting, interpretation, or dissemination of the study or state no involvement.	
RESULTS				
Participants	20a	D;E	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.	
	20b	D;E	Report the characteristics overall and, where applicable, for each data source or setting, including the key dates, key predictors (including demographics), treatments received, sample size, number of outcome events, follow-up time, and amount of missing data. A table may be helpful. Report any differences across key demographic groups.	
	20c	E	For model evaluation, show a comparison with the development data of the distribution of important predictors (demographics, predictors, and outcome).	
Model development	21	D;E	Specify the number of participants and outcome events in each analysis (e.g., for model development, hyperparameter tuning, model evaluation)	
Model specification	22	D	Provide details of the full prediction model (e.g., formula, code, object, application programming interface) to allow predictions in new individuals and to enable third-party evaluation and implementation, including any restrictions to access or re-use (e.g., freely available, proprietary)[5]	
Model performance	23a	D;E	Report model performance estimates with confidence intervals, including for any key subgroups (e.g., sociodemographic). Consider plots to aid presentation.	
	23b	D;E	If examined, report results of any heterogeneity in model performance across clusters. See TRIPOD Cluster for additional details[3].	
Model updating	24	E	Report the results from any model updating, including the updated model and subsequent performance	
DISCUSSION				
Interpretation	25	D;E	Give an overall interpretation of the main results, including issues of fairness in the context of the objectives and previous studies	
Limitations	26	D;E	Discuss any limitations of the study (such as a non-representative sample, sample size, overfitting, missing data) and their effects on any biases, statistical uncertainty, and generalizability	
Usability of the model in the context of current care	27a	D	Describe how poor quality or unavailable input data (e.g., predictor values) should be assessed and handled when implementing the prediction model	
	27b	D	Specify whether users will be required to interact in the handling of the input data or use of the model, and what level of expertise is required of users	
	27c	D;E	Discuss any next steps for future research, with a specific view to applicability and generalizability of the model	

From: Collins GS, Moons KGM, Dhiman P, et al. *BMJ* 2024;385:e078378. doi:10.1136/bmj-2023-078378

[4] This relates to the analysis code, for example, any data cleaning, feature engineering, model building, evaluation.
[5] This relates to the code to implement the model to get estimates of risk for a new individual.

5.1.2 Towards ethics and legal policies improvement

Globally, in medicine, despite the increasing number of predictive modelling approaches, very few are used in clinical practice (Wynants et al., 2020). As shown in the Section 4.1, all studies and models included were in a development stage and not used in practice. Apart from the implications for methodological concerns regarding study design and analysis or incomplete reporting (Section 5.1.1), which could limit the integration of such an approach, there is also an ethical and legal policy challenge. Indeed, in the context of public health, machine learning is also developed taking into account the main ethical principles mentioned in the existing artificial intelligence guidelines, such as transparency, justice and fairness, non-maleficience, responsability, privacy, beneficience, freedom and autonomy, trust, sustainability, dignity and solidarity (Figure 32) (Jobin et al., 2019).

Ethical principle	Number of documents	Included codes
Transparency	73/84	Transparency, explainability, explicability, understandability, interpretability, communication, disclosure, showing
Justice and fairness	68/84	Justice, fairness, consistency, inclusion, equality, equity, (non-) bias, (non-)discrimination, diversity, plurality, accessibility, reversibility, remedy, redress, challenge, access and distribution
Non-maleficence	60/84	Non-maleficence, security, safety, harm, protection, precaution, prevention, integrity (bodily or mental), non-subversion
Responsibility	60/84	Responsibility, accountability, liability, acting with integrity
Privacy	47/84	Privacy, personal or private information
Beneficence	41/84	Benefits, beneficence, well-being, peace, social good, common good
Freedom and autonomy	34/84	Freedom, autonomy, consent, choice, self-determination, liberty, empowerment
Trust	28/84	Trust
Sustainability	14/84	Sustainability, environment (nature), energy, resources (energy)
Dignity	13/84	Dignity
Solidarity	6/84	Solidarity, social security, cohesion

Figure 32: Ethical principles identified in existing AI guidelines, from (Jobin et al., 2019).

The aforementioned ethical principles are even more important now since the WHO has included artificial intelligence in the digital health strategy in 2020 pushing artificial intelligence in a global health level (World Health Organization, 2021). Therefore, the use of machine learning as an injury risk reduction measure may pose an ethical and responsibility challenge in the context of an evolving ethical and legal context, which may explain why there has been no field study using this technology in interaction with athletes since 2013 (Section 4.1). The IPredict-AI study that we conducted (Sections 4.2 and 4.3) was, to our knowledge, the first and the only in the field of sports medicine and we were confronted with this evolving legal and ethical context. A practical example of this was that we were not able to conduct a randomised control trial, mainly because we lacked the knowledge of these legal and ethical aspects. This means that further scientific projects using this technology should partner with artificial intelligence ethics and legal experts or try to find people who are close at another level in the early stages of the project to anticipate the development and integration of machine learning as a strategy to reduce the risk of injury.

5.1.3 Towards a planetary crisis

"The concept of planetary health is based on the understanding that human health and human civilisation depend on ourishing natural systems and the wise stewardship of those natural systems. However, natural systems are being degraded to an extent unprecedented in human history" (Whitmee et al., 2015). Specifically, "Planetary Health" stands for the health of human civilisation and the state of the natural systems on which it depends, through a multi- and transdisciplinary research paradigm (Whitmee et al., 2015). Human activities like medicine (Lenzen et al., 2020) and sports (Orchard, 2023; Reid et al., 2023) are impacting the planetary health by altering natural cycles and are responsible for climate change and pollution inducing a challenge to ecosystems, biodiversity and human well-being (Richardson et al., 2023). More specifically the use of digital health is questionable (Coiera and Magrabi, 2022). In fact, digital technologies are responsible for the carbon emissions associated with the design, creation and use of information technology (Borthwick et al., 2022). In addition, computing resources such as cloud computing are very energy-intensive notably with the energy consumption of data center accounted for 1% of global energy consumption in 2018 (Masanet et al., 2020). Therefore, in the

context of the impact of health care on climate change (Lenzen et al., 2020), interest in understanding and assessing the effects that artificial intelligence and machine learning approaches may have on climate action is important and needed (Kaack et al., 2022; Lokmic-Tomkins et al., 2022). The acquisition, development and application of machine learning in sports medicine could indeed contribute to the deterioration of planetary health. Indeed, the development of hardware and software and their requirements could overly promote a techno-solutionist approach that exploits the latest technologies such as smartphones, sensors and mobile data as well as maximising data storage in a consumerist way that promotes quantity rather than quality and efficacy (Lemarchand et al., 2024). For example, our IPredict-AI project required about 10 hours of computing time per week to train the machine learning model, a constant Wi-Fi access, database storage and resources for development (computers, servers, etc.), all of which require energy sources that increase the carbon footprint for their design, development and deployment. Consequently, the sports and exercise community should weigh up the pros and cons of using such technology effectively (i.e., amount of storage use by the system, choice of data collected to minimise the amount of storage, level of internet connection and hardware and software required to operate the system) at an important time in the digital carbon footprint in this game for life (Lemarchand et al., 2024).

5.2 A time challenge

The results of our scoping review on describing the machine learning techniques to develop machine learning prediction models for sports injuries Section 4.1 highlighted two different approaches to performed data collection in sports medicine and injury prediction. These two data collection approaches was associated with two predicting approaches: predicting once a year if an injury can happen within the season (traditionally in screening approaches) or several times, weekly, monthly or daily in monitoring approaches. However, in a field context that requires real-time data management and interactions with athletes of stakeholders, it seems more realistic and practical to use monitoring approaches to predict injuries, as the health status of athletes is constantly evolving. Using monitoring approaches have important implications, particularly on the management of data collection (i.e., frequency), data processing (i.e., time management procedures within the collected data) and validation (i.e., time partitioning) over

the machine learning pipeline.

5.2.1 Time and data collection

In terms of data collection approaches, increase the frequency of data collection to maximise the number of input data could be beneficial to increase the machine learning model performance metrics, and consequently increase the prediction of the injury. However, despite an increase in the performance of an machine learning model metric over time, the results are limited with only one study reporting the retrospective cumulative evolution of an machine learning model metric over a season (Figure 33) (Rossi et al., 2018). In our study, as presented in Section 4.3, the metrics of the machine learning models were stable despite the increasing amount of input data and no increase in performance seems to appear. This could be due to the fact that increasing the amount of data without keeping a certain amount of distribution between the number of cases (i.e., injured and non-injured) will increase the imbalanced problem and reduce the capacity of the model to predict the injury. In a monitoring approach, by increasing the data collection frequency, we are faced with a paradoxical situation. We want to accumulate an important amount of data to predict a "rare" outcome that we hope to see decrease, but in doing so, we are exacerbating the unequal balance of classes between injured and non-injured, reducing our chance to predict the injury.

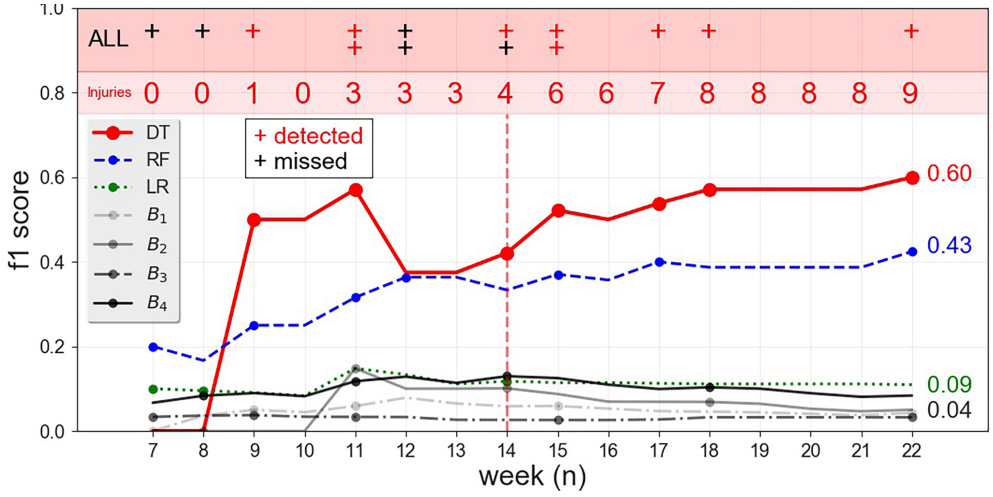


Figure 33: Performance of different predictive machine learning models in an evolutive scenario. As the season goes by, we plot week by week the cumulative F1-score of predictive machine learning models DT, RF, LR, B1, . . ., B4 trained on the data collected up to that week. Black crosses indicate injuries that not detect by the DT model, red crosses indicate injures correctly predicted by the DT model. For every week i we highlight in red the number of injuries detected by the DT model up to week i., from (Rossi et al., 2018).

5.2.2 Time and data processing

In terms of data processing, the time management strategies currently used in monitoring approaches impact the time dependency of input data (Section 4.1). Indeed, we have found that two techniques are used to deal with time dependency in monitoring approaches: time window processing (i.e., when the input data is processed at a fixed time interval such as weekly) and moving averages (i.e., where the time dependency cannot be considered an independent input because the output at a time depends on all the previously recorded input and output). In the Sections 4.2 and 4.3 we made a day by day prediction meaning that each day was considered as "independant" in our dataset thus implying not considering the time evolution. This represents a limit. In fact, the risk factors for an injury could evolve over time without making the same contribution to the injury, depending on how far they were from the time of the injury (Pol et al., 2018). Therefore the method used in Sections 4.2 and 4.3 could be not sufficient to forecast the injury as they not consider a phase-transition approach (Fonseca et al., 2020). A phase-transition approach is defined as "the point at which a transformation between states occurs (e.g., states of matter: gas, liquid, and solid). In synergetics, it refers to the critical points, where the behaviour of the system changes qualitatively on the macroscopic scale (critical transitions)" (Fonseca et al., 2020). In sports, a phase-transition approach can be illustrated by an abrupt change in the state of sports-related systems: loss of players mental concentration during matches, athletes heart rate variability diminution, important increase of athlete's anxiety. Indeed, injury could be considered as a phase transition preceded by an increased of risk factors fluctuations (Figure 34). Thus, the time dependency could be also integrated into the expression of the variation of a factor from a period of time (Fonseca et al., 2020). In terms of injury, too short a period (such as the daily data collection and prediction we use) represents rapid changes in the athletes health status and may not be useful for prediction, so the period of interest for injury prediction should be increased.

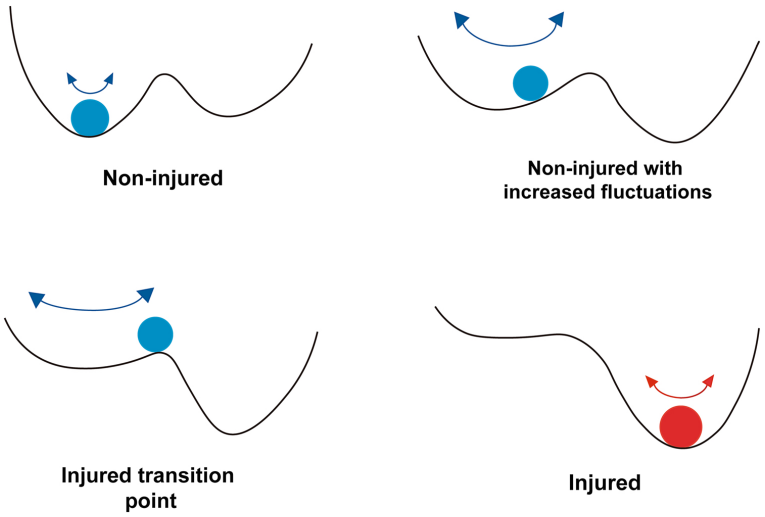


Figure 34: Injury as a phase transition preceded by increased fluctuations, from (Fonseca et al., 2020).

5.2.3 Time and model validation

In terms of validation, during model training, future data cannot be used to predict past injuries; temporality must thus be considered (Section 4.1). In prognostic modelling, temporal validation consisted in evaluating the performance of an existing prediction model in data from the same or similar setting in a different time period (Collins et al., 2024a). In a context of monitoring approach during a season using prognostic modelling through machine learning models, Rossi et al. (Rossi et al., 2018) performed an internal validation over different time period in order to provide a weekly performance metrics (Figure 33). Therefore, Rossi et al. (Rossi et al., 2018) were able to retrospectively evaluate their models using a recursive training-testing strategy over the 22 weeks of their procotol by training their models on n-weeks and evaluate them chronologically on the n+1 week (Figure 33). In our settings, we could not internally validate our model using a different time period as performed by Rossi et al. (Rossi et al., 2018) because our athletes were aware about the prediction made by the predictive model through a feedback (i.e., IREF). Thus, this feedback had potentially influenced their behaviour for the following day. For example, in our settings, based on the hypothesis that our model makes a good prediction by predicting an injury for the next day for an athlete who is supposed to get injured in his training session on that particular day. On the one hand, the athlete can avoid injury if he does not train according to the feedback of the machine learning model. On the other hand, the internal validation of the model will be erroneous, as the prediction of the model will be

considered wrong, although in reality it has allowed the athlete to avoid injury. This previous example illustrates the paradox mentioned in Section 5.2.1 that we were trying to reduce the number of an outcome (i.e., an injury) using an injury risk strategy while obtaining data about it in order to develop this strategy. Due to this particular settings (Sections 4.2 and 4.3) we are not able to follow the same validation strategy as performed by Rossi et al. (Rossi et al., 2018) (Figure 33). Thus, the main limitation of our approach (i.e., using real-time development and integration) is that it is difficult to understand whether the model's performance changes (and especially whether it deteriorates) over the study period, as it is a new model each week without the possibility of an internal validation using different time period.

5.3 A field challenge

5.3.1 Be performant?

All studies included in Section 4.1 had attempted to retrospectively develop machine learning models by maximising different performance metrics. Despite the fact that standardisation is required to report the metrics of the machine learning model for injury prediction (Figure 23), it seems that they tried to develop the best algorithm before thinking about the feasibility of its application. Indeed, as far as we know from the published articles, not all the developed models have been used in the field. Thus, they were not able to shown that the performance of the machine learning model is based on different and paradoxical criteria than the performance of an injury prevention strategy. Indeed, when trying to use predictive machine learning models in real-time as an injury prevention strategy, maximising the number of injured and non-injured cases to train the model and potentially maximise its performance is in fact the opposite than minimising the number of injuries using an injury prevention strategy (Sections 5.2.1 and 5.2.3). Another limit affecting performance in terms of predictive machine learning models and injury prevention strategy is the impact of the level of response rate, which is constantly decreasing over the course of the various follow-up studies in athletics (Edouard et al., 2014b, 2021c) and also in our study (Sections 4.2 and 4.3). On the predictive machine learning models side, this decrease in response rate has a direct impact on the amount of data available to build a model and can affect its development (Russell and Norvig, 2021). On the intervention evaluation side, this led to dealing with missing data that may influence the epidemiological outcomes and the

results of the study (Edouard et al., 2024b). In order to maximise the level of response rate, we used digital strategies such as providing athletes with a statistical dashboard of the variables collected. However, such kind of approaches may dilute the effectiveness of the intervention (e.g., providing feedback such as I-REF) and precautions should be considered to isolate the effectiveness of a digital intervention. Thus, when several feedback are available on a digital support, isolating their individual effect is challenging. Finally, efforts should be made to improve the performance of the algorithm as well as the integration of this new strategy to reduce the risk of injury in the field, as they have no benefit if the perfect model is not used. Without studies to evaluate the efficiency/effectiveness of such a technology, we would also not be able to translate the theoretical performance metrics of machine learning (Table 4) to everyday life evidence.

5.3.2 Be 'X'-plainable?

The main focus of explainable artificial intelligence is usually on the reasoning behind the decisions or predictions made by the artificial intelligence which are made more understandable and transparent (Loyola-Gonzalez, 2019). On the one hand, a black-box model is a model that contains a complex mathematical function that is difficult to understand even for experts (e.g., deep learning) (Loyola-Gonzalez, 2019). On the other hand, white-box models can be understood by experts in practical applications as they provide a model that is closer to human language (e.g., decision tree) (Loyola-Gonzalez, 2019). In our study (Sections 4.2 and 4.3), we opted for a random forest model based on a decision tree, considered as a white-box model (Loyola-Gonzalez, 2019), which may explain its popularity in studies on the prediction of sports injuries, as addressed in our scoping review (Section 4.1). To individualise the feedback, we leveraged recent advances in explainable artificial intelligence by showing to athletes the individual contribution of each predictor to injury prediction (Figure 24) (Lundberg et al., 2020). A machine learning model can be created from any database to predict the injury. Therefore, predictive models using machine learning can use both causal and non-causal predictors to establish the prognostic of future injuries (Bullock et al., 2021). Defining the causality could be challenging as shown in Section 2.1.3.2. Thus, researchers and clinicians can made the choice to include or not causal factors based on risk factors analysis in their model to predict the injury like we

partially performed in our study Sections 4.2 and 4.3 based on previous studies on athletics (Section 2.3.6). Also, factor(s) selection can be performed by humans based on expert knowledge (e.g., coaches, health professionals) or based on data processing strategies that can use the number of missing values, the variability of the continuous predictor (Royston et al., 2005) or the sparsity of the categorical predictor (Greenland et al., 2016). Consequently, in our study (Sections 4.2 and 4.3), we used a model-agnostic method through Shapley values (Heskes et al., 2020) to present to athletes their individual among of contribution of each predictor on their injury risk level (Figure 25). These exploratory tools are indeed used to look for associations between predictors and outcomes, however the popular adage "correlation is not causation" still holds (Heskes et al., 2020). Thus, caution should be taken when selecting predictors that can guide athletes' behaviour in the future.

Causal attributions by humans depend heavily on understanding the generative model, which explains how different causes lead to an effect for which the relationships between these causes are essential (Gerstenberg et al., 2012). Despite the efforts made to create a "transparent" tool in our study on developing and assessing an injury prevention strategy using prediction models developed using machine learning in order to reduce the occurrence of sports injuries in the specific context of athletics (Sections 4.2 and 4.3), further efforts should be made to increase education and health literacy related to the use of machine learning in sports medicine to "prepare" athletes and stakeholders to interact with this technology in a reasoned way and to involve experts such as coaches or health professionals to defined what could be used as relevant factors.

5.3.3 Be personalised?

We conducted a study on the exploration of the perceptions and beliefs of elite athletics (track and field) athletes, coaches, and health professionals, on the use of injury prediction as an injury prevention strategy (Section 4.4). Our results are relevant for the development of injury prediction as an injury prevention strategy as they provide insights into how elite athletics stakeholders may respond to this preventive measure. As an exercise could not be adapted for a particular patient, provided athletes with personalised feedback without accompanying them could have negative effect (Section 4.4). It is therefore a challenge to manage individualisation of a high number of athletes through digital devices in a clinical trial. However knowledge from de-

terminant (e.g., motivation, beliefs) to adopt an injury prevention strategy as well as context, environmental, social, and delivery factors (e.g., culture, other end-users behaviour, resources, time) are could help to success adherence in a sports setting (Edouard et al., 2022b). Therefore, feedback to an athlete should be tailored to its individual ability to understand and use the information.

Chapter 6

PERSPECTIVES

6.1 Algorithm

Several systematic reviews (Van Eetvelde et al., 2021; Bullock et al., 2022a) and our scoping review (Section 4.1) have reported a high risk of bias in published injury prediction studies. A first perspective of the present work will be to use the last guideline on transparent reporting of a multivariable prediction model for individual prognosis or diagnosis using artificial intelligence (TRIPOD+AI) (Collins et al., 2024b) to report based on a checklist (Figure 31) the model development of our IPredict-AI study (Sections 4.2 and 4.3).

A second perspective, based on Section 5.2, will be to use retrospectively the database created from our IPredict-AI (Sections 4.2 and 4.3) project to answer several objective such as:

- Retry the development of new machine learning to see if different types of models (Section 2.2.2.3) induced change in the predictive performance.
- Retry the validation stage to follow recommendations regarding predictive machine learning models evaluations using bootstrapping methodology.(Collins et al., 2024a; Riley et al., 2024b,a).
- Retry the processing of the predictors to account for time dependence by using different time management strategies we found in our scoping review (Section 4.1), such as moving averages, time windows, but also the one proposed by Fonseca et al. (Fonseca et al., 2020) to see if it can improve the performance of the predictive machine learning model.

6.2 Something human

The use of injury prediction with machine learning as an injury prevention strategy could be another tool in the panel of injury prevention strategies available to athletes and stakeholders in athletics (Section 4.3). We also showed that using injury prediction could be a matter of context as different perceptions could induce different behaviour (Section 4.4). Maximising the individualisation of sports injury risk reduction approach is needed to increase the compliance and integration of injury prevention strategy (Edouard et al., 2022b). Therefore, based on the recent advancement of digital strategies in elite sports, it might be of interest to understand the interaction patterns between stakeholders via their respective perceptions of the role of digital strategies as injury risk reduction measures. Following our first published explorations (Navarro

et al., 2022, 2023), we can continue efforts trying to understand specific environment such as athletics clubs to better understand the determinants of adoptions of injury prevention strategies from different stakeholders (i.e., coaches, parents, team leaders, volunteer) and their role and inter-relationship among these injury prevention strategies to guide and individualise the integration of injury prevention strategies in the field.

Based on practical experience, particularly through active participation in injury and illness surveillance studies during international championships educating elite stakeholders about artificial intelligence seems to be a priority, as one of the main concerns is the feeling of losing legitimacy in the face of these new tools that could be mystified. However, machine learning should be seen as a tool that helps experts such as clinicians and coaches to better answer complex questions and not replace them because this technology needs them. Given the current performance of algorithms to predict the injury and the complexity of developing and use a monitoring system, it is far from being a magic recipe (Section 4.1). Therefore, this predictive machine learning modelling strategy should be considered as an additional injury prevention strategy that could help to reduce the risk of injury.

6.3 Won't stand down

Developing effective strategies to reduce the risk of injury requires an understanding of the aetiology of injuries (Section 2.1.3.2). The last decade has seen a paradigm shift in the study of sports injury causality, from monocausality to multifactorialism, recognising the complexity of a system of factors that interact with each other and have an integrative and recurrent influence on injury risk. This means that injury prevention strategies should also be developed using a holistic approach that recognises the complex aetiology of sports injuries (Jacobsson et al., 2017). An injury prediction feedback (I-REF) by machine learning tested in this PhD work was directly used by athletes Sections 4.2 and 4.3, and its implementation has been reported to be generally accepted by athletes and their entourage Section 4.4. Therefore, such feedback could be a part of an injury risk prevention strategy, which could include other domains of prevention approaches such as education and exercise-based programmes. Therefore, a direct perspective of the present works is to extend the capability of IPrevApp, i.e., the platform developed as part of this PhD thesis that hosts IPredict-AI, to add various injury risk reduction measures following

the same aim, trying to reduce the injury risk on athletics.

This doctoral project enabled the development of a digitalised monitoring system (IPrevApp) for research purposes in parallel with the implementation of the IPredict-AI project. Thus, several studies on athletics competitions have been covered through the use of this technology (Edouard et al., 2024a,c, 2023b,d; Dandrieux et al., 2024), which improves the possibilities of disseminating and completing the surveillance of injuries and illnesses. Over the years, a database of high-level track and field athletes has been built that can be used to predict injuries at championships based on predictors prior to the championships (Table 5).

6.4 Futurism

It is common to combine the terms machine learning and "big data". As the name suggests, this involves large amounts of data that are no longer manageable with conventional software or internet-based platforms (Dash et al., 2019). They exceed the amount of storage, processing and analysis power traditionally used (Dash et al., 2019). The "large" part of big data refers to the large volume. In addition to volume, the description of big data also includes velocity and variety. Velocity refers to the speed of data collection and the provision of data for further analyses. Variety refers to the different types of organised and unorganised data that can be captured in any form or system, such as video, audio, text or log files. Let's take a simple example of a table with several predictors (x columns) and a result (y column) column in a certain number of rows. We can enter in the paradigm of big data for predictive machine learning model by explore how manage an increase in the number of column, a number of rows or an increase in the both in term of feasibility (should we have enough outcome to build a model against the number of predictor?) and technics (are this predictors in the same format? Organized? Inducing the management of different sources like signals, images leading to more complexe models (Huang et al., 2022)). Indeed, one of the main problems with entering a "big data" paradigm is that it implies a model that is challenging in terms of transparency (e.g., deep learning models) because it implies the processing of different types of data (Huang et al., 2022). The era of "big data" has not yet began in the context of sports injury prediction. The challenges that already exist in healthcare, such as interpretability and transparency, should be given even greater consideration for the future of sports and exercise medicine and the integration of such technologies

in this area. Thus a fourth perspective is the feasibility of managing a "big data" paradigm with machine learning in the context of sports injury prediction by following the current challenge in terms of time, integration and explainability.

Chapter 7

CONCLUSION

This thesis work took place in a multi-institutions and multidisciplinary field with the aim to reinforce the collaboration between engeneering, data science, sports medicine and sports science around the investigation of the use of artificial intelligence and in particular machine learning in sports medicine in the context of injury prevention and specifically in athletics (track and field).

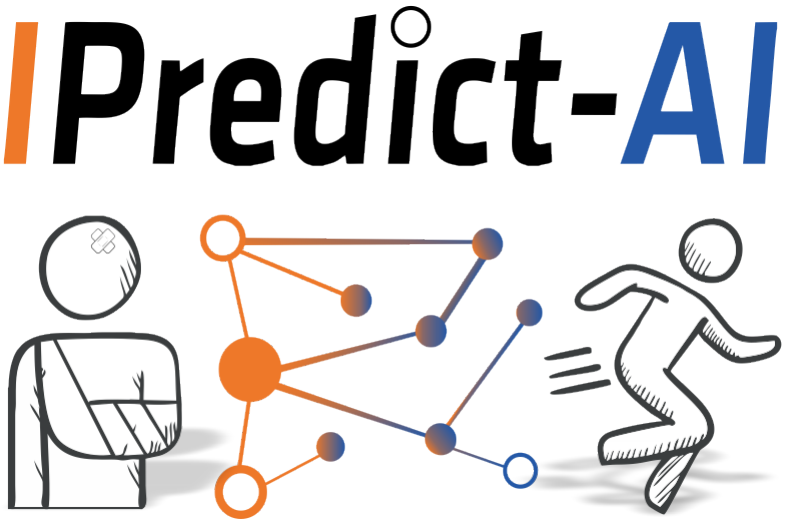
The first aim of this PhD was to describe the current machine learning approaches used to develop prediction models for sports injuries. A literature review was performed through a scoping review (Section 4.1) raising a need to tailor the machine learning approaches for sports injury prediction according to screening and monitoring data collections. Machine learning seems to be a promising tool to estimate injury risk, however if it is not well used it can be misleading. We suggested developing clear guidelines devoted to monitoring models due to time-dependency, class imbalance and management of missing data in order to increase the performance and reliability of these models.

The second aim of this PhD was to develop and assess the effectiveness of an injury prevention strategies using machine learning to reduce the occurrence of sports injuries in the specific context of athletics. Through a prospective cohort study (Sections 4.2 and 4.3) over a follow-up of 38 weeks in competing track and field athletes licensed with the French Federation of Athletics (FFA) we investigate the effectiveness of providing a daily individual injury risk estimation feedback from a machine learning model to athletes in reducing the injury burden in athletics. Thus, such individual injury risk estimation feedback can be considered as an additional injury prevention approach as the use of a daily injury risk estimation feedback, based on prognostic modelling using machine learning, allowed to reduce injury burden.

The third aim of this PhD was to maximise the integration of the injury prediction as an injury prevention strategy. Through a cross-sectional study we investigated the perceptions and beliefs of elite athletics athletes, coaches, and health professionals regarding the use of injury prediction as an injury prevention strategy. The interest in injury prediction as a strategy to reduce the risk of injury, the intention to use it, the support and the dissemination by elite athletics

stakeholders were high. However, caution is required as the potential stress caused by providing a prognostic of injury appears to be more nuanced and influenced by individual factors and appears to be of greater importance to athletes than to coaches and health professionals. Therefore, it is important to consider the context of implementation before integrating such technology in the field.

To conclude, the use of machine learning to predict sports injury is feasible as an injury prevention strategy and could therefore be considered as another tool among the existing injury prevention approaches for athletes, coaches and health professionals. However, despite the enormous progress of machine learning applications in our society, the use of sports injury prediction using machine learning is not ready to be effectively implemented without a shift to a more ecological and a rigorous modelling process.



Chapter 8

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Injury prediction in sports using artificial intelligence (IPredict-AI)

Summary

To minimise injury-related effects and consequences, injury prevention strategies are needed. Injury prevention strategies should be improved mainly due to the challenges of developing, implementing and analysing interventions and better addressing the complexity and multifactorial nature of injuries. To address these challenges, the area of knowledge and practice related to the development and use of digital technologies to improve health represents an opportunity.

In this context, the overall goal of this PhD work was to explore the use of artificial intelligence and in particular machine learning in sports injury prevention, and specifically in athletics (track and field) following three objectives: 1) to describe the current machine learning approaches used to develop prediction models for sports injuries, 2) to develop and assess the effectiveness of an injury prevention strategy using prediction models developed using machine learning in order to reduce the occurrence of sports injuries in the specific context of athletics, 3) to explore perceptions and beliefs of elite athletics (track and field) athletes, coaches, and health professionals, towards the use of injury prediction as an injury prevention strategy.

Our personal contributions have led to the following results: The scoping review included 28 studies, including 99 methods and 106 different models describing the current machine learning techniques used to develop prediction models for sports injuries. Two data collection approaches have been found, namely monitoring or screening, which lead to specific implications in the management of the machine learning process with methodological implications.

An individual injury risk estimation feedback based on prognostic modelling using machine learning could be considered as an additional injury prevention approach, while further research is mandated to determine its efficacy and mechanism of action.

Among elite athletics stakeholders (athletes, coaches and health professionals) the potentials perceived help, interest and intent to use of sports injury prediction as an injury prevention strategy were high, while potential psychological consequences such as stress appear to be of greater concern to athletes compared to coaches and health professionals.

To conclude, the use of machine learning to predict sports injury is feasible as an injury prevention strategy and could be therefore considered as another tool among the existing injury prevention approaches for athletes, coaches and health professionals. However, despite the enormous progress of machine learning applications in our society, the use of sports injury prediction using machine learning is not ready to be effectively implemented without a shift to a more ecological and a rigorous modelling process.