

Health challenges and acute sports injuries restrict weightlifting training of older athletes

Marianne Huebner ,^{1,2} Wenjuan Ma³

To cite: Huebner M, Ma W. Health challenges and acute sports injuries restrict weightlifting training of older athletes. *BMJ Open Sport & Exercise Medicine* 2022;**8**:e001372. doi:10.1136/bmjsem-2022-001372

► Additional supplemental material is published online only. To view, please visit the journal online (<http://dx.doi.org/10.1136/bmjsem-2022-001372>).

Accepted 11 June 2022



© Author(s) (or their employer(s)) 2022. Re-use permitted under CC BY-NC. No commercial re-use. See rights and permissions. Published by BMJ.

¹Department of Statistics and Probability, Michigan State University, East Lansing, Michigan, USA

²Department of Kinesiology, Michigan State University, East Lansing, Michigan, USA

³Center for Statistical Training and Consulting, Michigan State University, East Lansing, Michigan, USA

Correspondence to
Dr Marianne Huebner;
huebner@msu.edu

ABSTRACT

Objectives To quantify acute injuries sustained during weightlifting that result in training restrictions and identify potential risk factors or preventative factors in Master athletes and to evaluate potentially complex interactions of age, sex, health-related and training-related predictors of injuries with machine learning (ML) algorithms.

Methods A total of 976 Masters weightlifters from Australia, Canada, Europe and the USA, ages 35–88 (51.1% women), completed an online survey that included questions on weightlifting injuries, chronic diseases, sport history and training practices. Ensembles of ML algorithms were used to identify factors associated with acute weightlifting injuries and performance of the prediction models was evaluated. In addition, a subgroup of variables selected by six experts were entered into a logistic regression model to estimate the likelihood of an injury.

Results The accuracy of ML models predicting injuries ranged from 0.727 to 0.876 for back, hips, knees and wrists, but were less accurate (0.644) for shoulder injuries. Male Master athletes had a higher prevalence of weightlifting injuries than female Master athletes, ranging from 12% to 42%. Chronic inflammation or osteoarthritis were common among both men and women. This was associated with an increase in acute injuries.

Conclusions Training-specific variables, such as choices of training programmes or nutrition programmes, may aid in preventing acute injuries. ML models can identify potential risk factors or preventative measures for sport injuries.

INTRODUCTION

The health benefits of aerobic and strength-based physical activities for older adults have been highlighted in many research studies and include improving physical health such as cardiovascular function and muscle and bone mass, physical function such as mobility and independent living, and psychological health.^{1,2} Furthermore, participation in competitive sports is associated with a multitude of physical and psychosocial benefits^{3–7} with evidence of prevention of chronic diseases⁸ and better mental health compared with unstructured physical activities.⁹ However, engaging in physical activities, leisure or competitive, can lead to

WHAT IS ALREADY KNOWN ON THIS TOPIC

- ⇒ While there are many health benefits of weightlifting and competitions in older adults, there is a risk of injury with physical activity and sports.
- ⇒ Physiological function and performance declines with older age, and thus there can be a higher prevalence of injuries.

WHAT THIS STUDY ADDS

- ⇒ Machine learning approaches and expert models were used to investigate complex interactions among sport history, training-specific variables and health-related variables to identify modifiable factors that may prevent injuries in older athletes during their weightlifting career.
- ⇒ Chronic inflammation or osteoarthritis were common among both male and female weightlifters. This was associated with injuries at shoulders, knees, back or wrists.

HOW THIS STUDY MIGHT AFFECT RESEARCH, PRACTICE AND/OR POLICY

- ⇒ Athletes, coaches and health professionals should be aware of the high prevalence of chronic inflammation or osteoarthritis that restricts weightlifting training of Master athletes, and thus older athletes should be screened for this condition.
- ⇒ More education is needed for coaches and athletes to design training and nutrition programmes that optimise health and performance for Master athletes.

injuries. In studies on leisure-time physical activity, the risk of accompanying injuries was highest in contact and team sports^{10,11} and injuries were more likely in vigorous physical activities compared with light-intensity activities.¹² In older athletes, mobility is reduced and muscle fibres of older athletes may be susceptible to contraction-induced injury.¹³ Definitions of injury rates differ in publications.^{14,15} For example, they can be reported per 1000 hours of training, occurring within a specified time period, requiring medical attention or leading to training disruptions. In our study on Master weightlifters, the definition of injury captured occurrences during their weightlifting career where athletes had

restrictions in their weightlifting training, but they may or may not have sought medical care or stopped training completely. Instead, weightlifters could have modified their training by performing exercises that do not burden specific areas of their bodies.

Only a limited number of studies investigated strength training-related injuries. Weight-related injuries seen in emergency department visits were reported as caused by unusual movements or too heavy weights.¹⁶ Soldiers who spent more time strength training per week had a greater percentage of injuries over a 1-year period.¹⁷ This conflicts with findings where concurrent strength training may reduce the risk of injury.¹⁸ Some injuries have minor physical consequences. Overuse syndromes (pain and functional limitations) may not prevent the majority of either sex from training or competing, they may be eager to return to training,¹⁰ but the training programme may be altered due to these injuries.^{14 19 20} However, even with minor consequences, a disruption of sport activities has negative psychological effects on athletes,²¹ thus it is important to understand how health concerns affect training and to identify factors associated with injuries that may present preventative strategies or could be consequences of injuries.

Master athletes have a long-term engagement in a specific sport, and thus repetitive stress or overuse injuries can occur.²² Olympic-style weightlifting has seen a dramatic increase in participation in recent years.⁶ It requires the athlete to attempt a lift of maximal weight to achieve the highest combined total of two lifts, which are the clean and jerk and the snatch. Common injury sites in this sport are shoulders, back, hips, knees and wrists.^{16 18 20 23} Studies on prevalence of injuries and preventative strategies in Master weightlifters whose physical function and performance declines with age are needed. No previous study has investigated acute injuries sustained during weightlifting for Master weightlifters.

The objectives of this study were (1) to quantify acute injuries sustained during weightlifting that resulted in training restrictions and identify potential risk factors or preventative factors in Master athletes and (2) to evaluate potentially complex interactions of age, sex, health-related and training-related predictors of injuries with machine learning (ML) algorithms. We developed separate models for five common injury sites in weightlifting.

METHODS

Study population

Participants were 1051 Master weightlifters ages 35–88 years from 6 countries, Australia (AUS), Canada, Germany, Great Britain, Spain and the USA (dataset).²⁴ In June 2021, Masters weightlifters were invited to participate in an online survey through email and newsletters by the national governing bodies of weightlifting, and via online platforms including Facebook and Instagram. The study was described in more detail in Huebner *et al.*⁷

Measures

Definition of injury

Definitions of sports injuries differ between studies, such as acute injuries or gradually developing overuse symptoms when athletes continue training.^{14 15} To capture occurrences where athletes may or may not have sought medical care or have stopped training completely, in this study injuries were defined in relation to participation in weightlifting, namely whether training restriction occurred due to acute injuries sustained during weightlifting. This was a response, ‘yes’ or ‘no’ to the question ‘Have you ever had training restrictions due to acute injuries sustained during or while performing weightlifting?’ Since the survey was conducted during the pandemic when athletes may not have had access to training facilities, the time frame for occurrence of injuries included an athlete’s history of weightlifting.

Information about concurrent training and sport participation prior to starting weightlifting was collected with categories power lifting, ball sports, endurance, fitness, mobility (eg, yoga or Pilates), martial arts, as well as an open-ended question to specify these or other activities. Time for specific elements of weightlifting training included warm-up, classic lifts (snatch, clean and jerk and accessories such as hang snatch or clean from blocks), strength exercises (squats, presses), additional exercises (pull-ups, core, machines, etc) and cool-down with options 0–15 min, 15–30 min, 30–45 min, 45–60 min or more than 60 min. A Likert scale (strongly agree, agree, neither agree nor disagree, disagree, strongly disagree) was used to ask participants whether following a training-specific nutrition programme was important for their weightlifting training (ie, recovery, muscle increase). Survey questions are included in the online supplemental file.

Statistical methods

The purpose of the ML models is the prediction of acute injuries at multiple locations (shoulders, back, hips, knees and wrists) sustained during weightlifting that result in training restrictions and to evaluate the contributions of subgroups of variables on the accuracy of the prediction models. We employed several classification algorithms developed in both the statistical and the ML literature. This included support vector machines, generalised boosted methods, regularised logistic regression, random forests, one-layer neural network and naïve Bayesian methods for classification and prediction. A brief overview is given in the online supplemental file, and more details can be found in Hastie *et al.*²⁵ The ML algorithms were evaluated by randomly selecting 80% of the sample as the training set and testing the performance on the remaining 20% of the sample.²⁶ We used a 10-fold repeated cross-validation to tune the parameter estimates for each ML algorithm. Accuracy of model performances was compared. A variable importance metric was calculated to ascertain the relative contribution of a particular covariate to the accuracy of the prediction.

In addition, an expert model was constructed by collecting feedback from a group of experienced coaches and athletes, three women and three men, on variables included in this dataset that may potentially be associated with weightlifting injuries. Variables with at least two mentions were included in logistic regression models to obtain estimates for ORs and 95% CIs for each covariate. Due to the serious impact of injuries on health and training, a cut-off *p* value 0.10 was considered statistically significant, so that important factors will not be missed. All statistical analyses were performed using R v.4.0.3.²⁷

Patient and public involvement

Active Master weightlifters provided feedback on survey questions.

RESULTS

Of the 1051 respondents, 976 had complete data and were included in the analysis (7% missing variables). Women accounted for 51% of the respondents with a median age of 48 years (table 1). Common sites for weightlifting injuries were shoulders (35%), knees (26%), back (23%) and wrists (21%). Less common were hips (13%), elbows (12%) and ankles (2%). Most of the respondents engaged in physical activities or had sport experience prior to starting weightlifting (92%) (online supplemental table S1).

High blood pressure was more common among men (26%) than women (7%), particular at older ages (figure 1). Morbidities such as cardiovascular disease, diabetes or cancer increased with older age. Chronic inflammation/osteoarthritis was present in all age groups.

Predictive performance

The prediction performances of the models are evaluated on a holdout set of 195 cases (20% of the cases) (online supplemental figure S1). Injury rates were comparable between the training and test sets (online supplemental table S2). Correlations between predictor variables were low (online supplemental figure S2). The accuracy of ensemble predictions ranged from 0.727 to 0.876 but was less accurate for shoulder injuries at 0.644 (table 2). Classic statistical models (logistic regression) were comparable to the ML models when using all variables. Random forest performed similarly as ensemble predictions for all variables as well as for the subgroup of variables selected by experts.

Variable importance of predictors

The variable importance metric ascertains the relative contribution of a particular covariate to the accuracy of the prediction but does not indicate whether a variable is a risk factor for injuries. Age-related variables such as age, age at start of weightlifting or years of experience were among the top three predictors for injury locations. Training frequency or length of session for groups of exercises (warm-up, cool-down, supplementary) were

also top predictors. Sex, chronic inflammation/osteoarthritis were rated high for shoulder injuries, while training programmes (own or coach) were important for back, knee and wrist injuries (table 3, online supplemental table S4, figure S3).

Expert model estimates

A subset of variables was selected based on expert feedback and included in logistic regression models to estimate the likelihood of an acute injury sustained during weightlifting for the injury locations. Men were almost two times as likely to sustain injuries for shoulders, back, knees or wrists than women (table 4). Injuries are more likely to occur at younger ages for knees and wrists. Chronic inflammation/osteoarthritis increased the risk at all injury locations. Following their own programme may be associated with shoulder injuries, but this could be confounded with age, since older male weightlifters are more likely to follow their own programme.²⁸ Longer time spent on supplementary exercises were associated with sustaining wrist injuries and longer time to cool-down was associated with an increased risk for shoulder injuries. Concurrent yoga/Pilates lowered the risk of back injuries. Those who believe that following a training-specific nutrition programme was important for their weightlifting training (ie, recovery, muscle increase) were less likely to report a shoulder injury. Following their own programme was associated with knee injuries. Concurrent training in CrossFit was associated with back injuries. However, prior sport participation (body building, power lifting, ball sports, gymnastics) was not associated with an injury risk sustained during weightlifting.

DISCUSSION

A total of 976 respondents from six countries, ages 35–88 years, were included in an analysis to predict acute injuries sustained during weightlifting that restrict training. The main findings were as follows: (1) men had a higher prevalence of weightlifting injuries than women; (2) chronic inflammation or osteoarthritis were common among both men and women. This was associated with injuries; (3) training-specific variables, such as choices of training programmes or nutrition programmes may aid in preventing injuries.

Sport injuries in older athletes

Self-reported locations for acute weightlifting injuries that affected training were shoulders, back, hips, knees and wrists with a prevalence from 13% to 35% during their weightlifting careers in this study cohort. Shoulders, knees, hips and lower back were also the most reported injury locations for weightlifting or powerlifting.^{15 20 29} In Swedish subelite powerlifters, ages 18 and above, 20%–40% experienced injuries in the prior year. However, while injuries affected the training practice, these did not prevent the athletes from training or competing.²⁰

**Table 1** Characteristics of respondents

	Females (n=499)	Males (n=477)	Total (n=976)
Age, years, median (first, third quartile)	46 (39, 55)	51 (42, 60)	48 (41, 58)
35–44	45%	33%	39%
45–59	42%	39%	40%
60+	13%	28%	21%
Age at start of weightlifting, median (first, third quartile)	39 (34, 46)	32 (16, 41)	36 (28, 45)
Years of experience, median (first, third quartile)	6 (3, 9)	11 (6, 39)	8 (4, 15)
Education level, high	77%	71%	74%
Chronic conditions			
High BP	7%	26%	17%
CV	1%	5%	3%
Cancer	6%	6%	6%
Diabetes	2%	3%	3%
Arthritis/osteoarthritis	46%	49%	48%
Acute injuries during weightlifting			
Shoulders	28%	42%	35%
Knees	19%	34%	26%
Back	19%	28%	23%
Wrists	17%	27%	22%
Hips	13%	12%	13%
Elbows	9%	16%	12%
Ankles	2%	3%	2%
Training-related variables			
Programme by self	12%	50%	31%
Programme by coach	70%	45%	58%
Programme by remote coach	21%	17%	19%
Days/week	3.96 (1.08)	3.61 (1.15)	3.79 (1.13)
Length of session	2.75 (0.81)	2.75 (0.81)	2.75 (0.81)
Hours/week (est.)	7.52 (2.79)	6.84 (2.75)	7.19 (2.79)
Time warm-up	1.42 (0.57)	1.46 (0.60)	1.44 (0.58)
Time classic lifts	3.68 (1.07)	3.65 (1.01)	3.67 (1.04)
Time strength exercises	2.70 (0.94)	2.79 (1.00)	2.75 (0.97)
Time supplementary exercises	1.71 (0.79)	1.64 (0.82)	1.67 (0.81)
Time cool-down	1.07 (0.27)	1.11 (0.36)	1.09 (0.32)
Attitude towards nutrition	1.65 (0.81)	1.90 (0.95)	1.77 (0.89)
Continuous variables are summarised as mean (SD) unless otherwise noted. BP, blood pressure; CV, cardiovascular disease.			

Injuries in older athletes are less well studied.^{13,30} While physiological function and sports performance declines with advancing age,³¹ competitive Masters are examples of resilience and functional capacity,⁴ but Masters athletes may be at an elevated risk of injury compared with their younger counterparts.³² In elderly male athletes, ages 70–81, the majority (81%) had experienced a sports-related injury in the past 10 years.³³ Masters runners at an international competition reported an injury rate of 49% in the previous year with knee injuries accounting for

19%. Furthermore, common medications used in older athletes for short-term symptom relief or for management of chronic conditions may have significant adverse effects on physiological functions.³⁴

Factors related to weightlifting injuries

In this international group of Masters weightlifters, men were almost twice as likely to sustain injuries than women. Sex differences in sport injuries have also been observed in prior studies.³⁵ Chronic inflammation or osteoarthritis

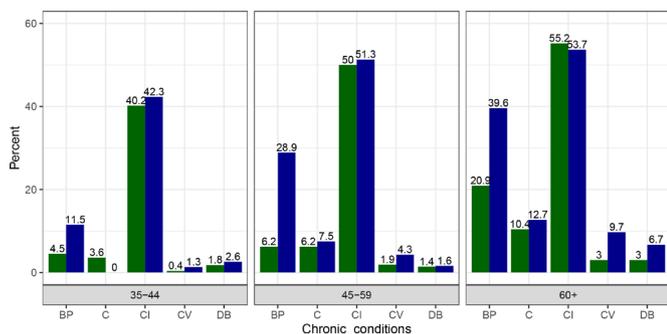


Figure 1 Chronic conditions reported by women (green) and men (blue). All except CI were based on the question ‘have you ever had a doctors’ diagnosis of...?’. BP, high blood pressure; C, cancer; CI, chronic inflammation/osteoarthritis; CV, cardiovascular disease; DB, diabetes.

was associated with injuries. A longer time for cool-down or supplementary exercises was associated with an increased injury risk. The length of time for specific exercises could be an indicator of overuse, adding more stress to joints after a training session. Older male weightlifters more commonly supplement a programme by their coach with their own programme than younger or female Master weightlifters.²⁸ While in our study following one’s own programme was associated with knee injuries, it is possible that the weightlifters found it necessary to adjust their programme due to pre-existing conditions or lack of access to qualified coaches familiar with the needs of older athletes. Mobility exercises lowered the risk of back injuries consistent with recommendations in other studies.³⁶ Higher training frequency was associated with injuries similar to previous findings for powerlifters²⁰ where overload could be a risk factor or lower training frequency as a consequence of injuries. Nutrition supporting training and recovery may reduce the injury risk. Access to qualified nutrition support has been highlighted for achieving competitive goals, energy and muscle gain or retention.³⁷ Adequate protein intake and optimising nutrition may affect training capacity, muscle mass and reduce inflammatory burden in older athletes.³⁸ While weightlifters often meet protein requirements, women placed more importance on nutrition than men, and older men were less aware of the utility of nutrition for training.²⁸

ML algorithms to predict sports injuries

Multiple factors can influence sports performances requiring coaches, medical professionals and knowledge

about nutrition. We explored the application of several ML algorithms to identify potential factors associated with weightlifting injuries in Master athletes. These probabilistic models can use increasing numbers of variables regarding training factors, health conditions and experience with prior sports. The accuracy of ensemble ML methods is highest for back, knee, hips and wrist injuries, 0.727–0.876, and lowest for shoulder injuries, 0.644. This level of performance is similar to ML models in team sports with an accuracy of 0.70³⁹ or 0.75–0.829⁴⁰ in a systematic review of 11 studies with number of participants ranging from 25 to 363 participants. ML models are only one step in identifying potentially important variables to investigate as risk factors, preventative measures or possible interaction effects. Classic logistic regression models using all variables had similar accuracy as the ML models and could provide further details regarding ORs for a subset of expert-selected predictors.

Study limitations and strengths

Injuries were self-reported in an online survey, and thus may suffer from recall bias. Injuries were defined as acute injuries sustained during weightlifting resulting in training restrictions. This does not address whether an injury required medical attention or led to training interruptions for any length of time. This is both a limitation and a strength, since there is no indication about severity of injuries or current prevalence, but it captures health restrictions more broadly in this population. The survey was given in June 2021, over a year since the start of the COVID-19 pandemic, and thus it was not possible to ask about injuries in the year prior, since athletes may have trained less or found new ways of physical activities due to closures of training facilities or cancellation of competitions. Causality between training practices and injury occurrence cannot be established since information about timing of the injuries was not available. Training practices could be risk factors for injuries, or practices may change as a consequence of injuries. Sport history and prior injuries as well as participation in other sports in addition to weightlifting could have an influence on injuries occurring during weightlifting. Chronic inflammation or osteoarthritis was self-reported, and thus does not meet the rigour of medical diagnoses. However, if the answer was affirmative to the question about presence of chronic inflammation, respondents were asked to specify, and thus more detailed information was available for data quality checks.

Table 2 Performance metrics of the prediction models

	Back injuries	Knee injuries	Shoulder injuries	Wrist injuries	Hip injuries
Ensemble—all variables	0.773	0.727	0.644	0.774	0.876
Random forest—all variables	0.768	0.742	0.619	0.790	0.876
Logistic regression—all variables	0.768	0.742	0.619	0.790	0.876
Random forest—expert variables	0.748	0.713	0.683	0.744	0.901

**Table 3** Top predictors for injury locations ranked by variable importance metric

Shoulder injuries	Knee injuries	Back injuries	Wrist injuries	Hip injuries
Sex	Age at start of weightlifting	Years of experience	Age	Number of training days
Arthritis/osteoarthritis	Years of experience	Age at start of weightlifting	Hours per week (estimated)	Hours per week (estimated)
Age	Programme own	Programme own	Length of training session	Age
Years of experience	Programme by coach	Programme by coach	Programme by remote coach	Time for supplementary exercises
Concurrent body building	Concurrent CrossFit	Prior CrossFit	Prior ball sports	Education level
Time for cool-down	Length of training session	Prior body building	Number of training days	Prior CrossFit
Concurrent fitness training	Prior martial arts	Concurrent CrossFit	Prior CrossFit	Time for warm-up
Age at start of weightlifting	Prior ball sports	Time for supplementary exercises	Age at start of weightlifting	Programme coach
Nutrition	Prior body building	Prior powerlifting	Time for classic lifts	Programme own
Prior ball sports	Time for strength training	Prior ball sports	Concurrent ball sports	Concurrent body building

Table 4 ORs and 95% CIs for predicting the likelihood of a weightlifting injury at different locations

	Shoulders		Knees		Back		Wrists		Hips	
	OR (95% CI)	P value								
Sex, male	1.81 (1.32 to 2.47)	<0.001	1.82 (1.29 to 2.57)	0.001	1.50 (1.05 to 2.15)	0.024	2.17 (1.51 to 3.12)	<0.001	0.81 (0.52 to 1.27)	0.365
Age (10 years)	0.98 (0.85 to 1.13)	0.811	0.78 (0.66 to 0.92)	0.004	0.92 (0.79 to 1.08)	0.319	0.73 (0.62 to 0.87)	<0.001	0.98 (0.85 to 1.13)	0.156
Age at start	1.01 (0.99 to 1.02)	0.389	1.01 (1.00 to 1.02)	0.229	0.99 (0.98 to 1.01)	0.208	1.00 (0.98 to 1.01)	0.831	1.01 (0.99 to 1.02)	0.992
Programme—own	1.27 (0.89 to 1.81)	0.186	1.38 (0.95 to 2.02)	0.093	1.25 (0.84 to 1.84)	0.273	1.04 (0.69 to 1.56)	0.865	1.27 (0.89 to 1.81)	0.110
Nutrition	0.86 (0.73 to 1.01)	0.064	1.08 (0.91 to 1.28)	0.406	0.91 (0.76 to 1.09)	0.321	1.12 (0.93 to 1.34)	0.245	0.86 (0.73 to 1.01)	0.894
Number of days per week	1.06 (0.94 to 1.21)	0.340	1.02 (0.88 to 1.17)	0.807	1.03 (0.90 to 1.19)	0.657	1.11 (0.96 to 1.29)	0.161	1.06 (0.94 to 1.21)	0.013
Time warm-up	1.09 (0.85 to 1.40)	0.499	1.22 (0.93 to 1.6)	0.151	1.08 (0.82 to 1.43)	0.574	1.01 (0.75 to 1.35)	0.969	1.09 (0.85 to 1.40)	0.147
Time cool-down	1.51 (0.98 to 2.34)	0.063	0.95 (0.6 to 1.53)	0.842	0.79 (0.48 to 1.31)	0.368	0.76 (0.45 to 1.29)	0.312	1.51 (0.98 to 2.34)	0.304
Time supplementary	1.04 (0.87 to 1.25)	0.637	0.96 (0.79 to 1.18)	0.715	1.06 (0.87 to 1.29)	0.581	1.23 (1.01 to 1.51)	0.038	1.04 (0.87 to 1.25)	0.979
Concurrent CrossFit	1.08 (0.7 to 1.68)	0.718	0.82 (0.49 to 1.36)	0.433	1.5 (0.94 to 2.4)	0.089	1.31 (0.80 to 2.16)	0.280	1.08 (0.7 to 1.68)	0.530
Concurrent yoga/Pilates	0.84 (0.62 to 1.13)	0.245	0.8 (0.57 to 1.11)	0.177	0.7 (0.50 to 0.98)	0.040	0.98 (0.69 to 1.38)	0.893	0.84 (0.62 to 1.13)	0.400
Prior sports	1.07 (0.79 to 1.44)	0.661	1.26 (0.90 to 1.76)	0.173	1.21 (0.86 to 1.69)	0.280	1.18 (0.83 to 1.67)	0.363	1.07 (0.79 to 1.44)	0.697
Chronic inflammation/osteoarthritis	1.54 (1.17 to 2.03)	0.002	1.98 (1.46 to 2.68)	<0.001	1.35 (0.99 to 1.84)	0.056	1.57 (1.14 to 2.17)	0.006	1.54 (1.17 to 2.03)	0.086

Implications

It is of note that Master weightlifters continue training despite health challenges due to injuries that could be minor. Commonly reported injury locations with prevalence 13%–35% were shoulders, knees, back, hips and wrists. Men were at higher risk of experiencing injuries at all injury locations, except hips. Athletes, coaches and health professionals should be aware of the high prevalence of chronic inflammation or osteoarthritis that restricts weightlifting training of Master athletes; thus, athletes should be screened for osteoarthritis and the training programme should be adjusted accordingly to avoid worsening of this condition or future sports injuries. Several training-related factors were identified as potentially associated with injury locations. A combination of factors rather than single factors may contribute to the risk of injuries and a holistic approach to athletes' health is needed. Modifiable factors for this population were training frequency and nutrition. Designing their own programme, a longer time on cool-down or supplementary exercises, or disregarding nutrition, were associated with increased risk of injury. It can be speculated that following one's own training programme may be necessary to modify exercises to fit their functional capacity. Longer cool-down time may be a proxy for adding more exercises at the end of a possibly strenuous training unit. Thus, training exercises and times scheduled for these should be carefully considered in a weightlifting training programme. Further prospective cohort studies with detailed training and nutrition diaries are needed to investigate effective preventative strategies for weightlifting injuries.

To our knowledge, this work represents one of the first direct comparisons of several probabilistic and deterministic prediction methods for injuries in an individual sport. Our results are encouraging for more widespread adoption of data-driven probabilistic risk-monitoring tools in Masters sports.

Twitter Marianne Huebner @MHuebnerPhD

Acknowledgements Expert coaches and athletes provided feedback on the variables in this dataset that are potentially associated with weightlifting injuries. Joelle Emery, President Michigan Weightlifting Federation; Daniela Jantzen, Germany, National Masters Chair; Jodi Stumbo, USA, National Masters Hall of Fame; Michael Cohen, USA, National Masters Chair; Mark Gomes, Canada, President, and National Masters Chair; Fred Lowe, 3 times Olympian. The results of this study do not constitute endorsement by these individuals.

Contributors MH conceptualised the study and reviewed the literature. MH is the guarantor of the study. Both authors performed statistical analyses and wrote the manuscript.

Funding The authors have not declared a specific grant for this research from any funding agency in the public, commercial or not-for-profit sectors.

Competing interests None declared.

Patient and public involvement Active weightlifters provided feedback on the survey questions.

Patient consent for publication Consent obtained directly from patient(s)

Ethics approval This study involves human participants but the study protocol was approved by the Michigan State University Human Research Ethics Committee and all participants provided online informed consent (STUDY00006179) exempted

this study. Participants gave informed consent to participate in the study before taking part.

Provenance and peer review Not commissioned; externally peer reviewed.

Data availability statement Data are available in a public, open access repository. Reference: Huebner, Marianne (2022), Weightlifting Injuries in Master Athletes, Dryad Digital Repository, Dataset, <https://doi.org/10.5061/dryad.51c59zwb3>.

Supplemental material This content has been supplied by the author(s). It has not been vetted by BMJ Publishing Group Limited (BMJ) and may not have been peer-reviewed. Any opinions or recommendations discussed are solely those of the author(s) and are not endorsed by BMJ. BMJ disclaims all liability and responsibility arising from any reliance placed on the content. Where the content includes any translated material, BMJ does not warrant the accuracy and reliability of the translations (including but not limited to local regulations, clinical guidelines, terminology, drug names and drug dosages), and is not responsible for any error and/or omissions arising from translation and adaptation or otherwise.

Open access This is an open access article distributed in accordance with the Creative Commons Attribution Non Commercial (CC BY-NC 4.0) license, which permits others to distribute, remix, adapt, build upon this work non-commercially, and license their derivative works on different terms, provided the original work is properly cited, appropriate credit is given, any changes made indicated, and the use is non-commercial. See: <http://creativecommons.org/licenses/by-nc/4.0/>.

ORCID iD

Marianne Huebner <http://orcid.org/0000-0002-9694-9231>

REFERENCES

- Jenkin CR, Eime RM, Westerbeek H, *et al*. Sport and ageing: a systematic review of the determinants and trends of participation in sport for older adults. *BMC Public Health* 2017;17:976.
- Langhammer B, Bergland A, Rydwick E. The importance of physical activity exercise among older people. *Biomed Res Int* 2018;2018:1–3.
- Eime RM, Harvey JT, Charity MJ, *et al*. Age profiles of sport participants. *BMC Sports Sci Med Rehabil* 2016;8:6.
- Tanaka H, Tarumi T, Rittweger J. Aging and physiological lessons from master athletes. *Compr Physiol* 2019;10:261–96.
- Dionigi RA. The competitive older athlete: a review of psychosocial and sociological issues. *Topics in Geriatric Rehabilitation* 2016;32:55–62.
- Huebner M, Arrow H, Garinther A, *et al*. How heavy lifting lightens our lives: content analysis of perceived outcomes of masters weightlifting. *Front Sports Act Living* 2022;4:778491.
- Huebner M, Ma W, Rieger T. Weightlifting during the COVID-19 Pandemic-A transnational study regarding motivation, barriers, and coping of master athletes. *Int J Environ Res Public Health* 2021;18:9343.
- Kettunen JA, Kujala UM, Kaprio J, *et al*. Health of master track and field athletes: a 16-year follow-up study. *Clin J Sport Med* 2006;16:142–8.
- Eime RM, Young JA, Harvey JT, *et al*. A systematic review of the psychological and social benefits of participation in sport for adults: informing development of a conceptual model of health through sport. *Int J Behav Nutr Phys Act* 2013;10:135.
- Parakkari J, Kannus P, Natri A, *et al*. Active living and injury risk. *Int J Sports Med* 2004;25:209–16.
- Pons-Villanueva J, Seguí-Gómez M, Martínez-González MA. Risk of injury according to participation in specific physical activities: a 6-year follow-up of 14 356 participants of the sun cohort. *Int J Epidemiol* 2010;39:580–7.
- Choe J-P, Kim J-S, Park J-H, *et al*. When do individuals get more injured? relationship between physical activity intensity, duration, participation mode, and injury. *Int J Environ Res Public Health* 2021;18:10855.
- Tayrose GA, Beutel BG, Cardone DA, *et al*. The masters athlete: a review of current exercise and treatment recommendations. *Sports Health* 2015;7:270–6.
- Timpka T, Jacobsson J, Bickenbach J, *et al*. What is a sports injury? *Sports Med* 2014;44:423–8.
- Aasa U, Svartholm I, Andersson F, *et al*. Injuries among weightlifters and powerlifters: a systematic review. *Br J Sports Med* 2017;51:211–9.
- Kerr ZY, Collins CL, Comstock RD. Epidemiology of weight training-related injuries presenting to United States emergency departments, 1990 to 2007. *Am J Sports Med* 2010;38:765–71.



- 17 Grier T, Brooks RD, Solomon Z, *et al.* Injury risk factors associated with weight training. *J Strength Cond Res* 2022;36:e24–30.
- 18 Lauersen JB, Bertelsen DM, Andersen LB. The effectiveness of exercise interventions to prevent sports injuries: a systematic review and meta-analysis of randomised controlled trials. *Br J Sports Med* 2014;48:871–7.
- 19 Foster C, Wright G, Battista RA, *et al.* Training in the aging athlete. *Curr Sports Med Rep* 2007;6:200–6.
- 20 Strömbäck E, Aasa U, Gilenstam K, *et al.* Prevalence and consequences of injuries in Powerlifting: a cross-sectional study. *Orthop J Sports Med* 2018;6:232596711877101.
- 21 Malcolm D, Pullen E. 'Everything I enjoy doing I just couldn't do': Biographical disruption for sport-related injury. *Health* 2020;24:366–83.
- 22 Baker BD, Lapiere SS, Tanaka H. Role of Cross-training in orthopaedic injuries and healthcare burden in masters swimmers. *Int J Sports Med* 2019;40:52–6.
- 23 Lavalley ME, Balam T. An overview of strength training injuries: acute and chronic. *Curr Sports Med Rep* 2010;9:307–13.
- 24 Huebner M. Dataset: Weightlifting injuries in master athletes. *Dryad Digital Repository* 2022.
- 25 Hastie T, Tibshirani R, Friedman J. *The elements of statistical learning: data mining, inference, and prediction*. 2nd ed. Springer-Verlag, 2001. <https://www.amazon.com/Elements-Statistical-Learning-Prediction-Statistics/dp/0387848576>
- 26 Liu Y, Chen P-HC, Krause J, *et al.* How to read articles that use machine learning: users' guides to the medical literature. *JAMA* 2019;322:1806–16.
- 27 R Core Team. *R: a language and environment for statistical computing*. Vienna, Austria: R Foundation for Statistical Computing, 2021. <http://www.R-project.org/>
- 28 Huebner M, Faber F, Currie K, *et al.* How do master Weightlifters train? A transnational study of Weightlifting training practices and concurrent training. *Int J Environ Res Public Health* 2022;19:2708.
- 29 Raske A, Norlin R. Injury incidence and prevalence among elite weight and power lifters. *Am J Sports Med* 2002;30:248–56.
- 30 Patelia S, Stone RC, El-Bakri R, *et al.* Masters or pawns? examining injury and chronic disease in male masters athletes and chess players compared to population norms from the Canadian community health survey. *Eur Rev Aging Phys Act* 2018;15:15.
- 31 Huebner M, Meltzer DE, Perperoglou A. Age-Associated performance decline and sex differences in Olympic Weightlifting. *Med Sci Sports Exerc* 2019;51:2302–8.
- 32 Opar D, Drezner J, Shield A, *et al.* Acute injuries in track and field athletes: a 3-year observational study at the Penn relays carnival with epidemiology and medical coverage implications. *Am J Sports Med* 2015;43:816–22.
- 33 Kallinen M, Alén M. Sports-Related injuries in elderly men still active in sports. *Br J Sports Med* 1994;28:52–5.
- 34 Ferry B, DeCastro A, Bragg S. Common prescription medications used in athletes. *Prim Care* 2020;47:49–64.
- 35 Bueno AM, Pilgaard M, Hulme A, *et al.* Injury prevalence across sports: a descriptive analysis on a representative sample of the Danish population. *Inj Epidemiol* 2018;5:6.
- 36 Buckwalter JA, Martin JA. Sports and osteoarthritis. *Curr Opin Rheumatol* 2004;16:634–9.
- 37 Close GL, Sale C, Baar K, *et al.* Nutrition for the prevention and treatment of injuries in track and field athletes. *Int J Sport Nutr Exerc Metab* 2019;29:189–97.
- 38 Strasser B, Pesta D, Rittweger J, *et al.* Nutrition for older athletes: focus on Sex-Differences. *Nutrients* 2021;13:1409.
- 39 Ramkumar PN, Luu BC, Haeberle HS, *et al.* Sports medicine and artificial intelligence: a primer. *Am J Sports Med* 2022;50:1166–74.
- 40 Van Eetvelde H, Mendonça LD, Ley C, *et al.* Machine learning methods in sport injury prediction and prevention: a systematic review. *J Exp Orthop* 2021;8:27.

SUPPLEMENTAL MATERIAL

PARTICIPATION IN OTHER SPORTS

Weightlifters train concurrently in other sports, of which CrossFit and endurance physical activities are the most common.

Reference:

Huebner M, Faber F, Currie K, *et al.* How Do Master Weightlifters Train? A Transnational Study of Weightlifting Training Practices and Concurrent Training. *International Journal of Environmental Research and Public Health* 2022;**19**:2708. doi:10.3390/ijerph19052708

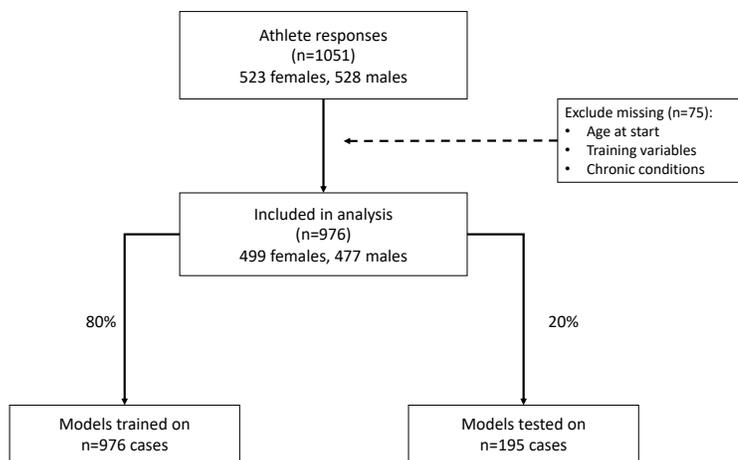
Table S1: Concurrent training and prior sport participation

	Concurrent training		Prior sport participation	
	Females	Males	Females	Males
CrossFit	0.45 ²²⁵ / ₄₉₉	0.30 ¹⁴¹ / ₄₇₇	0.68 ³⁴¹ / ₄₉₉	0.42 ²⁰² / ₄₇₇
Ball sports	0.05 ²⁷ / ₄₉₉	0.14 ⁶⁵ / ₄₇₇	0.30 ¹⁴⁹ / ₄₉₉	0.51 ²⁴³ / ₄₇₇
Martial arts	0.02 ¹⁰ / ₄₉₉	0.04 ¹⁹ / ₄₇₇	0.11 ⁵³ / ₄₉₉	0.18 ⁸⁵ / ₄₇₇
Body building	0.11 ⁵⁴ / ₄₉₉	0.16 ⁷⁶ / ₄₇₇	0.37 ¹⁸⁶ / ₄₉₉	0.40 ¹⁹¹ / ₄₇₇
Powerlifting	0.06 ²⁸ / ₄₉₉	0.07 ³³ / ₄₇₇	0.13 ⁶⁵ / ₄₉₉	0.21 ⁹⁸ / ₄₇₇
Fitness	0.20 ¹⁰¹ / ₄₉₉	0.21 ¹⁰¹ / ₄₇₇	0.39 ¹⁹⁴ / ₄₉₉	0.28 ¹³³ / ₄₇₇
Endurance	0.24 ¹¹⁹ / ₄₉₉	0.28 ¹³² / ₄₇₇	0.45 ²²³ / ₄₉₉	0.33 ¹⁵⁸ / ₄₇₇
Track and field	0.01 ⁷ / ₄₉₉	0.04 ²¹ / ₄₇₇	0.16 ⁸⁰ / ₄₉₉	0.25 ¹¹⁸ / ₄₇₇
Yoga/Pilates	0.19 ⁹⁴ / ₄₉₉	0.05 ²⁴ / ₄₇₇	0.24 ¹¹⁸ / ₄₉₉	0.05 ²⁵ / ₄₇₇
Gymnastics	0	0	0.07 ³⁴ / ₄₉₉	0.02 ⁹ / ₄₇₇

METHODS FOR MACHINE LEARNING

The aim of is to predict a binary outcome, namely injury, as a function of covariates. For machine learning approaches the dataset is divided into a training set and then performance is evaluated in a validation or test set (ref Liu, Jama 2019). Machine learning models have prespecified settings, called hyperparameters. These hyperparameters regulate the trade-off between over-fitting and under-fitting a model. The optimal values of hyperparameters cannot be found by fitting the models with data. Tuning is the process to identify the value of the hyperparameter through searching among a series of values. We used a 10-fold repeated cross-validation to tune the parameter estimates for each ML algorithm.

A flow chart summarizing the number of athletes and exclusions due to missing training variables or chronic conditions is shown in Figure S1.

Figure S1. Study flow diagram for training and test data.

There were 41 variables divided into the following groups of predictors:

- demographic variables (p=5): sex, age, education level, age at start of weightlifting, and years of experience
- chronic conditions (p=5): high blood pressure, cardiovascular disease, cancer, diabetes, and arthritis/osteoarthritis
- training frequency (p=3): number of days per week, length of training session, hours per week (estimated)
- time for core weightlifting training (p=2): classic lifts (snatch, clean and jerk), strength exercises (squats, presses)
- training extensions (p=4): time for warm-up, cool-down, or supplementary exercises, attitude towards nutrition to support training (recovery, muscle gain)
- training program (p=3): following own or a coach's program (in-person or remote)
- concurrent training (p=9): CrossFit, ball sports, martial arts, body building, powerlifting, endurance training, general fitness, track and field, mobility (e.g. yoga/Pilates)
- prior sport participation (p=10): all concurrent sports and gymnastics

For each test set the models produce a probability of injury based on the covariates. Finally, the predictions were ensembled across the algorithms to combine information from each ML algorithm and possibly achieve better prediction performance for each injury location. This was repeated for all variables and leaving out the specified groups of variables. Performance was measured as accuracy which is the proportion of correctively predicted results out of the entire sample. We used the algorithms to classify the injury cases and ensemble the predictions for injuries at these locations. The performance of random forest and logistic regression models were used as references, using all variables and using a selection of variables.

The R packed caret was used to implement the algorithms, tuning the hyperparameters and ensemble the predictions.

Reference:

Kuhn M. Caret package. *Journal of Statistical Software* 2008; **28**(5)

OVERVIEW of machine learning algorithms used for the ensemble prediction models

1. Support vector machine (SVM)
were developed by Cortes and Vapnik (1995) for classification and regression problems. For classification tasks in SVM, all data points are mapped in an n-dimensional space which is formed by the n features or covariates. Then the algorithm searches for an optimal decision hyperplane using the covariates to separate points to different classes. SVM uses a kernel function to project the input data space in certain form. There are several choices of kernel functions, we tried the most popular kernels including linear, radial, and polynomial kernels. The selection is decided by the accuracy of the holdout set. The c parameter controls the trade-off between the sensitivity of the boundary among groups and misclassification rate. When c is small, the penalty for misclassification is low the boundary is less sensitive to noise, but the misclassification rate will be higher. When c is large the effects are the opposite. We identified the best value of c by trying a range of values (“tuning of the c parameter”).

Reference:

Cortes C, Vapnik V. Support-vector networks. *Machine Learning*. 1995; **20**: 273–297.

2. Stochastic Gradient Boosting is one of the ensemble methods, which ensemble predictions of a series of weak learning models, usually decision tree models. These models perform only a little better than random guessing, hence are called weak learning models. Each weak learning model improves upon the previous model. Stochastic gradient descent samples a subset of data to grow the subsequent tree. This method helps the algorithm to avoid local minima and to approach the global minimum. We tuned several Tuning parameters are the number of trees, depth of each tree (how many branches to ensemble), learning rate (how quickly the algorithm proceeds down the gradient descent), and the minimum number of observations allowed in the trees’ terminal nodes.

Reference:

Friedman JH. Stochastic Gradient Boosting, *Computational Statistics and Data Analysis* 2002; **38**(4):367-378.

3. Regularized logistic regression uses regularization to penalize model complexity. Regularization constrains the sizes of the coefficients. There are two main types of regularizations: Ridge regression and least absolute shrinkage and selection operator (LASSO). Both methods use a tuning parameter lambda to decide the importance of the penalty. Higher penalty reduces the magnitude of the coefficients. We used a hybrid model of Ridge and LASSO called Elastic Net, which linearly combines the two. The best combination is identified through cross-validation.

Reference:

Friedman J, Hastie T, Tibshirani R. Regularization Paths for Generalized Linear Models via Coordinate Descent. *Journal of Statistical Software*, 2010; **33** (1): 1–22. <https://doi.org/10.18637/jss.v033.i01>.

Tibshirani R, Bien J, Friedman, J *et al.* 2012. Strong Rules for Discarding Predictors in Lasso-Type Problems. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)* 2012; **74** (2): 245–66. <https://doi.org/10.1111/j.1467-9868.2011.01004.x>.

4. Random forests is another type of ensemble method. It creates multiple classification trees by drawing bootstrapped samples of the data and randomly select subsets of the predictors. Then, it ensembles the predictions of the trees. Random forests can capture the nonlinear associations between predictors and outcome variables. We tuned the Tuning parameters are the number of randomly selected predictors, splitting rules (Gini index and `extratrees`), and minimal node size.

Reference:

Breiman, L. Random forests. *Machine Learning* 2001; **45**:5-32. 10.1023/A:1010933404324.

Wright MN, Ziegler, A. ranger: A fast implementation of random forests for high dimensional data in C++ and R. *J Stat Softw* 2017; **77**:1-17. 10.18637/jss.v077.i01.

5. Single-hidden-layer neural network models can be viewed as nonlinear regression models. These models extract features (or units) from data and then come up with predictions. The complexity of the models is partially dependent on the number of layers. Each layer can be considered as one time of feature extraction. The number of features is determined by the number of units. The type of neural networks that are considered in this paper is the single-hidden-layer neural network. This function allows the users to adjust the number of units and the regularization parameter to avoid overfitting. We tuned two hyperparameters: Tuning parameters are number of hidden units and decay, which are used for avoiding over-fitting.

Reference:

Venables WN, Ripley BD(2002) *Modern Applied Statistics with S*. Fourth edition. Springer.

6. Naïve Bayes is a classification method employing Bayes' rule to estimate the conditional distribution of the input variables given the value of the outcome variable. Naïve Bayes assumes conditional independence of the input variables given the outcome class. The algorithm allows the users to add Laplace smoother to avoid zero posterior probability. Users can also adjust the how flexible density estimate is. The tuning parameters included Laplace Correction, and Bandwidth Adjustment. The Laplace correction is a solution of zero probability problem for test data. The bandwidth controls the spread in kernel density estimates function.

Reference:

Zhang Z. Naïve Bayes classification in R. *Ann Transl Med* 2016; **4**(12):241. doi: 10.21037/atm.2016.03.38

Ensembling combines information from multiple machine learning models to improve predictive accuracy. We used a generalized linear model to create a simple linear blend of models. It calculates weighted averages of variable importance for each model.

TABLE S2. Number and proportion of injuries at different locations in training and test sets

Injury location	Training set, n (%)	Test set, n (%)
Shoulders	277 (35.4)	66 (34.0)
Knees	204 (26.1)	54 (27.8)
Back	184 (23.5)	45 (23.2)
Wrists	172 (22.0)	39 (20.1)
Hips	103 (13.2)	20 (10.3)

RESULTS FOR MACHINE LEARNING MODELS

The accuracy of the ensemble model was 0.773 (back), 0.727 (knees), 0.644 (shoulders), 0.774 (wrists), 0.876 (hips) (Table S3). Leaving out groups of variables (demographics, training, concurrent, or prior sports) did not appreciably lower the accuracy. This could be explained that at least one variable in each group was ranked among those with high importance metric. Model predictions of shoulder injuries were less accurate compared to knee, back, or wrist injuries.

Random forest models alone had similar or better accuracy when using the expert selected subgroup of variables, with 0.748 (back), 0.713 (knees), 0.683 (shoulders), 0.744 (wrists), 0.901 (hips) (Table S3).

Table S3. Accuracy of performance for ensemble predictions and groups of variables

	Back injuries	Knee injuries	Shoulder injuries	Wrist injuries	Hip injuries
All variables	0.773	0.727	0.644	0.774	0.876
Without demographics	0.749	0.749	0.696	0.774	0.899
Without chronic conditions	0.737	0.716	0.655	0.841	0.866
Without training frequency	0.727	0.687	0.677	0.789	0.864
Without time for core weightlifting training	0.769	0.733	0.651	0.776	0.877
Without training extension	0.785	0.712	0.659	0.762	0.883
Without training program	0.764	0.733	0.662	0.776	0.872
Without current sports	0.763	0.722	0.639	0.759	0.876
Without prior sports	0.773	0.711	0.660	0.780	0.876
Reference: Random forest, all variables	0.768	0.742	0.619	0.790	0.876

Reference: logistic regression, all variables	0.737	0.711	0.613	0.759	0.876
Ref Random forest, selected variables	0.748	0.713	0.683	0.744	0.901
Ref logistic regression, selected variables	0.564	0.609	0.620	0.647	0.643

Due to the nonlinear prediction functions, it is not straightforward to interpret the results of ML algorithms. However, it is possible to obtain a variable importance metric (VIM) to ascertain the relative contribution of a particular covariate to the accuracy of the prediction. The exact method of calculating the variable importance often depends on the algorithm in use. For example, if the algorithm is linear regression, the importance is the absolute value of the t-statistic for each variable in the model. The R package, *caretEnsemble*, provides a weighted estimate of the importance of variables of a series of algorithms used. Variable importance does not indicate whether a variable is a risk factor for injuries or might contribute to prevention, it only indicates the relative contribution to prediction power of a variable.

Reference:

Strobl C, Boulesteix AL, Kneib T, *et al*. Conditional variable importance for random forests. *BMC Bioinform* 2008; **9**: 307.

The variables importance measures for the injury locations are shown in Table S4 and Figures S3 A-E.

Table S4. Variable importance measures for the ensemble method

Variable	Back injuries	Knees injury	Shoulder injuries	Wrist injuries	Hip injuries
Sex	0.0201	2.1675	8.9561	0.4699	0.0000
Age	1.5027	0.7611	6.4249	7.9517	5.4208
Education level	2.5486	0.7719	2.0882	2.2403	5.0546
Age at start of weightlifting	6.9056	7.9342	3.9839	4.5010	1.6997
Years of experience	7.5524	6.1908	6.0684	0.4628	0.6879
Number of training days	0.0150	1.0462	2.1764	4.8406	7.4276
Length of training session	0.6902	4.3760	1.3179	5.6153	2.2368
Hours per week (estimated)	0.5224	2.3640	2.7262	7.8245	7.0177
Time warm-up	1.1213	0.8427	3.1203	0.4793	4.9092
Time for classic lifts	1.5705	0.9438	1.8379	3.9940	0.5399
Time for strength training	2.3268	2.8536	2.4605	2.7149	2.4790
Training supplementary	3.4117	0.5477	1.8633	2.1798	5.3947
Time cool down	0.5126	0.4109	5.4972	0.1788	2.0645
Program coach	5.4603	5.2367	0.9530	2.4628	3.8571
Program remote coach	0.9236	1.0850	0.4139	5.4796	2.0420
Program own	6.8504	5.3986	2.3675	1.8715	3.6771
Nutrition	1.0233	2.4454	3.6426	0.5174	0.4557

Prior powerlifting	2.9224	1.2432	0.3769	0.0736	2.9948
Prior body building	4.7814	2.8995	1.1029	1.9375	1.9689
Prior CrossFit	4.9925	1.7108	1.5094	4.5809	4.9684
Prior endurance training	0.7614	1.0079	1.0033	0.3228	0.0000
Prior track& field	2.2164	1.6686	0.5051	1.9601	1.7163
Prior ball sports	2.7812	3.6487	3.3653	5.2771	3.2946
Prior fitness training	0.0093	0.6097	1.0763	0.9928	3.5728
Prior martial arts	2.3335	4.3317	1.1520	2.5985	1.9946
Prior yoga/Pilates	1.4434	2.5184	0.8633	0.2614	3.3285
Prior gymnastics	1.5823	1.0371	0.3183	0.2130	0.5750
Current powerlifting	1.0384	0.6188	0.5111	0.8423	1.9794
Current body building	1.4878	0.8020	5.6467	1.7056	3.5829
Current CrossFit	4.7338	4.5291	2.6723	0.7968	0.6809
Current endurance training	0.9502	1.9974	0.5935	2.7244	0.4411
Current track & field	0.0281	0.3657	0.3752	1.5516	0.2093
Current ball sports	0.0304	0.5015	0.4743	3.1253	0.8678
Current fitness training	1.5137	1.2812	4.6571	0.4202	0.8590
Current martial arts	1.8218	1.6803	0.0142	0.8301	0.3289
Current Yoga/Pilates	1.9394	1.4955	0.3201	0.1092	0.7106
Chronic inflammation/osteoarthritis	0.0156	2.1485	8.5201	0.1611	0.0004
High blood pressure	0.0046	0.0370	1.1085	0.1175	0.0004
Cardiovascular diseases	0.0000	0.6192	0.0700	0.0421	0.0001
Cancer	0.0069	0.4201	0.0965	0.0534	0.0000
Diabetes	0.0111	0.8562	0.1002	0.0377	0.0001

Figure S3A. Variable importance measure for shoulder injuries

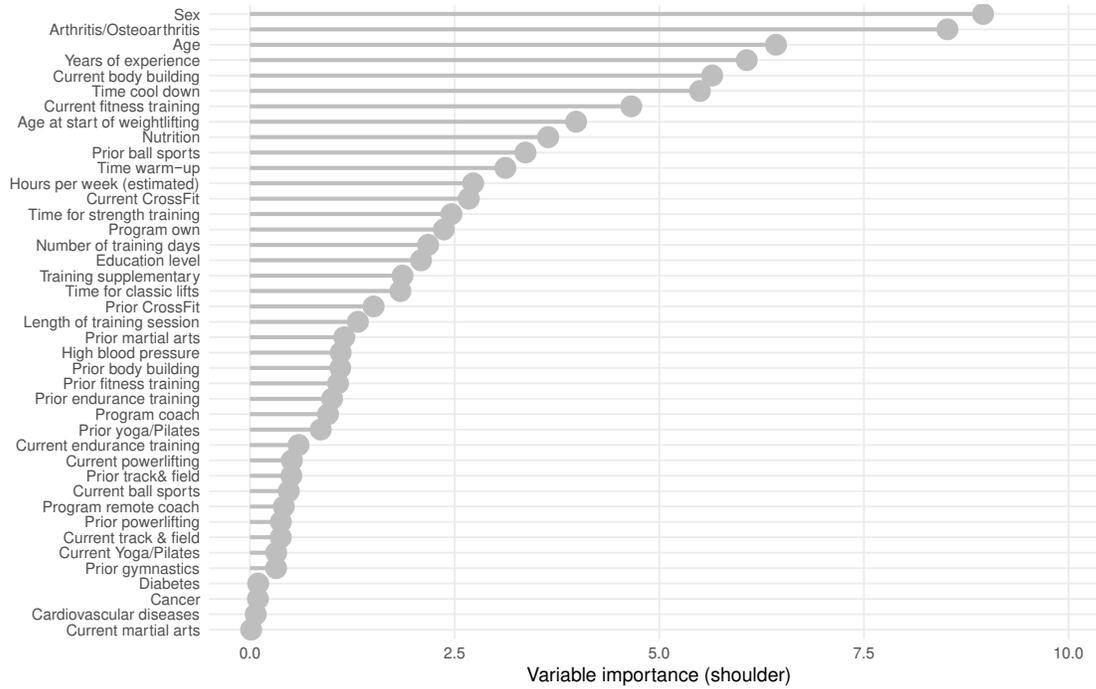


Figure S3B. Variable importance measure for back injuries

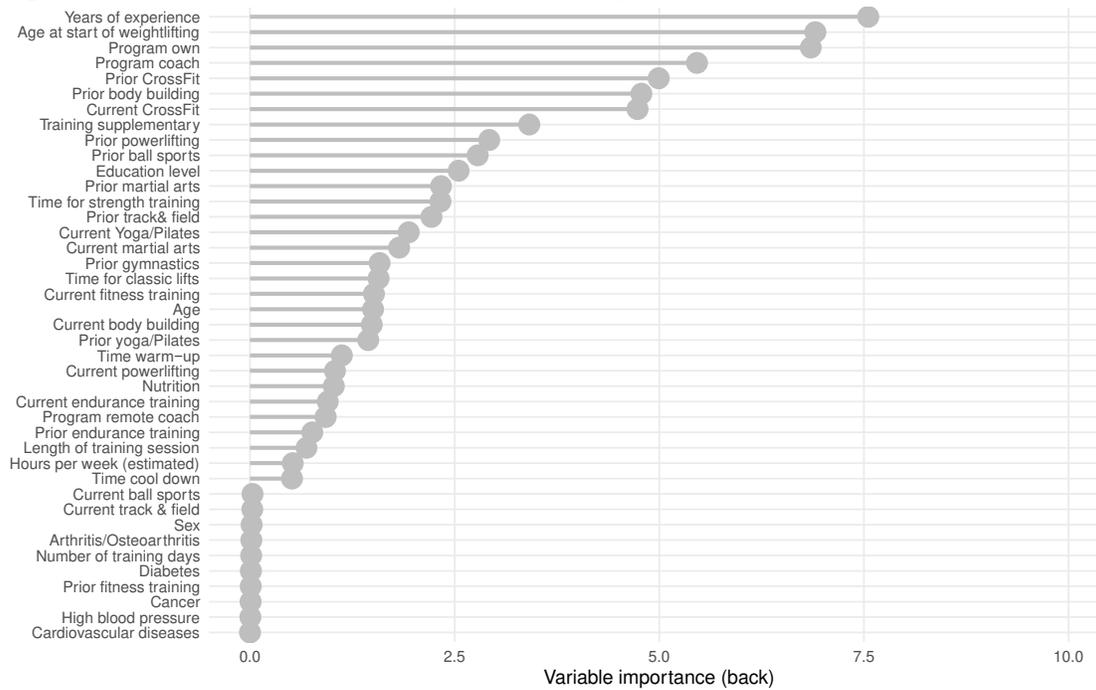


Figure S3C. Variable importance measure for hip injuries

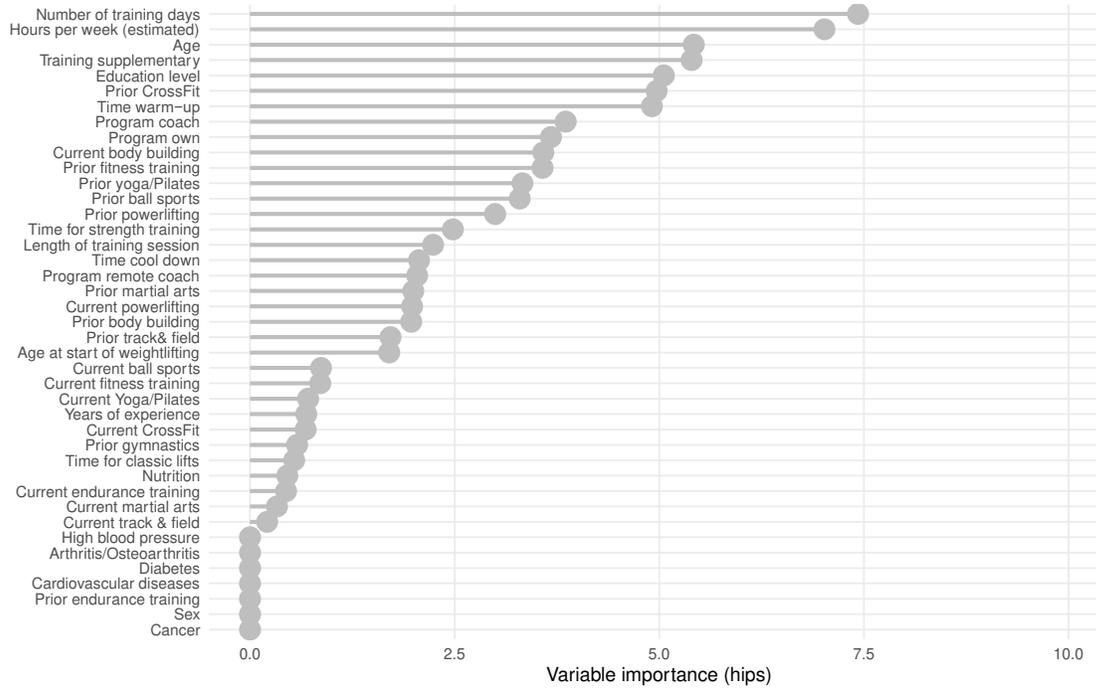


Figure S3D. Variable importance measure for knee injuries

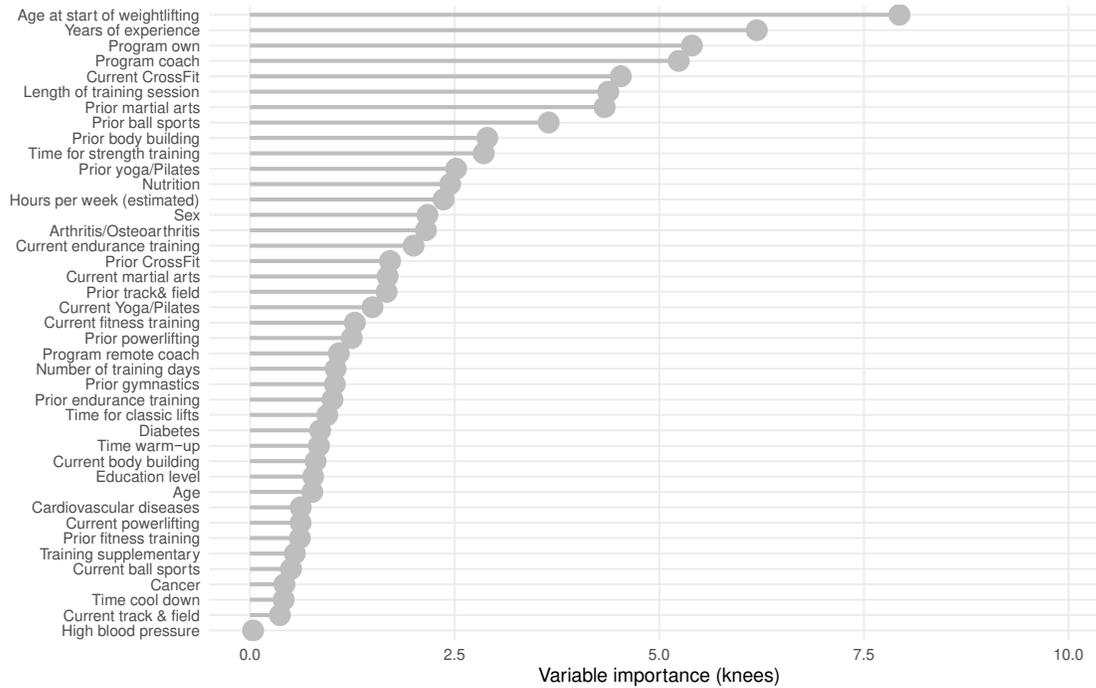
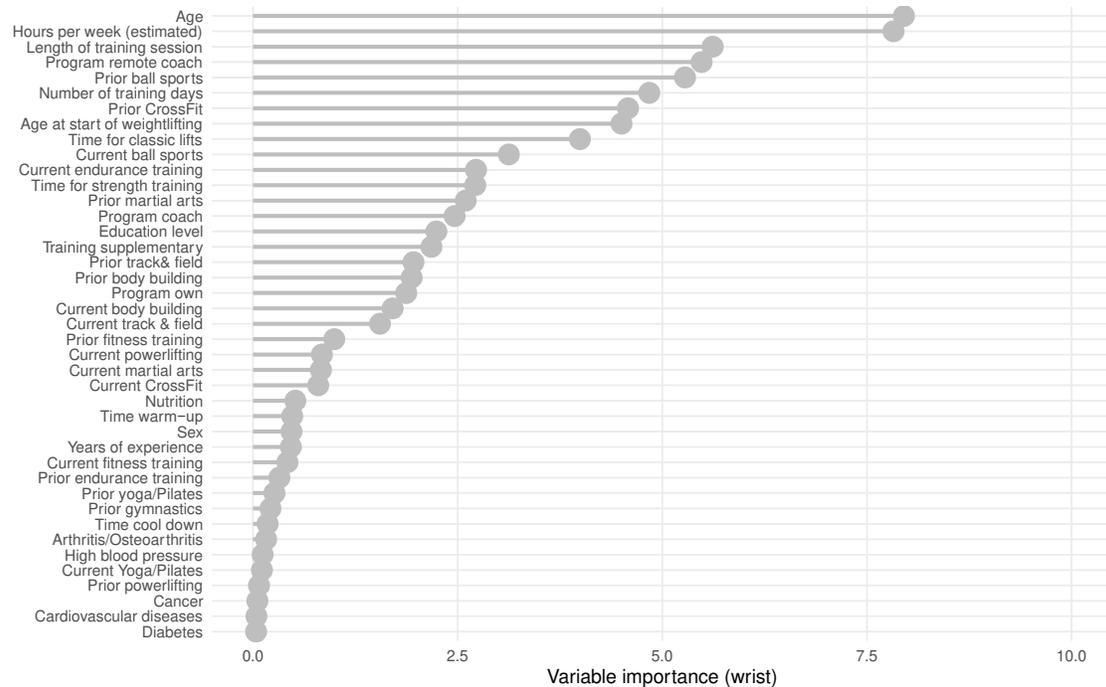


Figure S3E. Variable importance measure for wrist injuries

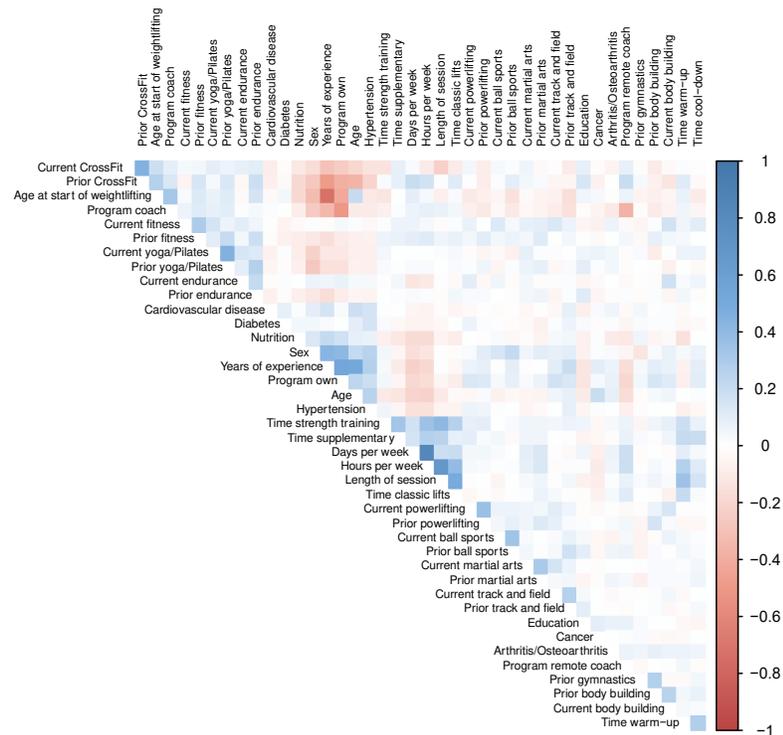
EXPERT MODEL

The selected variables comprised sex, age, nutrition, chronic inflammation, and training variables such as days per week, time for warm-up, time for cool down, and time for supplementary exercises. Prior sports (body building, power lifting, ball sports, gymnastics) were combined (1= prior participation in any vs 0 = no prior participation). Concurrent mobility such as yoga or Pilates and concurrent participation in Crossfit were also selected. Due to the collinearity of years of experience and age at start of weightlifting, the latter was included in the model since it was mentioned more often. Interactions between variables were mentioned by the experts, but did not improve the model fit as measured by the concordance statistic.

CORRELATIONS

Correlation coefficients of absolute values 0.5 or higher are in derived variables such as number of training days and with hours per week or age at start of weightlifting and years of experience.

Figure S2. Correlation plot of predictor variables.



SURVEY QUESTIONS

What is your current age?

Have you participated in sports or physical activities before you started weightlifting?

- Yes
- No

→ If yes, which activities/sports have you participated in? _____

- Bodybuilding
- Powerlifting
- CrossFit
- Fitness
- Endurance sport (e.g. running, swimming, cycling, skiing, hiking)
- Track and Field
- Martial arts
- Ball sports
- Pilates/Yoga
- Other, please specify: _____

In a typical week have you also participated in the following physical activities/sport in addition to weightlifting before the pandemic? (click all that apply)

- Bodybuilding
- Powerlifting
- CrossFit
- Fitness
- Endurance sport (e.g. running, swimming, cycling, skiing, hiking)
- Track and Field
- Martial arts
- Ball sports
- Pilates/Yoga
- Other, please specify: _____

What program(s) were you following in your weightlifting training before the pandemic? (click all that apply)

- The program assigned by my in-person coach.
- The program assigned by my remote coach.
- My own program
- A program from a website/book/subscription
- Other (please specify) _____

In a typical week on how many days have you trained in weightlifting prior to the pandemic?

- 1 day
- 2 days
- 3 days
- 4 days
- 5 days
- 6 days
- 7 days

How long was a typical weightlifting training session for you including warm-up and cool-down prior to the pandemic?

- <1 hour
- 1-<1.5 hours
- 1.5-<2 hours
- ≥2 hours

How long was your typical warm-up before the pandemic?

- 0-<15 minutes
- 15-<30 minutes
- ≥30 minutes

On average how much time in your typical training session before the pandemic was devoted to the competition lifts (snatch, clean & jerk) and partial competitions lifts (such as hang snatch or clean from blocks)?

- 0-<15 minutes
- 15-<30 minutes
- 30-<45 minutes
- 45-<60 minutes
- ≥60 minutes

On average how much time in your typical training session was devoted to strength exercises (squats, presses) before the pandemic?

- 0-<15 minutes
- 15-<30 minutes
- 30-<45 minutes
- 45-<60 minutes
- ≥60 minutes

On average how much time in your training session was devoted to additional exercises prior to the pandemic? (pull-ups, core, GHD, machines, etc)

- 0-<15 minutes
- 15-<30 minutes
- 30-<45 minutes
- 45-<60 minutes
- ≥60 minutes

How long was your typical cool-down (stretching, cycling, rowing,...)

- 0-<15 minutes
- 15-<30 minutes
- ≥30 minutes

Have you ever had training restrictions due to acute injuries **during weightlifting** (click all that apply)?

- Shoulder joints
- Elbow
- Wrist
- Hips
- Knees
- Ankles
- Spine/back
- Bone, muscle, or tendon injuries (Please specify) _____
- no acute injuries

Have you ever experienced chronic inflammation or wear and tear?

- Yes (Please specify) _____
- No