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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

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]

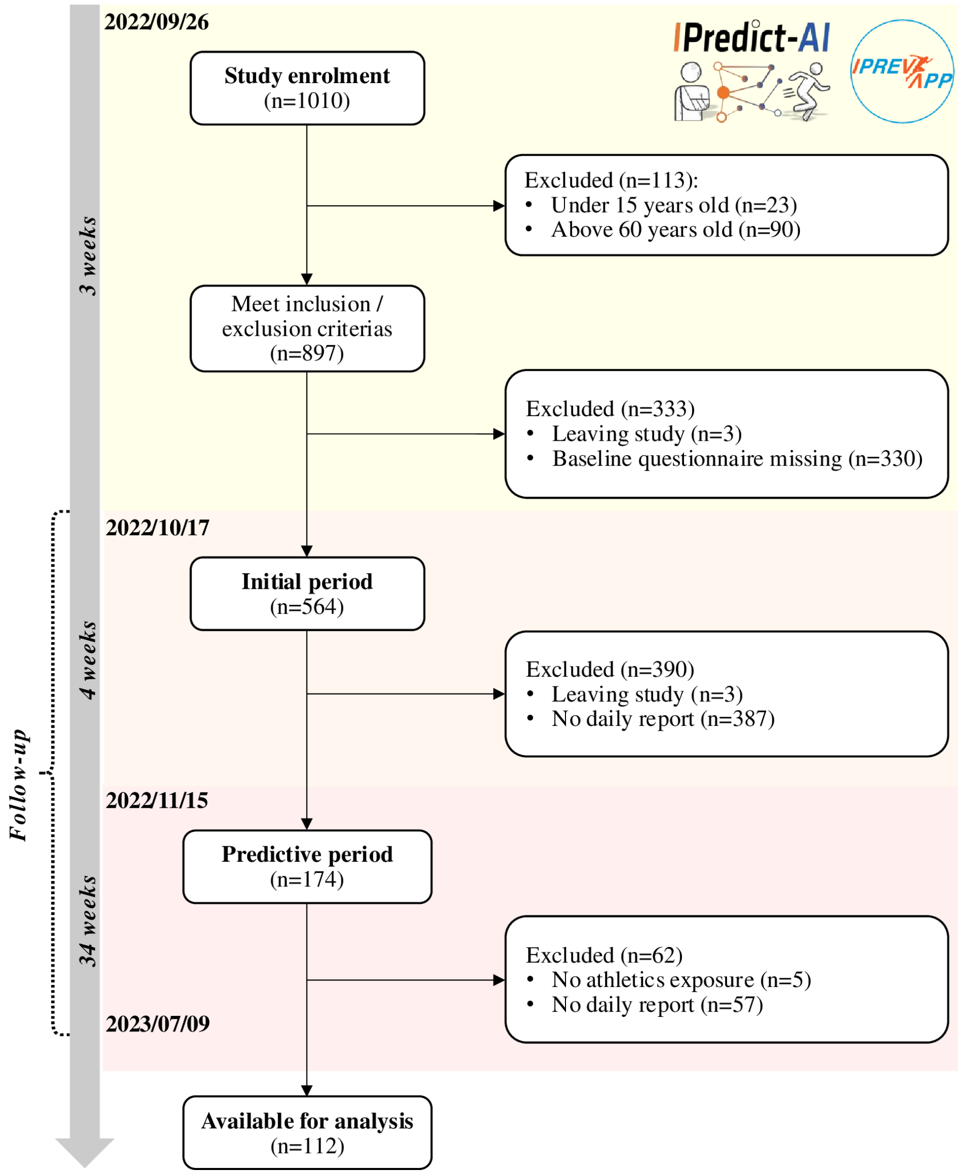

Figure 1 Flowchart of the IPredict-AI study.

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 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 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

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

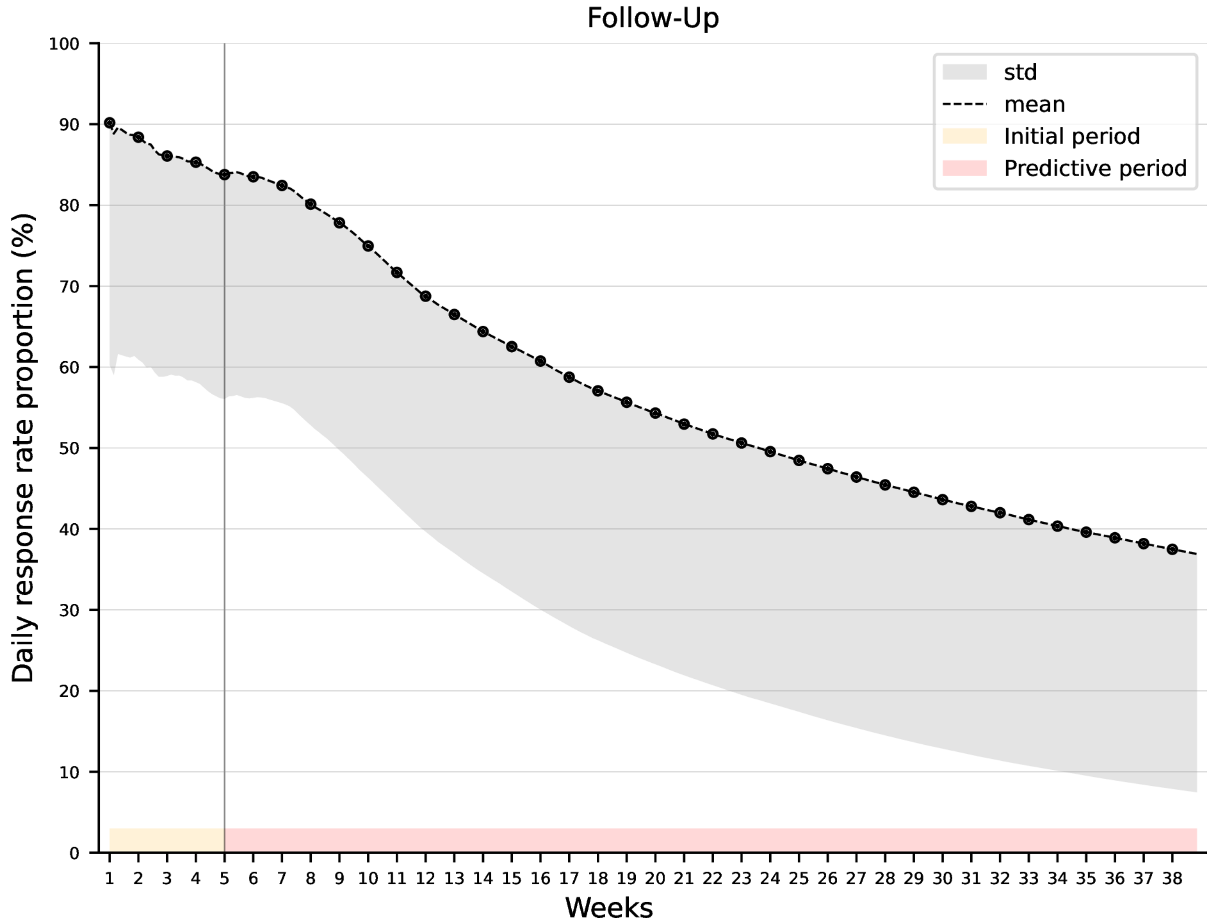

Figure 2 The mean daily response rate proportion (n=112) over the 38 weeks of the follow-up. The mean daily response rate was 90.2±29.9 on the first day of the initial period. It decreased steadily during the entire study period until a mean daily response rate of 36.9±29.4 on the last day of the predictive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

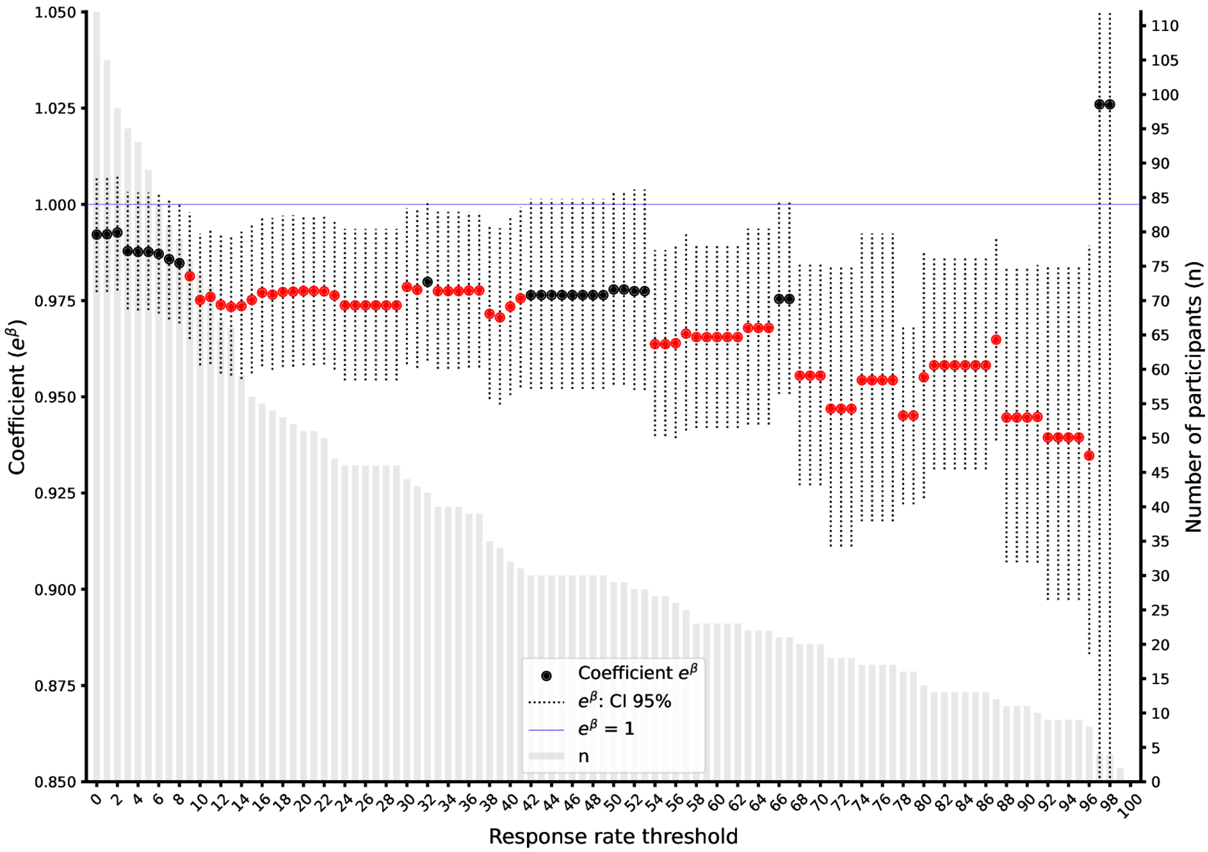

Figure 3 Response rate threshold analysis including one negative binomial regression model per each minimum response rate threshold (x-axis). For a minimum response rate threshold, the analysis was performed for all athletes whose response rate was equal to or above that threshold. The circular dots 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 ($e^{\beta}=1$). 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).

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%.

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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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.

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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.

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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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