Hack Track

Improving Performance, Preventing Injury

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Abstract

Distance and middle distance runners keep detailed logs to understand the relationship between their training, performance and injury. However, the current online running log tools fall short of helping them achieve this goal. Many websites do not track injuries and performances and none will display this information alongside training data. Furthermore, the current online running log tools have not integrated the latest sports medicine research which sheds light on the relationship between training and injury. In response to this need, we developed HackTrack: an online running log that helps athletes understand training, performance and injury. HackTrack incorporates four novel features to achieve this goal: (1) we track an athlete's session rate of perceived exertion (sRPE) to measure their training intensity; (2) we display $acute : chronic$ sRPE and distance – a ratio the literature has shown to be predictive of injury; (3) we allow athletes to log and visualize performance and injury alongside training volume; (4) we allow athletes to track customizable tags and visualize them alongside training volume. We launched HackTrack to Princeton's Women's Cross Country team and 20 athletes used it consistently for 1.5 months. While around 20% of participants were unhappy with HackTrack's tag visualization, nearly 90% of our users liked the way HackTrack logged and visualized their training. Furthermore, many of the users who logged injuries or performances said HackTrack's visualization tool helped them understand training, performance and injury. While we did not collect enough data to formally investigate the relationship between $acute : chronic$ ratio, injury and performance, an initial analysis supports the existing literature by suggesting our athletes who reported injury had relatively high $acute : chronic$ ratios the proceeding week.

1. Introduction

For distance runners, coaches and athletic trainers, training is a delicate balance between injury and success. If their training is too frequent or too intense, athletes put themselves at high risk for injury. If their training is too infrequent or mild, athletes will not improve. Given that runners want to maximize their performance, two questions are paramount: How much training is too much?

How much training is not enough? Identifying when you've "crossed the line" into overtraining or under-training is difficult and far too many competitive runners don't meet their performance goals due to overuse injuries or excessive caution.

In an attempt to understand the training-injury-performance paradigm, many runners keep detailed running logs with two goals in mind: if they get injured, they want to be able to look back and understand what went wrong; if they perform well, they want to be able to look back and understand what went right. With the introduction of GPS watches in the early 2000s, the information in these running logs has become quite extensive. It is now possible to keep track of every meter and heartbeat you take during a run.

Despite all of this information, understanding the relationship between training, performance and injury is not trivial. In fact, sports medicine researchers have spent the past 50 years trying to understand it. While maximizing performance has largely been left to coaches, sports medicine researchers have sought to understand the relationship between training and injury. There is a consensus in the literature that sudden increases, or "spikes," in training are likely to cause injury [1, 12, 2, 14, 16, 29, 25, 27] and more recently, researchers have begun to understand exactly how to measure "training" and "spikes" [1, 12, 2, 14, 16, 29]

Researchers have described two types of training workloads which are equally important: external workload and internal workload. [19] External workload measures the physical amount of work an athlete performed during a training session. [19] An easy proxy for this measure is distance. Internal workload describes an athlete's physiological response to a training session. [19] While there are many ways to measure this, research in the past year indicates that subjective measures of how an athlete feels during and after a workout are inexpensive and surprisingly accurate proxies for internal workload. [24]

Not only has research given us a better understanding of how to measure training workload, but recent studies have described a way to measure "spikes" in training. In 2015, Gabbett et al. found a particular ratio, the $acute : chronic\ workload$ ratio that captures training spikes. In the ratio, $chronic\ workload$ is the average workload over the past month and $acute\ workload$ is the workload of the current week. [2] The denominator of the ratio describes the type of training that you are prepared for given the past month while the numerator describes the training you perform under this preparation. [2] This ratio can be applied to both internal and external workload measures and both have been shown to be predictive of the likelihood of injury in various sports including rugby, cricket and soccer. [17, 16, 1] While this ratio does not perfectly capture all injury risks, it gives us a concrete way to quantify and monitor spikes in training.

Given the sports medicine research and an athlete's goal of understanding performance and injury, it seems like online running logs should gather subjective and objective data about training and present athletes with comprehensive graphs to show how these measures change over time. However, an indepth analysis of popular online running logs reveals that they fall short. While almost all online running logs will display a graph of weekly mileage (a measure of acute external workload), none will allow you to view more than a few weeks of data at a time. Furthermore, the current online running logs available lack mechanisms to track injuries, performances and subjective data about a runners internal workload. Given that the current tools are not aligned with sports medicine research nor do they meet athletes' needs, we sought to develop a running log website that would fill this void.

In this paper, we present HackTrack: an online running log that tracks subjective data alongside objective data to give distance and middle distance runners a better understanding of their training, performances and injuries. HackTrack allows athletes to log runs, their rate of perceived exertion (RPE) on runs, injuries and performances. With distance as a proxy for external workload and RPE as a proxy for internal workload, HackTrack displays acute internal and external workloads, chronic internal and external workloads and $acute : chronic$ internal and external workload ratios. Furthermore, it displays these ratios alongside a user's performance and injury data to so that the user can understand the relationship between the three. We also recognize that injuries and performances are not isolated events. An athlete might have shin pain before a stress fracture or a few good workouts before a good race. Therefore, HackTrack allows athletes to enter another type of subjective data: custom tags. For example, an athlete could log "#sleep 8" to indicate that they slept 8 hours or "#right_ankle_hurt 10" to indicate that their right ankle was hurting on a run. HackTrack presents these custom tags alongside *acute* : *chronic* internal and external workload ratios to further facilitate athlete's understanding of training, performance and injury. Finally, as collegiate runners ourselves, we know that many runners are not training in a vacuum, but rather have coaches and athletic training helping them perform to their potential. Therefore, while HackTrack is fully functional to an individual runner, we have also allowed coaches and athletic trainers to create accounts to monitor their athletes.

In summary, HackTrack is unique in its collection and presentation of subjective and objective training data alongside objective and subjective measures of injury and performance. We piloted HackTrack with 24 runners on Princeton's Women's Cross Country Team, Princeton's cross country coach and Princeton's cross country athletic trainer. In the remainder of this paper, we present the background research which motivated HackTrack. We define our goals for the website and discuss our approach and implementation of HackTrack. Finally, we evaluate HackTrack via user surveys and objective metrics about how athletes interacted with the website. We also highlight the type of information we might learn from HackTrack by conduct a preliminary exploration into the data we collected.

2. Background and Related Work

In order to motivate our website and explain the design decisions we made along the way, we will first present results from our initial survey, which asked runners about their running logs habits. We will then describe the sports medicine perspective on training and injury in more depth and highlight how an online running log might help athletes achieve their tracking goals. Finally, we will evaluate some prominent online running logs, and explain why they fall short based on our survey results.

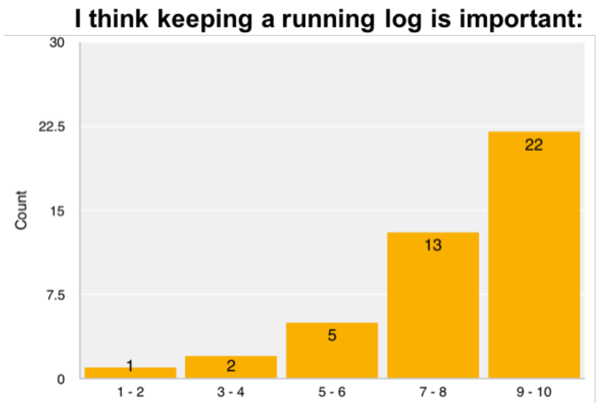
2.1. Running Log Survey Results

Before we embarked on this project we conducted a survey to understand how and why runners use running logs. We wanted to ascertain how many runners use running logs, what type of running logs they keep, what type of data they track, why they track it and what features they think would be valuable in an online logging tool. We sent the survey to a group of varsity collegiate runners and received 27 responses. In this section, we present the results of this survey.

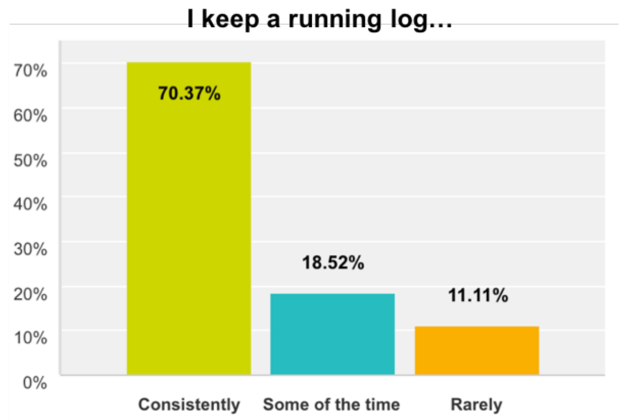
Of the runners we surveyed, the vast majority believe that keeping a running log is very important. Twenty-two respondents valued keeping a running log at either 9 or 10 on a scale of 1 - 10 where 10 is extremely important (Figure 1-a). Furthermore, more than 70% of our participants keep a running log consistently (Figure 1-b). Additionally 51% of our respondents keep online running logs while 40% keep them on paper (Figure 1-c). Together these data suggest that running logs are very important to runners at the collegiate level and that the majority of them keep online running logs.

Next we asked participants why they keep running logs. While answers varied, injury and performance were common themes. One participant said she keeps a running log to "monitor mileage, reflect on workouts, look back at training after illness/injury to figure out what went wrong." Another said: "I use [a running log] to see where I run and how far I ran, mainly because I want to avoid injuries. I also like being able to see how I felt on runs and the paces that I go/ whether they are getting faster." Yet another participant said she uses a running log to "[track] mileage and workouts and races. How I feel and injury/health." Another said she used a running log because "I am often injured, so it allows me to keep a hold on mileage and make sure training doesn't get out of control. If I do get injured, I can look back on what I've done, and plan places to sub cross training for next time." A pattern becomes apparent: the vast majority of survey respondents use running logs to monitor training so they can understand the relationship between training, performance and injury.

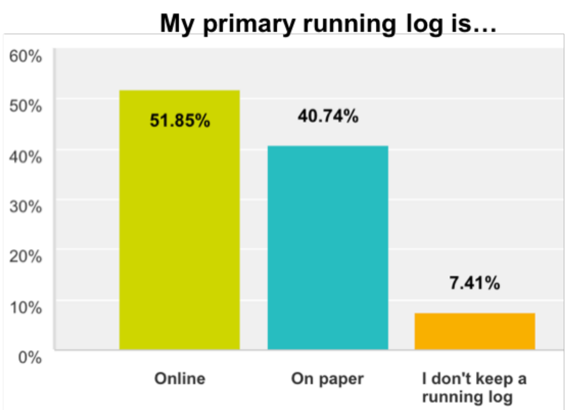
Finally, we asked participants to rank a set of potential running-log features that they wish were available to them (Figure 1-d). The most important feature was "custom tracking" – which was described to participants as the ability to "track customized variables such as how much you've slept, your right hamstring pain, how stressed you are etc." While we are not sure which variables our survey participants plan to track, we suspect that they might use custom tagging to track more



a) Participants were asked how important they think keeping a running log is on a scale of 1 – 10 where 1 is not important at all and 10 is extremely important.



b) Participants were asked how consistently they currently keep running logs.



c) Participants were asked whether they keep their running logs online or on paper.

d) Participants were asked what features they wished their running logs had. The higher the number the more they wish they had access to the feature.

Figure 1: Initial Survey Results

fine grained information about injury or performance.

The second most important feature was "detects fatigue" which was described to participants as "the ability to give you information on your training volume and warn you if it gets too high." This finding is in-line with the survey participants' goal of using running logs to avoid injury.

Overall the survey confirmed that runners primarily use running logs to understand training, injury and performance. In reaching that goal, survey respondents indicate that it would be helpful if a running log could track subjective, customized variables and help them understand when their training volume is too high.

2.2. Sports Medicine Perspective: Training, Performance and Injury

In this section, we will give a brief overview of the most relevant sports medicine research on distance running training. We will first discuss the relationship between training, performance and fatigue and then delve into a more specific discussion of injury and injury prevention models. This discussion will help us understand how a running log website could help athletes understand training, performance and injury.

2.2.1. Training, Performance and Fatigue. In 1976, Banister et al. characterized performance as a function of both fatigue and fitness. [5] They hypothesized that after a workout, fatigue spikes and then decreases exponentially while fitness parabolically increases and then decreases again. As a function of both fitness and fatigue, performance initially decreases (you are too tired right after a workout to perform well) and then increases as the effects of fatigue wear off. [5]

Remarkably, this model of training has held up. The modern view, of high-performance training closely parallels Banister's model. The model, dubbed "The Training Dose-Response Relationship" in Aaron Coutt's Chapter in *High-Performance Training for Sports*, says that for fitness to increase, you must carefully balance training dose and recovery. As seen in Figure 2, there are three stages of physiological response after physical work. (1) shock, (2) resistance and (3) supercompensation. In the shock phase, acute fatigue from the workload sets in and performance decreases. In the resistance phase, performance increases as fatigue decreases. Finally in the supercompensation, the body adapts to the stress of the workout and a higher level of fitness is achieved. This supercompensation to the workload will eventually wear off and performance will return to baseline. The goal of training is to apply the next workload in the supercompensation phase to capitalize on the gains from each workout. [19] If you apply the next workload too late, the previous workout session's gains are inconsequential. [19] However, if you apply the next workload too early when the body is maladapted, athletes can enter a state called "overreaching." [19] If overreaching continues, you increase the likelihood of injury, illness and low performance. [19]

If too intense training can cause injury, a natural question is how do we model the workload

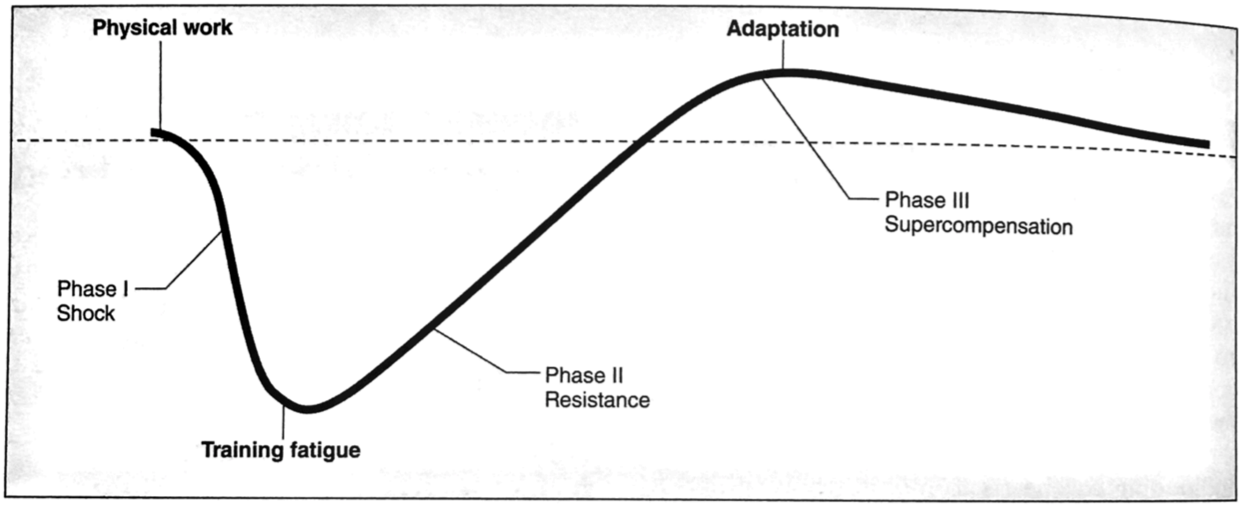


Figure 2: The effect of physical work on performance. The x-axis represents time and the y-axis represent performance. This figure is drawn from Coutt's Chapter in *High-Performance Training for Sports*. [19]

associated with training sessions? Coutts presents two types of training load: (1) external workload – the amount of "work" you've achieved in the physics sense of the word and (2) internal workload – the physiological response to an external workload. [19] Measuring external workload is fairly straightforward – it can be measured via distance, speed, duration etc. [19] However, measuring internal workload is more complicated. Methods include using physiological markers such as heart rate, cortisol levels or lactate levels. [19] While these methods are expensive and out of reach for the average runner, recent evidence suggests that subjective measures of how an athlete feels during her run are just as accurate as the objective measures of internal workload. [26]

More specifically, Wallace et al. studied a group of swimmers and found that athletes' session rating of perceived exertion (sRPE) were highly correlated with objective measures of internal workload. Wallace et al. defined $sRPE = RPE * session\ time$, where RPE is a number from 1 - 10 on Gunnar Borg's rating of perceived exertion scale [4] and *session time* is the time (in minutes) of the training session. [26] Wallace et al. found that heart rate and sRPE were highly correlated and concluded that "session-RPE may provide a practical, noninvasive method for quantifying internal [workload]." [26]

In summary, Sports Medicine researchers posit that performance is a function of fitness and fatigue. Training increases both fitness and fatigue and the key to success is in the timing. Thus, it is reasonable to conclude that many overuse injuries can be tied back to "errors" in training.

2.2.2. Modeling Injury. Now that we have a better sense of how training, performance and injury interact, we will focus on injury models. As see in Figure 3, the most recent models for injury suggest that previous injury, modifiable factors and non-modifiable factors predispose an athlete to injury. However it is the application of workload that causes injury. There are certainly feedback loops – for instance positive training effects can change modifiable factors and decrease an athlete's predisposition to be injured – but the general premise is similar to the training, performance and fatigue paradigm discussed in Section 2.2.1.

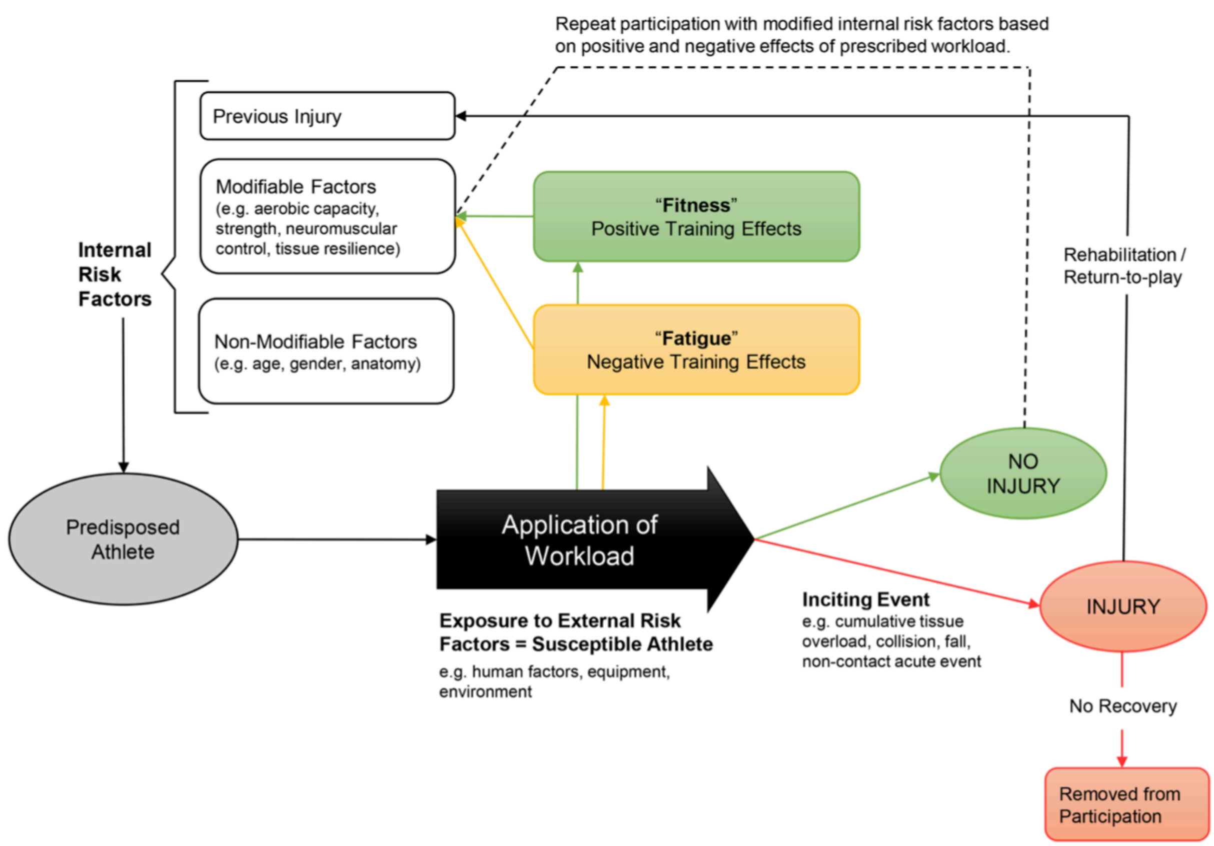


Figure 3: A model describing the factors which contribute to injury. This figure is redrawn from Windt and Gabbett, 2016. [29]

The more interesting question is what is it about workload that results in no injury – and a number of positive effects from training – or injury? In his 2010 paper, Blanch and Gabbett provide a potential answer: the acute to chronic workload ratio. [1] Blanch and Gabbett followed a number of rugby, cricket and soccer players through their training. They modeled Banister's "fatigue" function via the acute workload – the workload of the current week. They modeled Banister's "fitness" function via the chronic workload – the running average of acute workloads over the past month. [1] Chronic workload measures the type of workload an athlete is prepared for based on the past month while acute workload measures the athlete's workload in the current week. As seen in Figure 4 Blanch and Gabbett observed that injury often occurs after "spikes" in $acute : chronic\ workload$. In more descriptive terms, if athletes perform a much higher workload in the current week then they have been prepared to perform over the past month, they are more likely to get injured. Blanch and Gabbett then modeled the likelihood of injury in the next week as a function of $acute : chronic\ workload$ of the current week and achieved $R^2 = 0.53$ via a fitted polynomial line (Figure 5). It is important to note that $acute : chronic$ ratio can be applied to both internal and external workload measures; Gabbett and Blanch found both to be predictive of injury in the next week. While the study was not directly looking at runners, it only considered the athletes' endurance (running) training and injuries which did not result from collisions. Therefore, we suspect that $acute : chronic\ workload$ is predictive of injury in distance runners as well.

Figure 4: A graph of $acute : chronic\ workload$ of one athlete's training. This figure is drawn from Blanch and Gabbett, 2015 [1]

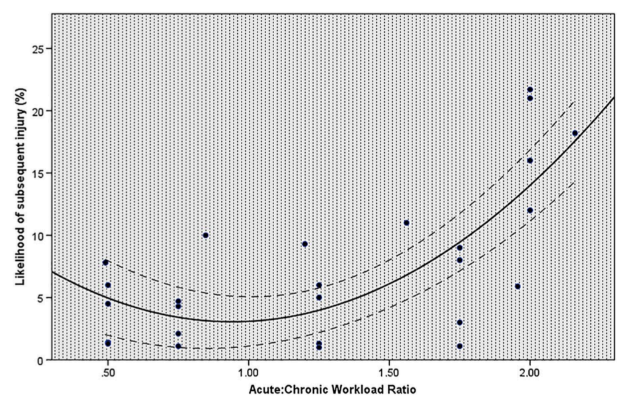


Figure 5: The likelyhood of injury as a function of $acute : chronic\ workload$. This figure is drawn from Blanch and Gabbett, 2015 [1]

In summary, spikes in training workload can can be measured via the $acute : chronic\ external\ and\ internal\ workl$ and have been shown to lead to injury in a variety of sports. From this, we can conclude that tracking $acute : chronic$ distance (external workload) and RPE (internal workload) over time might help athletes understand their injuries. While no research has been conducted on the ratio's relationship to performance, it is possible it might shed light onto this outcome as well.

2.3. Online Running Logs

In this section we will explore current online running logs. Namely, we will evaluate whether the current online running logs help athletes understand their training, performance and injury based on the sports medicine research described in Sections 2.2.1 and 2.2.2

While there are many different running log websites available, we picked five of the most popular (Garmin Connect, Fitbit, Strava, Running2Win, FinalSurge) and analyzed the features they provide. A summary of this analysis can be seen in Table 1.

As seen in Table 1, all of the websites we surveyed allow users to upload GPS files of runs and to visualize data from individual runs. Furthermore, every running log website provides some way to view weekly mileage and visualize weekly mileage over time. These visualizations describe a user's acute external workload over time, and running log websites are doing well in this respect. However, no websites incorporate the more complex notion of $acute : chronic$ workload ratios, which have been shown to be more predictive of the likelihood of injury.

From Table 1, it's clear that Running2Win and FinalSurge both allow users to enter RPE for runs. While this value might allow users to gain insight into their internal workload, users are severely limited because neither website does anything with RPE data. Neither Running2Win nor FinalSurge graph RPE over time. In fact, the only way to view a run's RPE is to click all the way into the details for the run. This makes it extremely difficult for users to gather information about RPE from these websites.

The online running logs we surveyed gather and visualize an athlete's acute external workload. However, they fall short in their visualization of internal workload and have not incorporated the more advanced notion of the $acute : chronic$ workload ratio.

The question remains: how well do the current websites fit athletes' goals as described in our initial survey? Understanding injury first requires the ability to log injury – a feature which Final-

Table 1: Online Running Log Survey

Feature	Garmin Connect	Fitbit	Strava	Running2Win	FinalSurge
Upload GPS files	✓	✓	✓	✓	✓
Automatically upload GPS files	✓	✓	✓		✓ (some brands)
Visualize run data	✓	✓	✓	✓	✓
Categorize a run	✓			✓	✓
Customize run categories				✓	✓
Add more than 1 category per run					
View run categories over time					
Add notes to a run	✓		✓	✓	✓
View notes of runs over time					
View weekly mileage	✓	✓	✓	✓	✓
View mileage over time	✓	✓	✓	✓	✓
Enter RPE or other subjective data about a run				✓	✓
View RPE or other subjective data about a run over time					
Log injuries					✓
View injury history over time					
View injury history alongside training data					
Log performance			✓	✓	✓
View performance history over time					
View performance history alongside training data					
Tracks workload ratios					
Connect with a coach			✓	✓	✓

Surge provides. However, this feature is very rudimentary. It does not allow you to distinguish between different types of injuries (i.e. you cannot specify that your strained your hamstring as opposed to sprained your ankle) nor does it allow you to specify to degree of your injury (i.e. does your hamstring hurt a lot, or is it just a twinge). Given the complexity of injury, it would certainly take a more fine-grained injury logging system to help athletes understand why they got hurt. Furthermore, FinalSurge does not allow you to visualize injuries over time or view them alongside training volume. Because of this it would be very difficult for athletes to understand the relationship between their training and injuries. Based on this, it seems that a more customizable injury tracking tool and visualization alongside training are necessary to enable athletes to understand what went wrong in their training should injury arise.

Understanding performance and how it relates to training requires the ability to log performance. Strava, Running2Win and FinalSurge all allow you to record how fast you've run in different events. For example, you could record that your fastest mile time is 5 minutes. Running2Win and Strava even allow you to view performance over time via a table. However, these websites do not allow you to view your performances in the context of your training. For example, there is no way to visualize your weekly mileage the week before a race. Thus the systems are not conducive to understanding performance as a function of training.

Understanding performance and injury in a more complex way might require that athletes track custom variables. Of the features listed in Table 1, the ability to categorize runs and add notes to runs seem like promising ways for athletes to track custom variable. Garmin Connect, Running2Win and FinalSurge allow you to categorize runs into groups. FinalSurge and Running2Win even allow users to add custom categories. However, this feature is limited because no website allows users to add more than one category to a run. While it is possible for a user to create a category called "right_foot_hurts," they cannot associate a run with more than one custom category. Furthermore none of the websites allow users to view run categories over time. Instead one must click on the details for an individual run to view its category.

Strava, Running2Win and FinalSurge allow users to add notes to runs – and it is possible runners would keep track of any number of custom variables via these notes. However, because none of the websites allow users to view their notes over time, it isn't easy to extract trends from these entries.

In summary, running log websites provide a lot of features which allow users to log and track information about their training. All websites allow users to log and track their acute external workload. Some websites allow users to track RPE (a measure of internal workload) but none allow them to track acute internal workload over time. Furthermore, no websites have integrated the more complex notion of $acute : chronic$ workload ratio. While some websites allow users to track injury and performance, none allow them to view this information alongside training information. Finally, no websites allows users to log subjective, custom variables about their runs. We conclude that these websites do not adequately facilitate a comparison between injury, performance and training. Since this seems like a primary goal of collegiate athletes who use online running logs, it would be useful to build a website centered around this goal.

3. Motivation and Goals

Our survey suggests that collegiate runners keep running logs with the hopes that if they get injured, they can look back and try to understand what went wrong; if they perform well, they can look back and try to understand what went right. However the current running logs do not allow athletes to compare training, performance and injury. Our goal in building HackTrack is to provide a platform that will do just this.

The novelty in HackTrack is four fold: (1) HackTrack tracks an athlete's internal workload via sRPE and displays this metric over time. The collection and comprehensive visualization of subjective running data is unique to HackTrack and will provide athletes with a better picture of their training intensity. (2) HackTrack provides summary graphs which track athlete's acute, chronic and $acute : chronic$ sRPE (internal workload) and distance (external workload). Because the $acute : chronic$ workload has been shown to be a good measure of training volume and predictive of future injury, this visualization will give athletes a better understanding of their training workload. (3) HackTrack provides mechanisms to track both injury and performance. While other websites provide this feature as well, HackTrack is unique in its visualization of injury and performance data alongside training workload. This graphic will help athletes understand the relationship between their training, performance and injury. (4) Finally, HackTrack provides a way to add custom tags to runs and visualize these tags over time. For example, an athlete could track "#great_run," "#hamstring_pain," or whatever else they'd like. If we consider injury and performance to be more objective outcome variables, the tagging features provides athletes with the ability to track subjective, customized information. HackTrack graphs these tags over time alongside training workload to help athletes see connections between their training and custom tags.

With these four key features, HackTrack is a tool that leverages the latest strides in sports medicine research to help athletes understand their training, injury and performance.

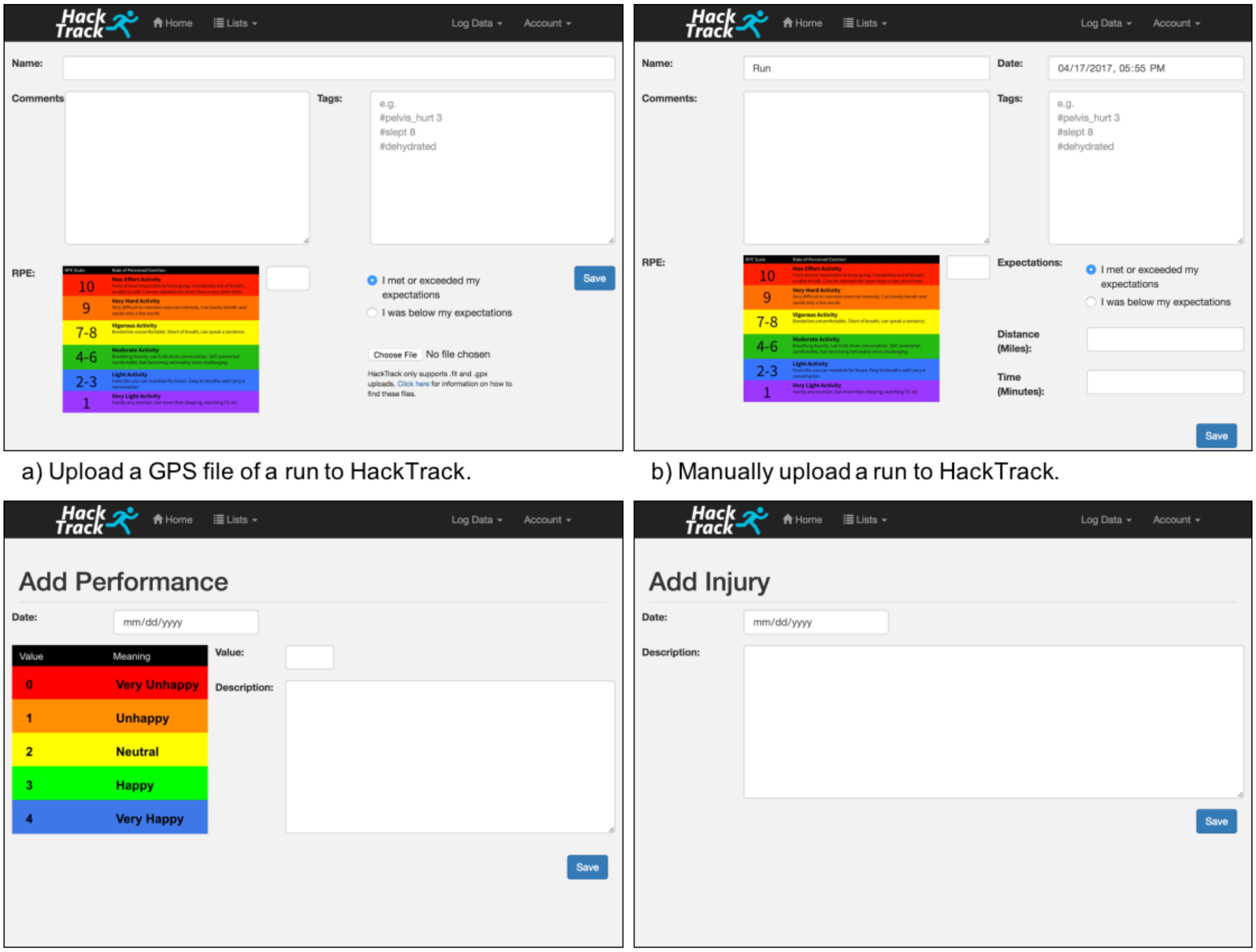
As a brief aside, it is interesting to note that gathering and visualizing subjective data is a central concept that sets HackTrack apart from other online running logs. It seems that with the introduction of GPS watches and wearable sensors, there has been a greater focus on objective data, such as heart rate, cadence, vertical oscillation etc. While these measures certainly add value, wearable sensors to date do not capture subjective data – which is oftentimes just as important as objective information. Therefore, research like co-investigator, Nicole Marvin's, is important as it helps athletes seamlessly record subjective information about their runs.

4. Approach

In this section we describe HackTrack's features and our design decisions in more detail. We break these features up into five sections: In Section 4.1, we describe how HackTrack allows users to log data. In Section 4.2, we explain HackTrack's visualization for runs, performances and injuries. In Section 4.3, we explain HackTrack's dashboard and the summary graphs it contains. In Section 4.4, we will explain HackTrack's interface for connecting with coaches. Finally, in Section 4.5, we describe HackTrack's coaches account interface.

4.1. Logging Data on HackTrack

HackTrack allows athletes to log runs, injuries and performances. Because our survey results indicated that some athletes run with GPS watches while others do not, HackTrack allows users to log runs via uploading GPS files (Figure 6-a) or manually enter a run via its distance, time and RPE (Figure 6-b). HackTrack allows athletes to upload FIT and GPX files from their GPS watches. These file types are available for a number of GPS watch brands including Garmin, Suunto, TomTom, FitBit, Polar, Mio, wahoo, and the Microsoft Band. Along with these measures, HackTrack also gathers information about whether a run met / exceeded the athlete's expectations



a) Upload a GPS file of a run to HackTrack.

b) Manually upload a run to HackTrack.

c) Add a performance to HackTrack.

d) Add an injury to HackTrack.

Figure 6: HackTrack's logging interface.

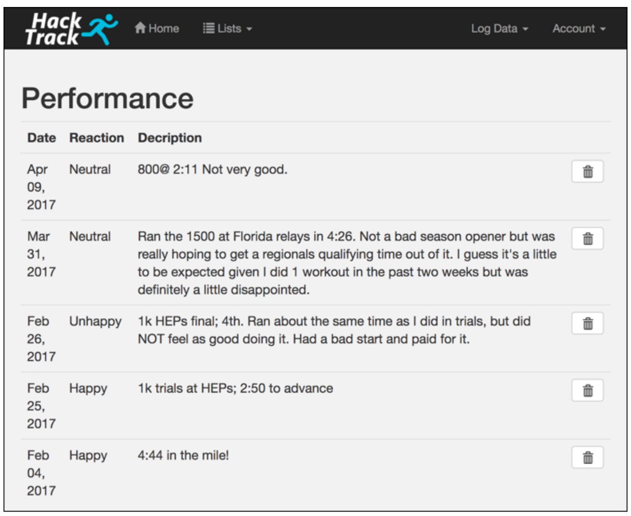
or fell below the athlete's expectations. While not strictly a measure of performance during a race, this binary value gives the athletes a sense of how they are performing on a day-to-day basis.

As seen in Figure 6-a and 6-b, when athletes enter a run, they have the option of adding additional tags. These tags may be entered on their own (e.g. #hard_workout, #very_sore or #great_run) or associated with numeric values (e.g. #pelvis_hurts 10, #right_foot_hurts 3, or #slept 8). Initially, HackTrack implemented tagging inline with comments. For example, a user might write: "I had a #great_run today after I #slept 8 hours." However, users reported that they often forgot the feature was available and would prefer that tags be a separate field. While HackTrack will still recognize tags entered in the "comments" section as described above, we also provide users with an explicit place to enter their tags.

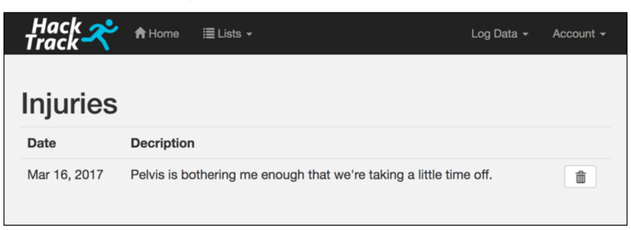
HackTrack also allows athletes to log performances (Figure 6-c). To provide athletes with a concrete way to visualize their performance, HackTrack associates each performance with a value ranging from 0, very unhappy, to 4, very happy. To allow users to add more information about their performances, HackTrack also allows them to enter comments with a performance.

Finally, HackTrack allows athletes to log injuries (Figure 6-d). Unlike performances, HackTrack considers injury a binary event so users cannot associate a "value" with an injury. However, HackTrack does allow athletes to describe their injury in more detail via the comments section.

4.2. Visualizing Runs, Performances and Injuries on HackTrack



a) Athletes can view a list of the performances they've uploaded. They can also delete their performances.



b) Athletes can view a list of the injuries they've uploaded. They can also delete their injuries.

Figure 8: HackTrack allows athletes to view lists of their performances and injuries.

HackTrack provides visualizations for the runs, performances and injuries that athletes enter. As seen in Figure 7, HackTrack provides users with a list of all the runs they've uploaded as well as a detailed view of each run.[1] HackTrack's list view displays all pertinent information about a run – its date, name, RPE, distance, time tags and comments. If the athlete logged their run via a GPS file, the details view (Figure 7-b) allows athletes to see graphs of their speed, heart rate, altitude and cadence. To put these metrics in perspective, the details view gives athletes a histogram of their average speed, heart rate, elevation gained and cadence across all runs they've uploaded. The details view also displays the run's comments, tags and met / did not meet expectations information. Finally,

[1] To protect our participant's privacy, all of the individual user graphs / data I display are from my account.

a) Athletes can view a list of all runs they've ever uploaded.

b) Athletes can view speed, heart rate, altitude and cadence information about a specific run along side histograms of their runs' average speed, heart rate, altitude and cadence. They can also delete runs from this view.

Figure 7: HackTrack allows athletes to view a list of their uploaded runs and view the details of a particular run.

HackTrack recognizes the RPE field gathered by co-investigator Nicole Marvin's iPhone app during an athlete's run. While not shown in the figure, files gathered from Nicole's app will have RPE values graphed alongside the speed, heart rate, altitude and cadence graphs.

As seen in Figure 8 HackTrack allows athletes to view lists of the injuries and performances they've uploaded. While quite simple in concept, these features allow athletes to view all the information about their injuries and performances in one place.

So far the visualizations we've described are rudimentary but necessary features. The run "list" and "details" views (Figure 7) might not be significantly different from ones that other running log websites offer, but runners expect running log websites to provide this functionality. Though the "list" visualization for injuries and performances do not facilitate a comparison with training, it is essential for users to be able to see and manage their logged injuries and performances in one place.

In summary, the features we've described in this section do not directly aid in achieving HackTrack's goal of facilitating a comparison between injury, performance and training. Rather, they comprise the minimum set of features that any athlete would expect of an online running log.

4.3. HackTrack's Dashboard

Its dashboard is where HackTrack implements novel visualizations to facilitate a comparison between training, injury and performance. It gives athletes a snapshot of their recent training, a detailed picture of their training over time, a graph of training volume alongside tags and a graph of training volume alongside injuries and performances.

At the top of HackTrack's dashboard, athletes can see information about the current week and a summary of their latests run. This information allows athletes to quickly get a sense of their most recent training.

In the top row of graphs, HackTrack displays information about a user's training. HackTrack's "Distance (External Workload)" graph shows an athlete's weekly (acute) mileage, chronic mileage and $acute : chronic$ mileage. The graph gives the user a better understanding of how her external training workload changes over time. HackTrack's "sRPE (Internal Workload)" graph shows an athlete's weekly (acute) sRPE, chronic sRPE and $acute : chronic$ sRPE ratio. This graph gives the user a better understanding of how her internal training workload changes over time. While most websites display some version of the light blue, weekly mileage bars, no running log websites

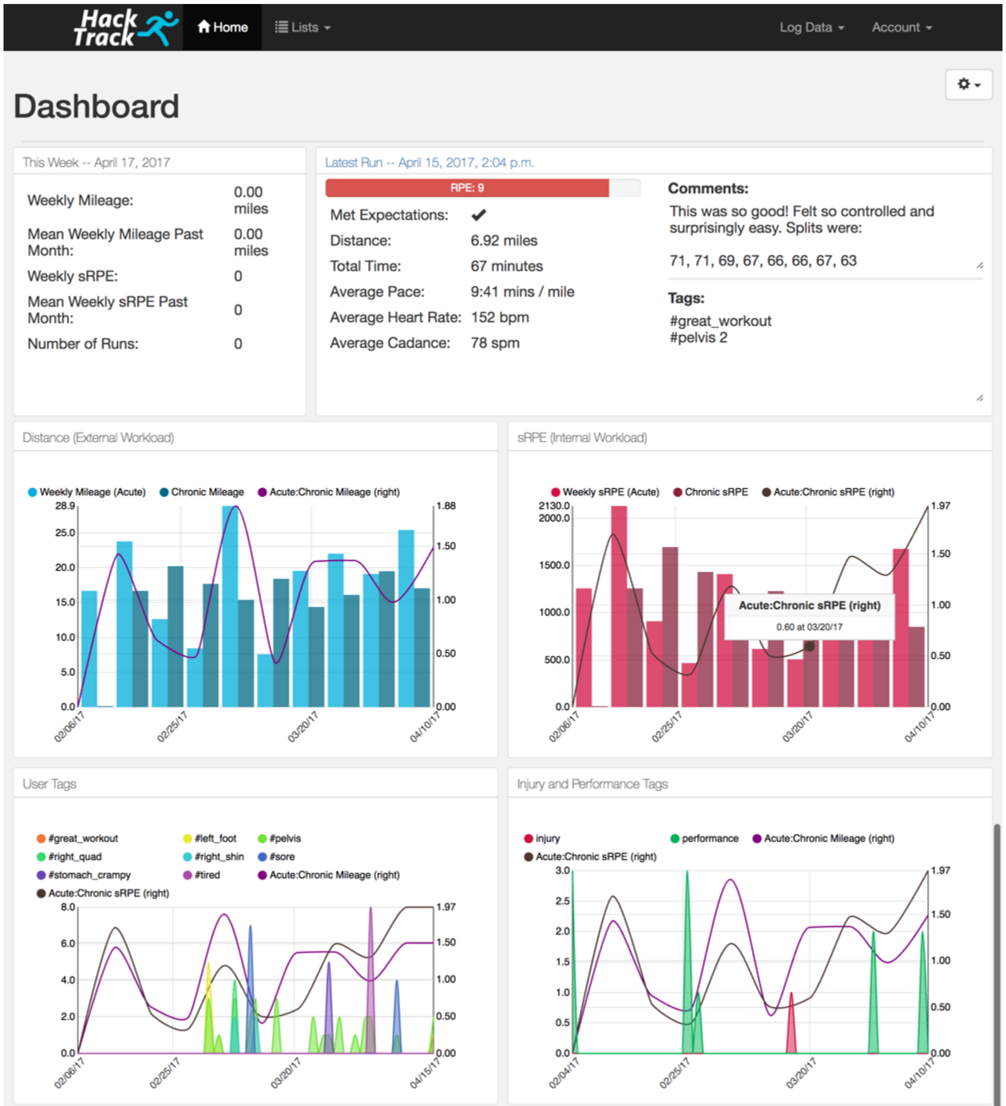


Figure 9: HackTrack's advanced dashboard. On the top right, HackTrack graphs acute, chronic and *acute* : *chronic* distance (external workload). On the top left, HackTrack also graphs acute, chronic and *acute* : *chronic* sRPE (internal workload). On the bottom right, HackTrack displays users tags alongside *acute* : *chronic* distance and sRPE. On the bottom left, HackTrack displays user injuries / performances alongside *acute* : *chronic* distance and sRPE.

incorporate the *acute* : *chronic* workload ratio. Furthermore, no running log websites allow users to view any measure of internal workload over time. Therefore, HackTrack's Distance and sRPE graphs give athletes information about their training which is not available elsewhere.

In the bottom half of its dashboard, HackTrack allows users to compare their training to subjective and objective injury and performance data. HackTrack's "User Tags" graph displays an athlete's custom tags alongside her internal and external *acute* : *chronic* ratios. The information a

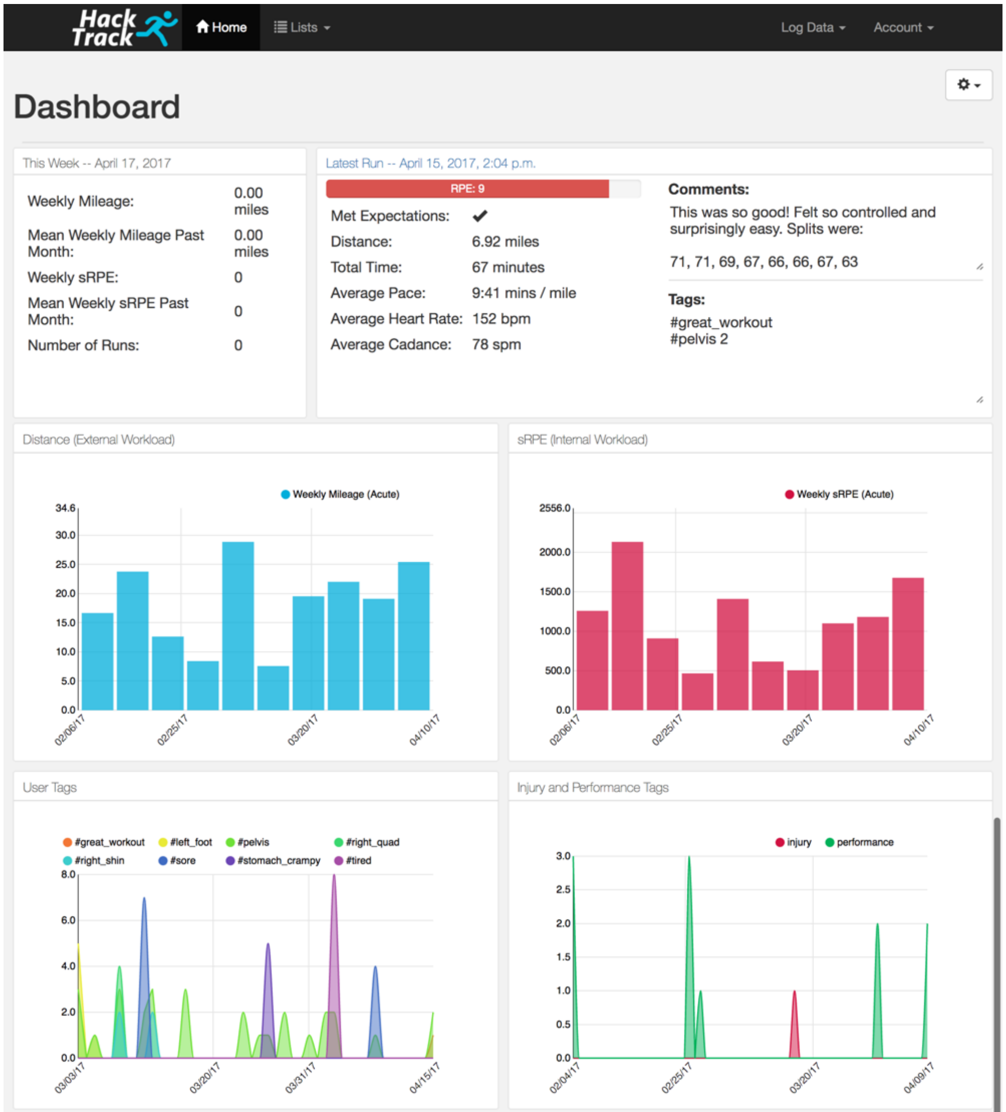


Figure 10: HackTrack's simple dashboard. On the top right, HackTrack graphs weekly mileage (acute external workload). On the top left, HackTrack graphs weekly sRPE (acute internal workload). On the bottom right, HackTrack displays users tags and on the bottom left, HackTrack displays user injuries / performances.

user can ascertain from this graph is highly dependent on the type of information the user tracks. However, it is possible it might help an athlete understand when and why her body started bothering her or when and why she started having a succession of good workouts. HackTrack's "Injury and Performance Tags" graph displays an athlete's injuries and performances alongside her internal and external *acute* : *chronic* ratios. This visualization helps a user make qualitative observations about how their training volume relates to their performance and injuries.

From Figure 9, it is clear that HackTrack's dashboard – particularly the concepts of *chronic* and *acute* : *chronic* workload – is heavily grounded in sports medicine research and many users reported that the graphs were confusing. Therefore, we decided to dub this dashboard the "Advanced Dashboard" and allow users to choose between it and simplified version (Figure 10). By default, athletes are presented with the simple dashboard, which omits *chronic* and *acute* : *chronic* workload measures. They still have weekly mileage and weekly sRPE graphs available to get a sense of their external and internal workloads. If athletes want to learn more about training workload and engage with the advanced graphs, they can toggle between the simple and advanced dashboards via the settings dropdown menu. Furthermore, we provide them with a video explaining the sports medicine research behind the advanced graphs.[2]

HackTrack's dashboard is the feature which sets it apart from other running log websites. By graphing users sRPE, HackTrack is the only running log website which displays and draws meaning from subjective training data. It is also the only running log that graphs the *chronic* : *acute* workload ratio and it graphs the ratio for both internal (sRPE) and external (distance) ratios. Finally HackTrack is the only running log website that will graph performance, injury, and customizable tags alongside an athlete's training volume. We believe the graphs HackTrack provides are much more useful to athletes who are trying to ascertain a qualitative relationship between training, injury and performance.

4.4. Connecting with Coaches on HackTrack

While HackTrack is fully functional for individual runners, we know that many athletes at the high school, collegiate and recreational levels train with coaches. To fully capitalize on the information an athlete can learn through HackTrack we believe it is important to include coaches / athletic trainer accounts to share data. However, the increase in fitness tracking and information flow between athletes and coaches over the past decade has led to increased concern about an athlete's right to privacy. [6, 23, 20] Therefore, we took many precautions when we built this feature.

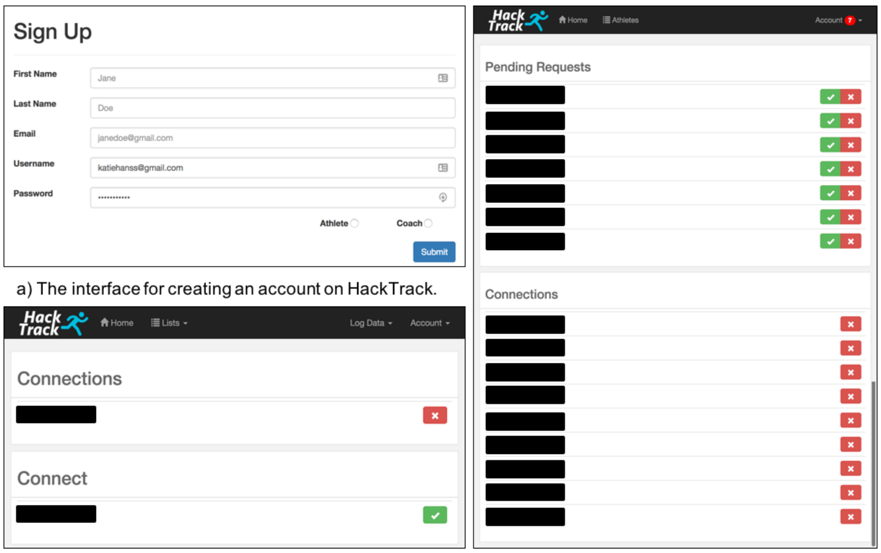
When you create an account on HackTrack, you can register as either a coach or an athlete (Figure 11-a). Coaches are searchable by athletes, but athletes are unsearchable on the site. Therefore,

[2] The explanatory video can be found at: https://youtu.be/QLj3fA9yTxo

an athlete can choose to connect with a coach (Figure 11-b) but a coach cannot search for any athletes. This set up allows athletes to use HackTrack without worrying that their coach (or someone else entirely) might pester them about connecting. Once a coach receives a request from an athlete, he or she can choose to accept or reject the request (Figure 11-a).

Furthermore, some of our test users explained that they were tracking variables on HackTrack, such as sleep or academic workload, that they did not want their coaches to access. Therefore, we also allow HackTrack athletes to choose which tags coaches can view.

In summary, the connection feature is meant to provide athletes with maximal privacy protection and give them the control to choose what information they share.



a) The interface for creating an account on HackTrack.

b) On HackTrack, athletes can search for coaches via the "Connect" box in the image above. However coaches cannot search for athletes on the website.

c) When an athletes connects with a coach, the request is pending until a coach accepts the request.

Figure 11: Athlete-coach connections on HackTrack.

4.5. Coaches Accounts

Coaches have three main features on HackTrack: (1) a comprehensive dashboard, (2) a summary list of their athletes and (3) a view of individual athletes' dashboard.

HackTrack provides coaches with a comprehensive dashboard (Figure 12) which displays their athletes' distance and sRPE over time. Coaches can opt to view weekly distance and sRPE or *acute* : *chronic* distance and sRPE. HackTrack's dashboard also shows coaches their athletes' new and most recent tags. The dashboard is meant to give coaches a quick way to check in on their

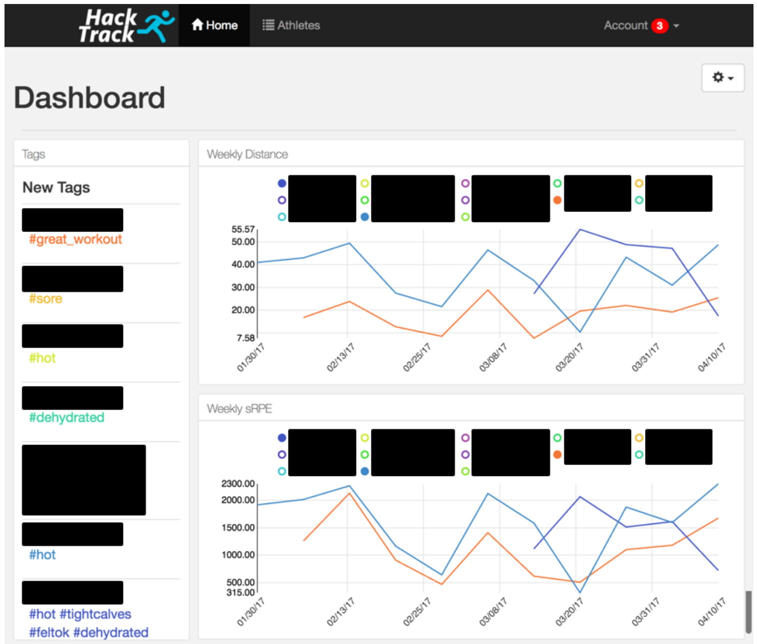


Figure 12: Coaches dashboard on HackTrack. On the left hand side, coaches can see new tags that their athletes have entered over the past 2 weeks. The top graph shows a graph of a coach's athletes weekly distance while the bottom graph displays their weekly sRPE. Coaches can also choose to see these same graphs for *acute* : *chronic* distance and sRPE.

team and visualize the training they've proscribed.

Coaches also have the ability to view a list of all the athletes they are connected with. It allows coaches to see their athletes' most recent performance and injury, their five most recent tags, and their five most frequent tags of the tags the coach is allowed to view.

Finally, coaches can see a modified version of their athletes' advanced dashboard. Unlike the dashboard in Figure 9, coaches cannot see their athletes comments on their most recent run, nor can they see user tags which the athlete has revoked permission to view. This view allows coaches to understand an individual athlete's training without getting more information than the athlete would prefer.

The coaches interface on HackTrack allows coaches to better understand their team and their athletes' training. Their comprehensive dashboard gives coaches a picture of their team's training overall while the ability to view particular athletes helps them understand how an individual athlete's training might relate to injury, performance, and user tags.

5. Implementation

In this section, we will first describe how we calculated sRPE, *chronic workload* and *acute* : *chronic workload* ratio. We will then explain HackTrack's architecture.

5.1. sRPE, Chronic and *acute* : *chronic* workload calculations

RPE Scale	Rate of Perceived Exertion
10	**Max Effort Activity** Feels almost impossible to keep going. Completely out of breath, unable to talk. Cannot maintain for more than a very short time.
9	**Very Hard Activity** Very difficult to maintain exercise intensity. Can barely breath and speak only a few words
7-8	**Vigorous Activity** Borderline uncomfortable. Short of breath, can speak a sentence.
4-6	**Moderate Activity** Breathing heavily, can hold short conversation. Still somewhat comfortable, but becoming noticeably more challenging.
2-3	**Light Activity** Feels like you can maintain for hours. Easy to breathe and carry a conversation
1	**Very Light Activity** Hardly any exertion, but more than sleeping, watching TV, etc

Figure 13: Borg's RPE-CR10 scale [15]

RPE, first described by Gunnar Borg, is a method that measures subjective information about how an athlete feels during exertion. [4] There are a few different Borg scales (some have numbers ranging from 6 to 20 and others 1 to 10) and we choose to work with Gabbett et al.'s choice of Borg's CR-10 scale for RPE (Figure 13). [13, 2, 14]

While RPE measures how an athlete felt on a run, the current literature, suggests that session RPE is the most affordable and accurate way to measure an athlete's physiological response to training. [24] [19]. Session RPE is defined as:

$$Session\ RPE = RPE * t$$

where RPE is an athlete's reported RPE on the Borg CR-10 scale and t is the time of the session in minutes. For example, if an athlete goes on a 20 minute run and her RPE is 8, her session RPE is $20 * 8 = 160$.

With sRPE and distance as proxies for internal and external workload respectively, we calculated *acute internal workload* as the sum of sRPE values over the past week and *acute external workload* as the sum of distance over the past week. [2] [19] [14]

We then calculated *chronic internal and external workload* as: [2] [13] [16]

$$chronic\ workload = \frac{1}{4} * \sum_{past\ 4\ week} acute\ workload$$

The $acute : chronic$ workload ratio is simply $\frac{acute\ workload}{chronic\ workload}$. [2] [13] [16]

5.2. HackTrack Architecture

In this section, we will describe HackTrack's backend and front end architecture and give a brief explanation of how we implemented HackTrack's features.

5.2.1. Backend We build HackTrack using Django's Python web framework with PostgreSQL as our database. We used Django's built in authentication system to create user accounts and log users in. [9] We used Django's concept of user groups to designate "coaches" and "athletes" [9] and we used Django's custom filters and authentication decorators to limit coaches and athletes to their respective side of the website. [8]

We used Django's Form class [10] to enable run injury and performance uploads. We stored runs via an "Activity" model we build via Django's Model class [7] and we stored the tags associated with each run via a "Tag" model, which also extends Django's Model class. While HackTrack presents tags as separate concepts from injuries and performance, the three are treated identically internally. Therefore, injuries and performances are also stored as Tag instances.

To facilitate connections between athletes and coaches, we used Frank Wiles' django-friendship Django application. [28] More specifically, we used their FriendshipRequest model to represent requests from athletes to connect with coaches and their Friendship model to represent connections between athletes and coaches.

5.2.2. Front-end HackTrack's front-end is built on Bootstrap3 [3], NVD3 [22] and Keen IO Dashboards [18]. We used Bootstrap3's components and CSS to make HackTrack more visually pleasing to users. We based our data visualization on two articles: Clinton Dreisbach's "Building Dashboards with Django and D3" [11] and Adil Moujahid's "Interactive Data Visualization with D3.js, DC.js, Python, and MongoDB." [21]

As suggested by Dreisbach [11], we used NVD3's re-usable charts to build HackTrack's graphs.

NVD3 is build on top of D3 and hides much of the intricacies and complexities that make building D3 graphs cumbersome. However NVD3 has a number of known bugs that we had to work around. We initially wanted to represent user tags as bar graphs; however, NVD3's API does not graph multiple bar graphs correctly if they do not share the same x-axis and coercing user tags to have identical axis made the bars at each time point very small. Therefore, we decided to graph user tags via line graphs to avoid this problem (Figure 9). Furthermore, we wanted to graph the $acute : chronic$ ratio alongside $acute$ and $chronic$ values, user tags and performances and injuries. Because the ratio is on a different scale than the latter values, we decided to use two different y-axis in our graphs. However, NVD3 does not align the x-axis of lines graphed on two different y-axis. Therefore, for all graphs we coerced the data graphed on y1-axis and y2-axis to have the same range.

As suggested by Moujahdi [21], we used Keen IO's dashboard templates [18] to frame our graphs (see the white boxes which contain graphs in Figure 9). These templates provided a clean and visually pleasing way to present and organize HackTrack's data. We used Keen IO's dashboard templates in HackTrack's dashboard views (Figures 9, 10 and 12), details of a run view (Figure 7-b), and connecting with a coach view (Figure 11).

6. Results

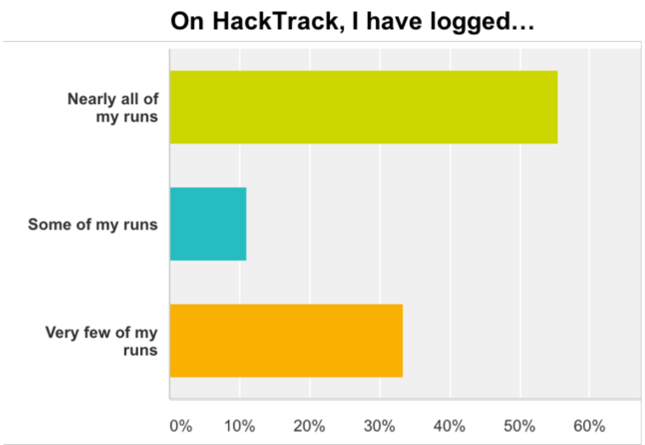
In this section we present our results for HackTrack. HackTrack implements four novel features which we believe will help athletes better understand their training, injuries and performances: (1) HackTrack allows users to log the RPE values associated with runs; (2) HackTrack visualizes acute, chronic and $acute : chronic$ sRPE and distance; (3) HackTrack allows users to log injury and performance and visualizes them alongside training data; and (4) HackTrack allows users to log custom tags and visualize them alongside training data.

Overall, we would like to know whether these key features enabled athletes to better understand their training, performances and injuries. To do this, it will be helpful to break these novel features up into two categories: (1) logging and (2) visualization. Athletes can only interact with visualizations for the data they have logged. Therefore, these categories allow us to first ask whether athletes logged the data and then how they like its visualization.

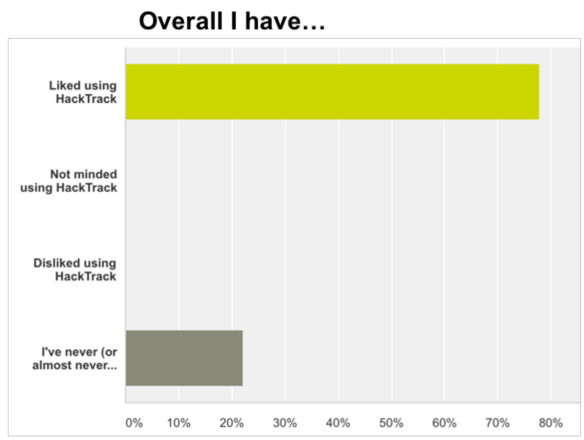
HackTrack allows athletes to log runs, injuries, performances and tags. To what extent did they use these logging features and were they helpful? To what extent do users engage in the distance, sRPE, injury and performance, and tags graphs and were they helpful? Finally we wanted to promote sharing with coaches through HackTrack. While this is not a "novel" feature (other running log websites provide this feature) we would also like to know how athletes and coaches interacted with the feature and whether they found it useful.

We will use the above framework to ground our result subsections. We will first discuss "Survey 1" – a user survey we released two weeks after we launched HackTrack to understand how users were interacting with the website. We will explain how this survey helped us modify HackTrack's tagging feature and modify and explain HackTrack's dashboard graphs to better fit user needs. We will then present objective data describing how users logged data on HackTrack. This will further support the user feedback we obtained through Survey 1 and will provide evidence that our interventions based on Survey 1 had an effect on user behavior. Next, we will present "Survey 2" – our final user survey evaluating HackTrack. We will then present three in-depth case studies which highlight how HackTrack helped some of our users understand their training, injuries and performance. Finally, we will present some preliminary data analysis that suggests that high $acute : chronic$ distance and sRPE ratios occurred before our users reported injury.

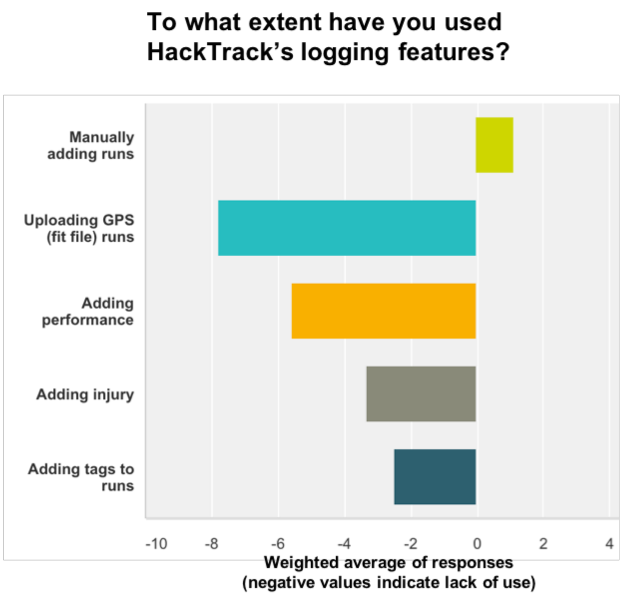
It is important to keep in mind that we know our test subjects personally and this might skew user feedback. Thus, it is particularly important to rely not just on survey feedback but also on objective data about how users have logged data on HackTrack. While it is certainly possible that this metric is also biased (our users might have logged data to help us in this study and not because HackTrack was useful to them), logging data consistently over time takes much more effort than filling out a survey and is therefore a more trustworthy measure of HackTrack's usefulness.



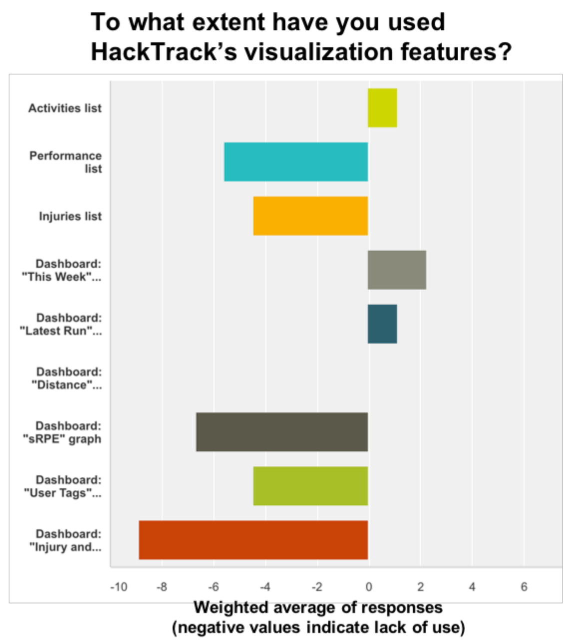
a) Results from our first survey indicate that around 66% of our users logged some or nearly all of their runs.



b) Results from our first survey indicate that around 77% of our users like using HackTrack



c) Results from our first survey indicate that users were manually adding runs. However the vast majority of users were not uploading GPS files, performances, injuries or tags.



d) Results from our first survey indicate that users were using the activities list and "this week" and "latest run" dashboard views. Users were evenly split regarding how often they used the distance dashboard graph and the majority were not using the other HackTrack features.

Figure 14: Survey 1 Results

6.1. Survey 1

When we released HackTrack to the Women's Cross Country team on March 5^{th}, 14 users signed up. To monitor how they liked and were using the website, we sent out Survey 1 and received 9 responses. We will use our results section framework to present a comprehensive analysis of the survey and we want to highlight two important findings: (1) many users did not understand that "tagging" was a feature and (2) many users found HackTrack's dashboard graphs confusing. Because these concepts are both key to HackTrack's mission, we made significant efforts to improve user experience in these areas. The following sections look at our users' experience: logging runs, logging performances and injuries, tagging, visualizing training data, visualizing performances, injuries and tags, and connecting with coaches.

As we discuss the results from this survey, it is important to remember that our sample size is very small. That said, we did take the survey results seriously and modified HackTrack based on what we found. The following sections look at

6.1.1. Logging Runs. As seen in Figure 14-a only 66% of the users we surveyed logged some or nearly all of their runs on HackTrack. As seen in Figure 14-c, the majority of these users logged runs manually (i.e. did not upload a GPS file) and did not upload GPS runs. It is possible that our users did not run with GPS watches or chose not up upload their GPS files.

Users who logged runs manually seemed to like the simplicity of the feature. One user said: "[HackTrack's manual logging is] clear and simple to use." Another user said: "[HackTrack] makes it easy to log runs and ... processes and logs everything very effectively. This is VERY WELL DONE." One user called HackTrack's manual logging "simple and straightforward" and another said it was "easy [and] self-explanatory."

Our users felt that uploading GPS files was cumbersome and "it would be great if [their] runs could just automatically upload using Bluetooth." In order to upload GPS files to HackTrack users must first sync their watches with their watch company (e.g. if you have a Garmin watch, you must sync your watch with the Garmin app). Many third-party running log websites will automatically sync with a watch company's database, so this first step is the only thing a user must do. However, to upload to HackTrack, users must download a "fit" or "gpx" file from their watch company's website and then upload the file to HackTrack. These steps are certainly cumbersome and we understand our users' frustration. However, because automatic data syncing is not a primary feature of HackTrack and uploading GPS files are not essential to HackTrack's functionality, we set this concern aside and focused on the features that are more central to HackTrack's mission.

Despite user frustration with GPS logging, users saw value in HackTrack's ability to log RPE alongside runs. Three of our 9 respondents cited RPE as their favorite logging feature. One respondent said "RPE is cool" and another said "I like adding in RPE as that's something I kind of think about but don't always really think about [enough]." While not as many users were consistently logging runs as we'd hoped, Survey 1 indicated that users found manually entering runs easy and were fond of HackTrack's RPE logging.

As an aside, we included Figure 14-b to highlight the existence of user bias in the survey. While only 66% of users said they were logging runs some or the time or most of the time, almost 77% said they liked using HackTrack (Figure 14-b). This result is surprising, because we see little value in using HackTrack without logging runs. Therefore, we suspect that some people reported that they liked HackTrack despite the fact they did not really use the website. It's interesting to notice that people seemed to be more honest answering specific questions and we therefore decided to limit the number of "generally did you like / dislike HackTrack" in Survey 2.

6.1.2. Logging Performances and Injuries. As seen in Figure 14-c, most of our survey participants did not add performances or injuries to HackTrack. This result was not surprising since the team had not competed in any races between HackTrack's launch and the survey and none of our users had not been injured during this time either. Therefore we could not draw any conclusions about injury and performance logging (Figure 14-c) or visualization (Figure 14-d) from our survey results.

6.1.3. Tagging. As seen in Figure 14-c, the majority of users did not use HackTrack's tagging feature. While three survey respondents were excited about tags (one respondent said: "[HackTrack's tagging] is super innovative and no other online logging site I've seen has anything similar"), the majority of users wanted the feature improved. One respondent said HackTrack needs "easier tagging." Another said that she wants "a prompt for tags [because she] usually forget[s] and [has] to go back and add them." This was particularly concerning since tagging is one of HackTrack's main features.

Initially we envisioned HackTrack's tagging feature to provide a way to extract data from the "comments" a user enters about a run. Thus we did not include a separate "Comments" and "Tags" entry as shown in Figures 6-a and 6-b. For example, we built HackTrack so that a user could enter a comment such as:

> *Today I ran with X, Y and Z on a super nice run. My #left_foot 5 felt horrible and my #pelvis 3 felt pretty bad too. Think it's just shaking out pains? Hopefully. Kind of worried about the foot.*

and HackTrack would recognize "#left_foot" and "#pelvis" as tags associated with 5 and 3 respectively.

However, this vision of tagging hid the feature from the user and the survey results helped us realize we needed to modify our approach. We decided we needed to make tags a more explicit feature by giving them their own entry field (Figure 6-a and 6-b). Furthermore, we decided we should release a video pitching HackTrack which would feature custom tagging and what you could do with tags on HackTrack. As we will see in Section 6.2, these interventions seemed to be effective as they coincided with increases in user tagging.

6.1.4. Visualizing Training Data. HackTrack visualized an athlete's training data with two main graphs: the dashboard distance graph and the dashboard sRPE graph. As seen in Figure 14-d, our users were evenly split on how often they used the distance graph and the majority did not engage with the sRPE graph.

User feedback was split on the distance graph. One user found the graph "easily accessible ... [and] very innovative" while another found it "a little busy" and another said they needed "more detailed info to understand [the graph]." User feedback on the sRPE graphs reflected a similar tone of confusion but was very consistent in this message. One person said "I'm not completely sure about the difference between RPE and mileage graphs" and another said "I don't understand the sRPE." Two people summed up the overarching concerns very nicely: "[there needs to be] a little more description and reminders of what the different graphs mean" and "there needs to be a bit more explaining when you first log on to the site so that you know what everything means and why it's significant."

Based on this feedback we planned two interventions: (1) we do not want our users to have to learn anything to appreciate HackTrack's dashboards – therefore we decided to introduce the concepts of "advanced" and "simple" dashboards. (2) we want users to engage with the data if they would like to so we decided to explain HackTrack's advanced dashboard in our promotional video. We will examine user response to these interventions in Section 6.2.

6.1.5. Visualizing Injury, Performance and Tags. Because users did not log these fields, they did not engage in the visualization of this data. Therefore, we were unable to analyze these visualizations in Survey 1.

6.1.6. Connecting with Coaches. We had not released the coaches portal at the time of this survey. Therefore, all results regarding coaches connections will be reserved for Section 6.3

In conclusion, Survey 1 indicated that people liked HackTrack's manual logging feature and RPE logging field. Users were less satisfied with HackTrack's tagging and dashboard graphs. As a result, we decided to change HackTrack's tagging mechanism, introduced the concept of "advanced" and "simple" dashboards and released a promotional video about HackTrack. In the next section we will see user responses to these interventions.

6.2. Objective User Data

In this section, we will present objective data about user behavior on HackTrack and highlight how logging behavior changed based on our interventions described in Section 6.1. By April 28^{th}, HackTrack had 30 users: 4 from the Princeton Men's Cross Country team, 24 from Princeton Women's Cross Country team, the Princeton Women's Cross Country athletic trainer and the Princeton Women's Cross Country coach. In total, these users, uploaded 614 runs, 568 tags, 32 performances and 10 injuries.

To get a better sense of how our athletes used HackTrack, we graphed their interactions with the

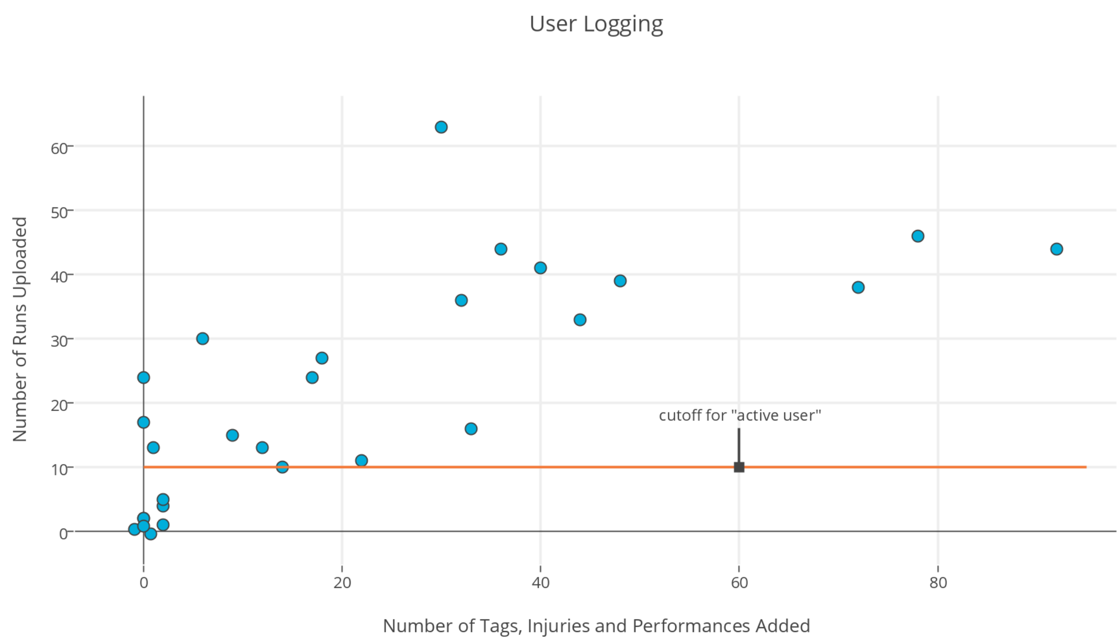


Figure 15: User Interaction with HackTrack. Each point is a user. The y-axis represents the number of runs the user has uploaded as of April 28^{th} and the x-axis measures how many tags, injuries and performances they've uploaded. We defined 10 runs uploaded to be the cutoff point between active and inactive users.

website via a scatter plot (Figure 15). Each point in this graph represent a user. The y-axis indicates the number of runs the user has uploaded to HackTrack while the x-axis indicates the total number of tags, injuries and performances they have added. Of the 28 athletes on our platform, 8 logged very few (< 10) runs. Since logging runs is the minimum feature a user must engage with to get any value out of HackTrack, we consider these users "inactive." Therefore, HackTrack had 20 active users through the trial period.

Before we move on, it is interesting to consider who the eight inactive athlete are and why they did not engage with HackTrack. Of the eight inactive users, four are the Men's Cross Country athletes. It is possible that the men's team participants were more reluctant to switch to a new system because they have used one online running log in the past. Furthermore, because we were focused on the Women's team, we made less of an effort to pitch HackTrack to the Men's team which may have contributed to their lack of interest. Unfortunately, we cannot speculate further than this because the four men's-team users did not complete HackTrack's user surveys.

Of four female athletes who were inactive, three were primarily cross training (biking or ellipticaling) during this time and did not find HackTrack useful for logging these types of activities. The other had trouble logging into her account initially and seemed to not engage in the website after that.

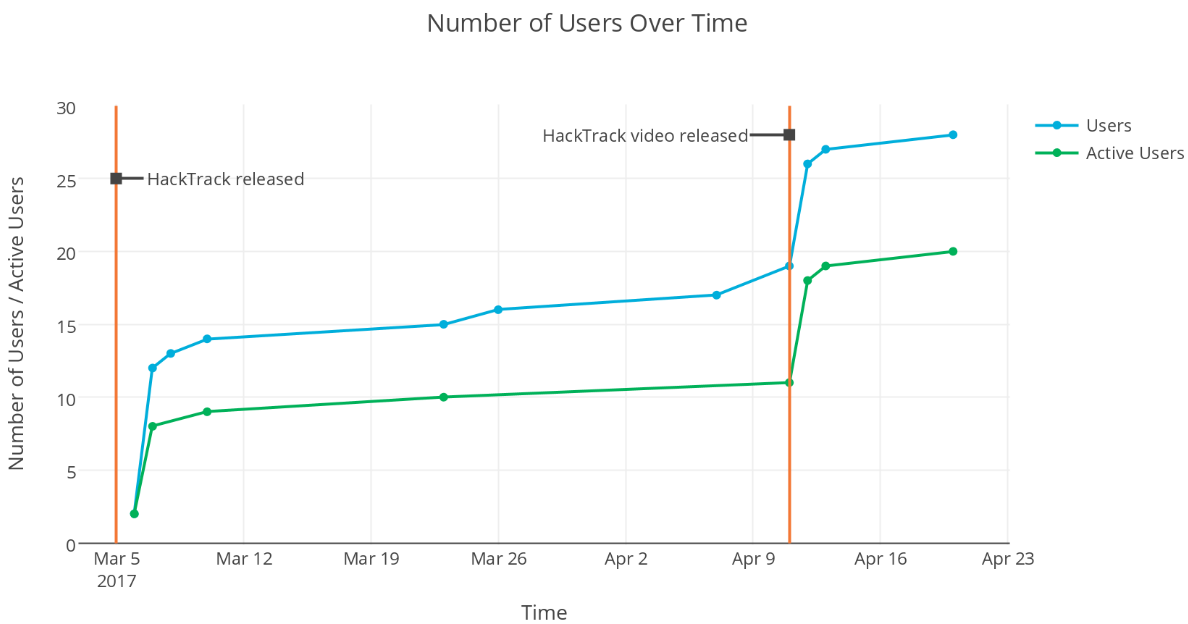


Figure 16: HackTrack Account Creation. This plot graphs number of HackTrack users over time. The blue line graphs all users whereas the green line graphs the number of active users.

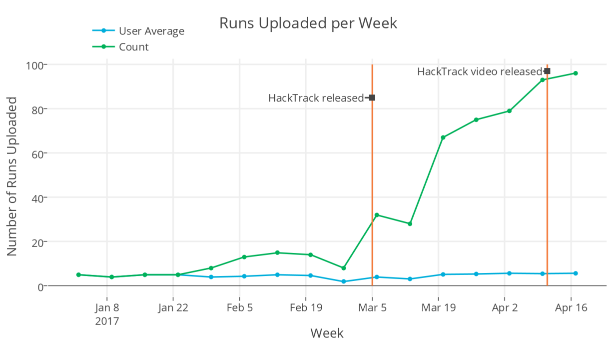


Figure 17: HackTrack Run Uploads. A scatter plot of the number of runs uploaded per week by active users. The blue line graphs average runs uploaded while the green line graphs the total number of runs uploaded.

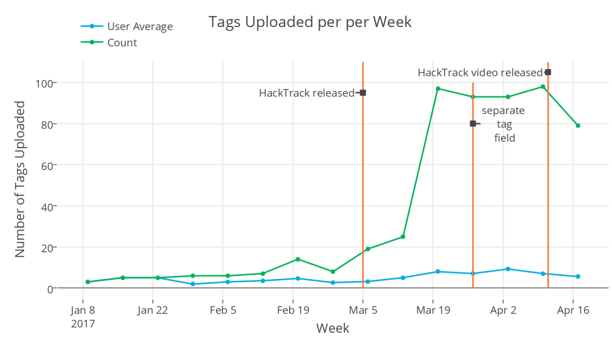


Figure 18: HackTrack Tag Uploads. A scatter plot of the number of tags uploaded per week by active users. The blue line graphs average tags uploaded while the green line graphs the total number of tags uploaded.

In addition to overall user engagement, we wanted to see when our users started using HackTrack. To do this, we first graphed the number of accounts on HackTrack over time (Figure 16). While HackTrack's initial release garnered 14 users, only 8 of these users were active (logged > 10 runs). It is interesting to note that this figure (around 60% of users are active) is similar to the finding we presented about users' engagement logging runs in Section 6.1. However, after we released a video pitching and explaining HackTrack more enthusiastically, we gained an additional 9 users, all of whom were active. These results indicate that at the very least our video intervention got more people on the Women's Cross Country team excited about HackTrack. The video was very clear about HackTrack's mission and it is possible that this mission appealed to these runners and motivated them to use the website.

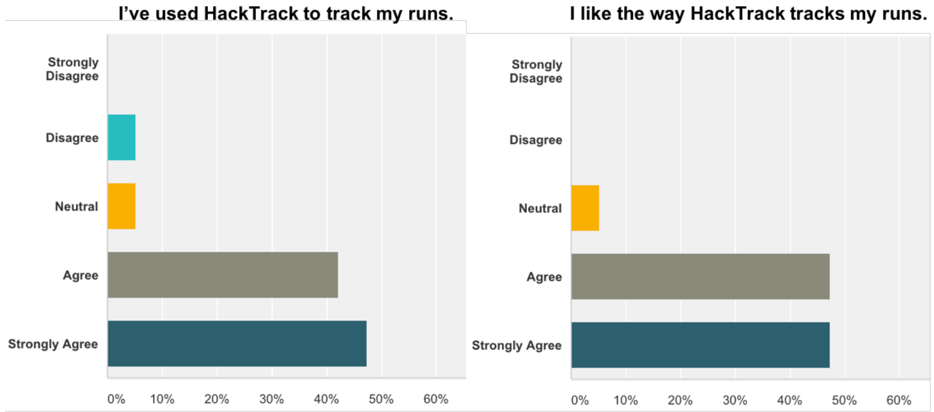
6.2.1. Logging Runs Next we examined how users logged runs on HackTrack (Figure 17. First, it is interesting to notice that HackTrack's users backlogged their runs quite a bit. For instance, one user who created a HackTrack accounts on March 6^{th} backlogged all the way to January 2^{nd}. Another user who created her account on the same day backlogged to February 5^{th}. From a results standpoint, this is great news. We believe that HackTrack has more value over time: finding trends is only possible if you've logged sufficient data. User backlogging suggests that they see HackTrack's value over time as well. However, it also makes it a little more difficult to analyze the effects of our interventions. There is a large spike in the number of runs logged 1.5 weeks before we released HackTrack's video. This seems odd – why would users suddenly change their logging behavior? It is important to notice that Figure 17, the x-axis represent the date the run was completed, not the date the run was uploaded. (Unfortunately we did not keep track of the latter metric.) Therefore, we suspect that the spike we see 1.5 weeks before HackTrack's video was released indicates that users changed their logging behavior in response to HackTrack's video and backlogged data. This backlogging of data is what caused the spike to appear 1.5 weeks before the video's release. Thus, it is possible that the video helped our users see the value in HackTrack and therefore we gained more users who were more committed to logging runs.

6.2.2. Tagging Finally, we examined user tagging behavior. Our active users averaged approximately 3 tags per week until March 19^{th} when the started averaging between 5 and 10 tags per week (Figure 18. This increase in average tagging occurs 1.5 weeks before we created a separate field to enter tags. Like with logging runs, we suspect that the intervention made users more inclined to enter tags and they backlogged tags as well, thus making a spike appear before the actual event. Furthermore, as with runs, we saw an increase in the number of tags entered per week as more users entered the platform. It is interesting to see that before March $19th$, the number of tags logged was always less than the number of runs logged, but after this date, the number of tags exceeded number of runs. These results indicate that our users became increasingly engaged with the tagging feature until they were tagging multiple items per run. Finally, it is interesting to note that tags decreased (both on average and in count) in the final week of data we analyzed. It is possible that users are still experimenting with this feature or are beginning to find it less useful than they originally hoped.

In conclusion, these objective data indicate that many of our interventions in response to Survey 1 were successful. HackTrack's promotional video may have encouraged more people to join and actively use the platform and redesigning the tagging mechanism may have caused an increase in tagging. However, many user concerns from Survey 1 regarded HackTrack's visualizations and we were unable to examine the effects of these interventions via objective logging data. Therefore, in the next section will will present Survey 2 to highlight user experience of our interventions.

6.3. Survey 2

Survey 2 serves as our final evaluation for HackTrack. We had participants rate statements about HackTrack's key feature on a Likert Scale (strongly dislike, dislike, neutral, like, strongly like) and asked them to elaborate on every key feature. To provide an easy way to compare Survey 1 and Survey 2, we also asked them to rank their use of logging features and HackTrack's visualizations. The results from this survey are presented below.



a) Results from our second survey indicate that 1 user disagrees with the statement, 1 user is neutral towards it, 42% agree with it, and 47% strongly agree. 19 users answered this question.

b) Results from our second survey indicate that 1 user is neutral towards the statement, 47% agree with it, and 47% strongly agree. 19 users answered this question.

Figure 19: Survey 2 Logging Runs

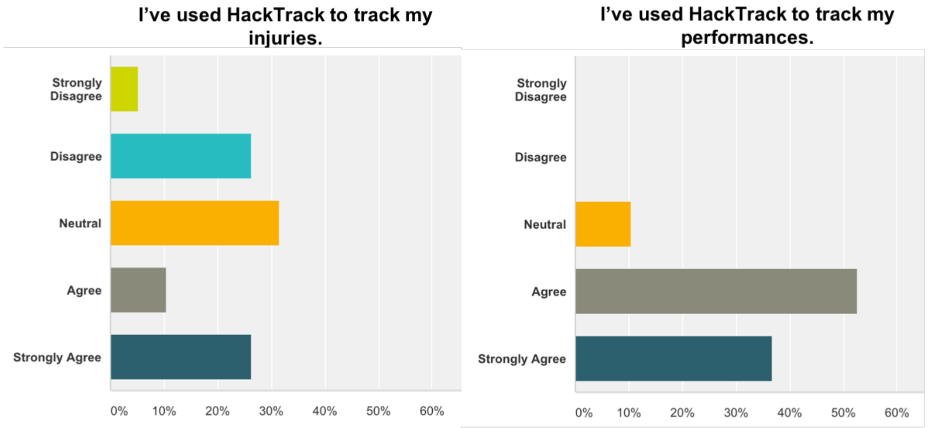
6.3.1. Logging Runs. As seen in Figure 19-a, two users reported that they disagreed or were neutral towards the statement "I've used HackTrack to track my runs." The critiques of HackTrack's run tracking were two fold: (1) HackTrack does not provide an easy way to log cross training. One respondent explained: "unfortunately most of my training consists of cross training right now, which isn't easily tracked using HackTrack." Another mentioned that "it would be helpful to add some logging specifically for cross training, especially since distance runners often always have that." (2) HackTrack does not provide an easy way to log "warmup" and "cool down" times. One respondent said: "I find tracking workouts (and pre-race, races, etc) kind of awkward with the RPE/distance/speed setup: for example if it's a short, hard speed workout I might rate the RPE for that part as a 9, but if I did a long warmup and cooldown, the total run time might be 60 minutes at much less than a 9." Another respondent said: "I think that there needs to be more flexibility in mileage because on workout days or even on some run days, we might have some additional mileage that is separate from our actual run."

While these features are not in the scope of HackTrack's novel concepts, these are two important critiques. For distance runners, many cardio workouts are cross training sessions and HackTrack does not make it easy to log these. Furthermore, while runners could enter "warm-up / cool-down" segments as separate runs, it would be much more convenient to allow them to enter different "segments" within a single run. As HackTrack continues to develop, these are important features we will consider.

The majority of respondents (89%, 17 people) either agree or strongly agree with the statement "I've used HackTrack to track my runs" (Figure 19-a) and the majority of respondents (94%, 18 people) agreed or strongly agreed with the statement "I like the way HackTrack tracks my runs." Many respondents are happy with the ease of entering data on HackTrack. One athlete said: "It's easy to input the most important cues that I should be reflecting on during training" Another said "Very easy, accessible way of tracking – especially inclusion of both manual log and upload functions." Yet another said: "I like how HackTrack gives a lot of freedom in describing runs and adding notes."

More importantly, respondents also indicated that they liked that HackTrack logs and tracks RPE and sRPE. While a few users did not understand the measure, others felt RPE / sRPE introduced a new measurement into their training logs which they found helpful. One participant said: "I think, for serious runners perhaps more so than recreational runners, RPE is the most important factor to keep track of in your log almost any day of the week you can complete a 40 minute generic run, but logging it without acknowledging how the effort felt/changes on a given day is really missing a big part of your training." Another said: "[sRPE is a] very useful thing to track that I don't normally track as specifically, but it is so important!!" Yet another said: "I had never thought to assess how I felt during each run. I think this is important for long term understanding of how my runs correlated with injuries correlates with performance." Overall, it seems like our users understood sRPE and RPE after the interventions and saw the value in tracking this subjective data.

6.3.2. Logging Performances and Injuries. As seen in Figure 20-a, 63% of respondents strongly disagreed with, disagreed with, or were neutral towards the statement "I've used HackTrack to track my injuries. The majority of these people indicated that they hadn't used the feature because they had not been injured during the season (in retrospect we should have put an "N/A" category in this question). In fact, the written feedback we got about HackTrack's injury logging feature was positive. One participant said: "I cannot comment on injury tracking because I've been lucky



a) Results from our second survey indicate that 1 user strongly disagrees with the statement, 26% disagree with the statement, 32% are neutral, 11% agree and 26% strongly agree. 19 users answered this question.

b) Results from our second survey indicate that 10% of users are neutral towards the statement, 53% agree with the statement and 32% are neutral, 11% agree and 37% strongly agree. 19 users answered this question.

Figure 20: Survey 2 Logging Performances and Injuries

to not have any real pain since I started logging my runs, but I do think it is helpful in the sense that it heightens your awareness of the volume and paces you've been maintaining if something starts bothering you, it would be helpful to look back and see if maybe it was coming from increased mileage, not enough recovery, etc." Another participant said: "So few online running logs make it easy to track injuries so this unique feature on hacktrack makes it an ideal platform for logging." Another participant said injury tracking was "definitely one of HackTrack's coolest features." Though not all of our participants used the feature, athletes found value in HackTrack's injury logging feature.

As seen in Figure 20-b, 84% of respondents agreed or strongly agreed with the statement "I've used HackTrack to track my performances." Many found this feature easy to use and helpful in keeping track of their efforts throughout the season. One respondent said: "[HackTrack's performance logging is] very user friendly and provides me with all of the data I want to know and need to know in order to analyze performance."

The minority of users who were neutral towards the statement: "I've used HackTrack to track my performances" cited lack of competitions as their reason for not using the feature. For example, one user said: "there wasn't much performance to track." Again it would have been very useful to create a "N/A" category for this question.

In summary, our users who raced and / or got injured used HackTrack's injury and performance logging. As one user nicely put, "I like that HackTrack added in performance and injuries because performances are what we train for, and injuries are what we aim to prevent, so it's important to understand why and how both happen."

6.3.3. Tagging. As seen in Figure 21, 31% of respondents disagreed with or were neutral towards HackTrack's tagging feature. These users cited two main issues. (1) users forgot exactly what tags they'd used in the past and ended up with more tags then intended (e.g. a user had a tag for #hot, and accidentally entered #hot_day as a new tag instead of #hot). For example, one user said: "when I was typing in tags sometimes I would forget the ones I had used before. I would recommend adding Autocomplete to the tag box, or maybe a list of all the tags that you have used could pop up. I think this would be helpful because then people would be more likely to create patterns with their tags." Another user said: "the hashtags [are] a great idea, but I could never remember which ones I had used before so I just ended up with all new tags each day." This is certainly problematic and annoying for users and something HackTrack seeks to fix in the future. (2) Users who were not as sold on HackTrack's tagging also found that the tagging feature provided so much flexibility that they weren't sure what to tag. For example, one user said: "There are so many possibilities for good tags (factors in running). Hours of sleep and pain are good ideas. I would have to think of other creative ideas that are relevant to me." In the future, HackTrack might want to provide more concrete examples of what type of information might be useful to tag.

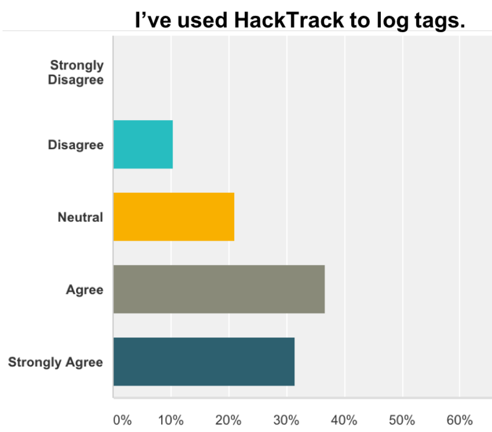


Figure 21: Survey 2 Tagging: Results from our second survey indicate that 10% of users disagree with the statement, 21% are neutral towards the statement, 37% agree with the statement and 32% strongly agree. 19 users answered this question.

The majority of respondents (69%) were happier with HackTrack's tagging and agreed or strongly agreed with the statement, "I've used hackTrack to log tags." Many of them found this new way to log data helpful in understanding their training. One respondent said: "I think [tagging] is a great idea, and presents information to you about your own body that you may not have even realized before." Another respondent said: "It was helpful for highlighting harder days and how many cross training days I was actually taking." Another said: "I love tagging my good workouts so I can see whether I am consistently running well. I find this a better way to monitor my progress."

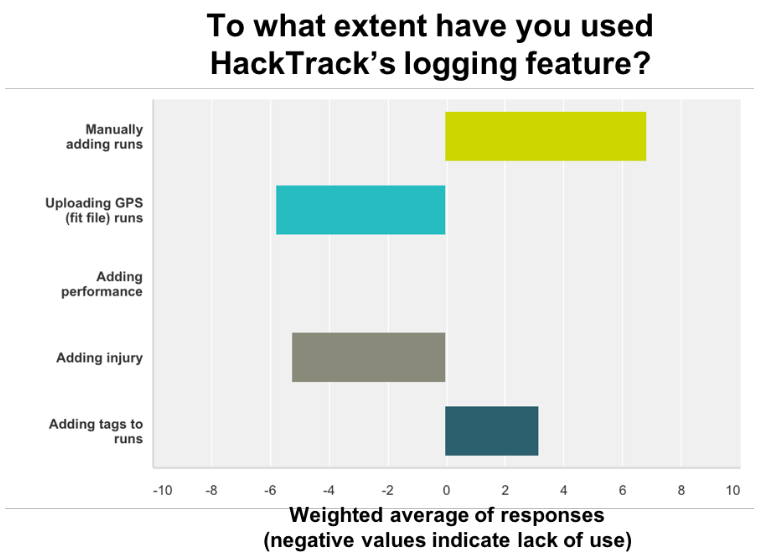


Figure 22: Survey 2 Logging: Since Survey 1, users have engaged with HackTrack more overall. A greater proportion of users are manually adding runs, uploading GPS files, adding performances, and adding tags. A smaller proportion of users are adding injury but we suspect this is because they have not been injured.

6.3.4. Logging Summary. Overall, our users were much more engaged with HackTrack's logging features by the end of our trial period. If we compare Figure 22 and Figure 14-c, we can see that a higher proportion of users were manually adding runs, uploading GPS files, adding performances and adding tags. These results support our hypotheses in Section 6.2 that the HackTrack promotional video got users more excited about using HackTrack and changing HackTrack's tagging feature made it more user friendly.

6.3.5. Visualizing Training Data. As mentioned previously, HackTrack provides two main graphs to visualize training data: a distance graph and an sRPE graph. As seen in Figure 23, 11% of users were neutral about the graphs – and the majority of them were still confused about sRPE. One user said "I don't understand [sRPE] much." Another said: "there needs to be assistance for the

user in analyzing the graphs and learning what to look for at first. I remember watching the video and understanding sRPE, but [I don't remember what it is]." From these results it is clear that HackTrack still needs
more support in understanding sRPE and it's other advanced dashboard features.

Still, the vast majority (89%) of users agreed or strongly agreed with the statement "I like the way HackTrack visualizes my sRPE and Distance." Users seemed to like these graphs for 3 main reasons: (1) A few users told us that they found both the distance and sRPE graphs more understandable after we explained them in HackTrack's video (2) Many users appreciated the sRPE graph because it gave them new and different information about their training. One user said: "I love that the graphs show not only my weekly mileage but also my sRPE, which allows me to see week-to-week differences in the difficulty of my runs as well. sRPE is certainly underrated by many athletes and coaches when they look at their typical training logs. I've learned from hacktrack that miles aren't necessarily the key thing to track when it comes to injury prevention." Another user said: "Visualizing RPE and mileage makes identifying spikes in my training so much easier." Another said: "I think visualizing mileage and sRPE like this is incredibly informative!" (3) A few users also cited the "simple" dashboards as a helpful tool. For example, on user said: "the [advanced] graphs were very confusing but I can make them go away with a button which is great!"

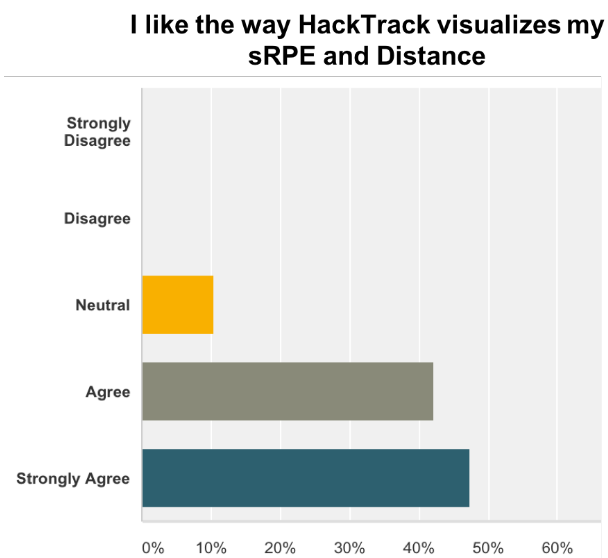


Figure 23: Survey 2 Training Visualization: 11% of users were neutral towards the statement, 42% agreed with the statement and 47% strongly agreed. 19 users answered this question.

In summary, HackTrack needs to provide more support to help users understand sRPE and the advanced graphs if they so choose. That said, HackTrack's video seemed to help a lot of our users understand and appreciate the training dashboard graphs and the majority of our users indicated that the training graphs give them insight into their running.

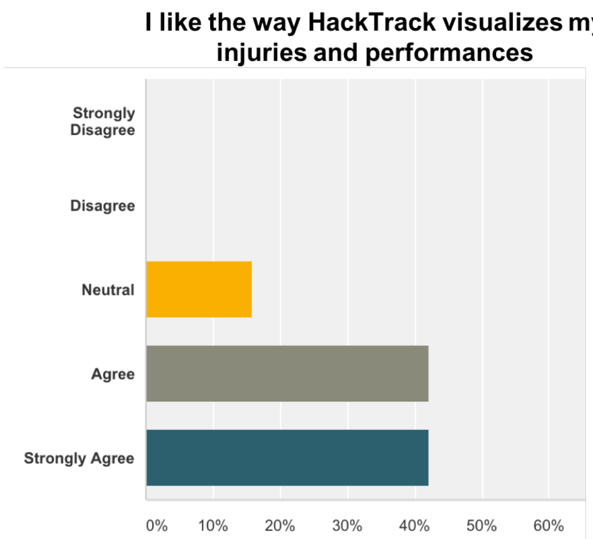


Figure 24: Survey 2 Performance and Injury Visualization: 15% of users were neutral towards the statement, 42% agreed and 42% strongly agreed. 19 people answered this question.

6.3.6. Visualizing Performance and Injuries. As seen in Figure 24, 15% of users were neutral towards the statement, "I like the way HackTrack visualizes my injuries and performances." Many of these 15% cited lack of logging as their main reason for not liking the visualization. Again, we should have added an "N/A" category to remedy this. Other users realized that there would be value in these graphs with more data but didn't find them as valuable if they only logged a few weeks. One user said: "I think that if I had more data over a long period of time, it would be more interesting." The latter issue points to one of HackTrack's main challenges: users will likely have to enter a lot of data in order to find it useful. While some users backlogged to get more out of HackTrack, the process must have been time consuming (you can only log one run at a time). It might be prudent to make backlogging easier on HackTrack.

The remaining 85% who agreed or strongly agreed with the statement were very enthusiastic about this graph. Many users thought the graphs helped them connect injury and performance with training. One user said: "The injury graphs are great because you can see how they line up with milage which gives a great insight into shaping/changing my running and training plan." Another said: "[It has been] interesting to see how spikes in RPE correlate with injury/performance." Another said: "You can see peaks and increases in training. Increased training exertion made easier runs feel much harder and resulted in poorer race performances." Another said: "HackTrack has helped me see all of my performances, injuries and training in one spot. This is great and super helpful."

Overall, athletes seemed to not only like the way HackTrack visualized their injury and performance data but also found the graph helpful in makinging connections between their injuries, performances and training. This is exactly HackTrack's mission and we are excited that users were able to do this. That said, user feedback in this area also highlights that HackTrack utility – and particularly the utility of these graphs – increases with volume. Therefore, HackTrack should aim to make backlogging data easier in the future.

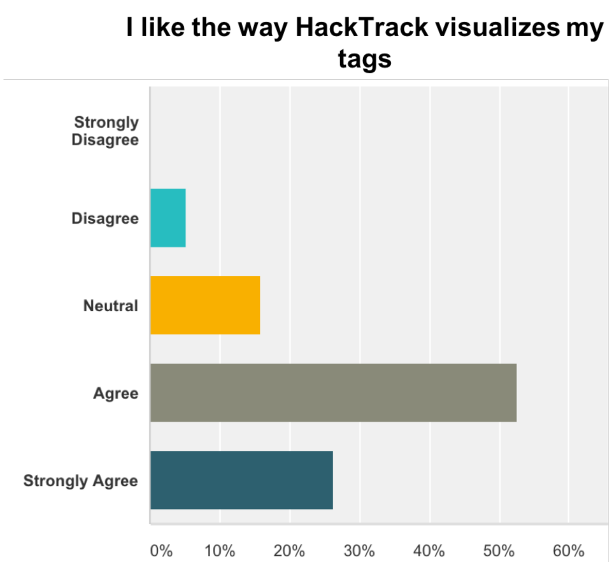


Figure 25: Survey 2 Tag Visualization: 1 person disagreed with the statement, 16% were neutral, 53% agreed and 26% strongly agreed

6.3.7. Visualizing Tags. Based on the survey, HackTrack's tagging visualization was its least popular visualization tool. 20% of users disagreed or were neutral towards the statement "I like the way that HackTrack visualizes my tags." Most of these people thought the graph was confusing because it displays all tags at once (Figure 9). One user said: "User tag graph is somewhat confusing: might be better if could select one tag graph to view at a time." Another said: "User tags a little difficult to read (lots of tags there, might be easier to visualize if could select a single tag to view at a time)." Another said: "I have a hard time interpreting the user tags graph, maybe because I was kind of all over the place in my tag use?"

Despite the critiques of this graph, many users still found it helpful in understanding patterns in training. For example, one respondent said: "I love the tags. Keeping track of sleep on my running log is something I didn't even realize how much I would value until I had it though HackTrack. It reminds me that there's more to my training than just running." Another said: "[My favorite graph is the user tagging graph because it helps me] track sleep." Another said "Very helpful for seeing how your tags relating to non-running factors relate to run performances. Useful to isolate certain factors and see how my performance jumped or dipped simultaneously or directly afterward. For me, is the most helpful function of HackTrack."

We hypothesize the mixed feedback about HackTrack's tagging visualization is due to our expectation about how athletes would use the feature. We anticipated that users would tag a few thing consistently – and the athletes who used tags in this way were often the ones who found the visualization helpful. Users who tagged many things found the graphs cluttered and confusing. Therefore, it is important for us to figure out how to make HackTrack's tag graph more usable for athletes who want to tag a lot. Furthermore, we did not consider that users might enter tags on very different numeric scales. For instance, one user entered #sore on a scale of 1 to 100 while she entered the tag #good_workout on a scale of 1 to 10. Because #sore and #good_workout are graphed on the same axis it is difficult to see variation in the lower scaled tag.

In summary, the tag graph was the most difficult to implement because we were not sure how our users would use tags. Now that we have more user data, it is clear that we need to better manage users with many tags and users with tags on different scales. Future iterations of HackTrack must work to make this graph more universally useful.

6.3.8. Visualization Summary. In conclusion, users interacted with and liked HackTrack's visualizations much more by the conclusion of our trial period. This is particularly apparent if we compare Figure 14-d and Figure 26. Perhaps the most impressive increase in popularity was HackTrack's sRPE graph, which was received a weighted average of -7 in Survey 1 and $+5$ in Survey 2. Because sRPE is a new variable, survey results indicate that it initially confused our users. However this confusion was reduced over time and with HackTrack's video. Users ultimately found that tracking and visualizing sRPE through HackTrack gave them important information about their training. Tracking and visualizing sRPE is unique to HackTrack and this result highlights the

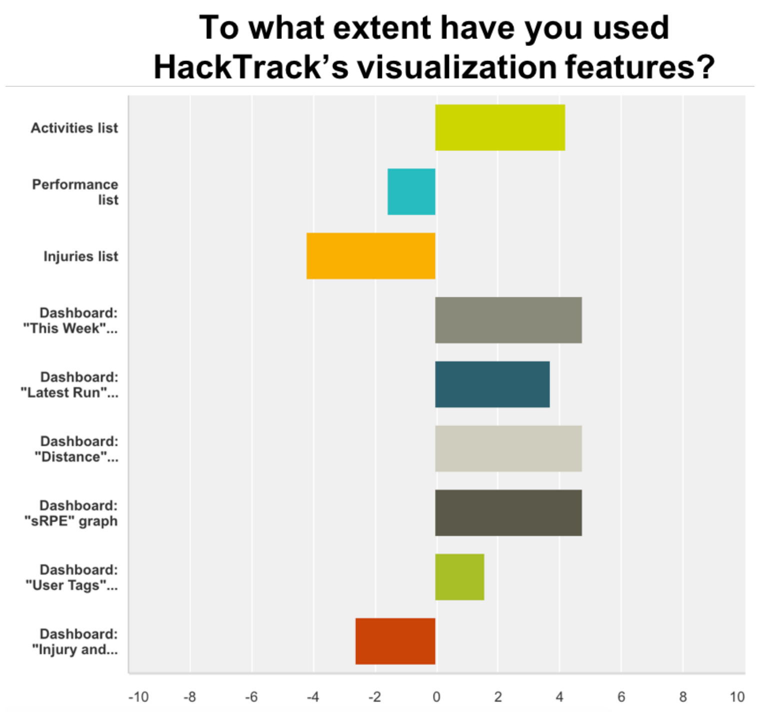


Figure 26: Survey 2 Visualization: Since Survey 1, users have engaged more with HackTrack's visualizations. The proportion of athletes who use HackTrack's Distance, sRPE and injury and performance graphs have increased dramatically (from a a weighted average of 0 to 5, -7 to 5, and -9 to -3 respectively). The proportion of athletes who use HackTrack's Tag's graph has also increased from -4 to 2.

importance of tracking subjective information.

6.3.9. Connecting with Coaches. HackTrack's connecting with coaches was not as meaningful to athletes as we'd hoped because they had no way of interacting with their coaches on the platform. While HackTrack certainly functions in isolation, we imagined that users might want to share their data with their coaches. We took great care in designing this feature so that athletes had maximum privacy – and our users appreciated it. For example, one user said: "I think that it is helpful for you to be able to select which tags other people see because then you can put honest tags, but still privatize your data." However, overall users did not find connecting with coaches helpful because there were no added capabilities once they connected. One user summed the sentiment up very nicely: "I didn't find this very helpful because once I connected with my coach, there wasn't anything else I could do."

On the other hand, our users on HackTrack's coaches platform saw value in their interfaces. Both participants liked HackTrack's tag visualization. One participant said: "The tags jump out immediately. I greatly appreciate the ability to click on one athlete to explore the hashtag it coincides with mileage and perceived exertion." The other said: "it can be helpful to see the spikes compared to sRPE and mileage if the [tags] predate an injury." They also thought the distance and sRPE graph was a great tool to monitor their team's training. One said: "[It is] great to be able to see visually weekly/chronic mileage, especially in trying to predict patterns or avoid injury if trending too high." The other said: "I really enjoy the visual presentation of the HackTrack Distance Graph. The colors specific to the athletes on the website allow me to compare and track athletes to themselves as well as others on the team." Both also agreed that "the true benefit of [HackTrack] will come with more data added. Being able to look at an entire year or several months of training will be huge in predicting trends and hopefully planning smarter training."

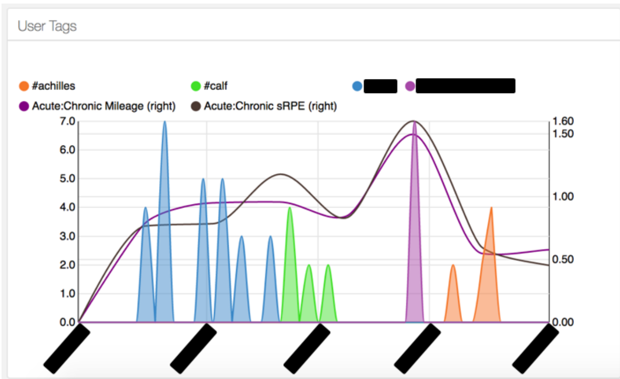
In conclusion, the concept of connecting with coaches remains important. The participants on HackTrack's coaches platform found value in the tags, distance and sRPE graphs. They saw these graphs as tools to understand how mileage and perceived exertion relate to injury and that they can use this information to modify training. They also noted that these graphs would be even more valuable with time. However, we did not implement this connection with enough interactive features to make it seem worthwhile to athletes. Further iterations of HackTrack ought to create mechanisms for coach-athlete communication so that both parties feel they are actively engaging with each other on the website.

This concludes our survey and objective data results. So far, we have found that athletes like HackTrack's mechanism for logging runs, sRPE, injuries and performance. While some users liked logging tags, others wanted the feature to be more structured. Athletes liked and engaged with HackTrack's distance, sRPE and injuries and performances visualizations. They found the sRPE visualization particularly informative and new metric and said that the injuries and performances visualization helped them understand how their training contributes to these events. However, HackTrack's tag visualization received mixed reviews and needs to be adapted to fit a wider range of user tagging behaviors.

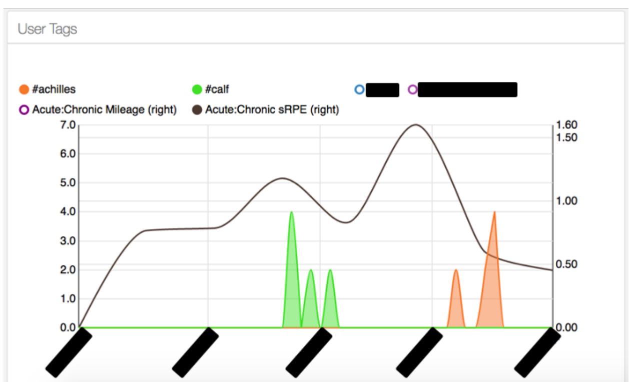
HackTrack's mission is to help athletes understand their training, performance and injury. Many of our results indicate that our novel features helped athletes do just this. One user said: "[HackTrack is] a good resource for tracking my mileage and seeing how it corresponds to injury." Another said: "Love [HackTrack]! It's made me much more consistent in logging because I really value the feedback it provides. No other running log has made it so easy to analyze your own training."

To illustrate the type of information our users have gained from HackTrack, we will now highlight three case studies. The first discusses someone who noticed her training might be connected to her tags; the second presents someone who noticed her training might be connected to her injury; the third present someone who felt that visualizing tags and performances together helped her understand a bad performance. Note that certain labels and all graph dates have been retracted in our figures to protect our users privacy.

6.4. Case Study 1



a) A user's Tag graph. This user attributes her calf pain (green) and achilles pain (orange) to the spikes in acute:chronic sRPE (brown line)



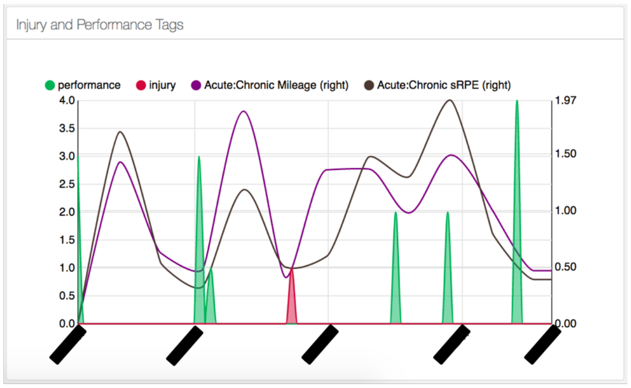
b) This figure is the same as subfigure (a) except we've isolated the user's sRPE (brown line), calf pain (green) and achilles pain (orange) for simplicity

Figure 27: Case Study 1: User Tags Graph

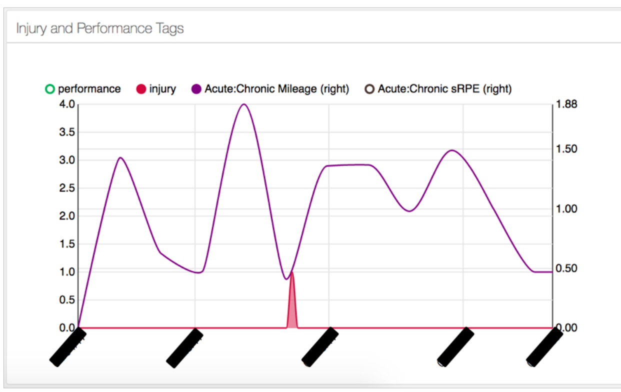
The user in this case study attributes her calf and achillies pain to spikes in her $acute : chronic$ sRPE (Figure 27). Her training was relatively stable but after a particularly intense week ($acute : chronicsRPE = 1.2$), her calf began to bother her. This subsided but after another spike in intensity ($acute : chronicsRPE = 1.6$), her achillies began to hurt. Fortunately, these aches and pains are not true "injuries" but they are they type of pain that this user suspects would lead to injuries if she did not address them. The user added that "[when I had] Foot and Achilles pain, HackTrack helped me identify what type of intensity contribute to this pain. Through HackTrack I was able to modify my training and connect with my physical trainer, to help my pain and eventually eliminate it all together."

This is a small sample size and certainly does not provide definitive results, but it does serve to illustrate they type of information a user might be able to learn from their user tags. Not only does this user believe that a spike in intensity led to problems she tracked via tags, but she also used the tags graph to help her monitor them.

6.5. Case Study 2



a) A user's Injury and Performance graph. This user attributes her injury (red) to the spikes in acute:chronic distance (purple line)



b) This figure is the same as subfigure (a) except we've isolated the user's acute:chronic distance (purple) and injury (red)

Figure 28: Case Study 2: Injury and Performance Graph

The user in this case study attributes her injury to the spike in her *acute* : *chronic* distance in the proceeding week (Figure 28). The week proceeding this injury was not particularly intense (*acute* : *chronic* sRPE = 1.18). Furthermore, in isolation, it didn't look like her mileage that week was very high. However, her past month of training had been relatively low volume, thus her *acute* : *chronic* distance was very high at 1.9. The athlete thinks: "at first I didn't think the week had been too much running, but after looking at my HackTrack graph and seeing the spike, I went back and realized I had tapered for two weeks before so it was way more running than I'd done in the last two weeks. Thankfully it wasn't a bad injury but I'd bet money that the sudden increase is what did it."

Again, this is merely an example and we ought not draw sweeping conclusions from it. But again, it illustrates some of the types of conclusions that people drew from the HackTrack's injury and performance graphs.

6.6. Case Study 3

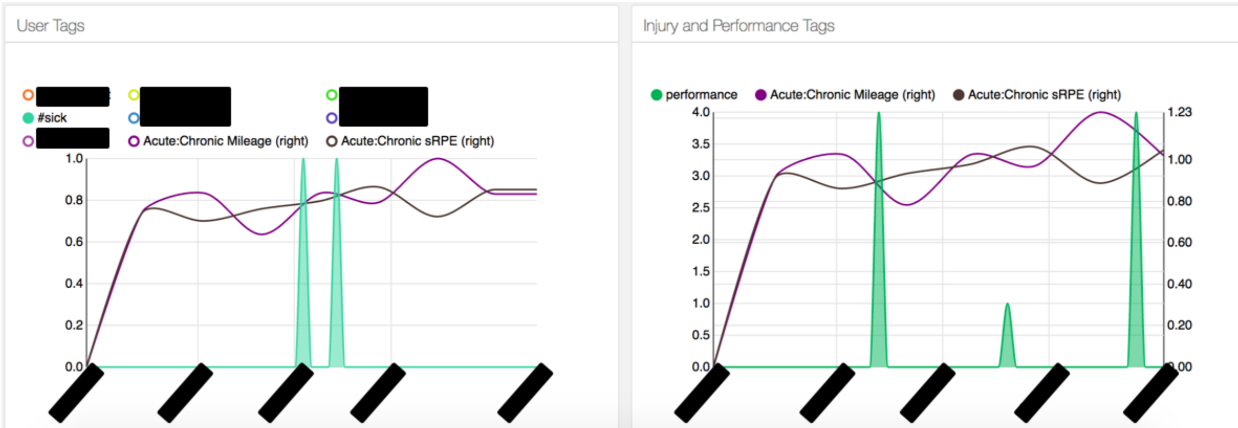


Figure 29: Case Study 3: User Tags and Performance and Injury Graphs This user attributed her poor performance (green spike in the middle) to being sick in the week preceeding the race.

The user in this case study found that HackTrack's Tags and Injury and Performance graphs helped her realize that a bad performance was probably due to being sick leading up to the competition (Figure 29). The athlete said she often gets very discouraged after bad races and has trouble moving forward from them. Associating each race with a numeric value and seeing all these performances in one place has "helped her look at race as a data point, not as a failures." Furthermore, in this specific case, the user realized through tagging that she had been sick in the week proceeding the race and this may have contributed to the bad performance. While this conclusion seems self explanatory, the user indicated that she blamed herself for running poorly until she saw very concretely that she had definitely felt sick earlier that week.

In this way, the user was able to understand and move past her poor performance and has a very strong performance at the next meet. Again, this is just an example, but we are happy HackTrack was able to help this athlete understand why her race was not as good as she'd hoped.

6.7. *Acute* : *Chronic* Ratio and Injury

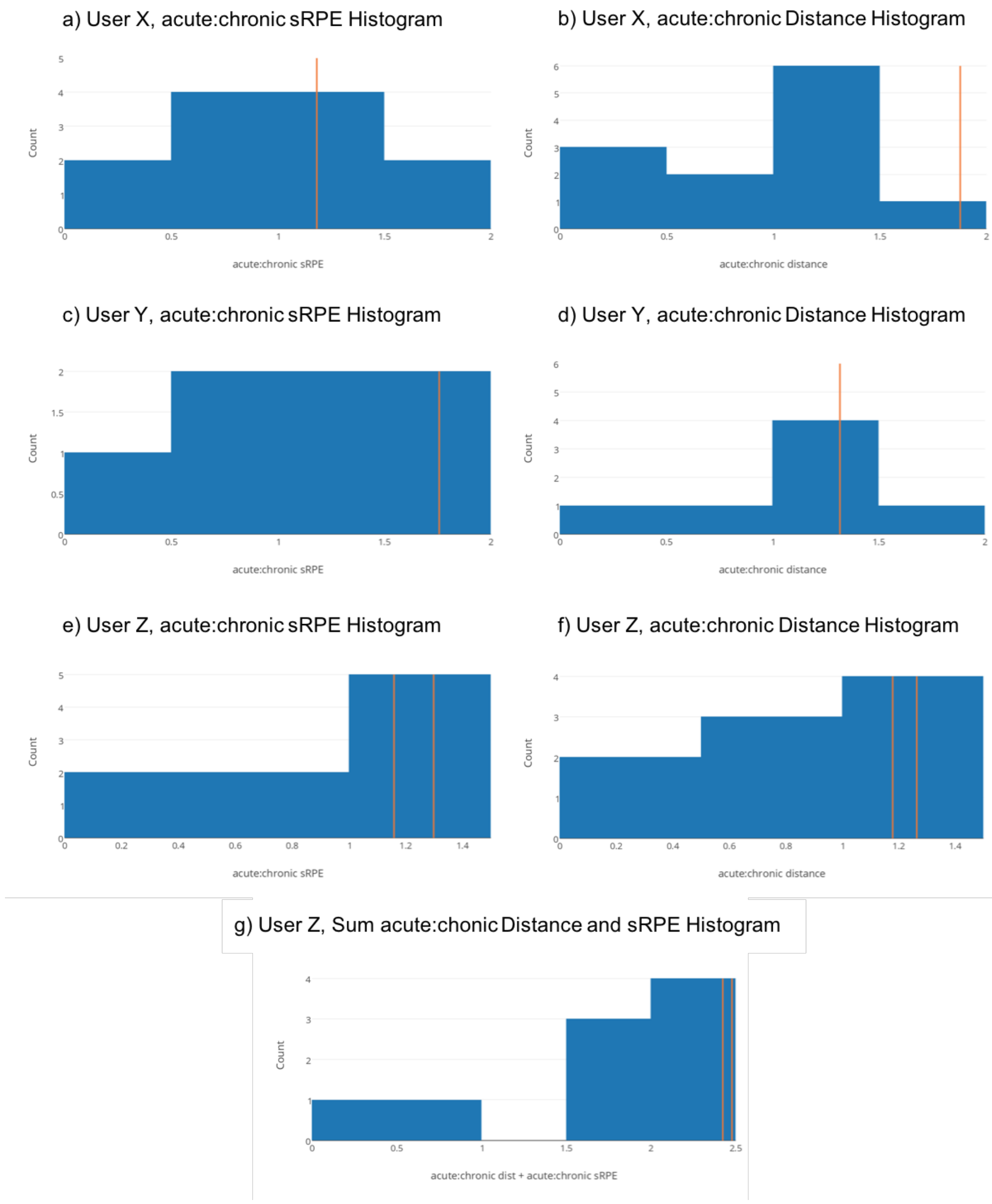


Figure 30: *acute* : *chronic* **Workload Ratios and Injury:** Subgraphs a, c and e are histograms of user X, Y and Z's weekly *acute* : *chronic sRPE* respectively. Subgraphs b, d and f are histograms of their weekly *acute* : *chronic distance* respectively. Subgraph g represents a histograph of Z's weekly *acute* : *chronic* sRPE + weekly *acute* : *chronic* distance. All orange lines represent the athlete's ratio the week before an injury.

Finally, HackTrack places significant value on the *acute* : *chronic* workload ratio. For example, in its advanced dashboard, HackTrack displays *acute* : *chronic* ratio in all four of its graphs. This ratio was draw from the work of Gabbett et al. [2] [13] [14], who showed that high *acute* : *chronic* workload ratios increased an athlete's risk of injury in the subsequent week. However, this relationship has never been investigated in distance runners. Case Study 1 and Case Study 2 suggest that users found the *acute* : *chronic* distance and sRPE ratios helpful in understanding their injuries and injury-related tags. This section will explore the relationship further. Namely, we examine whether our athletes who reported injury had a relatively high *acute* : *chronic* ratio the week proceeding it.

Of the nine athlete who reported injury, only three logged data for at least eight weeks and are therefore, the only users we consider in this section. We will call these athletes, X, Y and Z. Figure 30 displays a histogram of their *acute* : *chronic* sRPE and distance ratios with an orange line(s) indicating the *acute* : *chronic* ratio the week before an injury. While user X's sRPE ratio was not particularly high the week before her injury, her distance ratio was the highest she recorded over a 12 week period (Figure 30-a and Figure 30-b). While user Y's distance ratio the week before her injury was not particularly high, her sRPE ratio was the second highest she recorded over eight weeks (Figure 30-c and Figure 30-d). User Z sustained two injuries and while neither injury coincided with excessively high sRPE and distance ratios the proceeding week (Figure 30-e and Figure 30-f), we noticed both ratios were above average for user Z. We hypothesized that the combination of these two values might be linked to Z's injury. Therefore, we summed *acute* : *chronic* distance and *acute* : *chronic* sRPE for user Z, and found that her injuries occurred a week after her first highest and second highest values respectively (30-g).

Clearly, these observations rest on a very small sample size and we should not place excessive weight on them. However, user X's high distance ratio the week before her injury and user Y's high sRPE ratio the week before her injury support Gabbett's finding that high *acute* : *chronic* ratios increase the likelihood of injury in the subsequent week. While user Z's data does not directly support Gabbett et al.'s *acute* : *chronic* ratio theory, it implies a possible extension. Gabbett et al. have shown that *acute* : *chronic* distance and *acute* : *chronic* sRPE independently increase the likelihood of injury in the subsequent week. If this is true, it seems reasonable to suspect that a function of both ratios might more accurately model the likelihood of injury. This is an interesting extension for future work.

Our data analysis is limited because our sample size is very low. However this line of inquiry illustrates the type of analysis we could delve into as HackTrack continues to collect data. In the future, we would like to not only investigate the relationship between *acute* : *chronic* workload and injury but also see if there is a predictive relationship between *acute* : *chronic* workload and performance.

7. Conclusion and Future Work

In this paper we presented HackTrack – an online running log which seeks to help athletes understand their training, performance and injuries. We approached this goal using four novel ideas: (1) HackTrack allows users to log not just runs but also the RPE values associated with runs; (2) HackTrack visualizes this training information over time via summary graphs which track acute, chronic and *acute* : *chronic* sRPE and distance; (3) HackTrack provides mechanisms to track injury and performance and visualize these data alongside training data; and (4) HackTrack allows users to log custom tags and visualize these tags alongside training data.

From user feedback, it is clear that HackTrack needs to improve its tagging feature. If HackTrack wants to compete with other running logs available, it also need to give users the ability to log cross training, distinguish between different segments of a run (e.g. warm-up versus workout) and provide support for automatic syncing with GPS watches. Furthermore, HackTrack's concept of connecting with coaches needs to allow athletes and coaches to actively engage on the platform.

That said, users seemed to like the way that HackTrack allowed them to log runs and RPE. Many users also found the distance and sRPE graphs helpful – particularly after we explained *acute* : *chronic* workload to our users and allowed them to choose between "simple" and "advanced" graphs. Our users liked that HackTrack allowed them to log injuries and performances and some users were able to better understand their injuries and performances via HackTrack's visualization.

The feedback we're most excited about, however, have been the requests to keep the website running after our thesis is due. One athlete wrote asking us to "please maintain the site because I want to use it over the summer!" A few others have emailed to double check that they'll still be able to use HackTrack after May 5^{th}. We know it's possible that many of our users have used HackTrack to help us in our project, but their interest in HackTrack beyond our paper deadline suggests that the tool has been genuinely useful.

In the future, we would like to implement the features described above so that HackTrack is more appealing to users. With more data, we would also like to more rigorously investigate the quantitative relationship between performance, training and injuries. Understanding this triad is the central goal of HackTrack. While HackTrack only provides qualitative information to athletes at the moment, we hope that with more data, it can provide quantitative answers as well.

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Thank you so much to my co-investigator, Nicole Marvin, who built a super cool app that asks runners for their RPE while their running! Subjective running data is awesome and as far as I know, hers is the only app or watch that will gather it as you run.

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IRB **Princeton University**
Institutional Review Board For Human Subjects, Office of Research Integrity and Assurance

NOTICE OF APPROVAL

To:	Thomas Funkhouser Katie Hanss Nicole Marvin	
Date:	October 25, 2016	
RE:	Protocol #:	0000007453
	Protocol Title:	Detecting Stride Degradation in Vivo: Does running form change with perceived levels of exertion?

Funding source(s): Internal

Approval Date:	October 25, 2016
Expiration Date:	October 20, 2017
Type of Review:	Expedited
Risk Level:	Minimal Risk
Submission Type:	Amendment

Title Change: Detecting Stride Degradation in Vivo: Does running form change with perceived levels of exertion?

Design: Participants will outfit themselves with wearable accelorometers and heart rate monitors.

1. **Adverse Events:** Any unanticipated problems involving risk to subjects or others that occurs in relation to this study must be reported to the IRB Office within 10 days.
2. **Continuing Review:** **It is the Principal Investigator's responsibility to obtain review and continued approval before expiration date** shown above. You may **not** continue any research activity beyond the expiration date without IRB approval. The IRB must review and approve all human subject research studies that are not exempt at intervals appropriate to the degree of risk, at least once per year, as required by 45 CFR 46.

   --In order to avoid lapses in approval of your research and automatic suspension of subject enrollment, please submit a completed Continuation Form and all current documents being used at least six weeks before the study expiration date.

   --Failure to receive continuation approval before the expiration date will result in the automatic suspension of the approval of this protocol on the expiration date.
3. **Changes/Amendments to Approved Research:** All changes or amendments to your protocol, consent form(s) or any other aspect of this study require review and approval by the IRB **BEFORE** implementation.
4. **Completion of Study:** If the research, including data analysis has been completed or you wish to terminate the study for any reason, please notify the IRB via email at irb@princeton.edu and include in the written notification, the reason for study termination.

5. This approval does not replace any departmental or other approvals that may be required.