An interdisciplinary examination of stress and injury occurrence in athletes

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2 ABSTRACT

This paper adopts a novel, interdisciplinary approach to explore the relationship between psychosocial factors, physiological stress-related markers and occurrence of injury in athletes using a repeated measures design across a 2-year data collection period. At three data collection time-points, athletes completed measures of major life events, the reinforcement sensitivity theory personality questionnaire, muscle stiffness, heart rate variability and postural stability, and reported any injuries they had sustained since the last data collection. Two Bayesian networks were used to examine the relationships between variables and model the changes between data collection points in the study. Findings revealed muscle stiffness to have the strongest relationship with injury occurrence, with high levels of stiffness increasing the probability of sustaining an injury. Negative life events did not increase the probability of injury occurrence at any single time-point; however, when examining changes between time points, increases in negative life events did increase the probability of injury. In addition, the combination of increases in negative life events and muscle stiffness resulted in the greatest probability of sustaining an injury. Findings demonstrated the importance of both an interdisciplinary approach and a repeated measures design to furthering our understanding of the relationship between stress-related markers and injury occurrence.

Keywords: Sports Injury, Stress, Interdisciplinary, Bayesian Network

1 INTRODUCTION

Over the last four decades sport-related injuries have received increased research attention (Ivarsson et al., 2017) in response to the high incidence (Rosa et al., 2014; Sheu et al., 2016) and associated undesirable physical and psychological effects (Leddy et al., 1994; Brewer, 2012). Multiple psychological (Slimani et al., 2018), anatomical (Murphy et al., 2003), biomechanical (Neely, 1998; Hughes, 2014) and environmental (Meeuwisse et al., 2007) factors have been associated with sports injury occurrence and several models of injury causation have been proposed that highlight the multifactorial nature of injury occurrence (Kumar, 2001; Meeuwisse et al., 2007; Wiese-Bjornstal, 2009), of which one of the most

widely cited was developed by Williams and Anderson (Fig 1; Andersen and Williams, 1988; Williams and Andersen, 1998).

Williams and Andersen's (Williams and Andersen, 1998) stress-injury model proposed that when faced with a potentially stressful athletic situation, an athlete's personality traits (e.g., hardiness, locus of control and competitive trait anxiety), history of stressors (e.g., major life events and previous injuries) and coping resources (e.g., general coping behaviours) contribute to the injury response, either interactively or in isolation. The stress response is central to the model and reflects the bi-directional relationship between athletes' appraisal of, and response to, a stressful athletic situation. The model predicts that athletes who have a history of stressors, personality traits that intensify the stress response and few coping resources, will exhibit greater attentional (e.g., peripheral narrowing) and/or physiological (e.g., increased muscle tension) responses that put these individuals at greater injury risk.

Within Williams and Andersen's (Williams and Andersen, 1998) model, major life events, which is a component of an athlete's history of stressors, most consistently predicts injury occurrence (Williams and Andersen, 2007); specifically, major life events with a negative, as opposed to positive, valence (Passer and Seese, 1983; Maddison and Prapavessis, 2005). Personality traits and coping resources have also been found to predict injury with athletes more likely to sustain an injury if they have poor social support and psychological coping skills, and high trait anxiety and elevated competitive state anxiety; compared to those with the opposing profile (Smith et al., 1990; Lavallée and Flint, 1996; Ivarsson and Johnson, 2010).However, the amount of variance explained by these psychosocial factors has been modest and typically between 5 - 30% (Galambos et al., 2005; Ivarsson and Johnson, 2010), which indicates a likely interaction with other factors.

While the psychosocial factors in Williams and Andersen's (Williams and Andersen, 1998) model have received the most research attention, less insight into the mechanisms through which these factors are proposed to exert their effect exists. To elaborate, the model suggests that injuries are likely to occur through either increased physiological arousal resulting in increased muscle tension and reduced flexibility or attentional deficits caused by increased distractibility and peripheral narrowing. However, to date, the research has largely focused on attentional deficits (Andersen and Williams, 1999; Rogers and Landers, 2005; Wilkerson, 2012; Swanik et al., 2007). For example, Andersen and Williams (Andersen and Williams, 1999) found athletes with high life event stress coupled with low social support had greater peripheral narrowing under stressful conditions compared to athletes with the opposing profile; these athletes went on to sustain an increased number of injuries during the following athletic season. Rodgers and Landers (Rogers and Landers, 2005) further supported Andersen and Williams's (Andersen and Williams, 1999) earlier findings by identifying that peripheral narrowing under stress mediated 8.1% of the relationship between negative life events and injury.

Knowledge of the physiological factors (e.g., increased muscle tension and reduced motor control) contributing to the remaining variance between negative life events and athletic injury remains sparse (cf. Williams and Andersen, 1998). One challenge faced by researchers addressing the sports injury problem through a psychological lens is the multifactorial nature of injury, and the possible interaction with physiological factors in the stress response (Meeuwisse et al., 2007; Wiese-Bjornstal, 2009). For example, a large body of research has suggested that training-related stress is also likely to contribute to the stress response and injury occurrence (Lee et al., 2017; Djaoui et al., 2017) and may account for the unexplained variance from the psychological predictors. Appaneal and Perna (Appaneal and Perna, 2014) proposed the biopsychosocial model of stress athletic injury and health (BMSAIH) to serve as an extension to Williams and Andersen's (Williams and Andersen, 1998) model. The BMSAIH enhances our

71 understanding of the mediating pathways between the stress response and injury alongside other health
72 outcomes and behavioral factors that impact sports participation (Appaneal and Perna, 2014). The central
73 tenet of the BMSAIH is that psychosocial distress (e.g., negative life events) may act synergistically with
74 training-related stress as a result of high-intensity and high-volume sports training, and "widen the window
75 of susceptibility" (Appaneal and Perna, 2014, 74) to a range of undesirable health outcomes including
76 illness and injury. Consequently, the BMSAIH provides an important framework that has enhanced insight
77 into the multi-faceted nature of the injury process by building on Williams and Andersen's (Williams and
78 Andersen, 1998) model whilst including other physiological markers of training-related stress.

79   Although research supporting the BMSAIH has mainly focused on the relationship between hormonal
80 responses to training and injury occurrence (Perna and McDowell, 1995; Perna et al., 1997, 2003), other
81 training-related stress markers including heart rate variability (Bellenger et al., 2016; Williams et al.,
82 2017), muscle stiffness (Pruyn et al., 2015) and postural stability (Romero-Franco et al., 2014) have been
83 reported to be associated with an increased risk of injury. However, the largely mono-disciplinary approach
84 to examining the role of these markers has provided limited insight into the multifaceted interactions
85 with psychological factors that may contribute to injury occurrence. Furthermore, a reliance on designs
86 that capture a single point of measurement precludes the assessment of intra as well as inter-individual
87 changes and the effect of the time interval between measurement and injury occurrence on subsequent
88 injuries (Johnson et al., 2014). Such an approach fails to capture changes in both psychological factors and
89 physiological markers that may occur preceding an injury. Importantly, a repeated measurement approach
90 would enable an assessing of how variables and their interactions change with respect to time provide
91 greater insight into the effect that repeated exposure to major life events and other stress-related factors has
92 on injury occurrence.

93   Recently, Bittencourt et al. (Bittencourt et al., 2016) advocated a move away from studying isolated risk
94 factors and instead, adopt a complex systems approach in order to understand injury occurrence. Such
95 an approach posits that injury may arise from a complex "web of determinants" (Bittencourt et al., 2016,
96 3), where different factors interact in unpredictable and unplanned ways, but result in a global outcome
97 pattern of either adaptation or injury. Capturing the uncertainty and complexity of the relationships between
98 different variables using an appropriate interdisciplinary analysis within the framework of a complex
99 systems approach is challenging. Bayesian network (BN) modelling provides one solution by allowing
100 the construction of graphical probabilistic models using the underlying structure that connects different
101 variables (Scutari and Denis, 2014). The learned BN structure can be used for inference by obtaining the
102 posterior probabilities of a particular variable for a given query (e.g., if the value of variable A is x and
103 the value of variable B is y, what is the probability variable C of being value z?). Furthermore, unlike
104 regression or structural equation models, BN's do not distinguish between dependent and independent
105 variables when the underlying relationship in the network may not be known (Olmedilla et al., 2018). BN
106 modelling subsequently provides a valuable but underused interdisciplinary approach to investigating the
107 complex and unpredictable interactions of psychological and physiological factors implicated in the injury
108 process.

109   Using the frameworks provided by Williams and Andersen's (Williams and Andersen, 1998) stress
110 injury model and Appaneal's BMSAIH model, the aim of this interdisciplinary study was to develop new
111 understanding of the multifaceted interactions of psychological and physiological stress-related factors
112 with injury occurrence. A prospective, repeated measures design incorporating field-based physiological
113 and psychological measures combined with a BN modelling analysis was used to address the study aim.

2 METHODS

2.1 Participants

A total of 351 athletes (male: $n = 231$, female: $n = 120$) were initially recruited for the study from a British University and local sports clubs (Table 1). Participants had an average age of 22.0 ± 7.0 years and represented a range of team (football, rugby, netball, cricket, lacrosse, basketball and field hockey) and individual sports (athletics, tennis, weightlifting, gymnastics, judo, swimming and golf. Participants self-rated competitive level ranged from recreational to international standard. They were engaged in training for their respective sports for at least five hours per week. A total of 126 (49.03%) participants had sustained an injury in the 12 months prior to the start of the study (male: $n = 114$ [49%], female; $n = 48$ [40%]). All participants were injury free (no modifications to their usual training routine due to a sport related medical problem for a minimum of four weeks) at the start of the study. Ethical approval was obtained from the University ethics committee prior to the start of the study and all participants provided informed consent.

2.2 Measures

2.2.1 Injury

Participants self-reported any injuries they sustained at each data collection during the study period. An injury was defined as any sports related medical problem causing the athlete to miss or modify their usual training routine for at least 24 hours (Fuller et al., 2006, 2007; Timpka et al., 2014). Minor scrapes and bruises that may require certain modifications (e.g., strapping or taping) but did not limit continued participation were not considered injuries (cf. Appaneal et al., 2009). Injury status (did / did not sustain an injury) served as the main outcome measure.

2.2.2 Major life events

A modified version of the Life Events Survey for Collegiate Athletes (LESCA) was used to measure participants' history of life event stress (Petrie, 1992). The LESCA is the most widely used measure of major life events for athletes in the sports injury literature. Modifications were made to the LESCA to ensure the suitability of the items for the study cohort (S1 Table). The LESCA comprises 69 items that reflect possible life events that participants may have experienced. Example items include, "Major change in the frequency (increased or decreased) of social activities due to participation in sport", "Major change in the amount (more or less) of academic activity (homework, class time, etc)" and "Major change in level of athletic performance in actual competition (better or worse)". Participants were asked to rate the perceived impact of each life event they had experienced within 12-months preceding the study onset on an 8-point Likert scale anchored at -4 (*extremely negative*) and +4 (*extremely positive*). Negative and positive life event scores were calculated by summing the negative and positive scores, respectively. A score for total life events was also calculated by summing the absolute values for both negative and positive events. Petrie (1992) (Petrie, 1992) reported test-retest reliabilities at 1-week and 8-weeks with values ranging from .76 to .84 ($p < .001$) and .48 to .72 ($p < .001$) respectively. Petrie also provided evidence of discriminant, convergent and predictive validity. For this study, composite reliability (Fornell and Larcker, 1981) was preferred to Cronbach's alpha as it does not assume parallelity (i.e., all factor loadings are constrained to be equal, and all error variances are constrained to be equal) and instead takes into consideration the varying factor loadings of the items in the questionnaire. The composite reliability for the LESCA in this study was .84.

2.2.3 Reinforcement Sensitivity Theory Personality Questionnaire

A revised version of the Reinforcement Sensitivity Theory Personality Questionnaire (RST-PQ) was used to measure motivation, emotion, personality and their relevance to psychopathology (Corr and Cooper,

157 2016). The revised version of the RST-PQ comprises 51 statements that measure three major systems:
158 Fight-Flight-Freeze System (FFFS; e.g., "I am the sort of person who easily freezes-up when scared"),
159 Behavioural Inhibition System (BIS; e.g., "When trying to make a decision, I find myself constantly
160 chewing it over") and four Behavioural Approach System (BAS) factors; Reward Interest (e.g., "I regularly
161 try new activities just to see if I enjoy them"), Goal Drive Persistence (e.g., "I am very persistent in
162 achieving my goals"), Reward Reactivity (e.g., "I get a special thrill when I am praised for something I've
163 done well") and Impulsivity (e.g., "I find myself doing things on the spur of the moment"). Participants
164 rated each item on a scale from 1 (*not at all*) to 4 (*highly*) to reflect how well each statement described
165 their personality in general. The responses to items associated with each subscale (FFFS, BIS, RI, GDP,
166 RR and I) were summed to give a total personality score that was subsequently used for further analysis.
167 The composite reliabilities for each subscale were; BIS = 0.92, FFFS = 0.77, GDP = 0.87, I = 0.71, RI =
168 0.77, RR = 0.81. Further details regarding the revised RST are in S1 Appendix.

2.2.4   Heart rate variability

170 A Polar V800 heart rate monitor (HRM) and Polar H7 Bluetooth chest strap (Polar OY, Finland) was used
171 to collect inter-beat interval (IBI) data. IBI recordings using the Polar V800 are highly comparable (ICC =
172 1.00) with ECG recordings (Giles et al., 2016), which are considered the gold standard for assessing HRV.
173 In addition, HRV indices calculated from IBI and ECG data have shown a strong correlation (r = .99) in
174 athletes (Caminal et al., 2018) and under spontaneous breathing conditions (Plews et al., 2017).

2.2.5   Musculoskeletal properties

176 A handheld myometer (MyotonPRO, Myoton AS, Tallinn, Estonia) was used to measure passive muscle
177 stiffness. The MyotonPRO is a non-invasive, handheld device that applies a mechanical impulse of 0.40 N
178 for 0.15 ms perpendicular to the surface of the skin. The impulse causes natural damped oscillations in the
179 tissue, which are recorded by a three-axis digital accelerometer sensor in the device. The raw oscillation
180 signal is then processed, and the stiffness parameter is calculated (Agyapong-Badu et al., 2016). The
181 MyotonPRO has previously been reported to be a reliable and valid tool for the measurement of in-vivo
182 tissue stiffness properties (Chuang et al., 2013; Pruyn et al., 2016; Nair et al., 2014), and has demonstrated
183 good internal consistency (coefficient of variation < 1.4%) over sets of 10 repetitions (Aird et al., 2012).

2.2.6   Postural stability

185 Postural stability was assessed with a modified version of the balance error scoring system (mBESS)
186 based on the protocol recommended by Hunt et al. (2009). In total, each trial of the mBESS was performed
187 without shoes (McCrory et al., 2013) and included six stances in the following order; dominant leg (DL;
188 standing on the dominant foot with the non-dominant foot at approximately 30-degrees of hip flexion and
189 45-degrees of knee flexion), non-dominant leg (NDL; standing on the non-dominant foot with the dominant
190 foot at approximately 30-degrees of hip flexion and 45-degrees of knee flexion) and tandem leg stance
191 (TS; standing heel-to-toe with the non-dominant foot behind the dominant) on firm and foam (Alcan airex
192 AG, Sins, Switzerland) surfaces respectively (Fig 2). To determine leg dominance, participants were asked
193 their preferred leg to kick a ball to a target, and the chosen limb was labelled as dominant (cf. Cingel et
194 al., 2017). Participants were asked to maintain each stance for a total of 20-seconds. Participants hands
195 were placed on hips at the level of the iliac crests. A Sony DSC-RX10 video camera (Sony Europe Limited,
196 Surrey, United Kingdom) was used to record each participants performance during the mBESS.

197 The error identification criteria from the original BESS protocol was used by the lead researcher who
198 scored all the BESS trials. One error was recorded if any of the following movements were observed during
199 each trial: a) lifting hands off iliac crests; b) opening eyes; c) stepping, stumbling, or falling; d) moving the
200 thigh into more than 30 degrees of flexion or abduction; e) lifting the forefoot or heel; and f) remaining out
201 of the testing position for more than 5-seconds (Riemann et al., 1999). A maximum score of 10 errors was

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possible for each stance. Multiple errors occurring simultaneously were recorded as one error. A participant was given the maximum score of 10 if they remained out of the stance position for more than 5-seconds. A total score was calculated by summing the total number of errors recorded on all stances (DL, NLD and TS, on foam and firm surfaces). To assess the intra-rater reliability, a single measurement, absolute agreement, two-way mixed effects model for the intraclass correlation (ICC; Koo and Li, 2016) was used on a sample of 40 participants from the first time point. The test-retest scoring of BESS resulted in a "good" to "excellent" ICC score (ICC = 0.93, 95% confidence interval = 0.88 - 0.96), indicating the scoring was reliable.

2.3   Procedure

At the start of the academic year (September), coaches of sports teams at a British University and local sports clubs were contacted and informed about the study. With the coaches' permission, the lead researcher attended training sessions to inform athletes about the overall purpose of the study and the requirements of participation. Athletes who met the participation criteria and volunteered to take part in the study were invited to attend scheduled testing sessions. A repeated measures prospective cohort design was used to assess athletes' major life events, stress-related physiological markers and injury status over two consecutive 12-month periods. Each participant was asked to attend a total of three data collections over a 12-month period, with each data collection separated by a four-month interval (Fig 3). Participants provided informed consent before data collection commenced.

For the first three data collections (T1, T2 and T3), participants followed the same protocol in a specific order (Fig 4). To ensure all measures could be collected within a viable time-frame, participants were separated into two groups. The first group completed all computer-based measures followed by all physical measurements, whereas the second group completed all physical measurements followed by computer-based measures. Participants were randomly assigned to one of the two groups and remained in those groups across all time points.

2.3.1   Questionnaires

The questionnaires, which included demographic information, the LESCA, RST-PQ (T1, T2, T3) and injury status (T2, T3, T4) were completed on-line (SurveyMonkey Inc., USA, www.surveymonkey.com). The instructions for the LESCA were modified at T2 and T3 so that participants reported major life events that had occurred since the previous testing session. For injury reporting, participants were asked to record any injuries that they had sustained since the last data collection. The data were downloaded from surveymonkey.com and imported into R (R Core Team, 2019) for analysis.

2.3.2   HRV

To minimise potential distractions, participants were directed to a designated quiet area in the laboratory where IBI data were recorded. Participants were instructed to turn off their mobile devices to avoid any interference with the Bluetooth sensor. Each chest strap was dampened with water and adjusted so it fitted tightly but comfortably, as outlined by Polar's guidelines. Participants were seated and asked to remain as still as possible for the duration of the recording. No attempt was made to control participants' respiratory frequency or tidal volume (Denver et al., 2007). Inter-beat interval (IBI) data was collected for 10-minutes at a sampling frequency of 1000 Hz.

Raw, unfiltered IBI recordings were exported from the Polar Flow web service as a space delimited .txt file and imported into R (R Core Team, 2019) where the *RHRV* package (**???**) was used to calculate HRV indices. Raw IBI data was filtered using an adaptive threshold filter, and the first 3-minutes and last 2-minutes of each recording were discarded, leaving a 5-minutes window that was used to calculate the

245 root mean square of successive differences (RMSSD) in RR intervals following the recommendations for
246 short term IBI recordings (Laborde et al., 2017; Malik et al., 1996). RMSSD was calculated as:

$$\overline{RR} = \frac{1}{N} \sum_{i=1}^{n} RR_i \tag{1}$$

247 Where N is the length of the time series, and RR_i the RR interval between beats i and $i - 1$, where each
248 beat position corresponds to the beat detection instant.

249 2.3.3 Muscle stiffness

250 To assess muscle stiffness, participants lay horizontally on a massage bed and four testing sites were
251 identified on each lower limb. The muscle belly of the rectus femoris (RF), biceps femoris (BF), medial
252 gastrocnemius (MG) and lateral gastrocnemius (LG) sites were identified using a visual-palpatory technique
253 to determine the exact location of each site (Chuang et al., 2012). The visual-palpatory technique required
254 the participant to contract the target muscle to aid the lead researcher to visually identify the muscle. The
255 participant was then asked to relax the muscle and the muscle was palpated to locate the muscle belly. A
256 skin safe pen (Viscot all skin marker pen, Viscot Medical LLC, NJ) was used to mark the testing site in the
257 centre of the muscle belly.

258 After the eight testing sites had been identified, the testing end of the MyotonPRO (diameter = 3 mm)
259 was positioned perpendicular to the skin on the testing site. A constant pre-load of 0.18 N was applied
260 for initial compression of subcutaneous tissues. The device was programmed to deliver five consecutive
261 impulses, separated by a one-second interval (Morgan et al., 2018). For each impulse, the device computed
262 passive stiffness values, with the median of the five values being saved by the device for further analysis.
263 In accordance with Myoton.com, a set of five measurements with a coefficient of variation (CV) of less
264 than 3% was accepted. Sets of measurements above 3% were measured again to ensure data reliability.
265 Measurements were uploaded using MyotonPRO software and imported in R (R Core Team, 2019) for
266 further analysis. For each participant, the sum of all eight testing sites was calculated to provide a total
267 lower extremity stiffness score and was used for further analysis

268 2.3.4 Postural stability

269 Instructions for the mBESS were read to each participant and a demonstration of the positions was
270 provided by the research assistant. For each position, participants were instructed to close their eyes, rest
271 their hands on their iliac crests and remain as still as possible for 20-seconds. Participants were instructed to
272 return to the testing position as quickly as possible if they lost their balance. The video recording was started
273 prior to the first stance position and stopped after all stances had been completed. Each completed mBESS
274 protocol took approximately four-minutes. Only one trial was performed to avoid familiarisation effects
275 across the repeated measurement (cf. Valovich et al., 2003). The video recordings for each participant were
276 imported from the recording equipment (Sony DSC-RX10) and the lead researcher scored each trial using
277 the error identification criteria.

278 2.4 Data Analysis

279 Two Bayesian Networks (BN) were used to explore the relationships between the psychological measures,
280 physiological markers of stress and sports injury. A BN is a graphical representation of a joint probability
281 distribution among a set of random variables, and provides a statistical model describing the dependencies
282 and conditional independences from empirical data in a visually appealing way (Scutari and Denis, 2014).
283 A BN consists of arcs and nodes that together are formally known as a directed acyclic graph (DAG),
284 where a node is termed a parent of a child if there is an arc directed from the former to the latter (Fig 5;

285 Pearl, 1988). However, the direction of the arc does not necessarily imply causation, and the relationship
286 between variables are often described as probabilistic instead of casual (Scutari and Denis, 2014). The
287 information within a node can be either continuous or discrete, and a complete network can contain both
288 continuous and discrete nodes; however, discrete networks are the most commonly used form of BN (Chen
289 and Pollino, 2012). In discrete networks, conditional probabilities for each child node are allocated for
290 each combination of the possible states in their parent nodes and can be used to assess the strength of a
291 dependency in the network.

292 In order to use discrete networks, continuous variables must first be split into categorical levels. When
293 there are a large number of variables in the network, limiting the number of levels has the benefit of
294 producing a network that is more parsimonious in terms of parameters. For example, a network with 10
295 variables each with two levels has 100 (10^2) possible parameter combinations, however the same network
296 with three levels has 1000 (10^3) possible parameter combinations, the latter being significantly more
297 computationally expensive. Using a larger number of splits in the data also comes at a cost of reducing the
298 statistical power in detecting probabilistic associations, and reduces the precision of parameter estimates
299 for the probabilistic associations that are detected because it reduces the sample-size-to-parameters ratio
300 (Scutari and Denis, 2014). Typically, no more than three levels have been used in Bayesian networks in the
301 sports injury literature (Olmedilla et al., 2018; Ruiz-Pérez et al., 2019)

302 Learning the structure of the network is an important step in BN modelling. The structure of a network
303 can be constructed using expert knowledge and/or data-driven algorithm techniques (e.g., search and score,
304 such as hill climbing and gradient descent algorithms; Scutari & Denis, 2014). The learned structure can
305 then be used for inference by querying the network[1] and obtaining the posterior probabilities of a particular
306 node for a given query. The posterior distribution can be obtained by $Pr(X|E, B) = Pr(X|E, G, \Theta)$,
307 where the learned network B with structure G and parameters Θ, are investigated with new evidence E
308 using the information in B (Scutari and Denis, 2014). In the example network presented in Fig 5, new
309 values assigned to each of the parent nodes (e.g., both set to "Low") could be used to investigate what
310 effect the new information has on the state of the child node (conditional probability of a particular state of
311 the child node). In a more complex network containing many nodes, the outcome of a particular node can
312 be assessed conditional on the states of any subset of nodes in the network. BNs therefore provide a unique
313 and versatile approach to modelling a set of variables to uncover dependency structures within the data.

314 BNs have recently been used in the sport psychology literature (Olmedilla et al., 2018; Fuster-Parra et al.,
315 2017) and offer several benefits over traditional statistical analysis. For example, predictions can be made
316 about any variable in the network, rather than there being a distinction between dependent and independent
317 variables in the data, such as in linear regression models that are often used within the sport psychology
318 literature (Olmedilla et al., 2018; Bittencourt et al., 2016). Furthermore, the structure of a network can be
319 obtained from both empirical data *and* prior knowledge about the area of study; the latter being particularly
320 useful when there are a large number of variables in the network, or only a small number of observations are
321 available in the data (Xiao-xuan et al., 2008). In such instances, a purely data driven approach to learning
322 the network would be time-consuming due to the large parameter space, and inefficiency at identifying an
323 approximation of the true network structure. Prior knowledge about dependencies between variables can
324 therefore be included in the network structure, while still allowing a data driven approach for unknown
325 dependencies, to improve the overall computation of the network structure (Heckerman et al., 1995; Xu et

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[1] The term "query" in relation to Bayesian Networks stems from Pearl's expert systems theory (1988). A query can be submitted to an expert (in this case, the network is the expert) to get an opinion, the expert then updates the querier's beliefs accordingly. Widely used texts on Bayesian Network analysis (Koller and Friedman, 2009) have widely adopted the terminology in favour of that used in traditional statistics.

8

326 al., 2015). The following sections detail the steps taken in the current study to firstly prepare the data for
327 each network, and then obtain the structure of each network that was used for further inference.

328 2.4.1   First network

2.4.1.1   Data Preparation

330 Of the 351 participants that were initially recruited for the study, 94 only completed the first time
331 point, and therefore had to be removed from the study as no injury information was obtained for these
332 participants following the first time point. To prepare the data for the BN, missing values in the dataset
333 were first imputed. Out of the 650 total measurements across all time points in the current study, there
334 were 31 (4.64%) missing muscle stiffness measurements and 70 (10.48%) missing heart rate recordings.
335 The missing data were due to technical faults in the data collection equipment and were considered to be
336 missing completely at random. A missing rate of 15-20% has been reported to be common in psychological
337 studies, and several techniques are available to handle missing values (Enders, 2003; Lang et al., 2013). In
338 the current study, the *caret* package (Kuhn et al., 2008) was used to impute the missing values. A bagged
339 tree model using all of the non-missing data was first generated and then used to predict each missing value
340 in the dataset. The bagged tree method is a reliable and accurate method for imputing missing values in
341 data and is superior to other commonly used methods such a median imputation (Kuhn et al., 2008).

342 A median split technique was used to discretise the data used in the network into "Low" and "High"
343 levels. All variables apart from negative and total life events were approximately normally distributed
344 (based on visual inspection, see supplementary material Sx) and required no further transformation prior to
345 the median split. For the LESCA questionnaire data, a cumulative total of the current, and previous time
346 points was calculated at each time point to account for the potential continuing effect of the life events
347 experienced by athletes over time. Given the limited support for a relationship between positive life events
348 and injury (Williams and Andersen, 2007), only negative and total life events were included in the network.
349 Cumulative negative, and cumulative total life event scores at each time point were first log scaled so
350 distributions were approximately normal, and then binarised using the median at each time point (nlelg
351 and tlelg respectively). In addition to the log scaled cumulative values, an untransformed NLE score from
352 the first time point was included as an additional variable based on previous literature that indicates this
353 variable should have a strong relationship with injury outcome (Ivarsson et al., 2017).

2.4.1.2   Network structure

355 To obtain the network structure, several steps were taken to ensure that both a theoretically realistic
356 network, and a network that was an appropriate fit to the collected data, was used for inference. Prior
357 knowledge about the network structure was included by providing a list of arcs that are always *restricted*
358 from being in the network (blacklist), and a list of arcs that are always *included* in the network (whitelist).
359 Additionally, there are several scoring functions such as Bayesian Information Criteria (BIC) and Bayesian
360 Dirichlet equivalent uniform (BDeu) that can be used to compare network structures with certain nodes
361 and arcs included or excluded (Scutari and Denis, 2014). To account for the repeated measures design
362 employed in this study and to maximise the use of the data, pairs of complete cases (e.g., participants who
363 completed T1 + T2, and T2 + T3) were used in a two-time Bayesian network (2TBN) structure (Murphy,
364 2002). In the 2TBN, variables measured T2 could depend on variables measured at T1 (e.g., T1 → T2) and
365 variables measured at T3 could depend on variables measured at T2 (e.g., T2 → T3). However, arcs were
366 blacklisted between T2 → T1 and T3 → T2 to preserve the order in which data was collected. Variables
367 were separated into two groups; "explanatory", for variables that did not change during the study (e.g.,
368 gender), or "independent", for variables that were measured at each time point and could vary during
369 the study. Independent variable names were suffixed with _1 for time point T, and _2 for time point T+1
370 (e.g., T1_1 → T2_2 and T2_1 → T3_2). Formatting the data in this way meant participants who completed

371 T1 and T2, but did not complete T3, could still be included in the analysis. Table 2 provides an example
372 of the formatted data and demonstrates that participants 1 and 3 have complete data, and therefore have
373 two rows of data each representing variables from T1 → T2 and T2 → T3, respectively. Participant 2
374 did not complete the final data collection at T3 and therefore only has one row of data representing the
375 variables collected at T1 and T2. In addition to the blacklisted arcs between T2 → T1 and T3 → T2, the
376 direction of arcs was restricted between independent variables and explanatory variables (e.g., independent
377 → explanatory); however, arcs were not restricted between explanatory → independent variables. Finally,
378 arc direction was restricted between specific nodes within the explanatory variables. Arcs from clevel →
379 gender, nlebase → gender and nlebase → ind_team were included in the blacklist, as arcs in these directions
380 did not make logical sense. All subsequent models used the same blacklist.

2.4.1.3 Preliminary network structures

382 Prior to the final network structure presented in the results section, several structures with different
383 combinations of variables were explored. Networks were learned using a Tabu search algorithm (Russell
384 and Norvig, 2009) and BIC was used to compare different models. A higher BIC value indicates the
385 structure of a DAG is a better fit to the observed data (Scutari and Denis, 2014). BIC values for each
386 combination of variables of interest are reported as the combination of variables with the highest BIC value,
387 followed by the relative scores of the other variables in the model.

388 Initially, both negative life events and total life events were included in the network structure, however,
389 the network score was improved when only nlelg or tlelg was included (highest BIC value = nleleg, BIC
390 values relative to nlelg; tlelg only = -83.64, tlelg and nlelg = -218.31). Additionally, despite strong evidence
391 in the literature that both negative (NLE) and total life event (TLE) stress are related to injury occurrence
392 (Williams and Andersen, 2007), network structures learned using the Tabu search algorithm failed to
393 identify a relationship between NLE and injury or TLE and injury in the data. Given that nlelg provided
394 the highest network score, and there is a stronger relationship between negative life events and injury in
395 the literature, an arc was whitelisted between nlelg_1 and injured_1 and nlelg_2 and injured_2 in the final
396 network structure. TLE score was not included in the final structure.

397 The subscales representing the BAS (RR, RI, GDP and I) showed limited connection to other variables in
398 the network. Therefore, several models were run with each scale individually to find the scale that resulted
399 in the highest BIC value (values are shown relative to the highest value). RI provided the highest BIC
400 value, compared to RR (-9.07), GDP (-15.06) and I (-16.33). Including all the variables (RR, RI, GDP
401 and I) resulted in a significantly lower score -894.33) indicating that including all the variables was not
402 beneficial to the model structure and did not offset the cost of the additional parameters. Therefore, only RI
403 was included in the final structure.

404 Finally, both total score and asymmetry for balance were included in the initial network. However, visual
405 inspection of the network revealed no arcs between bal_asym_1 or bal_asym_2 and any other node in the
406 network. Therefore, balance asymmetry was removed from the final network structure. To summarise,
407 Table 3 reports the variables that were included in the final network structure.

408 Preliminary network structures also revealed strong dependencies between the same variables at sequential
409 time points. For example, the probability that stiffness_1 and stiffness_2 were both "High", or both "Low"
410 was approximately 80%. Including the arcs between the same variables from X_1 → X_2 did not provide
411 any theoretically meaningful information to the network structure as the majority of participants would
412 either be in a "Low" or "High" state for each pair of variables in the network. Therefore, these arcs were
413 blacklisted from the network. To obtain the final network, the appropriate blacklist and whitelists were
414 provided and a Tabu search algorithm identified the remaining structure of the network. The final network

415 structure was obtained by averaging 1000 bootstrapped models (Efron and Tibshirani, 1994) to reduce the
416 impact of locally optimal, but globally suboptimal network learning, and to obtain a more robust model
417 (Olmedilla et al., 2018). Arcs that were present in at least 30% of the models were included in the averaged
418 model. The strength of each arc was determined by the percentage of models that the arc was included
419 in, independent of the arc's direction. An arc strength of 1 indicated that the arc was always present in
420 the network, with the value decreasing as arcs were found in fewer networks. In the respective study arcs
421 above 0.5 were considered "significant" with arcs below 0.5 and above 0.3 "non-significant" (Scutari and
422 Nagarajan, 2013). Arcs below 0.3 were not included in the model. The full table of arc strengths for the
423 first and second network are available in S2 Table and S3 Table respectively.

2.4.1.4 Network Inference

425 Conditional probability queries (CPQ) were used to perform inference on both network structures. To
426 conduct a CPQ, the joint probability distribution of the nodes was modified to include a new piece of
427 evidence. The query allows the odds of a particular node state (e.g., injured_1 = "injured") to be calculated
428 based on the new evidence. CPQs were performed using a likelihood weighting approach; a form of
429 importance sampling where random observations are generated from the probability distribution in such
430 a way that all observations match the evidence given in the query. The algorithm then re-weights each
431 observation based on the evidence when computing the conditional probability for the query (Scutari
432 and Denis, 2014). Inference was first performed on arcs that had a strength greater than 0.5 between
433 the explanatory variables and independent variables and between different independent variables in the
434 network. Of particular interest were the variables that were connected to "injured" nodes, which were
435 examined in the network using the Markov blanket of "injured_1" and "injured_2". A Markov blanket
436 contains all the nodes that make the node of interest conditionally independent from the rest of the network
437 (Fuster-Parra et al., 2017). CPQ's were used to determine what effect the variables in the Markov blanket
438 of injured nodes had on the probability of the injured node being in the "injured" state.

2.4.2 Second network

2.4.2.1 Data preparation

441 Change scores between timepoint 1 and timepoint 2 were standardized to allow relative changes between
442 variables to be compared.
443 For the second network, change scores for continuous variables between T1 → T2 and T2 → T3 were
444 standardized to allow relative changes between variables to be compared. The "injured" variable was
445 also modified to represent whether a participant had sustained an injury at any point over the duration
446 of the study or were healthy for the duration of the study. Setting the data up in this way enabled the
447 construction of a network that explicitly modelled the *amount* of change within variables between time
448 points, as opposed to the first network that only captured changes when the median threshold was crossed
449 from "Low" to "High".

2.4.2.2 Network structure

451 Similar to the first network, blacklists were used to prevent arcs from independent variables → explanatory
452 variables. In addition, "nlebase" variable was dropped from the list of explanatory variables to allow the
453 *changes* in negative life events to be the only life event variable in the network. The final network was
454 obtained using the same approach as the first network.

2.4.2.3 Network Inference

456 Conditional probability queries (CPQ) were again used to perform inference the network structures.
457 The Markov blanket of the "injured" node was of particular interest, and the probability of injury was
458 investigated with combinations of variables in the Markov blanket below the mean change, at the mean

459 change and above the mean change. Initial visual inspection of the network structure also revealed arcs
460 between BIS → FFFS and HRV → FFFS. To investigate this relationship further, random samples were
461 generated for BIS, HRV and FFFS based on the conditional distribution of the nodes included as evidence
462 in the query. The samples were then examined using a Bayesian linear regression models with the *brms*
463 package (Bürkner, 2017) to determine the relationship between these nodes. Weakly regularising priors
464 (normal prior with mean of 0 and standard deviation of 5) were used for all parameters in the model.

3 RESULTS

465 During the study, 26% of participants reported at least one injury with an average severity of 11 ± 31, days
466 (range = 2 - 365 days). Both male and female participants reported a greater number of acute compared
467 to chronic injuries (male, acute = 85 [69%], chronic = 39 [31%]; female, acute = 38 [72%] chronic = 15
468 [28%]), and non-contact injuries were more common than contact injuries (male, non-contact = 83 [67%],
469 contact = 39 [31%]; female, non-contact = 35 [66%] contact = 18 [34%]). Table 4 shows the number and
470 percentage of injury types sustained by both male and female participants.

```
471  ## Note: Using an external vector in selections is ambiguous.
472  ## i Use `all_of(vars)` instead of `vars` to silence this message.
473  ## i See <https://tidyselect.r-lib.org/reference/faq-external-vector.html>.
474  ## This message is displayed once per session.
```

```
475  ## Note: Using an external vector in selections is ambiguous.
476  ## i Use `all_of(outcome)` instead of `outcome` to silence this message.
477  ## i See <https://tidyselect.r-lib.org/reference/faq-external-vector.html>.
478  ## This message is displayed once per session.
```

3.1 First network structure

480 The first network structure obtained from the data is shown in Fig 6. Several of the explanatory variables
481 showed strong connections with independent variables in the network. The arc from nlebase → RI_1
482 had a strength of 0.84, and the probability of RI_1 being in the "High" state increased from 0.23 to 0.47
483 when nlebase increased from "Low" to "High". The ind_team node had strong arcs to hours (0.90) and
484 nlebase (0.84). Individual athletes were more likely to have "High" hours per week (0.84) compared to
485 team-based athletes (0.60). Individual athletes were also more likely to have "High" negative life events
486 in the 12 months preceding the start of the study compared to team based athletes (individual athletes =
487 0.65, team-based athletes = 0.41). The arcs from gender → stiffness_1 and gender → stiffness_2 were
488 0.76, and 0.65 respectively, with males more likely to have "High" stiffness compared to females (males
489 = 0.62, females = 0.43). The arc from pi → stiffness_1 was 0.55 with athletes who reported an injury
490 in the preceding 12 months more likely to have "High" (0.65) compared to "Low" (0.35) stiffness. The
491 arc from clevel → balance_1 had a strength of 0.51, with lower level performers more likely to have
492 decreased balance ability (0.48), compared to national level athletes (0.29). Arcs were also present between
493 independent variables in the network. Strong arcs were present between BIS_1 → FFFS_1 (0.98) and BIS_2
494 → FFFS_2 (0.68). In both instances, "High" FFFS was more likely when BIS was "High" (0.65 for _1,
495 0.61 for _2) compared to "Low" (0.32 for _1, 0.36 for _2). The arc between nlelg → BIS had a strength of
496 0.62 for nlelg_1 → BIS_1, however no arc was present between nlelg_2 and BIS_2. For nlelg_1 → BIS_1,
497 "Low" negative life events increased the probability of BIS being in the "High" state from 0.33 to 0.55.

3.1.1 Markov blanket for injured_1

The Markov blanket for injured_1, which contained hours spent training per week (hours), negative life events (nlelg_1), muscle stiffness (stiffness_1), current competitive level (clevel) and balance (balance_1), is shown in Fig 7. The arc between nlelg_1 and injured_1 was fixed in the network, so has the maximum strength of 1.

The CPQ for injured_1 in the "injured" state for all variables that were directly linked to injured_1 is shown in Table 5. The probability of injured_1 = "injured" rose from 0.17 to 0.31 when stiffness was "High" compared to "Low". Negative life events had a negligible effect when moving from the "Low" to "High" state.

The second CPQ investigated the outcome of injured_1 being "injured" conditional on all variables in the Markov blanket. The Markov blanket contained five nodes, each with two possible states resulting in 2^5 combinations of variables, therefore only the three lowest and highest probabilities are shown in Table 6 (complete results in S4 Table). The combination of lower competitive level, "High" hours per week, "Low" negative life events, "High" balance and "High" stiffness resulted in a probability of 0.53 for injured_1 being in the "injured" state. When all variables were in the "Low" state the probability of "injured" was approximately 0.04 Negative life events only had a substantial effect on injured_1 when all other variable were fixed to "Low". In this instance the probability of injured_1 being "injured" rose from 0.04 to 0.19, when negative life events was in the "Low" and "High" states respectively.

Table 7 shows the states of all explanatory and independent variables suffixed with _1 that resulted in the highest and lowest probability of injured_1 being in the "injured" state. The probability of injured_1 being "injured" rose from 0.03 to 0.54 with the combination of variable states in Table 7. Notably, hours per week, stiffness_1 and balance_1 had the greatest effect on raising the probability of injured_1 being in the "injured" state.

3.1.2 Markov blanket of injured_2

The Markov blanket for injured_2 is shown in Fig 8 and contained gender, FFFS_1, stiffness_2, balance_2 and rmssd_2. The arc between stiffness_2 and injured_2 was comparable to the arc between stiffness_1 → injured_1. Very weak arcs (0.3) between injured_2 → balance_2 and injured_2 → rmssd_2 were also present in the Markov blanket for injured_2. Results of the first query for injured_2 in the "injured" state are presented in table 8. Similar to injured_1, stiffness_2 doubled the probability of injured_2 being "injured" from 0.13 in the "Low" state to 0.27 in the "High" state. FFFS_1 in the "Low" state increased probability of injured_2 being "injured" by 0.19 compared to the "High" state. "High" negative life events decreased the probability of injury from 0.24 to 0.19.

The conditional probabilities based on all the variables in injured_2 Markov blanket are presented in Table 9. Again, only the three lowest and highest probabilities are shown (complete results in S5 Table). The combination "Low" FFFS_1, "High" stiffness_2, "High" balance resulted in the greatest probability of injured_2 being "injured", with the highest probability of injury being 0.52. With all other variables held in the "High" state, the probability of injured_2 being "injured" rose from 0.14 to 0.34 when FFFS_1 was in the "Low" compared to "High" state. The combination of "Low" stiffness, "Low" balance and "High" FFFS resulted in the lowest probability of injured_2 being "injured".

3.2 Second network structure - changes within variables

The network for changes within variables is presented in Fig 9. An arc between BIS → FFFS with strength 1 was present in the network. Arcs between clevel → BIS and gender → stiffness had a strength of 0.60. The arc between RMSSD → FFFS was 0.56. The arcs between BIS → FFFS and RMSSD →

541 FFFS were examined further by drawing random observations from the conditional probability distribution
542 and examining the relationship in a linear regression model. While the continuous nodes in the second
543 network are already parameterised using linear regressions, it was not possible to investigate the interaction
544 between explanatory variables. The use of a separate linear regression enabled the interaction between BIS
545 and RMSSD to be examined.

546 Results from the Bayesian linear regression model are presented in Table 10 and include 95% credible
547 intervals (CrI). Increases in BIS were associated with increases in FFFS (b = -0.14, 95% CrI = [-0.20,
548 -0.08]), whereas positive changes in RMSSD where associated with decreased changes in FFFS (b = 0.4,
549 95% CrI = [0.34, 0.45]). There was no clear interaction between RMSSD and BIS (b = -0.04, 95% CrI =
550 [-0.10, 0.02]).

551 The Markov blanket for the "injured" node contained previous injury, gender, hours per week, stiffness
552 and nlec (Fig 10). For stiffness and nlec the values in the nodes represent the standardised change between
553 time point. Combinations of nlec and stiffness at one SD below the mean change, at the mean change, and
554 1 SD above the mean change are presented in table 11. Changes in both nlec and stiffness 1SD above the
555 mean change resulted in a probability of being injured of 0.71 over the duration of the study. With stiffness
556 held at the mean change, the probability of "injured" rose from 0.35 to 0.64 with nlec at 1 SD below an 1
557 SD above respectively.

558 Table 12 shows the three highest and lowest probabilities for injury for all variables in the Markov blanket.
559 The combination of 1 SD above the mean change for nlec and stiffness and "High" hours per week and
560 previous injury resulted in the highest probability that an injury would be sustained during the study (0.77).
561 In contrast, below average changes in nlec and stiffness combined with "Low" hours per week and no
562 previous injury resulted in the lowest probability of an injury (0.12).

4   DISCUSSION

563 Informed by Appaneal and Perna's (2014) extension to the widely cited Williams and Anderson's (1998)
564 stress-injury model, the purpose of this study was to examine how psychosocial stress-related factors,
565 and physiological stress-related markers may interact and act synergistically to increase the risk of injury;
566 therein addressing several of the limitations of the sport injury literature (Johnson et al., 2014). Potential
567 relationships between psychosocial stress-related factors, physiological stress-related markers of stress
568 and injury were investigated using two BN structures; the first was a two-time Bayesian Network that
569 investigated the relationships between variables *across* time points in the study (Fig 5), and the second
570 network used differential equations to model the changes in variables *between* time points (Fig 8).

571 The first network revealed several links between the injured nodes and other variables in the network.
572 For example, Fig 6 and Fig 7 show the Markov blankets for the injured_1 and injured_2 nodes in the first
573 network and include all the variables that had a direct effect on the probability of injury. The combination
574 of high stiffness and poor balance resulted in the highest probability of injury in the Markov blankets for
575 injured_1 and injured_2. The presence of these factors at both injured nodes indicates that the combined
576 action of these variables is important for determining an athlete's risk of injury. In the second network,
577 the highest probability of injury was observed when changes in stiffness *and* negative life events were
578 both greater than average (Table 11), indicating that the combination of changes in psychological and
579 physiological measures of stress may combine additively to increase the risk of injury (Appaneal and Perna,
580 2014). Table 7 shows the combinations of variables that resulted in the highest and lowest probabilities of
581 injury conditional on all explanatory variables and variables suffixed with _1. Although only the highest
582 and lowest values are shown, there were over 16000 possible combinations of variables states that could

583 influence the risk of injury. The adopted approach attempts to take the complex systems view of injury
584 recommended by Bittencourt et al. (Bittencourt et al., 2016), where injury is an emergent property from a
585 web of determinants that interact in different ways.

586 Of all the variables measured in the study, muscle stiffness appeared to be most strongly related to
587 injury. Both "High" levels of stiffness in the first network, and greater than average increases in stiffness
588 in the second network were found to increase the risk of injury. In this study, a novel hand-held device
589 (MyotonPRO) was used to measure muscle stiffness. To date, one of only a small number of studies that
590 have used the MyotonPRO to explore the relationship between muscle stiffness and sports injury, found
591 that increased muscle stiffness in the soleus and Achilles tendon was related to increased injury incidence
592 in elite level netball players (Pickering-Rodriguez et al., 2017). The results of the current study build on
593 these findings, with a larger sample of athletes from a range of different sports, strengthening the evidence
594 for a relationship between higher levels of muscle stiffness and injury. However, high levels of muscle
595 stiffness, as measured by the MyotonPRO, have also been found to be related to improved performance,
596 with elite level athletes having increased lower extremity stiffness (Pruyn et al., 2015; Kalkhoven and
597 Watsford, 2017). Collectively, therefore, these findings suggest that while muscle stiffness plays a vital
598 role in performance, increased levels of stiffness also increase the risk of injury, with each athlete likely
599 to have an optimum level of stiffness that maximises performance while minimising the risk of injury
600 (Butler et al., 2003). Additionally, high stiffness may only increase the risk of injury if other factors are
601 also present. To elaborate, the combination of high stiffness *and* poor balance was found to result in the
602 greatest probability of injury. In contrast, athletes with high stiffness and good balance were less likely
603 to be injured, suggesting that improved postural stability may counteract the potential harmful effects of
604 high levels of muscle stiffness. Several studies have identified how balance (Romero-Franco et al., 2014;
605 Trojian and McKeag, 2006) and muscle stiffness (Butler et al., 2003; Pickering-Rodriguez et al., 2017) are
606 related to injury individually; however this study has demonstrated how these two factors may have an
607 additive effect in relation to injury occurrence.

608 In addition to stiffness, balance is also linked to injury at both injured nodes in the first network,
609 however the strength of the arc was only 0.35 and 0.30 from balance $\rightarrow$ injured_1 and balance $\rightarrow$ injured_2
610 respectively. Despite the weak arc strength, a "High" balance score, indicating impaired postural stability,
611 was found to increase the probability of injury. This finding is consistent with previous research that has
612 reported an association between decrements in postural stability and increased injury risk (Riemann et
613 al., 1999; Romero-Franco et al., 2014; Trojian and McKeag, 2006). Postural stability is often used as an
614 indicator of athlete performance level, with higher level athletes demonstrating better postural stability
615 over their lower level counterparts (Paillard et al., 2006). In the current study, athletes who competed at a
616 higher level were also more likely to have good balance ("Low" balance), compared to their lower level
617 counterparts. These findings suggest that better postural stability is associated with both a higher level of
618 performance and a lower probability of sustaining an injury, reinforcing the importance of postural stability
619 as a feature of athletic training programmes designed to prepare athletes for the demands of high intensity
620 training and competition (Hrysomallis, 2011).

621 Of the psychological variables in the study, negative life events have previously been reported to be most
622 strongly associated with injury (Williams and Andersen, 2007; Ivarsson et al., 2017). In the current study,
623 the second network revealed that greater than average increases in negative life event stress increased the
624 probability of being injured during the study period. However, negative life event stress had almost no
625 effect on the probability of injury in the first network. This finding suggests that the *relative change* in life
626 events may be more important than the *absolute score* for life events, despite the latter being commonly

used in sports injury research to date. For example, an athlete who reports a negative life event score of 1 during the first time point, but then a score of 5 at the second time point will have a 400% increase in their life event score. Although the absolute score would be "Low", the relative increase could have been caused by a significant event in the athlete's life, that could have a considerable psychological and physiological effect (Appaneal and Perna, 2014). Future research should therefore consider study designs and appropriate analysis methods that enable relative changes in an individual athlete's life events to be assessed (cf. Ivarsson et al., 2014).

The finding that negative life events had almost no impact on the probability of injury in the first network was surprising given that the majority of research has consistently identified major life events, particularly those events with a *negative* valence, as the strongest predictor of injury in Williams and Andersen's (Williams and Andersen, 1998) model (Ivarsson et al., 2017). During the initial network structure development, no arcs between the negative life event nodes and injured nodes were found by the Tabu search algorithm. However, given the strength of the literature indicating that negative life events are related to injury, an arc was fixed between nlelg_1 $\rightarrow$ injured_1 and nlelg_2 $\rightarrow$ injured_2 to allow this relationship to be examined more closely. When negative life events were "High" the probability of injury showed a negligible change at the injured_1 node and decreased by -0.05 at the injured_2 node. One possible explanation for these findings may be due to the use of the LESCA questionnaire in a repeated measures design. In the original LESCA instructions, participants are asked to report major life events that have occurred over the previous 12-months (Petrie, 1992). However, in the current study, participants completed the LESCA at approximately 4-month intervals after baseline and were therefore asked to report any events which had occurred *since the previous data collection session*, to avoid inflated scores caused by reporting the same event on multiple occasions. The reduced 4-month time interval between data collections may have reduced the likelihood for life events listed in the LESCA to have taken place. For example, at the second and third time points, 26% of participants reported 0 negative life events for the preceding four-month period. Simply, it may be that the items on the LESCA are less suitable for repeated measurements with durations shorter than the original 12-months than a measure that captures minor life events (cf. Fawkner et al., 1999).

Another possible explanation for the findings for major/negative life events is that participants in the study may have had access to the necessary coping resources to mitigate against the effects of any negative life event stress they experienced. Williams and Andersen's (Williams and Andersen, 1998) model proposed a number of coping resources that were either directly related to injury or moderated the relationship between life stress and injury occurrence; for example, general coping strategies (e.g., good sleeping habits and self-care), social support systems and stress management skills. Although coping was not measured in the current study, several studies have found high levels of social support can reduce the risk of injury (Petrie, 1993; Petrie et al., 2014; Johnson et al., 2014). Therefore, future research should consider including a measure of coping alongside that of life event stress to help explain the possible moderating effect.

Of the remaining variables, both FFFS and RMSSD were also linked to injury. A weak arc was observed between RMSSD_2 $\rightarrow$ injured_2 (arc strength = 0.30), however no arc was present between RMSSD_1 and injured_1, suggesting the link between RMSSD and injury was weaker than muscle stiffness and balance, where stronger arcs existed at both of the injured nodes. Despite the uncertainty regarding the relationship between injury and RMSSD in the first network, "Low" RMSSD increased the probability of injury from 0.17 (RMSSD = "High' ') to 0.27 (RMSSD ="Low' '). This finding is consistent with previous research that has found reduced RMSSD to be indicative of illness or maladaptation to training due to decreased parasympathic activity, which often precedes injury (Williams et al., 2017; Bellenger et al., 2016;

671 Gisselman et al., 2016). An arc between FFFS_1 and injured_2 (arc strength = 0.40) was also observed in
672 the first network, where the risk of injury was increased from 0.13 to 0.29 with FFFS in the "High" and
673 "Low" states respectively. Interestingly, the "Low" FFFS score was also related to injuries at subsequent
674 time points; for example, the "Low" FFFS recorded at the first time point was related to injuries recorded at
675 the second time point in the study. One possible explanation for this finding could be that those athletes who
676 reported "Low" FFFS score were less fearful, and may therefore engage in more risk taking behaviours,
677 increasing the probability of injury. The RST theory proposes that higher levels of FFFS increase avoidance
678 motivation (Corr et al., 2016), and therefore "High" FFFS may have acted as a deterrent from taking risks
679 while training and competing, reducing exposure to situations that could have resulted in injury.

680 In the first network, "High" BIS was associated with "High" FFFS, while in the second network, increases
681 in BIS were associated with increases in FFFS. RST proposes that the combination of high BIS and high
682 FFFS is likely to result in a more anxious disposition due to high levels of avoidance and high goal conflict
683 characterised by high levels of FFFS and BIS (Corr, 2013). High levels of anxiety and anticipation of
684 stressful situations have been associated with reductions in HRV indices including RMSSD (Chalmers et al.,
685 2014; Pulopulos et al., 2018), which is supported by the negative relationship between FFFS and RMSSD
686 in the second network (Table 10). These findings align with the proposed actions of the RST theory (Corr et
687 al., 2016). For example, high levels of BIS are proposed to be the result of goal conflict between the FFFS
688 (avoidance) and BAS (approach) systems. The goal conflict is likely to elicit a physiological response (e.g.,
689 decreased HRV) in preparation to engage in the required behaviour to resolve the goal conflict (Corr et
690 al., 2016). To extend these findings, the BAS should also be considered. Specifically, to establish how the
691 BAS and FFFS interact, and how these two systems affect the BIS. However, in the current study, initial
692 network structures revealed the BAS sub-scales to have limited connectivity with other measures in the
693 network, therefore only one of the BAS sub-scales (RI) was included in the final network structure. In the
694 first network, RI_1 was connected to both BIS_1 and BIS_2, and in both instances, the probability of "High"
695 BIS was increased when RI was also "High". However, the arcs between RI_1 and BIS were weak (< 0.50),
696 and RI represents only one component of the BAS system. Other BAS factors such as impulsivity may be
697 more closely related to risk-taking behaviours and may reveal additional links to sports injury. Therefore, a
698 more detailed examination of the different elements of RST, and specifically the BAS in relation to injury
699 occurrence is warranted.

700 The current research had several strengths, including the longitudinal repeated measures design and
701 modelling approach. A major critique of the sport injury literature has been the use of only one wave
702 of measurement that may not be reflective of and capture the dynamic nature of the variables that are
703 associated with injury (Johnson et al., 2014). The longitudinal repeated measures design of the current
704 study allowed *changes* over time and between time points to be captured and explored. Another significant
705 strength of the current research was the interdisciplinary approach, which enabled an examination of the
706 complex interplay between psychosocial and physiological markers of stress. Although there are unique
707 and significant challenges with research employing longitudinal repeated measures designs, they provide
708 for far more fine-grained understanding of the dynamic relationships between stress-related factors and
709 injury occurrence in athletes. Sport injury research has been criticised for adopting analytic approaches that
710 are reductionist in nature (Bittencourt et al., 2016) that fail to account for the complex, emergent behaviour
711 that is characteristic of injury occurrence. To address this issue, Bayesian networks (BN) were used to
712 more closely align with the complex, multifactorial nature of injury. The networks allowed several markers
713 of stress that were free to interact with each other, as well as injury, to be explored. Consequently, BN's
714 provided a contemporary approach that improved upon traditional methods such as logistic regression
715 (Olmedilla et al., 2018).

716 As with most research, there were several limitations with the present study. Firstly, the choice was
717 made to binarise variables in the first network so only "Low" and "High" states were observed. Although
718 binarising variables is a common procedure in Bayesian network analysis and has several advantages,
719 Qian and Miltner Qian and Miltner (2015) highlighted that both a loss of statistical accuracy and potential
720 difficulty in subsequent interpretation of the model may arise when following a binarising procedure.
721 For example, the meaning of a "Low" and "High" value in the current study is only meaningful for
722 the population that was studied, and there could be additional levels within each category that were not
723 investigated. A second limitation was the nature of the physiological measures used in the current study.
724 In order to collect data on a large sample of participants, suitable measures were required to ensure the
725 viability of the data collection; however, some of these measures may not have been sensitive enough to
726 detect more subtle variation in athletes. For example, postural stability could have been assessed with the
727 use of a force plate, which is considered the gold standard, to provide detailed data and enable a more
728 fine-grained analysis (Ross et al., 2011).

729 In addition to the future directions already outlined, the findings from the current study offer several
730 avenues for future research. Although the current study used a range of measures to capture "stress"
731 from both a psychological and physiological perspective, there may be additional measures available that
732 could provide further insight into the relationship between stress-related factors and sports injury. For
733 example, stress hormones such as cortisol have been found to be a marker of both psychological and
734 training-related stress (Appaneal and Perna, 2014; Perna and McDowell, 1995), and could help elucidate
735 the relationship between stress and injury. Additionally, although the LESCA is the most widely used
736 measures of major life events in sports injury research, the current study found several limitations with
737 using the LESCA in a repeated measures design, including how the items were scored. For example, there
738 is no way to differentiate between an athlete who has answered four items as moderately negative, and
739 one item as extremely negative. Both responses would be scored a "-4"; however, there could be vastly
740 different psychological and physiological effects between moderately negative and extremely negative
741 events. Therefore, future research could develop a modified version of the LESCA that could distinguish
742 between these types of responses and their effects.

743 In conclusion, the purpose of this research was to explore the multifaceted nature of the stress-injury
744 relationship, and several psychosocial and physiological markers were found to combine and exacerbate
745 the risk of injury. Specifically, muscle stiffness and *increases* in negative life event stress were identified as
746 strong predictors of injury, while other factors including personality characteristics and postural stability
747 were also found to contribute to the probability of injury occurrence. Taken together, the interdisciplinary
748 approach coupled with the advanced analytical techniques used and complex systems framework has
749 provided a novel examination of the stress-injury relationship that has addressed many of the limitations
750 identified in previous research.

5 DISCLOSURE/CONFLICT-OF-INTEREST STATEMENT

751 The authors declare that the research was conducted in the absence of any commercial or financial
752 relationships that could be construed as a potential conflict of interest.

6 AUTHOR CONTRIBUTIONS

753 The statement about the authors and contributors can be up to several sentences long, describing the tasks
754 of individual authors referred to by their initials and should be included at the end of the manuscript before
755 the References section.

7 SUPPLEMENTAL DATA

756 Supplementary Material should be uploaded separately on submission, if there are Supplementary Figures,
757 please include the caption in the same file as the figure. LaTeX Supplementary Material templates can be
758 found in the Frontiers LaTeX folder

8 REFERENCES

759 A reference list should be automatically created here. However it won't. Pandoc will place the list of
760 references at the end of the document instead. There are no convenient solution for now to force Pandoc to
761 do otherwise. The easiest way to get around this problem is to edit the LaTeX file created by Pandoc before
762 compiling it again using the traditional LaTeX commands.

9 FIGURES

Figure 1. Stress and injury model (Williams and Andersen, 1998).

Figure 2. mBESS positions (A-F). Top row, firm surface. Bottom row, foam surface. Left column, dominant leg stance. Middle column, non-dominant leg stance. Right column, Tandem leg stance.

Figure 3. Study design. For each time point (T), each box contains the number of participants who completed the data collection (N), the measures used for data collection and the approximate date of the data collection.

Figure 4. Session protocol. Outline of the protocol for each data collection.

Figure 5. Example network. A simple discrete network contain nodes, possible states of the nodes and the arcs connecting nodes.

Figure 6. Network structure. The full Bayesian network structure was plotted using the strength.plot function in bnlearn. The strength of each arc is shown graphically by the style of the arc. Thin, dashed arcs indicate the weakest arcs (arc strength below 0.50), whereas thick solid arcs indicate the strongest arcs (arc strength of 1). White nodes in the network indicate the explanatory variables, blue nodes indicate T1_1 and T2_1 variables, and red nodes indicated T2_2 and T3_2 variables. The injured_X nodes have been coloured gold as they are the main nodes of interest within the network.

Figure 7. Markov blanket of injured_1. Arc strengths are included as arc labels.

Figure 8. Markov blanket for injured_2.

Figure 9. Change network. Network structure of the changes within variables between time points.

Figure 10. Markov blanket for the injured node in the network reflecting changes within variables between time points.

10 TABLES

Table 1. Participant characteristics.

	Female (n = 120)	**Male (n = 231)**
Demographics M (SD)		
Age (yrs)	26.0 (11.3)	20.2 (1.8)
Height (cm)	167.4 (7.6)	177.8 (7.8)
Body mass (kg)	67.0 (9.5)	82.0 (14.6)
Hours per week training	8.5 (4.5)	11.2 (8.8)
Current competitive level n (%)		
Recreational	3 (4)	7 (4)
University	45 (56)	141 (80)
National/International	33 (41)	28 (16)

Table 2. Example of the data arrangement used for the network.

Participant	**X_1**	**X_2**
1	T1	T2
1	T2	T3
2	T1	T2
3	T1	T2
3	T2	T3

Table 3. Variables included in the final Bayesian network structure.

Variable	Definition	State 1	State 2
clevel	Current competitive level	Club_university_county	National_international
gender	Gender of the participant	Female	Male
hours	Number of hours spent training per week	0-9 (Low)	¿9-35 (High)
ind_team	Participate in an individual or team based sport	Individual	Team
pi	Previous injury - Whether an injury had been sustained in the previous 12 months prior to the study	No Injury	Injury
nlebase	Untransformed NLE at TP 1	0-13 (Low)	¿13-93 (High)
FFFS	Fight-Flight-Freeze System	8-16 (Low)	¿16-30 (High)
BIS	Behavioural Inhibition System	17-38 (Low)	¿38-68 (High)
RI	Reward Interest	4-10 (Low)	¿10-16 (High)
stiffness	Sum of all stiffness locations	1543-2330 (Low)	¿2330-4518 (High)
HRV	Root mean squared difference of successive RR intervals	2.03-4 (Low)	¿4-5.94 (High)
balance	Total balance score	5-15 (Low)	¿15-46 (High)
nlelg_1	Log NLE at TP 1	0-2.64 (Low)	¿2.64-4.54 (High)
nlelg_2	Log NLE at TP 2	0-3.04 (Low)	¿3.04-5.19 (High)
nlelg_3	Log NLE at TP 3	0-3.18 (Low)	¿3.18-4.79 (High)

Table 4. The number and percentage (%) of types of injuries sustained by male and female participants.

	Female		**Male**	
	Lower body	**Upper body**	**Lower body**	**Upper body**
Joint / ligament	14 (36)	5 (36)	37 (43)	14 (38)
Muscle / tendon	17 (44)	6 (43)	45 (52)	12 (32)
Other	8 (21)	3 (21)	5 (6)	11 (30)

Note:

Other included bone, skin and brain injuries.

Table 5. Probability of injured_1 being in the "injured" state, conditional on each variable.

Variable	Low	High
balance_1	0.21	0.30
hours	0.18	0.28
nlelg_1	0.24	0.26
stiffness_1	0.17	0.31

Table 6. Highest and lowest probability of injured_1 being in the 'injured' state, conditional on the all variables in the Markov blanket for injured_1.

Probability	clevel	hours	nlelg_1	stiffness_1	balance_1
Highest					
0.53	club_university_county	High	Low	High	High
0.46	national_international	High	Low	High	Low
0.43	national_international	High	Low	High	High
Lowest					
0.06	national_international	Low	Low	Low	Low
0.05	national_international	Low	Low	Low	High
0.04	club_university_county	Low	Low	Low	Low

Table 7. Probability of injured_1 being in the "injured" state conditional on explanatory variables and independent variables suffixed with _1.

Variable	High risk	Low risk
Probability	0.54	0.03
pi	injury	no injury
clevel	club_university_county	club_university_county
hours	High	Low
ind_team	individual	individual
nlebase	High	High
stiffness_1	High	Low
balance_1	High	Low
RI_1	Low	High
BIS_1	Low	High
FFFS_1	High	Low
nlelg_1	Low	Low
rmssd_1	High	High
gender	male	female

Table 8. Probability of injured_2 being in the "injured' state, conditional on each variable in the Markov blanket for injured_2.

Variable	Low	High
balance_2	0.17	0.27
FFFS_1	0.3	0.11
nlelg_2	0.24	0.19
rmssd_2	0.24	0.19
stiffness_2	0.13	0.27

Table 9. Highest and lowest probability of injured_2 being in the 'injured' state, conditional on the all variables in the Markov blanket for injured_2.

Probability	FFFS_1	nlelg_2	stiffness_2	rmssd_2	balance_2
Highest					
0.52	Low	Low	High	Low	High
0.45	Low	High	High	Low	High
0.43	Low	Low	High	High	High
Lowest					
0.06	High	High	Low	Low	Low
0.05	High	Low	Low	High	Low
0.04	High	High	Low	High	Low

Table 10. Estimate, error and 95% credible intervals for the fixed effects in the linear model containing FFFS, BIS and RMSSD.

Term	Estimate	Error	95% CI
Intercept	0.00	0.03	[-0.06, 0.05]
BIS	0.40	0.03	[0.34, 0.45]
rmssd	-0.14	0.03	[-0.20, -0.08]
BIS:rmssd	-0.04	0.03	[-0.10, 0.02]

Table 11. The probability of injury with values of stiffness and nlec held at 1SD below the mean change, at the mean change and 1 SD above the mean change.

Probability	nlec	Stiffness
0.70	+1SD	+1SD
0.64	+1SD	mean
0.62	+1SD	-1SD
0.53	mean	+1SD
0.45	mean	mean
0.44	mean	-1SD
0.42	-1SD	+1SD
0.35	-1SD	mean
0.35	-1SD	-1SD

Table 12. Highest and lowest probability of injury, conditional on the all variables in the Markov blanket for "injured".

Probability	hours	pi	nle	stiffness
Highest				
0.77	High	injury	+1SD	+1SD
0.74	High	no injury	+1SD	+1SD
0.72	Low	injury	+1SD	+1SD
Lowest				
0.15	Low	no injury	-1SD	+1SD
0.13	Low	no injury	-1SD	mean
0.11	Low	no injury	-1SD	-1SD

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