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ORIGINAL RESEARCH ARTICLE

# Understanding the Complexity of Athlete Sleep: A Systems Approach to Modelling the Athlete Sleep Environment

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## Abstract

**Background** Athlete sleep can be disrupted by sport- and non-sport-related factors. However, the interactions of these sleep-related factors are not well understood. Systems science approaches, such as causal loop diagramming (CLD), provide an opportunity to map these interactions. This project aimed to (1) develop a CLD of the athlete sleep system describing the interacting variables, (2) identify feedback loops and potential leverage points to optimise athlete sleep, and (3) demonstrate the applicability of a CLD to guide the development of a sleep monitoring framework.

**Methods** A systems-based model of athlete sleep was developed using CLD, informed by existing literature and refined through a consensus process involving ten subject matter experts (nine from Australia, one from the USA). The model was then interrogated using network analysis to identify key variables based on their position and connectivity within the system. These findings informed the development of a generic sleep monitoring framework.

**Results** The CLD comprised 48 variables and 120 relationships across four domains: travel demands, behavioural and lifestyle factors, athlete condition and readiness, and resourcing and scheduling constraints. Overall, 12 key variables were identified, with hours of travel, number of time zones crossed, dose of caffeine, and amount of resources or expenditure available being the most connected upstream variables. Level of pre-sleep arousal, sleep opportunity, travel fatigue, and level of performance received the greatest number of incoming relationships, representing points at which multiple pathways converge. Physical condition, level of performance, quality of diet, and importance of competition most frequently linked different quadrants of the system. These variables informed a three-tier monitoring framework capturing upstream determinants and downstream consequences of sleep.

**Conclusions** According to the CLD, sleep health in athletes extends beyond an individual behaviour issue and is influenced by the structure and functioning of sport systems. Interactions among travel demands, physical readiness, behavioural and lifestyle factors, and organisational constraints sustain athlete sleep health over time. Consequently, meaningful improvements in sleep health are likely to arise from both system-level interventions and individual behaviour change strategies.

## 1 Introduction

Sleep is a fundamental component of athlete health, recovery, and performance [1]. However, athletes often experience inadequate sleep duration, irregular sleep timing, and difficulties initiating or maintaining sleep [2, 3], with 50–78% of elite athletes reporting regularly disturbed sleep [4–6]. These challenges may be particularly pronounced in elite athletes due to intensified training and competition demands, frequent travel, and heightened performance pressures, making this population a relevant starting point for examining complex sleep-related interactions. In addition to non-sport related factors (e.g., family and social commitments) known to influence sleep, athletes face unique sport-related factors (e.g., unfamiliar sleep environments and high training loads) that likely contribute to the high occurrence of sleep-related disruptions and deficiencies [1]. Despite the clear importance of sleep, achieving sleep of sufficient duration, continuity, and quality remains a persistent and challenging issue for athletes.

Athlete sleep is multifaceted and influenced by a network of interdependent influences, rather than discrete, isolated pathways. In this context, the 'athlete sleep system' refers to the set of interacting physiological, behavioural, psychological, and environmental factors that collectively influence sleep outcomes in athletes, where changes in one factor may affect others over time. For instance, sleep behaviours

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**Key Points**

Athlete sleep problems are not primarily a matter of individual habits or willpower; they emerge from the structure of elite sport itself, including travel schedules, training demands, and organisational constraints that interact to sustain disruption over time.

Mapping these interactions allows for the identification of leverage points where targeted changes, whether at the system level (e.g., scheduling, travel management) or the individual level (e.g., behavioural strategies), are most likely to produce meaningful improvements in sleep health.

Practitioners who monitor only sleep outcomes, without tracking upstream scheduling, travel, and training demands that drive them, are likely observing consequences rather than causes and are therefore poorly positioned to intervene effectively.

and outcomes can be shaped by training and competition schedules [7], competition loads [8], psychological stress [9], pre-sleep cognitive arousal [10], nutritional practices [11], technology use [12], pain [13], and environmental conditions [14]. Furthermore, individual characteristics such as chronotype [15], sex/gender [16], and age [17] can further shape sleep timing, sleep quality, and circadian alignment in athletes. However, these factors are largely investigated in linear cause-and-effect ways (e.g., the effect of nutritional interventions on sleep [18], the effect of acute bouts of exercise on sleep [19], and the effect of caffeine on sleep [20]) which do not capture the interconnections, feedback loops, and emergent actions of multiple variables in the athlete sleep system. For example, high training loads may elevate pre-sleep arousal, reducing athlete sleep health, which in turn increases daytime fatigue, and prompts napping. Napping may reduce homeostatic sleep pressure and further delay sleep onset the following night, forming a reinforcing loop. The same reduction in sleep health may also impair performance, which may prompt a reduction in training load and thereby reduce arousal, forming a balancing loop. The two loops act on the same variable in opposite directions, and the resulting behaviour depends on which dominates, an outcome that cannot be determined by examining either pathway in isolation.

Systems thinking-based methods offer a structured analytical approach for examining complex systems which exhibit interdependence, feedback, and dynamic interactions [21, 22]. Sterman [23] emphasises that effective applications of systems thinking involve examining organisational learning mechanisms, decision rules, and feedback processes to enhance institutional performance. Systems analysis methods [24, 25] are used in various safety critical domains [26], public health (e.g., obesity [27, 28] and COVID-19 [29]), sleep [30], and sport science [31–33], providing a new lens for viewing existing complex issues. Causal loop diagramming (CLD) is one such method that is used to provide a visual representation of stakeholder views on these complex relationships via the elicitation and depiction of the reinforcing and balancing feedback loops that drive system behaviour. The application of CLD to athlete sleep will move beyond linear cause-and-effect explanations, complementing them with a systems perspective that captures the dynamic interactions among multiple determinants shaping sleep behaviour over time. Thus, adopting a systems thinking-based approach can elucidate new information regarding the interconnections of variables that influence sleep, identify whether feedback loops exist, and provide a more holistic view of the athlete sleep system.

The variables influencing athlete sleep have been well reported [1, 34–36] but are often examined in isolation. This approach is problematic, as interventions to improve athlete sleep often target individual variables without accounting for how these factors interact and influence one another or how factors might interact to diminish the effectiveness of new interventions. To date, these variables have not been systematically examined through a systems lens or integrated into a cohesive, system-level conceptual framework. This limits our understanding of how multiple factors interact to influence sleep health, how changes in one factor (e.g., late-night competition or travel fatigue) can influence others (e.g., arousal or sleep opportunity) and why targeted interventions often demonstrate modest or inconsistent effects.

No systems-based model currently exists that comprehensively maps the broader network of variables influencing athlete sleep to identify leverage points [37] and guide more effective intervention strategies. Addressing this gap is important for advancing both our understanding and applied approach to improving athlete sleep. Therefore, the aims of this paper are three-fold; to develop a CLD of the athlete sleep system that describes the interacting variables influencing athlete sleep; to identify feedback loops and potential leverage points that could be targeted to optimise athlete sleep; and to demonstrate the potential applicability of using a CLD to guide the development of a sleep monitoring framework for use by practitioners, coaches, and sport scientists seeking to systematically assess, track, and intervene in the multifactorial determinants of athlete sleep in applied performance settings. The model presented here is intended as hypothesis-generating rather than predictive. Its purpose is not to forecast sleep outcomes or to estimate strength of causal relationships,

but to make explicit a structured and testable account of how variables influencing sleep may interact, affording a lens into specific pathways and feedback processes that can be subjected to empirical testing. Accordingly, the model represents a synthesis of published evidence and expert judgment, and its value lies in the hypotheses it generates rather than in the confirmation of any single relationship it depicts.

## 2 Methods

### 2.1 Study Design

This study used a systems-based design incorporating qualitative CLD development and quantitative network analysis, with the aim of characterising the interacting variables influencing sleep in elite athletes. Network analysis was applied to further examine the structure of the system, identifying variables with greater relative connectivity within the model, and to demonstrate its practical applicability. These findings were then used to inform the development of a generic sleep monitoring framework.

### 2.2 Procedure

#### 2.2.1 Constructing the Causal Loop Diagram

Causal loop diagrams are used to elicit and represent the reinforcing and balancing loops that drive system behaviour. Links between variables are based on causal relationships and possess positive or negative polarity. Variables linked with a + (i.e., positive polarity) indicate a reinforcing relationship (e.g., when variable A increases, variable B also increases), and variables linked with a — (i.e., negative polarity), indicate a balancing relationship (e.g., when variable A increases, variable B decreases). A simple example of a reinforcing and balancing loop for athlete sleep is shown in Fig. 1.

The initial draft athlete sleep CLD was developed using data from peer-reviewed and relevant grey literature identified through a purposive, iterative search of Scopus and Google Scholar. Searching was structured around key athlete sleep domains (e.g., training load, travel, recovery), derived from existing consensus statements [1] and reviews of sleep in athletes [34, 38, 39]. Searching began with systematic reviews, meta-analyses, and consensus statements within each domain and proceeded through searching of their reference lists, with targeted searches conducted when a variable proposed during model development was not addressed by the sources already identified. Literature was selected based on relevance to these domains rather than through a formal systematic review process. This is consistent with model conceptualisation in system dynamics, in which model structure is derived from a combination of sources and the knowledge of those familiar with the system rather than quantitative evidence alone [40] and with previous causal loop diagrams [30]. Sources were retained where they reported an association between the candidate variable and a sleep outcome in athletes, or, where athlete-specific evidence was unavailable, in adult populations. Searching continued until additional sources no longer generated new candidate variables. The search was not systematic and was not intended to be exhaustive. Its purpose was to specify a plausible and evidence-informed initial structure of the athlete sleep system for the research team to review. An overview of the sources informing the model is provided in Supplementary Table 1 [1–10, 12–20, 30, 34–36, 41–57]. Variables that do not appear in Supplementary Table 1 were derived from expert judgement during model development rather than an identified source. The model was refined using a group modelling process [58] involving only members of the research team. Two members of the research team were unable to attend the workshop but were provided with the same instructions and opportunities to refine the model over email. The process consisted of an initial 2-h online workshop followed by multiple iterative rounds of review and refinement. The workshop proceeded in two stages. First, draft variables and connections were systematically reviewed to confirm causal directions, identify omissions, and resolve any redundancies. Second, all relationships and their polarity were reviewed, with connections added, removed, or modified as required. Decisions were made by discussion until no author raised any objection. When an objection was raised, the link or variable was either modified until agreement was reached or was removed from the model. Subsequent refinements were conducted offline via email, with the model iteratively updated until consensus was achieved. Consensus was defined as agreement among all members of the research team on the inclusion of variables, causal relationships, and polarity, with no outstanding objections.

The CLD was constructed and analysed using Vensim software (Ventana Systems Inc, Harvard, MA). In line with systems thinking principles, defining a system boundary is necessary to ensure the model remains interpretable and focused on the relationship of interest. In this study, the boundary of the system was defined as athletes competing at the elite level in any competitive sport (i.e., Tier 3: highly trained/national level, athletes competing in national and/or state leagues/tournaments, completing structured and periodised training; Tier 4 competing at the international level, athletes competing in international leagues/tournaments, maximal or near maximal training [43]). The intention was to develop a CLD that provides a high-level representation of the generic sleep system for elite athletes, rather than to

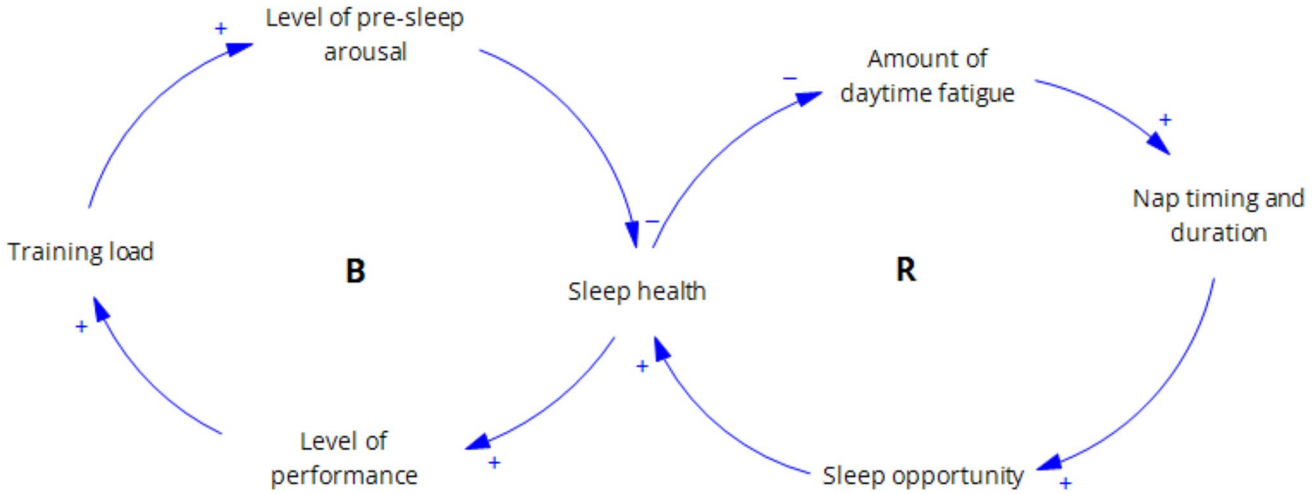



**Fig. 1** A simplified causal loop diagram representing elements of the athlete sleep system. The capitalised R represents a reinforcing loop, which indicates that an increase in one variable induces an increase in the subsequent variable. The capitalised B represents a balancing loop, which indicates that an increase in one variable has a corresponding decrease in the subsequent variable. Of note, relationships are represented as directed links. Where two variables influence one another reciprocally, two separate directed links rather than a bidirectional arrow can be depicted, as each direction may carry a different polarity and contribute to a different feedback loop. Figure 1 is a simplified illustration of notation and does not depict all reciprocal relationships represented in the full model

catalogue sport- or individual-specific circumstances. This approach is based on the premise that, while magnitude and expression of key variables (e.g., travel demands, competition schedules) may differ substantially across sports and individuals, the underlying structure of interactions between these variables should be broadly consistent within elite sports. As such, the model focuses on the relationships between variables, rather than their absolute levels, allowing common system dynamics underpinning sleep disruption to be represented across contexts. This approach enables the CLD to capture how sleep disruption emerges within elite sport environments, while acknowledging variability in individual experiences and sport-specific demands.

#### 2.2.2 Research Team Positionality and Reflexivity

The CLD was developed by the author team, who also served as the subject matter experts in the modelling and consensus process. Accordingly, we adopted a constructivist–interpretivist position, treating the model as a co-constructed representation of the athlete sleep system rather than an objective description of it. This position is consistent with the purpose of causal loop diagramming, which is to make explicit, and therefore open to examination, mental models and beliefs about a system [58–60]. The credibility, dependability, and confirmability of the resulting CLD were therefore considered alongside conventional assessments of model validity and reproducibility, recognising that the quality of the model depends on the rigour of the modelling process and the credibility of the knowledge and assumptions underpinning the model [61].

The research team comprised ten authors whose primary expertise is in sleep and circadian science (S.H., C.G., D.M., and J.C.), sport and exercise science (J.W., M.M., and M.W.), and human factors and systems science (S.M., P.S., and G.R.), with several authors holding expertise across more than one of these areas. Authors have also held applied practitioner and/or embedded research roles within professional or national sporting organisations, and several have published research on variables represented in the model, including effects of caffeine [20], nutritional interventions [62], and effects of exercise on sleep [63]. These positions and the specific experiences and expertise of the research team members may have shaped the model in terms of the selection of variables and representation of interactions.

Three features of the model development process were adopted to address potential bias and provide transparency regarding these influences. First, peer-reviewed sources were used to inform the initial draft model. Second, the disciplinary heterogeneity of the team enabled variables to be reviewed by authors with expertise outside the discipline from which the evidence originated. Third, successive versions of the model were retained, allowing the development of the structure to be traced. We note that we did not use an independent facilitator for consensus discussions and disagreements were not formally recorded during the process.

## 2.3 Application of CLD to Develop a Sleep Monitoring Framework

### 2.3.1 Network Analysis

To further examine the structure of the CLD and provide a quantitative description of relationships between variables, network analysis metrics were derived. This approach has been applied in previous research to summarise the structure of CLDs and support interpretation of complex systems [64–66]. In the present study, network analysis was used as an exploratory, descriptive tool to quantify the relative position and connectivity of variables within the model, rather than infer causal importance or identify definitive leverage points.

To conduct the network analysis, the CLD was transposed into an adjacency matrix using Vensim, preserving directionality (e.g., from variable A to variable B), and exported to Microsoft Excel. To enable network analysis, the matrix was transformed into a binary format by squaring all entries, such that negative relationships (− 1) were recoded to 1, while 0 and 1 values remained unchanged. This transformation was applied to focus the analysis on the presence or absence of connections, rather than the polarity of relationships, which was retained and interpreted in the CLD.

Network analysis was conducted using Social Network Visualiser (SocNetV version 3.2). Both global network properties and nodal centrality were examined. Global network metrics included total connections and network density to describe the overall level of interconnectedness within the system. Nodal metrics included out-degree centrality, in-degree centrality, and betweenness centrality (Table 1), which were used to describe the relative connectivity and structural position of variables within the network. All measures were standardised to allow for comparison across variables. Variables with values greater than one standard deviation (SD) above the mean were identified as structurally prominent variables, consistent with previous applications of network analyses [55, 67, 68]. These variables were interpreted as being more highly connected or more strongly influencing the structure of the network, and therefore of potential relevance for further consideration in the context of athlete sleep. Consistent with recent critiques of applying network metrics to CLD to identify leverage points [69], these measures were not interpreted as indicating causal importance or definitive intervention targets, but rather as providing a quantitative summary to support interpretation of the CLD structure.

### 2.3.2 Development of an Example Athlete Sleep Monitoring Framework

The network analysis metrics were used to support the development of a generic sleep monitoring framework by providing a structured summary of the relative connectivity and positioning of variables within the CLD. The framework was primarily informed by the interpretation of the CLD structure with the network metrics used as a complementary input to assist in organising variables into three tiers. Variables with high out-degree centrality (i.e., exceeded 1SD above the mean) were those connected to a greater number of other variables within the framework and might represent potential exposure or screening variables (e.g., modifiable inputs such as caffeine dose). These variables were placed in tier 1 of the proposed monitoring framework. Variables with high in-degree centrality (i.e., exceeded 1SD above the mean) were considered as variables connected to multiple other variables and were positioned as monitoring and escalation indicators, reflecting points where multiple relationships converge (e.g., system state indicators such as level of performance). These variables were placed in tier 2 of the proposed monitoring framework. Variables with high betweenness centrality were considered as variables more frequently positioned along connections linking different parts of the system and were used to identify potential response and decision points within the framework (e.g., modifiable behaviours such as quality of diet that relate to multiple pathways). These variables were placed in tier 3 of the proposed monitoring framework. The translation of network metrics was intended to support structured organisation and interpretation of variables within the framework, rather than infer causal roles, directional effects, or predictive relationships. The framework therefore reflects an integration of CLD structure, network-derived descriptors, and domain-specific knowledge of athlete sleep. This mapping is an interpretative decision of the network analysis, not a result of it. Therefore, alternate mappings are possible and would likely yield a different framework.

# 3 Results

## 3.1 Athlete Sleep Causal Loop Diagram

The athlete sleep CLD is shown in Fig. 2. The model is organised into four domains including: (1) travel demands (lower left quadrant), (2) behavioural and lifestyle factors (upper left quadrant), (3) athlete condition and readiness variables (upper right quadrant), and (4) resourcing and scheduling constraints (lower right quadrant). A total of 48 unique variables (Supplementary Table 2) were represented

**Table 1** Nodal metrics applied to the athlete sleep CLD

| Network metric | Definition |
|---|---|
| Out-degree centrality | Out-degree centrality represents the number of directed connections a variable initiates to other variables within a network. In the context of athlete sleep, variables with high out-degree centrality interact with a greater number of other variables and may represent upstream positioning within the system structure. However, this measure reflects the number of connections only and does not indicate the strength or direction of influence. In the present analysis, out-degree centrality was expressed as the proportion of all possible variables that a given variable directly connects to, calculated by dividing the number of outgoing causal links by the maximum number of outgoing links. Values range from 0 to 1, with higher values indicating that a variable is connected to a larger proportion of the variables within the CLD. An out-degree centrality of zero indicates that no outgoing relationships from that variable were represented within the network |
| In-degree centrality | In-degree centrality represents the number of incoming connections a variable receives from other variables within a network. In the context of athlete sleep, variables with high in-degree centrality are connected to a greater number of other variables and may reflect points within the system where multiple relationships converge. However, this measure reflects the number of connections only and does not indicate strength, direction, or the effect of these relationships. In the present analysis, in-degree centrality was expressed as the proportion of all possible variables that are directly connected to a given variable, calculated by dividing the number of incoming causal links by the maximum number of incoming links. Values range from 0 to 1, with higher values indicating that a variable is connected to a larger proportion of the variables within the CLD. An in-degree centrality of 0 indicates that no incoming relationships to that variable were represented in the model |
| Betweenness centrality | Betweenness centrality represents the extent to which a variable lies on the shortest paths between other variables within a network. In the context of the CLD, this metric was used to describe variables that are more frequently positioned along connections linking different parts of the system structure. However, as causal relationships in CLDs do not represent the transfer of material or information along the shortest paths, this measure is interpreted as a structural descriptor only. In the present analysis, betweenness centrality was expressed as the proportion of all possible shortest pathways that pass through a given variable, calculated by dividing the variable's raw betweenness value by the theoretical maximum number of shortest pathways it could occupy. Values range from 0 to 1, with higher values indicating that a variable is more frequently involved in connecting different variables within the CLD. A betweenness centrality of 0 indicates that the variable does not lie on any shortest paths between other nodes within the network model |

Metrics are calculated by SocNetV

within the athlete sleep system, with 290 unique feedback loops involving athlete sleep health identified (Supplementary Table 3).

Variables across all quadrants demonstrated cross-domain connectivity. Travel demands were connected to behavioural and lifestyle factors, resourcing and scheduling constraints, and athlete condition and readiness variables. Behavioural and lifestyle factors were connected to fatigue- and sleep-related variables, while athlete condition and readiness variables were connected to both behavioural influences and resourcing and scheduling constraints. Together, these connections indicate that sleep-related outcomes are part of an interconnected system spanning behavioural, physiological, and organisational components.

## 4 Application of a CLD to Develop an Example Sleep Monitoring Framework

### 4.1 Network Analysis

The network comprised 48 variables and 120 total connections, with a density of 0.053. This indicates that approximately 5% of all possible connections between variables were represented, suggesting a relatively sparse but interconnected system. Based on the pre-defined threshold (> 1 SD above the mean), 12 variables were identified as structurally prominent within the athlete sleep system (Table 2). Variables with higher out-degree centrality included: amount of resources/expenditure available, athlete sleep health, dose of caffeine, hours of travel, and number of time zones crossed. Variables with higher in-degree centrality included: athlete sleep health, level of performance, level of pre-sleep arousal, sleep opportunity, and travel fatigue. Variables with higher betweenness centrality included: athlete sleep health, importance of competition, level of performance, level of pre-sleep arousal, physical condition, and quality of diet.

### 4.2 Development of Example Sleep Monitoring Framework

Variables identified through the network analysis were used to inform a systems-informed monitoring framework for athlete sleep health, shown in Fig. 3. The framework comprises three tiers corresponding to the structural organisation of variables within the CLD, including variables with higher out-degree centrality, higher in-degree centrality and variables with higher betweenness centrality. These tiers reflect

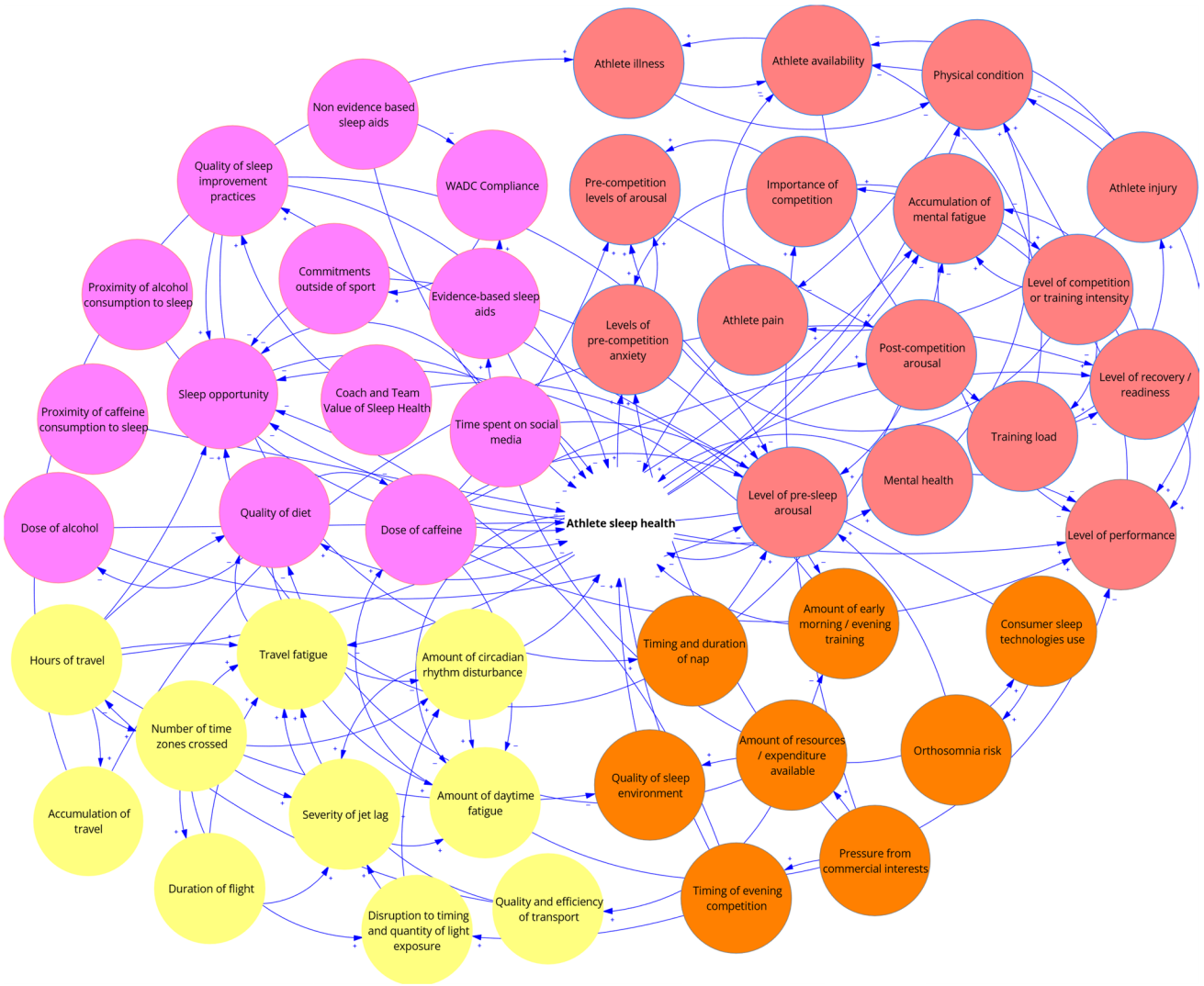



**Fig. 2** Causal loop diagram of the athlete sleep system. The upper left quadrant (pink) represents behavioural and lifestyle factors, the upper right (red) represents physical condition and readiness, the lower right (orange) represents scheduling and resourcing constraints, and lower left (yellow) represents travel demands. WADC, World Anti-Doping Code

differences in how variables are positioned within the system structure, rather than implying causal roles or directional effects.

The framework is operationalised as a flexible, three-tier process. Tier 1 represents variables connected to multiple other variables and may be considered as potential exposure or screening variables. Tier 2 represents variables connected to multiple incoming relationships and may reflect points where system strain or disruption is observable. Tier 3 represents variables more frequently positioned along connections linking different parts of the system and may be considered when organising potential response options. Importantly, the framework is not intended to represent a strictly linear process. Monitoring may begin at any tier, and movement between tiers may occur iteratively depending on the context. For example, changes observed in tier 2 variables may prompt examination of tier 1 variables, while decisions made at tier 3 may be evaluated through subsequent monitoring of tier 2 variables. This structure allows the framework to accommodate variability in how sleep-related issues emerge and are managed in practice.

**Table 2** Network metrics calculated for the variables in the athlete sleep system

| Variable | Out-degree centrality | In-degree centrality | Betweenness centrality |
|---|---|---|---|
| Accumulation of mental fatigue | 0.021 | 0.106 | 0.008 |
| Accumulation of travel | 0.043 | 0.021 | 0.006 |
| Amount of circadian rhythm disturbance | 0.064 | 0.064 | 0.036 |
| Amount of daytime fatigue | 0.043 | 0.106 | 0.062 |
| Amount of early morning training | 0.043 | 0.043 | 0.009 |
| Amount of resources/expenditure available | **0.128** | 0.021 | 0.011 |
| Athlete availability | 0.021 | 0.085 | 0.048 |
| Athlete illness | 0.043 | 0.043 | 0.009 |
| Athlete injury | 0.064 | 0.021 | 0.017 |
| Athlete pain | 0.043 | 0.043 | 0.037 |
| Athlete sleep health | **0.170** | **0.298** | **0.323** |
| Coach and team value of sleep health | 0.043 | 0.000 | 0.000 |
| Commitments outside of sport | 0.043 | 0.021 | 0.013 |
| Consumer sleep technologies use | 0.043 | 0.021 | 0.003 |
| Disruption to timing and quantity of light exposure | 0.043 | 0.043 | 0.002 |
| Dose of alcohol | 0.043 | 0.021 | 0.006 |
| Dose of caffeine | **0.128** | 0.043 | 0.064 |
| Duration of flight | 0.043 | 0.021 | 0.000 |
| Evidence-based sleep aids | 0.043 | 0.021 | 0.004 |
| Hours of travel | **0.149** | 0.021 | 0.015 |
| Importance of competition | 0.064 | 0.043 | **0.083** |
| Level of competition or training intensity | 0.064 | 0.021 | 0.020 |
| Level of performance | 0.021 | **0.149** | **0.090** |
| Level of pre-sleep arousal | 0.043 | **0.170** | **0.088** |
| Level of recovery/readiness | 0.064 | 0.064 | 0.015 |
| Levels of pre-competition anxiety | 0.021 | 0.064 | 0.002 |
| Mental health | 0.064 | 0.021 | 0.000 |
| Non-evidence-based sleep aids | 0.043 | 0.000 | 0.000 |
| Number of time zones crossed | **0.106** | 0.021 | 0.005 |
| Orthosomnia risk | 0.021 | 0.021 | 0.000 |
| Physical condition | 0.064 | 0.106 | **0.093** |
| Post-competition arousal | 0.021 | 0.043 | 0.042 |
| Pre-competition levels of arousal | 0.021 | 0.085 | 0.038 |
| Pressure from commercial interests | 0.085 | 0.000 | 0.000 |
| Proximity of alcohol consumption to sleep | 0.021 | 0.000 | 0.000 |
| Proximity of caffeine consumption to sleep | 0.021 | 0.000 | 0.000 |
| Quality and efficiency of transport | 0.043 | 0.021 | 0.006 |
| Quality of diet | 0.064 | 0.064 | **0.086** |
| Quality of sleep environment | 0.021 | 0.043 | 0.004 |
| Quality of sleep improvement practices | 0.085 | 0.043 | 0.019 |
| Severity of jet lag | 0.043 | 0.085 | 0.010 |
| Sleep opportunity | 0.021 | **0.170** | 0.029 |
| Time spent on social media | 0.043 | 0.000 | 0.000 |
| Timing and duration of nap | 0.064 | 0.021 | 0.001 |
| Timing of evening competition | 0.064 | 0.021 | 0.002 |
| Training load | 0.064 | 0.043 | 0.061 |
| Travel fatigue | 0.021 | **0.128** | 0.010 |
| WADC Compliance | 0.021 | 0.043 | 0.004 |
| Mean | 0.053 | 0.053 | 0.029 |
| Standard deviation | 0.034 | 0.056 | 0.052 |
| Mean + 1 standard deviation | 0.087 | 0.109 | 0.081 |

Bolded values indicate the variable is > 1 SD greater than the mean

*WADC* world anti-doping code

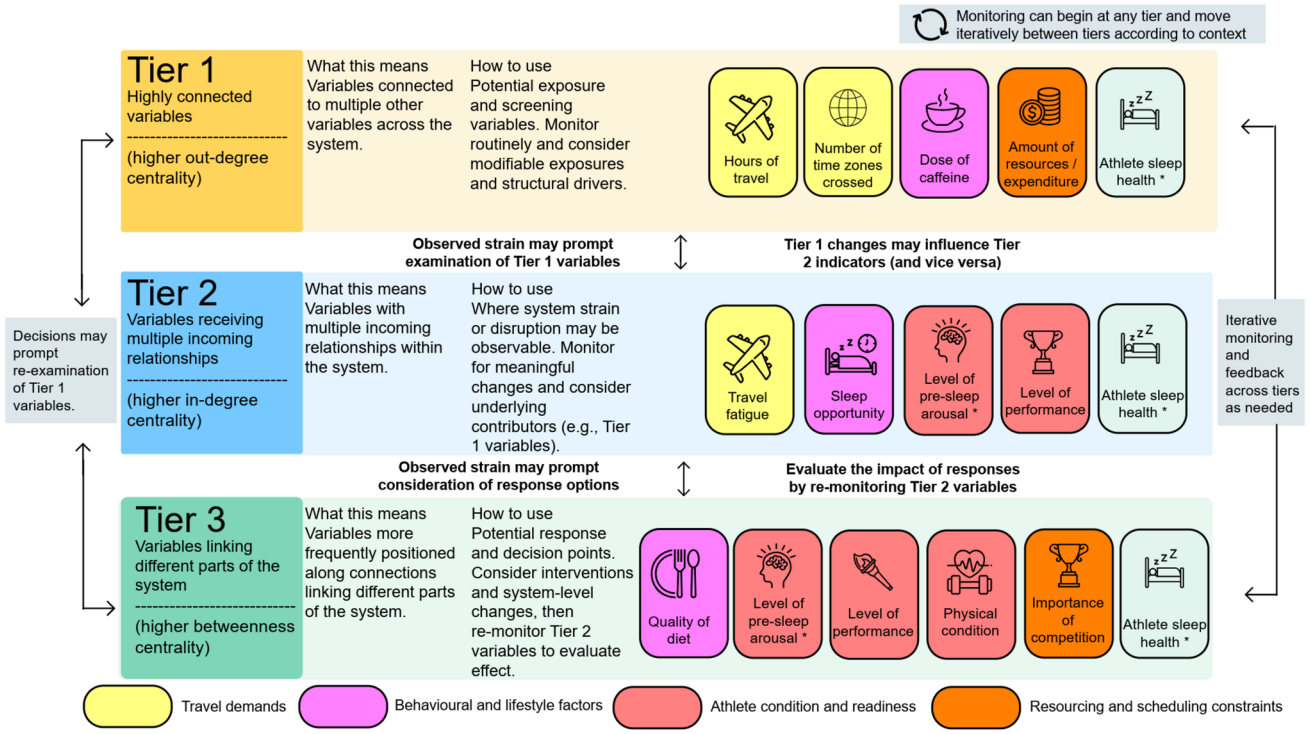



**Fig. 3** Systems-informed flowchart for monitoring athlete sleep health. * represents variables that appear in more than one tier because they carry high values on multiple metrics

Overall, the framework demonstrates one potential application of the CLD by translating structural features of the model into a practical approach for organising monitoring and decision-making, without inferring causal or predictive relationships. It should therefore be viewed as an illustrative rather than definitive framework, with its specific application adaptable to the characteristics and demands of different sporting contexts.

An example application of the framework for a team's sport scientist is as follows. An athlete reports elevated pre-sleep arousal and reduced sleep opportunity to the sport scientist via daily wellness monitoring (tier 2), which may prompt further examination of tier 1 variables, such as recent travel demands or caffeine intake. However, tier 2 changes may also emerge without clear changes in tier 1 variables, reflecting the multifactorial and context-dependent nature of the system. Where system strain is identified, the sport scientist may consider acting on tier 3 variables such as competition importance and diet quality when organising potential response options. Subsequent monitoring of tier 2 variables may then be used to assess changes in system state following these decisions. This iterative process allows for the framework to be applied flexibly across different contexts and encourages collaboration and coordination between stakeholders within a performance department of a sporting team.

## 5 Discussion

The aims of this paper were to develop a CLD of the athlete sleep system that describes the interacting variables influencing athlete sleep, to identify feedback loops and potential leverage points that could be targeted to optimise athlete sleep, and demonstrate the potential applicability of using a CLD to guide the development of a sleep monitoring framework. The CLD represents the athlete sleep system as a network of interacting variables and feedback loops, within which athlete sleep health is both influenced by and an influence on other variables. There was notable influence arising from factors beyond individual athlete behaviour, which suggests interventions may require coordinated strategies addressing behavioural, organisational, and system-level factors to meaningfully influence athlete sleep health. Critically, many of the factors that constrain athlete sleep health, including competition scheduling, travel demands, and organisational resource allocation, operate at structural and organisational levels that are largely outside the athlete's direct control, suggesting that potentially important leverage points for improving sleep health may extend beyond the individual athlete to the systems and organisations that shape their performance environment. Broadly, the variables identified were represented by a quadrant consisting of travel demands,

behavioural and lifestyle factors, athlete condition and readiness, and resourcing and scheduling constraints. Collectively, these findings demonstrate the importance of considering how interactions between variables may contribute to downstream and potentially emergent effects when monitoring or intervening in athlete sleep health. Furthermore, the interconnected structure of the CLD may help explain why single-factor sleep interventions can produce inconsistent or equivocal outcomes [41], as changes targeting isolated variables may be constrained or offset by influences arising elsewhere in the system. For example, extending sleep opportunity may have limited benefit when travel demands, late competition scheduling, or elevated pre-sleep arousal continue to disrupt sleep initiation and recovery. Although quantitative system dynamics models can be used to simulate interactions within complex systems over time [58], the present CLD provides an accessible and theoretically grounded first step for identifying potential leverage points influencing athlete sleep health.

The CLD can be compared with practice recommendations for sleep and conceptual frameworks for organising sleep determinants. The four domains represented in the CLD correspond closely to the categories used in existing consensus recommendations for athlete sleep [1] and for travel and jet lag management [42]. This is unsurprising, as both draw on substantially the same evidence base. A primary difference between these perspectives and frameworks is that the CLD specifies relationships between variables and identifies feedback loops in the sleep system, rather than identifying factors known to influence sleep in isolation. A consensus recommendation to extend sleep opportunity, for example, is directed at a variable that the CLD represents as constrained by competition scheduling, travel demands, and organisational resourcing; none of which the athlete directly controls. Existing recommendations are typically organised by factor and are therefore implicitly addressed to whomever is assumed to control that factor. Conceptual frameworks such as the socio-ecological model of sleep health [70], differ from recommendations in they also represent structure, organising determinants according to their level of influence. Such a framing makes the level at which an intervention might act more apparent than the thematic quadrants used here. The CLD provides a complementary perspective by explicitly representing relationships between variables both within and across different levels, including feedback between downstream and upstream variables that is not explicitly represented by a nested socio-ecological structure. Thus, the primary contribution of the CLD is not the identification of novel determinants of athlete sleep, but the representation of established determinants as an interconnected system in which relationships, feedback, and potential intervention points can be considered together.

The behavioural and lifestyle quadrant represents an area in which evidence-based intervention is feasible and could meaningfully improve athlete sleep health. The timing and proximity of caffeine consumption [20] is a well-established modifiable target and appeared as a distinct variable within the CLD. Education distinguishing between performance-motivated and compensatory caffeine use may help athletes control intake in ways that support performance rather than disrupt sleep. However, the amount of early morning training and timing of evening competition represent scheduling variables that may constrain sleep opportunity or elevate post-competition arousal, and targeted adjustments to training timing, where organisationally feasible, may produce meaningful benefits for sleep health. Time spent on social media and levels of pre-competition anxiety also featured within the CLD as contributors to elevated pre-sleep arousal, and psychological and behavioural strategies targeting pre-sleep arousal, including cognitive behavioural approaches, relaxation techniques, and structured wind-down routines, have demonstrated efficacy in sporting contexts [71, 72]. These variables represent accessible intervention targets that may be acted upon even when upstream structural factors remain constrained.

The feedback structures represented in the CLD may be usefully compared with the predisposing, precipitating, and perpetuating framework used in the conceptualisation of insomnia [73]. For instance, the reinforcing and balancing loops in the model can be considered in relation to perpetuating processes, in that they describe interactions through which sleep disruption may be maintained or counteracted once initiated. Competition congestion or long-haul travel may act as precipitating events, while the behavioural and organisational responses they elicit may maintain disruption after the initiating event has passed. This comparison also identifies a boundary of the present model. Predisposing characteristics including chronotype [15], sex/gender [16], and age [17], are not represented, having been treated as moderators of the relationships depicted rather than as variables within the system. The CLD model therefore describes how sleep disruption may be driven and maintained by elite sport, but not why individual athletes differ in their susceptibility to it.

Another comparison can be made between the present CLD and a previously published CLD of adolescent sleep health, which was developed using comparable methods [30]. Although the populations differ substantially, the two models converge on domains that extend well beyond individual behaviour. Alongside expected commonalities in behavioural, arousal-related, and environmental variables, the adolescent model identifies institutional scheduling (school starting times, evening homework, late-night deadlines), household resourcing constraints, and the commercial interests of digital platforms as structural influences on

sleep health. These structural influences correspond closely to the scheduling, resourcing, and commercial variables represented in the present model. Travel demands appear specific to the elite sport context and have no clear analogue. The fact that the two independently developed models converge on institutional and commercial determinants, in populations as different as school-aged adolescents and elite athletes, offers some support for the argument that sleep health is shaped by structures within which sleep is attempted rather than principally by individual choice. This support should not be overstated, as both models were developed by systems thinking-trained research teams. Of note, the adolescent model also excluded age, sex, and chronotype on the grounds that these are biologically determined and fell outside the boundary defined around modifiable factors, consistent with the boundary decision taken here.

Overall, the CLD shows that athlete sleep health emerges from interactions between multiple interconnected variables, rather than from isolated factors operating independently. Consequently, changes in one part of the system are likely to propagate across other aspects of the performance environment, influencing sleep health directly and indirectly. Further, focusing on individual variables when attempting to intervene is likely to have only minimal impact, as other interacting system influences may continue to constrain or offset change. For instance, as travel requirements accumulate there may be a decrease in the quality of an athlete's diet [47], which in turn may cause an athlete to increase caffeine consumption to mitigate potential fatigue [46], increase pre-sleep arousal [45], and subsequently influence an athlete's sleep opportunity and sleep health. This reinforces sleep as a core tenet of performance and recovery, rather than a peripheral behaviour, as sleep is shaped by interacting influences related to travel, training, scheduling, and recovery. The highly connected nature of the athlete sleep system also suggests that relationships between variables may not operate linearly, as changes in one part of the system may produce disproportionate downstream effects across other aspects of athlete functioning. For example, increased competition congestion may contribute to elevated physiological and psychological strain, increased pre- and post-competition arousal, altered recovery opportunities, and subsequent sleep disruption, with these effects potentially propagating across multiple components of the system. Conversely, large changes in one variable may only produce modest improvements in sleep outcomes when other constraints, such as travel-related disruption or elevated pre-sleep arousal, remain present. Further, timing and context can matter as much as magnitude, as in the case of caffeine intake, where a relatively small dose consumed close to bedtime may have a greater influence on sleep than the same dose earlier in the day [44]. This may help to explain why sleep interventions sometimes appear effective in one context but not in another and further highlights the potential value of future system dynamics modelling approaches capable of representing temporal delays, accumulations, and non-linear system behaviours.

Incorporating variables from the network analysis into the monitoring framework acknowledges that disturbances to athlete sleep often arise from systemic exposures rather than isolated behavioural choices, and allows practitioners to identify periods in which heightened risk may be anticipated before measurable impairments in sleep and subsequent performance occur. For example, a practitioner observing an elevated level of pre-sleep arousal and reduced sleep opportunity (tier 2 indicators) during a high-travel competition block could use the out-degree structure of the CLD to examine upstream variables, such as hours of travel, number of time zones crossed, or dose of caffeine, rather than treating arousal as an isolated clinical target. Where potential system strain is identified, higher betweenness variables such as quality of diet, importance of competition, and physical condition may be considered when organising potential response options. Collectively, this positions the framework as a monitoring tool grounded in system structure, rather than a prescriptive or causal model, highlighting the utility of CLD-informed network analysis for supporting applied decision-making across sport organisations and wider systems (e.g., leagues, academies). Additionally, the CLD shows the need for communication and coordination amongst athlete support staff, as many of the variables influencing athlete sleep are shaped or managed by different actors across the system [74]. Consequently, not only are the variables within the system interacting, but so too are the practitioners and organisational actors responsible for influencing them.

The broader domains represented in the CLD suggest opportunities exist for higher-level intervention to support athlete sleep health, aligned with Meadows [37] leverage points in complex systems. Leverage points are locations in the system where a small change has the potential to produce disproportionately large or sustained shifts in system behaviours; they are distinguished from conventional intervention targets by their ability to shift the system as a whole, rather than modify isolated outcomes. Importantly, the CLD reveals that even behaviours which appear to be individual choices, such as use of sleep aids, sleep scheduling, and timing or durations of a nap, frequently arise as responses to structural system pressures including hours of travel, competition scheduling, and amount of resources/expenditure available. Athletes therefore retain limited autonomous control even over individual-level factors, as these are continuously shaped by the systemic conditions in which they operate. For example, organisational scheduling and constraints, including travel and competition demands, may reflect system rules, while modifications to competition scheduling or travel requirements, represent structural

changes. At a deeper level, explicitly prioritising sleep and recovery alongside performance outcomes reflects a potential shift in system goals and may constitute a higher-order leverage point. Thus, recognising sleep as a central determinant of performance requires a shift in underlying assumptions. Collectively, these observations indicate that improving athlete sleep is unlikely to be achieved through isolated interventions alone, and may instead require coordinated strategies across behavioural, organisational, and system-level factors.

The CLD deliberately excludes individual characteristics such as chronotype, age and sex or gender, which we conceptualise as moderators of the relationships represented rather than as variables within a system. This exclusion represents a boundary decision with consequences for how the model should be applied. There is evidence that sleep characteristics in athletes differ by sex and age [16, 17], and that chronotype interacts with training and competition scheduling to determine circadian alignment [15]. Within the structure represented here, such characteristics would likely be expected to alter the strength of specific links rather than to add new ones. For example, the link between amount of early morning training and sleep opportunity would be expected to be stronger for later chronotypes, and the psychosocial conditions surrounding sex and gender in sport, including differences in scheduling, resourcing, media exposure, and caregiving responsibilities, may alter the strength of relationships between resourcing and scheduling constraints and sleep opportunity and pre-sleep arousal. Practitioners applying the framework should therefore treat the structure as generic and the strength of individual pathways as requiring individualisation.

Several variables did not reach the threshold for structural prominence despite supporting evidence from the sleep literature. Quality of sleep environment, amount of circadian rhythm disturbance, and level of recovery or readiness are well-established influences on athlete sleep [1, 42, 75], yet occupied comparatively peripheral positions within the model. Centrality reflects the number and position of connections specified in the model, not the magnitude of an effect, and a variable with a strong, well-evidenced but narrow influence may be structurally peripheral while a weakly evidenced but broadly connected variable may be structurally central. Readers should therefore not interpret Table 2 as a ranking of importance to athlete sleep, and structurally peripheral variables should not be deprioritised in practice based on this analysis.

A key strength of this study is the use of a CLD to model athlete sleep as a complex, interacting system, rather than a collection of independent risk variables. This approach allows for the identification of feedback loops, interdependencies, and potential leverage points which are challenging to capture using traditional linear methods. A further strength of the CLD is the capacity to use the model to create practical tools for athlete support personnel to use in practice (e.g., the example monitoring framework developed (Fig. 3) and others). Importantly, the CLD, accompanying network analysis, and example monitoring framework are intended as hypothesis-generating approaches rather than predictive models. Their purpose is not to forecast sleep outcomes or quantify the relative strength of causal relationships, but to identify plausible hypothesised pathways, structural interdependencies, and feedback processes through which sleep disruption can arise and be maintained within elite sport. Future work should explore the transformation of the CLD into a quantitative system dynamics model that could be used to simulate athlete sleep over time in different contexts. This would also provide a way of exploring how changes in different variables could impact athlete sleep, allowing testing of proposed interventions or exploration of system perturbations (e.g., travel constraints due to global conflicts, a major competition, such as the World Cup or Olympic Games, or athlete doping). Despite the strengths of the study, there are limitations worth noting. First, the model was developed by the author team, who were also the subject matter experts. No participants external to the research team contributed to the model development, and the model has not been externally validated. The model therefore represents the collective judgement of this team, informed by the evidence identified, and we acknowledged that alternative teams may produce a different structure. Second, while some bias mitigation techniques were used (e.g., use of peer reviewed sources, a research team with diverse experience), formal mitigation procedures such as independent facilitation were not used, which may have contributed to variables being specified at finer granularity where areas of expertise were concentrated. Third, the literature informing the model (Supplementary Table 1) was identified through purposive rather than systematic searching, which limits the reproducibility of the evidence base. Fourth, because individual characteristics such as chronotype and sex were treated as moderators of the relationships rather than as variables within the system, the model describes how sleep disruption may be maintained in elite sport but does not address why individual athletes differ in their susceptibility to it. Nevertheless, these limitations bound the claims that can be made from the model. They do not prevent its use as a conceptual tool for interpreting sleep-related challenges in sport, provided the structure is treated as a hypothesis for empirical testing rather than as a validated description of the system.

## 6 Conclusions

The athlete sleep CLD represents sleep health in elite athletes as an emergent property of the structure and functioning of the elite sport system, rather than principally as an outcome of individual behaviour. The relationships represented operate in both directions, the same structures that can sustain sleep disruption over time can, under favourable conditions, support sleep health. By developing a generic model of the athlete sleep system, this manuscript depicts a structured account of how travel demands, physical condition and readiness, behavioural influences, and organisational constraints and scheduling may interact through feedback loops to influence sleep over time. This account represents a synthesis of published evidence and expert judgement and is offered as a basis for empirical testing rather than as a validated description. Consequently, meaningful improvements in athlete sleep health are likely to require both system-level interventions and individual behaviour change strategies, and the relative contribution of each is a question the model is intended to help formulate, rather than definitively answer.

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## Declarations

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**Code availability** The CLD was developed using Vensim software (Ventana Systems Inc, Harvard, MA). Data used to inform the model are presented in the Supplementary Materials.

**Availability of data and material** Data used to inform the model are presented in the Supplementary Materials.

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