Developing methodologies to improve return-to-sport decision quality through a complex systems approach

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BSc (Hons) Physio, MSc Sports Med & Health Sci

Thesis submitted in fulfilment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

Victoria University, Australia

March 2023

Abstract

Making a return-to-sport (RTS) decision is often challenging, as the rehabilitation process is complex, and the decision affects the health and performance of the athlete. Clinicians have been harnessing the advantages of sports technology to capture and leverage data in the hope of securing competitive advantages in professional sports. With the extensive application of technologies and wearable sensors, increasingly more data are collected continuously during training and rehabilitation sessions. This has spurred a drive for clinicians to process, aggregate and interpret different metrics. However, humans have a limited capacity for information processing and are prone to biases and influences that may affect decision making. Given the data collected in sports settings are increasingly complex and the interactions are of nonlinear nature, clinicians seek to improve their decision quality in RTS by combining their clinical expertise with scientific data. This thesis addresses this gap, using a complex systems approach to underpin the study methodology. The first study discusses how to evaluate a RTS decision from a decision analysis perspective and proposes a framework to improve decision-making quality. Then, the second study discusses the characteristics of complex systems and provides examples of this approach in decision making. Two case studies in football (soccer) are used to investigate how advanced analytics may assist clinicians in decision making. Specifically, this thesis addresses the practicability, feasibility and interpretability of two analytical techniques: change point and association rule methods. Collectively, the findings from these studies may assist clinicians in improving decision making practically.

Student’s declaration

Doctor of Philosophy

“I, Kate Yung declare that the PhD thesis entitled

Developing methodologies to improve return-to-sport decision quality through a complex systems approach

is no more than 100,000 words in length including quotes and exclusive of tables, figures, appendices, bibliography, references and footnotes. This thesis contains no material that has been submitted previously, in whole or in part, for the award of any other academic degree or diploma. Except where otherwise indicated, this thesis is my own work”.

“I have conducted my research in alignment with the Australian Code for the Responsible Conduct of Research and Victoria University’s Higher Degree by Research Policy and Procedures.”

“All research procedures reported in the thesis were approved by the Victoria University Human Research Ethics Committee, HRE22-071.”

Signed: [redacted] Date: 28 March 2023

Name: Kate Yung

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DETAILS OF INCLUDED PAPERS: THESIS WITH PUBLICATION

Please list details of each scholarly publication and/or manuscript included in the thesis submission. Copies of published scholarly publications and/or manuscripts submitted and/or final draft manuscripts should also be included in the thesis submission.

This table must be incorporated in the thesis before the Table of Contents.

Chapter No.	Publication Title	Publication Status • Published • Accepted for publication • In revised and resubmit stage • Under review • Manuscript ready for submission	Publication Details • Citation, if published • Title, Journal, Date of acceptance letter and Corresponding editor's email address • Title, Journal, Date of submission
3	A framework for clinicians to improve decision making process in return to sport.	Published	Yung, K.K., Ardern, C.L., Serpiello, F.R. et al. A Framework for Clinicians to Improve the Decision-Making Process in Return to Sport. Sports Med - Open 8, 52 (2022).
4	Characteristics of Complex Systems in Sports Injury Rehabilitation: Examples and Implications for Practice	Published	Yung, K.K., Ardern, C.L., Serpiello, F.R. et al. Characteristics of Complex Systems in Sports Injury Rehabilitation: Examples and Implications for Practice. Sports Med - Open 8, 24 (2022).
5	A change point method to detect meaningful changes in return to sport progression in athletes.	In revised and resubmit stage	Science and Medicine in Football (Submitted 12 Sept 2022, first revision submitted 10 Jan 2023)
6	Application of rule association to rehabilitation training design: a football exemplar.	Under review	Journal of Sports Sciences (Submitted on 26 Jan 2023)

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Date: 9 Feb 2023

Updated: September 2020

Acknowledgements

This doctoral thesis, which was completed mostly during the COVID-19 pandemic, has been a rollercoaster of emotions and challenges. The global crisis brought professional sports to a standstill and made even the simplest tasks, such as travelling, a challenge as it required weeks of quarantine in a hotel.

This journey would not have been possible without the unwavering support and guidance of a number of wise and highly supportive individuals. My sincere gratitude goes out to my superstar principal supervisor, Professor Sam Robertson, who taught me to view things from different angles and forever changed my perspective on how I see things. You have instilled in me a drive to be different, innovate, and achieve an extraordinary PhD journey. For this, I wish to express my eternal and sincere gratitude. You helped shape this thesis in a way I could never envisage. Your drive to be innovative and achieve excellence has left a lasting impact on me. I am also grateful to my co-supervisors, Dr. Clare Ardern and Professor Fabio Serpiello, who provided me with invaluable guidance and support throughout this journey. Clare, I have always admired your exceptional leadership qualities. Your writing and communication skills have been an inspiration to me. Fabio, your consistent check-ins and sports science insights helped shape my thinking and research. Thank you.

I am also grateful to Western United Football Club and its staff and players, who gave me the opportunity to apply my skills and made me feel like a part of their team. Winning the grand final in the 2021/2022 season is a memory that I will cherish forever.

To my fellow research students at W202, thank you. I really missed the time we spent on the balcony before the COVID-19. The diversity in our research topics was just extraordinary, and I have learnt much from you all. Especially Ben Teune, you are a wonderful teammate.

To the staff and students at Institut of Sports and Preventive Medicine, Saarland University in Saarbrücken, Germany. To Professor Tim Meyer, Anne Hecksteden and Karen aus Fünten, You are exceptionally warm-hearted hosts. Your warm welcome and hospitality opened up another world for me, and I am forever grateful. To my housemates, Lola and Hagen, I would not be able to navigate the German administration systems or even open a bank account without you both.

To all the researchers and clinicians I have met at local and international conferences. Thanks for taking me under the wings, especially during 2021, when I was always the sole participant from the Asia and Ocean Pacific region due to border restrictions. Especially to Nicol van Dyk, Alan McCall and Stephen Mutchy. Thanks for being so supportive, even though most of the time we were far apart. Also, thank you Paul Wu, for your invaluable guidance in using the Bayesian networks. You not only demystified this complex subject but also opened up an entirely new world of knowledge for me.

To my lovely friends in Melbourne, you have helped me to feel settled and remain sane throughout this rollercoaster ride. To my friends and colleagues in Hong Kong, thanks for your support despite the distance and border closures. To Professor Patrick Yung, Mok Kam Ming, and Justin Lee - you all reminded I was not alone on this journey, and it is a massive reassurance knowing colleagues who had my back down through this journey. And a lot of people have helped me get to this point. If you are reading this, please know that I'm forever grateful for your presence and support.

Finally, this PhD is dedicated to my family, who have been my constant source of encouragement and support. Thank you for always being there for me.

Publications arising during candidature

The following work has been published in peer-reviewed journals in support of this thesis:

1. **Yung, K.K.**, Ardern, C.L., Serpiello, F.R. Robertson, S. A Framework for Clinicians to Improve the Decision-Making Process in Return to Sport. *Sports Med - Open* **8**, 52 (2022). https://doi.org/10.1186/s40798-022-00440-z (Chapter Three)
2. **Yung, K.K.**, Ardern, C.L., Serpiello, F.R. Robertson, S. Characteristics of Complex Systems in Sports Injury Rehabilitation: Examples and Implications for Practice. *Sports Med - Open* **8**, 24 (2022). https://doi.org/10.1186/s40798-021-00405-8 (Chapter Four)
3. **Yung, K.K.** A flock of birds and the complex systems. Football Medicine and Performance 35, 10-11 (2021). (Chapter Four)
4. **Yung, K.K.**, Wu PP, Ardern C, Tröß T, Abed H, aus der Fünten K, Hecksteden A, Serpiello, F.R. Robertson, S, Meyer T. 427 Applying Bayesian networks to injury occurrence in professional football. *British Journal of Sports Medicine* 2021;55:A163.

Presentations arising during candidature

1. **Yung, K.K.**, Ardern, C.L., Serpiello, F.R. Robertson, S. Use of machine learning techniques and Bayesian Network in return-to-sports. Presented at Complex systems in Sports 2022. (Chapter Four)
2. **Yung, K.K.**, Ardern, C.L., Serpiello, F.R. Robertson, S. Characteristics of Complex Systems in Sports Injury Rehabilitation: Examples and Implications for Practice. Presented at World Congress of Sports Medicine 2021. (Chapter Four)
3. **Yung, K.K.**, Teune, B., Ardern, C.L., Serpiello, F.R. Robertson, S. A change point method to detect meaningful changes in return to sport progression in athletes. Presented at Sports Medicine Australia Conference 2022. (Chapter Five)
4. **Yung K.K.**, Wu PP, Ardern C, Tröß T, Abed H, aus der Fünten K, Hecksteden A, Serpiello, F.R. Robertson, S, Meyer T. Applying Bayesian networks to injury occurrence in professional football. Presented at the International Olympic Committee World Conference on Prevention of Injury and Illness in Sport 2021.
5. **Yung, K.K.**, Teune, B., Ardern, C.L., Serpiello, F.R. Robertson, S. Application of association rule to rehabilitation training design: a football exemplar. Abstract (oral presentation) accepted at Isokinetic Conference 2023. (Chapter Six)

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List of symbols and abbreviations

=>	implicate
#	number
£	British pound sterling
ACC	acceleration
ACL	anterior cruciate ligament
AI	artificial intelligence
AU	arbitrary unit
AUD$	Australian Dollar
BN	Bayesian network
CCT	cognitive continuum theory
COD	change of direction
DEC	deceleration
DPT	dual process theory
DSS	decision support system
e.g.	for example
GNSS	global navigation satellite systems
HSR	high speed running
LSI	limb symmetry index
Max.	maximum
OFR	on-field rehabilitation
ROM	range of motion
RTC	return to competition
RTPlay	return to play
RTPerf	return to performance
RTRun	return to high-speed running
RTS	return to sport
RTTrain	return to train
SCAT5	Standard Concession Assessment Tool 5
SD	standard deviation
SRC	sports-related concussion
StARRT	Strategic Assessment of Risk and Risk Tolerance

T	training day
T+1	one day after training
T+2	two days after training
TD	total distance
Z5	zone 5
Z6	zone 6
h	hour
i.e.	that is
km	kilometre
$km \bullet h^{-1}$	kilometre per hour
m	metre
min	minute
$m \bullet s^{-1}$	metre per second
$m \bullet s^{-2}$	metre per second square
$m \bullet min^{-1}$	metre per min
s	second

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Ethics approval

All research procedures reported in the thesis were approved by the Victoria University Human Research Ethics Committee, HRE22-071”..

1 Chapter One: Introduction, Aims and Objectives

Chapter overview

This chapter offers an introduction to return to sport (Section 1.1), outlines the background and objectives of the thesis (Section 1.2) and the thesis structure (Section 1.3).

1.1 Thesis background and objectives

This thesis aims to provide sports clinicians with theoretical frameworks and analytical tools that may enhance the quality of decision making. The data are collected from the applied environment of a professional Australian A-League football club to understand clinicians' challenges and improve the practical utility of the research outcome.

In professional sports, RTS decisions can be challenging as the outcome pertains to the athlete's well-being and performance. The RTS process can vary among clinicians and sports organisations due to various factors such as the availability of resources (e.g., time, equipment, human resources), personal preference, and operational style. Research has indicated that clinicians take into account a range of biopsychosocial and contextual factors, including biological healing, playing position, and social support, in making RTS decisions (Ardern, Glasgow, et al., 2016; Shrier, 2015). Based on the information gathered, clinicians can weigh the risk(s) and benefit(s) to make the best choice. Nevertheless, not all RTS decisions are straightforward. For example, if RTS is delayed for a lesser chance of re-injury, reduced players' availability may negatively impact team performance (Eirale et al., 2013; Hägglund et al., 2013). On the contrary, premature RTS has been suggested as a possible risk factor for re-injury in football codes (Hägglund et al., 2016; Stares et al., 2018; Stares et al., 2019). Thus, substantial pressure rests on the shoulders of decision makers to reach a decision that balances the best interest of the athlete's health and the team's performance.

Furthermore, with advancements in sports technology, increasingly large quantities of data are being collected routinely in training, competition and rehabilitation. For instance, off the field, wellness scores and screening tests, such as countermovement jump, adductor isometric strength, hamstring isometric and hamstring eccentric strength tests, are routinely undertaken in field team sports (Gallo et al., 2016; Malone et al., 2017; Thorpe et al., 2016). On the field, voluminous data on physical output (e.g., running distance), physiological measures and skilled actions (e.g., passing frequency and accuracy) are also available readily (Browne et al., 2022; McIntosh et al., 2018; Teune et al., 2021).

Similarly, modern technology facilitates the capture of rehabilitation and training data within daily operations. However, the real challenge is to comprehend, extract, process, and interpret pertinent data that underpin their clinical judgments. Specifically, clinicians have to identify the clinical tests that can track the athlete's rehabilitation process, collect the data that can inform clinical decisions, and select the methodologies that can analyse data effectively. Simultaneously, clinicians are susceptible to decision-making errors and bias (Croskerry, 2009a). Coping with an abundance of data, clinicians might resort to procrastination and a perpetual quest for more refined information, often known as decision paralysis (Sarma, 1994). As such, there is value in using frameworks to guide clinicians in making good decisions consistently.

Additionally, a theoretical framework may provide a foundation and rationale for appropriately and systematically structuring the decision-making process. One of the appropriate theoretical frameworks is the complex systems approach (Bittencourt et al., 2016). Complex systems are open systems consisting of many factors that can interact among themselves and the environment (Bertalanffy, 1969; Bittencourt et al., 2016; Philippe & Mansi, 1998). As a result of the interactions between factors, new behaviours and patterns constantly emerge and create a dynamic system that may be difficult for people to predict. These characteristics have been recognised to align well with most sporting environments, including sports performance, game analysis and sports injury (Bittencourt et al., 2016; Dalton-Barron et al., 2020; Hulme & Finch, 2015). Specifically, the complex systems approach suggests that injuries result from the interaction between the individual and the environment (Hulme et al., 2019). Similarly, sports rehabilitation is also complex, and multiple factors can influence the outcome concurrently. Scope exists to show how clinicians can use the complex systems approach to represent the rehabilitation environment (Bittencourt et al., 2016). Specifically, adopting the complex systems approach would require clinicians to move from analysing isolated risk factors to pattern recognition (Bittencourt et al., 2016).

Given the sporting environment's complexity and high data volume, clinicians may require advanced analytical tools, such as machine learning, to support the decision-making process. These analytical techniques can handle large complex datasets and discover meaningful relationships between interacting factors that are otherwise not readily observable to the human practitioner (Ruddy et al., 2018; Teune et al., 2022b). Consequently, these analytical techniques may be viable tools to support clinical decisions.

1.2 Objectives

This thesis aims to investigate how to improve RTS decisions and adopt supporting analytical tools.

Four studies are conducted to achieve these objectives, as outlined in Figure 1.1.

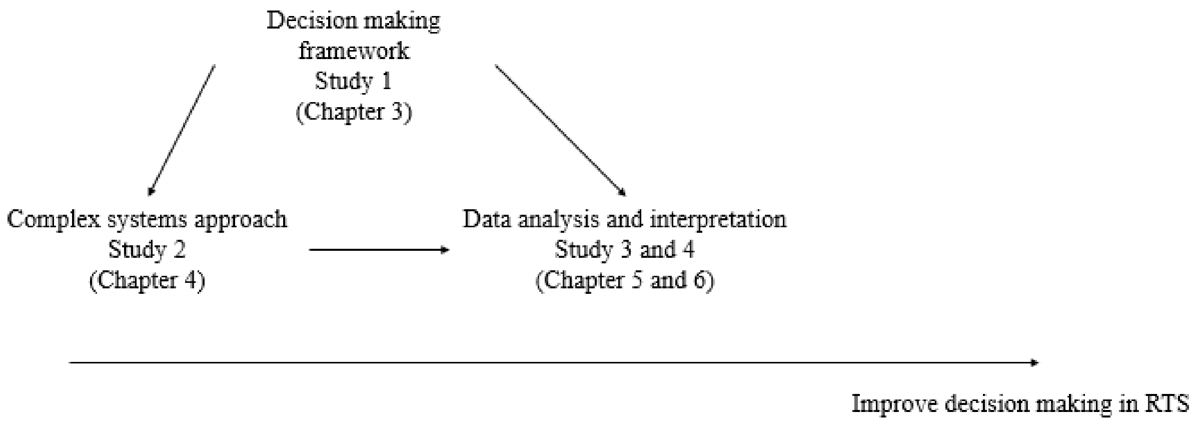

Figure 1.1 The sequencer of research and how each study relates to complex systems and decision-making framework, with the overarching goal of improving RTS decisions.

1.3 Thesis outline

Following this introductory chapter which introduces the background and objectives of the thesis, there are two sections that can be read independently. Following the two sections is a grand discussion of the concepts and implications arising from the preceding chapters, and a conclusion summarising this thesis's key points.

Two main parts for the studies:

Part 1. Frameworks

Synthesis of decision-making and complex systems frameworks to aid decision quality.

Part 2. Practical applications

Methodological studies of analytical techniques that may complement the theoretical framework.

Part 1 – Frameworks

This part includes Chapters Three and Four, which consist of two published works that provide a detailed evaluation of decision-making and complex systems frameworks that may improve decision quality. Chapter Three synthesises available literature in the RTS decision-making framework to provide an overview of the topic and propose a framework for improving decision quality. Chapter Four discusses the hallmark features of complex systems and their relevance to RTS decision making and daily practice.

Part 2 – Practical application

Part 2 builds on Part 1 and adopts tools that may support complex systems thinking in practice. This part includes Chapters Five and Six, which consist of two original studies that adopt two different analytical methods. Adopting complex systems approach in decision making is challenging because, practically, it may be near impossible for clinicians to integrate multiple data types and consolidate them within a timely manner due to their limited short-term memory and cognitive processing power. Part 2 complements the frameworks in Part 1 by adopting two analytical methods that can help clinicians 1) integrate multiple data types, 2) consolidate a high volume of data, and 3) accommodate the characteristics of the complex systems, such as non-linearity and emergence.

Diverse analysing methods exist for examining issues using a complex systems approach, with many of these methods demanding proficiency in statistics and data science. This thesis provides an overview of the terminology used in complex systems, with by a brief introduction to the relevant analytical methodologies. This information can assist clinicians in effectively communicating with statisticians and data science experts and fostering collaborations in future research projects. While the in-depth details of the analytical methods lie beyond the scope of this thesis, the thesis directs clinicians to additional resources that may aid them in delving extensively into the methodology.

Overview of the Chapters:

- Chapter Two reviews the relevant literature in RTS, decision making and analytical techniques.
- Chapter Three synthesises available literature in the RTS decision-making framework to provide an overview of the topic and propose a framework for improving decision quality.
- Chapter Four explains the hallmark features of complex systems and their relevance to RTS decision making and daily practice.
- Chapter Five investigates how continuous time-series analysis can inform meaningful change points in one or multiple variables in rehabilitation. A change point method is used in a case of football injury to exemplify the approach.
- Chapter Six uses the association rule approach to assist clinicians in integrating multiple data types and consolidating complex data into interpretable information that can be directly acted upon for training and return to sports decisions. The association rule method is applied to a case of football injury to exemplify the approach.

- Chapter Seven summarises the preceding chapters and discusses the applications and implications for clinicians. It also outlines directions for future work in the area.

2 Chapter two: Review of literature

Chapter overview

Chapter Two summarises the literature related to the research contained in this thesis. This chapter contains sections outlining literature from RTS (Section 2.1), decision making in RTS (Section 2.2) and analytical techniques (Section 2.3). This chapter does not include materials in the first two review studies in Chapters Three and Four. These include decision-making theories, methodological concerns in information gathering (Chapter Three) and complex systems theory and its characteristics (Chapter Four).

2.1 Return-to-sport in football

2.1.1 Impact of injury

Injury is common in football and is the primary factor affecting a player's availability for team selection and training (Parry & Drust, 2006). In a large-scale injury surveillance study, the injury incidence for a player is 12 to 23.8 per 1000 game-hours and 3.4 per 1000 training-hours (Ekstrand et al., 2021). The injury burden is 60.5 days /1000 hours during training and 504 days/1000 hours during match (Ekstrand et al., 2021). Injuries lead to players' unavailability, which is often associated with poor team performance (Chamari & Bahr, 2016; Eirale et al., 2013; Hägglund et al., 2013; Lu et al., 2021). Besides the negative impact on sports performance, injuries also have financial implications for sports organisations directly (e.g., salaries paid to injured players) and indirectly (e.g., team's underachievement due to injured players) (Eliakim et al., 2020; Gouttebarge, Hughes Schwab, et al., 2016; Hickey et al., 2014; Lu et al., 2021; Mather et al., 2013). For example, an average English Premier League team lost approximately £45 million (AUD$76 million) per season due to injury (Eliakim et al., 2020) [team underachievement due to injured players £36 million (AUD$ 61 million); direct calculation of salaries paid to players £9 million (AUD$ 15 million)]. In the Australian professional football A-League, the player-salary cost of injury per team per season averages AUD$0.25 million (Lu et al., 2021).

To minimise the impact of injury to the athlete and the team, sports organisations may investigate injury prevention program and return-to-sport (RTS) protocol. While extensive research has been done on football injury prevention (Crossley et al., 2020; Thorborg et al., 2017), there is relatively less research on improving RTS decision quality. However, RTS decision is an important topic. Often, the first question asked by an injured athlete is: 'When can I play again?'. While the question may sound simple, the answer to this is rarely straightforward. As with most medical decisions, there are many factors that a clinician needs to consider and – as a result - there is scope for applied research to investigate how to improve RTS decision quality.

2.1.2 **Theoretical frameworks in return to sport**

RTS can be viewed as a continuum that consists of recovery and rehabilitation (Ardern, Glasgow, et al., 2016), with an objective to bring the athlete back to their pre-injury performance level in the shortest time possible and minimise the risk of re-injury (Zambaldi et al., 2017). In general, it consists of three critical stages, including:

1) Return to participation: The athlete may be participating in rehabilitation, training, or in sport, but at a level lower than the RTS goal.
2) Return to sport: The athlete has returned to the sport, but not performing at the desired performance level.
3) Return to performance: The athlete has returned to the sport and performing at or above pre-injury level.

With the development of research in RTS, more details have been added to the above framework to address the specific need of the sports. For example, in football, the following phases have been included to reflect the critical milestones in football rehabilitation (Dunlop et al., 2019):

1) Return to high-speed running (RTRun): The player is being cleared to run on-field and progress to high-speed running.
2) Return to train (RTTrain): The player is allowed to return to on-field unrestricted training.
3) Return to play (RTPlay): The player is cleared to return to competitive match-play with the team, regardless selected or not.
4) Return to performance (RTPerf): The player returned to pre-injury levels of performance or higher.

The above four stages have highlighted the key stages for a football player to return to performance. Between the stages RTTrain and RTPerf, a four-stage functional recovery process was introduced (Buckthorpe et al., 2019). The four-stage functional recovery process was proposed to highlight the transition from rehabilitation to performance. The functional recovery process starts with on-field rehabilitation (OFR), progressing to return to training (RTT), return to competition (RTC) and lastly, return to performance (RTPerf). The above theoretical RTS frameworks have been summarised and shown in Figure 2.1

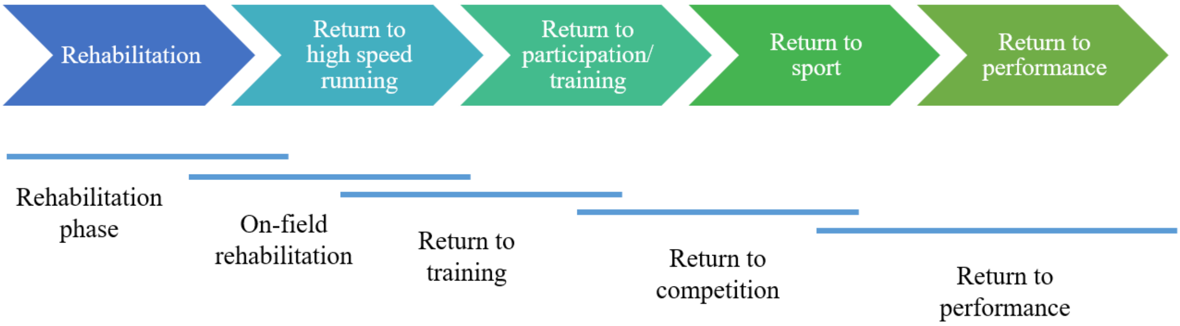

Figure 2.1 Summary of RTS frameworks

The above continuum broadly defines sports rehabilitation stages, which move from high control to high chaos (Taberner et al., 2019). Based on the Figure 2.1, clinicians can structure rehabilitation plans accordingly and use the framework to facilitate communication and manage the expectations between stakeholders, such as the technical coach, strength coach and athletes. It is important to note that each phase overlaps with the other because RTS is a dynamic process that requires careful balancing of the benefits and risks to progress to the next phase (McCall et al., 2017). For this thesis's clarity, RTS decisions refer to 1) granting medical clearance to players for competition and 2) deciding when a player may progress or regress along the RTS continuum. (Ardern, Glasgow, et al., 2016; Buckthorpe et al., 2019; Gordon O Matheson et al., 2011).

The first formal RTS framework, a 3-step decision-based model, was proposed by Creighton et al. in 2010 (Creighton et al., 2010). The framework was designed to guide clinicians on when to clear an athlete for full participation in sport without restriction. In 2015, minor revisions were made to the 3-step framework, and it was renamed the Strategic Assessment of Risk and Risk Tolerance (StARRT) (Shrier, 2015). The StARRT has helped make the decision-making process transparent by guiding the key variables that the clinician could consider (Shrier, 2015). However, the industry still lacks a decision framework that can guide clinicians on the decision-making process. A decision framework is worthwhile in competitive sports because the sporting environment is often chaotic, fast-paced, dynamic and stressful. In this environment, decision makers may be more susceptible to emotional interference, impulses and other biases (Croskerry, 2003; Lazarus, 2000). An improved understanding of decision theories may help clinicians to 1) conceptualise the decision-making process, 2) investigate the workflow further, and 3) eventually establish a methodology to make a better RTS decision.

2.2 Decision making in RTS

2.2.1 Complexity and volume in data

In the context of RTS, where time is usually not a limiting factor, clinicians may gather more information regarding athletes' physical and mental conditions to make decisions. Technological advancement has made gathering clinical and physical performance data easier than before. For instance, more types of data collection are now made possible with the availability of different sensors and equipment at affordable costs (e.g., wearables, heart rate monitors, shoe insoles and motion capturing systems) (Sikka et al., 2019). Accordingly, clinicians may gather more information to reduce uncertainty, making them more confident in identifying a likely successful decision (Drews et al., 2015; Gould, 1974; Raiffa, 1968). Nevertheless, collecting more data from multiple sources may pose new challenges in handling, cleaning and interpreting the data. Furthermore, in professional sports, it is indisputable that the increasing amount of data will - or has already - exceeded human processing capacity, thus challenging clinicians' ability to make an informed decision.

Accordingly, the amount of information humans can process is limited by the working memory storage capacity (Saaty & Ozdemir, 2003; Simon, 1957). Working memory capacity is vital for decision making because a human can only complete cognitive tasks when the brain can retain information (Cowan, 2010). Research has suggested that the human's working memory can hold approximately four

(Cowan, 2001) to seven pieces of information (Saaty & Ozdemir, 2003). Providing more information than the upper limit may exhaust the decision maker’s cognitive information processing capacity, potentially leading to information overload and compromised decision making (Cowan, 2001). Further, the additional information obtained may no longer improve the decision maker's ability to identify a likely successful decision (Glöckner et al., 2012). A possible reason is that the inconsistency between the information produced by additional items is too small for a human mind to identify, which leads to confusion (Gigerenzer, 1999). On the contrary, when fewer items are available, the inconsistencies between the information brought by additional items are significant enough for a human mind to identify which item(s) cause the most remarkable inconsistency (Gigerenzer, 1999). Further, different search strategies exist as a result of age, for example, younger adults request more information than older adults in medical decision tasks (Meyer et al., 1995).

Currently, there are no guidelines regarding the optimal amount of information that should be included when making a RTS decision. The complexity of a RTS decision can be illustrated by a sports-related concussion (SRC) case. In SRC, an athlete’s recovery rate varies based on the injury's severity (McCrea et al., 2003) and the athlete’s pre-existing psychological factors (Trinh et al., 2020). Consequently, clinicians need to consider the athlete’s recovery rate individually. The clinician may also consider other medical, social and legal factors (Maroon et al., 2000) (See Table 2.1 RTS factors for sports-related concussion injury). Collectively, in a complex SRC case, a clinician may need to consider more than seven pieces of information to assess the RTS readiness of an athlete (Dayton et al., 2020; Dessy et al., 2017; McCrory et al., 2017). It may be challenging for clinicians to analyse and process all the available information within a limited timeframe. Given the complexity of RTS decisions, there is scope to investigate a decision-making framework and methodology that can help clinicians to streamline the RTS workflow process.

Table 2.1 RTS factors for sports-related concussion injury

RTS factors for sports-related concussion injury	
Clinical assessment	
1	The Balance Error Scoring System balance test (McCrory et al., 2017)
2	Vestibular (Alsalaheen et al., 2010) / vision assessment (Akhand et al., 2019)
3	Rivermead Post-Concussive Symptom Questionnaire (Eyres et al., 2005)
4	Physical examination of cervical spine (Cheever et al., 2016)
5	Standard Concussion Assessment Tool 5 (SCAT 5) (Echemendia et al., 2017)
Diagnostic testing	
6	Imaging (Herring et al., 2011)
7	Neuropsychological Testing (Herring et al., 2011; McCrory et al., 2017)
8	Blood biomarkers (McCrory et al., 2017)
Others	
9	Social and legal factors

2.2.2 Decision-making theories

Theories are important for clinicians to link concepts and understand phenomena. Clinicians may harness decision-making theories to develop relevant conceptual frameworks and methodologies to enhance the RTS workflow process. Two fundamental approaches to reasoning, intuitive and analytical, have been established in the literature, which is now widely recognised as the dual process theory (DPT) (Croskerry, 2009c; Evans, 2008; Sloman, 1996; Stanovich, 2004). The DPT encompasses both intuitive and analytical processes, referred to as System 1 and System 2, respectively. System 1 involves heuristic, intuitive decisions, while System 2 involves systematic, analytical decision making (Table 2.2).

Table 2.2 Comparison of System 1 and System 2 approaches in decision making. ↓ indicates the feature has a lower prevalence than the other system, while ↑ indicates a higher prevalence.

Characteristics	**System 1 (intuitive)**	**System 2 (analytic)**
Cognitive style	Intuitive Heuristic	Analytical Normative
Operation	Associative	Deductive
Processing	Parallel	Serial
Conscious control	↓	↑
Automaticity	↑	↓
Reliability	↓	↑
Error	Normative distribution	Few but significant
Effort	↓	↑
Emotional valence	↑	↓
Detail on judgement	↓	↑
Reliability	↓ Variable	↑ Consistent
Importance of context	↑	↓

The subsequent subsections cover details of the DPT. Other schools of thought are also covered in this thesis, including cognitive continuum (Section 2.3), normative models and descriptive models (Bell et al., 1988) (Chapter 4). Normative models have theoretical value and concerns about how to make the best possible decision when a person is fully rational and informed (Bell et al., 1988). In contrast, descriptive models are psychological theories that explain how people make judgements and decisions (Baron, 2012).

2.2.3 System 1 intuitive approach

In the DPT, System 1 decision making is characterised by an intuitive approach based on a rapid selection of options without systematic evaluation (Doubravsky & Dohnal, 2015; Gigerenzer & Gaissmaier, 2011). This approach utilises the decision maker's prior experience and intuition to recognise patterns in the information and make quick judgments. Heuristics, or cognitive shortcuts, are often employed in this type of decision making (Tversky & Kahneman, 1974).

Heuristics are viewed as the human mind's 'adaptive toolbox' that allows a person to associate new information with existing patterns or thoughts (Gigerenzer & Gaissmaier, 2011; Regehr & Norman, 1996; Schmidt et al., 1990). Decision makers may use a range of heuristics (Tversky & Kahneman, 1974), depending on the context and the individual's social and learning process (Rieskamp & Otto, 2006). The use of heuristics has been studied in diverse domains, such as psychology (Gigerenzer, 1999), law (Gigerenzer & Engel, 2006), sports (Pachur & Biele, 2007; Raab, 2012), medicine (Marewski & Gigerenzer, 2012; Wegwarth et al., 2009), finance (Ortmann et al., 2008), and political science (Gaissmaier & Marewski, 2011). In medicine, using heuristics can help clinicians make accurate, transparent and quick decisions (Croskerry, 2002; Marewski and Gigerenzer, 2012), yet only limited research is available in the field of RTS (Muir, 2022).

Although heuristics are a shortcut to an automatic brain, this does not imply that heuristics are inferior to other decision-making strategies (Gigerenzer, 1999; Hoffrage & Reimer, 2004; Raab & Gigerenzer, 2005, 2015). In certain circumstances, a simple decision strategy with less information input may outperform deliberate reasoning via detailed analyses (Glöckner et al., 2012; Klein, 2003; Raab & Johnson, 2007; Wilson & Schooler, 1991). However, heuristics may also result in stereotypes, false associations, and a disregard for causality (Croskerry et al., 2013a; Tversky & Kahneman, 1974). As heuristics are adaptive in nature, they are neither good nor bad *per se* if applied appropriately in situations where they have been adopted. The following are several examples of heuristics and their relevance to RTS.

Availability

The availability heuristic is the mental shortcut that relies on the most readily available data that comes to the person's mind when evaluating a decision, topic or event. This is because people have a tendency to place greater weight on information that can be easily remembered and quickly retrieved (Tversky & Kahneman, 1973). For instance, an athlete with a syndesmosis injury may estimate their recovery time based on a teammate's recent experience with the same injury. However, the accuracy of this heuristic can be influenced by the recentness and vividness of memories (Hunink et al., 2014a). It may lead to availability bias if the decision maker disregards data that does not support the belief. Accordingly, the availability heuristic may negatively impact the diagnostics accuracy in medical residents, but the residents can improve their judgement by reflective reasoning (Mamede et al., 2010; Saposnik et al., 2016).

Representative

The representative heuristic refers to when decision makers categorise an object or incident based on similarity with the existing one in their minds (Tversky & Kahneman, 1974). The representative heuristic has been found to influence decision-making in triage station nurses (Brannon & Carson, 2003). However, the representative heuristic has not been studied in sports medicine and rehabilitation. Clinicians may possibly use a representative heuristic to determine an athlete's injury risk. For instance, if an athlete displays a valgus knee while landing and scores low on movement screening tests, the clinician may associate these factors with the likelihood of ACL injury due to their prior knowledge. However, recent research suggests that poor movement quality is only associated with but not necessarily predictive of injury (Bahr, 2016; Hughes et al., 2020).

Anchoring-adjustment

Anchoring-adjustment is when decision makers are "anchored" on the initial values and later update their perception with better information (Hunink et al., 2014a). For example, internal medicine residents use anchoring-adjustment when they estimate the probability of a disease by using a high or low anchor for the target conditioning (Phang et al., 2015). In the context of RTS, a clinician's decision on medical clearance may be anchored on existing knowledge of the athlete, familiarity with the injury and the initial diagnosis and plan.

Take-the-best

Take-the-best refers to a situation where decision makers search through the alternatives in order of validity and base the choice on the "best" option (Gigerenzer & Gaissmaier, 2011). In the context of RTS, a clinician may evaluate an athlete's fitness for return to play by considering the best available indicators such as running speed, strength, and mental preparedness.

Elimination by aspects

Elimination by aspects is when decision makers reduce the number of alternatives by eliminating those that do not meet the aspiration level of a specific attribute (Tversky, 1972). For example, when a clinician prescribes exercise for an athlete with a tibia stress fracture, the clinician will first compare a selection of exercises on the lower limb and eliminate the weight-bearing ones.

Fast and frugal trees

A fast-and-frugal tree is similar to a decision tree, where decision makers classify and decide quickly with a few attributes (Gigerenzer & Gaissmaier, 2011). There has been a range of applications in different fields. For example, physicians to determine if a patient with severe chest pain has a heart attack or not (Green & Mehr, 1997), and London magistrates to make bail decisions in court (Gigerenzer & Engel, 2006). In sports medicine, clinicians can use the Ottawa ankle rules to decide whether an injured ankle requires X-ray to rule out a fracture (Stiell et al., 1994). Ottawa ankle rules have successfully been implemented in applied settings and reduced unnecessary radiographs by 30-40% (Bachmann et al., 2003). In the context of RTS, clinicians may use a fast-and-frugal tree to decide whether an athlete may walk without crutches after an anterior cruciate ligament (ACL) reconstruction surgery (Figure 2.2).

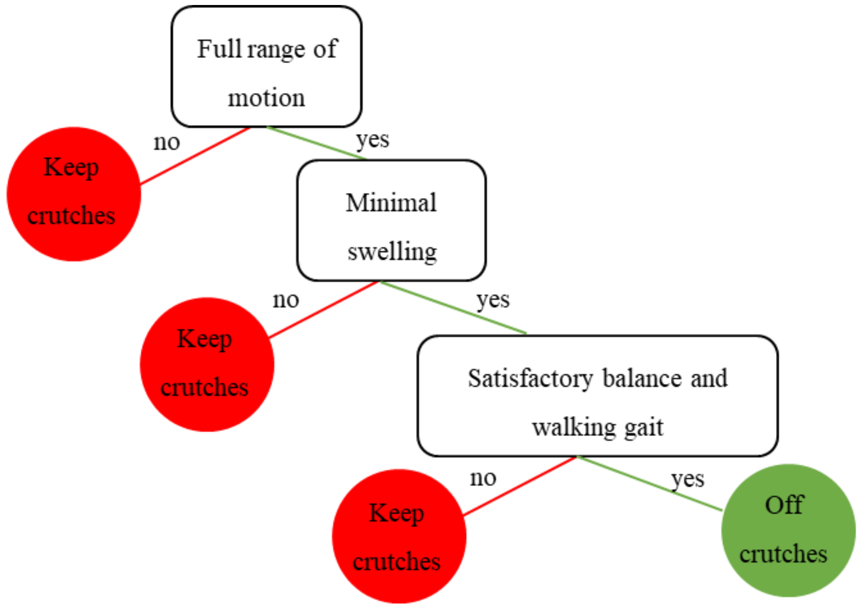

Figure 2.2 Fast and frugal tree to decide if the athlete can walk without crutches after ACL injury.

2.2.4 System 2 analytical approach

Contrary to System 1, System 2 is a deliberate, conscious and controlled process characterised by rational thinking (Bate et al., 2012). System 2, also known as explicit cognition, involves logical judgement and mental search for additional information (Croskerry, 2009b). System 2 may be engaged when clinicians need to analyse information to support clinical decisions. For example, when a clinician diagnoses a sports injury with atypical signs and symptoms, System 2 may be required. System 2 is analytical and follows explicit computation rules, such as adhering to the rationality criteria of expected utility theory, or where a clinician decides based on a set of defined criteria (known as rule-based theory) (Grindem et al., 2016; Kyritsis et al., 2016). The rules may be applied on a binary scale (i.e., pass or fail). In RTS, one of the passing criteria for a knee injury may be a single-leg hop test to achieve 90% of the uninjured side (Kyritsis et al., 2016). In contrast, the expected utility theory is a decision-making model that considers the expected value of different options and the probability of each outcome (Connolly et al., 1999; Edwards, 1977). It illustrates how one decides in uncertain conditions based on the outcomes of different options and the probability of each outcome (Connolly et al., 1999; Edwards, 1977). It presumes that a decision maker will make a rational choice based on evaluating the costs and benefits associated with each option. (Ashby & Smith, 2000; Reyna & Rivers, 2008). In this theory, a clinician’s decision is determined by the subjective value assigned to each potential outcome and the estimated likelihood of each outcome (Connolly et al., 1999; Edwards, 1977). According to this model, System 2 assumes decisions are made by fully rational individuals who have access to complete information about the probabilities and consequences of each option in terms of time, resources, and knowledge (Shrier, 2015). Expected utility theory and other normative theories are covered in Section 3.4.2.

2.2.5 Interaction between the systems

System 2, although known for being more reliable and rational, can also be time-consuming and requires significant cognitive resources. As a result, it may not always be feasible for sports medicine professionals to engage in extensive cognitive analysis for every clinical decision they make. Consequently, clinicians may naturally opt for System 1, which is quicker and less demanding on the mind. (Croskerry, 2009c). In some clinical conditions, clinicians may start making diagnoses using System 1 based on pattern recognition (Norman, 2006). However, when clinicians cannot recognise the pattern, they may switch to System 2, deliberate and conscious thought processes (Croskerry, 2009a). In the context of RTS, clinicians may switch to System 2 in complex conditions, such as when an athlete is eager to participate in an important game despite not being fully healed from an injury.

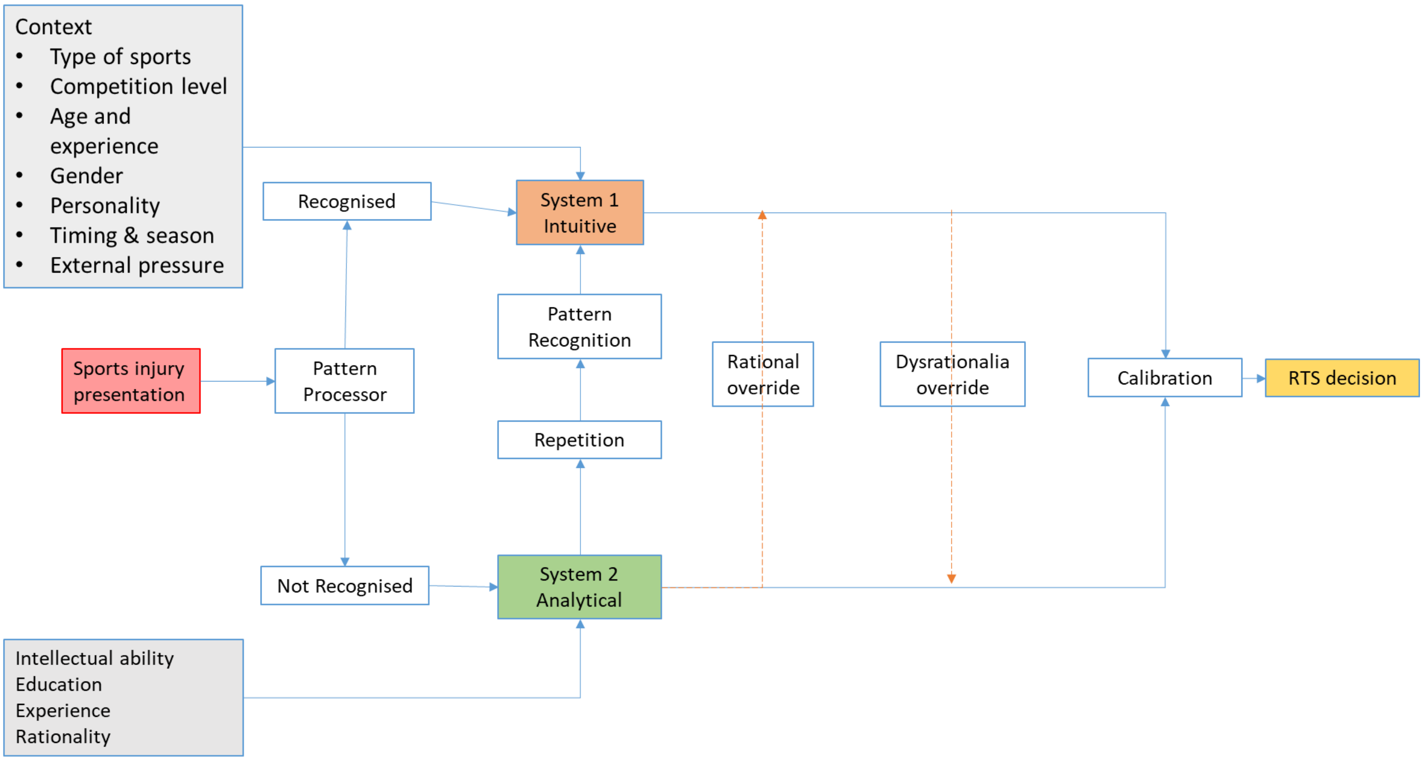

Figure 2.3 Schematic model for RTS decision-making. Based on Croskerry (2009a), adapted for RTS context.

There are also several ways in which the two systems interact with each other, as indicated by the orange dashed lines in Figure 2.3. System 2's analytical approach, when used repeatedly, can eventually become automatic, much like the intuitive approach of System 1 (Croskerry & Norman, 2008; Norman, 2006; Norman & Brooks, 1997). This is analogous to building up sports taping skills, where after considerable practice, the clinician can tape an ankle with little conscious effort. This shows the importance of building up experience and familiarity with clinical practice. In addition, System 2 can rationalise and override the intuitive output of System 1 (rational override) (Croskerry, 2009c). This overriding function requires deliberate mental effort, and its ability to perform can be negatively impacted by distraction, sleep deprivation and fatigue (Landrigan et al., 2004). System 1 can also override System 2, in which the decision maker overrides a rational judgement based on intuitive feeling, known as dysrationalia (Stanovich, 1993). Various reasons, such as habitual practice, emotions and context, may contribute to dysrationalia. An example of when System 1 overrides System 2 is when clinicians ignore well-developed clinical decision guidelines (McGlynn et al., 2003) and persist with clinical practice with little solid evidence (Croskerry & Norman, 2008).

In short, the DPT allows clinicians to scrutinise the underlying decision-making process and realise the systems' vulnerable aspects. Despite most errors occurring in System 1 (Tversky & Kahneman, 1974), there is still a value of using System 1 in some contexts, such as where there is limited time and resources. Both systems are essential for clinicians to function in the applied sports environment. One of the keys to an improved decision-making process is a well-calibrated balance between the two.

2.2.6 **Cognitive continuum for RTS**

Beyond the DPT, which has distinct intuition and analysis, there is another theoretical decision-making orientation framework known as the cognitive continuum theory (CCT) (Hamm, 1988; Hammond, 1978). CCT models human judgement and decision making with six modes of inquiry based on the task and cognition (Figure 2.4). They are positioned along the continuum based on the degree of cognitive activity they are predicted to induce, such as task structure, cognitive control, and time required (Hamm, 1988). Similar to DPT, CCT may assist clinicians and interdisciplinary teams in understanding the decision-making process (Parker-Tomlin et al., 2017). Specifically, clinicians can use CCT to 1) recognise the kind of cognition used and potential cognitive pitfalls, 2) adjust and select the appropriate cognition strategy based on the task, and 3) improve decisions' transparency for multidisciplined professionals (Cader et al., 2005; Hamm, 1988).

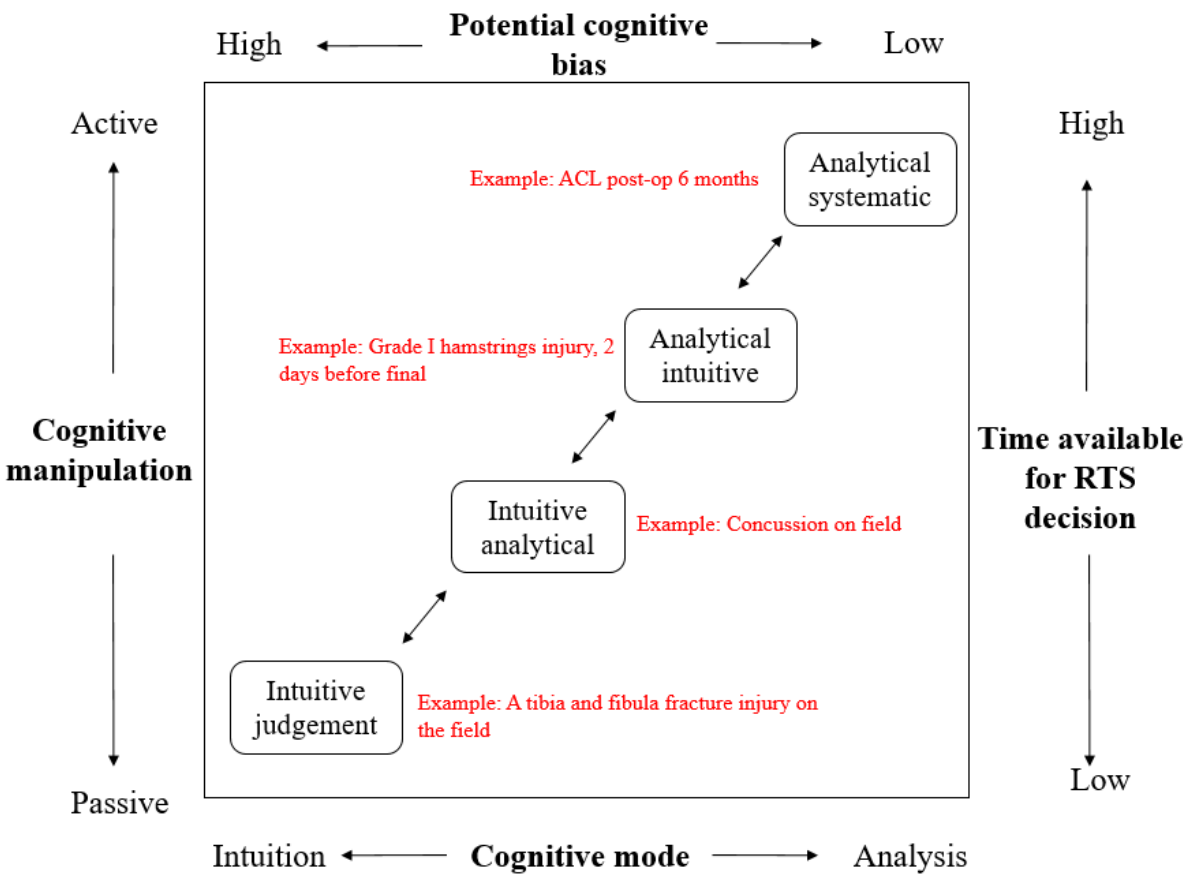

Figure 2.4 Cognitive continuum theory adapted to the context of RTS, based on Hamm (1988); Hammond (1978).

Here are examples to illustrate how CCT can be applied in the context of RTS.

1. **Managing an on-field fracture injury (intuitive judgement)**

   When an apparent fracture injury (e.g., a tibia and fibula fracture) occurs on-field during a football game, the immediate response of a clinician is to remove the player from the field and send the player to the hospital. This is an intuitive judgement because the clinician is unlikely to allow the injured player to return to the game with a fracture injury due to safety reasons. The time available for decision is short, and the degree of cognitive manipulation is low.

2. **RTS from a concussion (intuitive analytical)**

   In case of a suspected concussion during a football game, a clinician will remove the player from the field and assess the player for any subtle change in response, such as facial expression and emotional changes (Ryan & Warden, 2003). Clinicians may also use decision aid (e.g., SCAT5) to evaluate the concussion at the sideline (Echemendia et al., 2017). In this case, the time available for the decision is longer than the previous condition (e.g., 5-10 minutes), and the degree of cognitive manipulation is higher. There is also some degree of intuition (e.g., to observe subtle changes in the player's response) and analytic involvement (e.g., to assess the condition with SCAT5).

3. **RTS for a Grade 1 Hamstrings injury (analytical intuitive)**

   For a player who sustained a grade one hamstring injury two days before the final, a clinician can take the time to assess the player physically, functionally and mentally. The clinicians can decide on RTS based on the assessments. Given the limited time frame to the final, some uncertainty may exist around rehabilitation, so a small degree of intuition may be required when making the judgement.

4. **RTS for an ACL reconstruction surgery (analytical systematic)**

   In the case of ACL rehabilitation, there is more time for clinicians to assess and decide on RTS (e.g., in terms of weeks). Clinicians can perform relevant RTS tests and analyse the results systematically. There is a high degree of cognitive manipulation, and the reliance on intuition may be minimal.

CCT is a simplified general framework that explains the cogitation strategy used and its relationship between the task features and progress. Understanding the methods and relationships may increase the transparency of the decision-making process (Cader et al., 2005).

2.2.7 **Bias in decision making**

Occasionally, humans may present with cognitive deficiencies when making decisions (Thaler, 2009). Accordingly, one obstacle to making good clinical decisions is the potential distortions and biases in how information is gathered and assimilated (Croskerry, 2002). Decision makers who rely on intuition may be quick in making the decision, but they may be subject to errors that can only be recognised upon reflection (Tversky & Kahneman, 1974). Knowing how decisions are made and how they may be biased is vital to improve decision quality.

There are over 30 known cognitive biases, many of which influence decision making as an "illusion" (Croskerry, 2002, 2003). Some biases may be inevitable, but some biases may be avoided by implementing strategies, such as increasing awareness of their existence and using decision aid (Croskerry, 2003). Below are some common cognitive biases with relevance to RTS:

2.2.7.1 Anchoring bias

Anchoring bias occurs when the decision maker relies heavily on the initial piece of information (anchor) offered to make a judgement (Croskerry, 2000). Accordingly, decision makers tend to fixate on the first impression of a clinical case, such as some specific clinical features early on in the diagnostic process (anchor) (Croskerry, 2002). Following the initial piece of information, interpretations are made around the anchor. This may be an effective strategy in clinical reasoning, yet clinicians may fail to adjust the hypothesis sufficiently in light of subsequent information. For example, a lacrosse player is hit on the ribs with a lacrosse stick, with signs of bruising. The player was able to continue playing afterwards. A clinician may anchor on the initial piece of information (a contact bruise injury) and neglect the subsequent information that there was significant localised swelling. In this case, the clinician may have missed a rib fracture injury.

2.2.7.2 Availability bias

Availability bias is the cognitive bias associated with availability heuristics, in which a human tends to rely on immediate examples that readily come to mind (Tversky & Kahneman, 1973). Accordingly, decision makers perceive the most readily available evidence to be the most relevant and important (Tversky & Kahneman, 1973). Thus, if a clinician sees an athlete with muscle soreness due to recent overtraining, there is a greater chance that the clinician believes the next athlete coming in with muscle soreness has a similar issue. However, that athlete may be suffering from a low-grade muscle strain injury. Inexperienced clinicians may tend to be driven by availability bias as they are more likely to bring common prototypes to mind, whereas experienced clinicians are more likely to suspect atypical cases (Kovacs & Croskerry, 1999).

2.2.7.3 Confirmation bias

Humans tend to search for, interpret, favour, and recall information that validates their pre-existing beliefs or hypotheses. Important data that weaken an illusory correlation would be neglected or discarded (Nickerson, 1998). This may also reinforce groupthink, where group members minimise conflict and reach a consensus without critically evaluating the idea. As a result, systematic errors and poor decisions may be generated (Williams, 2010). Confirmation bias may occur in a medical meeting, where attending staff may agree with the physician’s suggestion on the RTS plan without critically assessing the context.

2.2.7.4 Framing bias

Humans may be susceptible to how others frame the options, known as the ‘framing effect’ (Tversky & Kahneman, 1986). Different phrasing ways can change a neutral message to an implicit recommendation and affect one’s decision, such as treatment selections (Gigerenzer, 2014). For example, patients are more inclined to consider surgery when the clinician uses a survival frame rather than a mortality one, although they are logically equivalent (Moxey et al., 2003). The framing effect may vary with the type of scenario and the responder’s characteristics. As such, how a clinician frames the chance of re-injury may affect the athlete’s perception of when to RTS. Fortunately, the framing effect tends to disappear when complete information is provided and expressed in more than one way (Gigerenzer, 2014; Moxey et al., 2003).

2.2.7.5 *Sutton's Law and Sutton's Slip*

Sutton's Law in clinical reasoning refers to the tendency of a clinician to go for the most apparent diagnosis, which helps to speed up clinical reasoning in some cases. However, clinicians may also avoid tests that are unlikely to be diagnostic and pursue tests thought to be of the highest diagnostic value (Watanuki et al., 2015). Due to Sutton's Law, clinicians may give insufficient consideration to other alternatives, known as the Sutton's Slip. For example, a clinician may mistreat an orthopaedic oncologic condition as a sports injury due to an overlap of clinical presentations and a lack of further investigation (Ayvaz et al., 2015).

2.2.7.6 *Search Satisficing*

Search satisficing is when someone might stop searching for information once a satisfactory result has been obtained (Simon, 1979). Accordingly, some clinicians may tend to cease diagnostic investigations once a presumed cause for a patient's symptoms has been found (Croskerry et al., 2013a). Due to search satisfaction, medical comorbidities, such as other fractures, may be overlooked (Berbaum et al., 1994). For example, a clinician treating a lateral ankle sprain may fixate torn ankle ligaments as the source of pain and overlook possible trauma to other foot structures, such as the Lisfranc joint complex.

2.2.7.7 *Emotion*

Decision quality may be affected when emotion, ego and motives are prioritised over objective information (Hunink et al., 2014b; Zeelenberg et al., 2008). These motives and emotions may be intertwined in the decision-making process unintentionally and unconsciously and shape the clinician's decision (Croskerry, 2005). For example, a person feeling anxious about a potential outcome of a risky choice may choose a safer option rather than a risky but potentially lucrative option (Lerner et al., 2015). The effect of emotional states may also render decision makers to avoid negative feelings (e.g., guilt and regret) or increase positive feelings (e.g., pride and happiness) (Lerner et al., 2015). To minimise the magnitude of the emotional effect on the decision process, decision makers can adopt strategies such as time delay, suppression and reappraisal (Lerner et al., 2015).

2.2.7.8 Blind spot bias

Generally, humans are assumed to be rational and prefer making objective decisions (Simon, 1979). At the same time, humans are also aware that factors, such as limited information, emotions and self-interest, may bias their decisions (Pronin et al., 2002). When evaluating their decision-making process, people tend to think they are smarter and less susceptible to cognitive biases than others (Pronin et al., 2002). In a study by Irene Scopelliti and colleagues, only one person out of 661 people said they were more biased than average (Scopelliti et al., 2015). As a result of blind spot bias, many clinicians may be overly confident (Mele, 1997). And unfortunately, people with a large blind spot bias are least likely to use strategies to improve their decision quality (Scopelliti et al., 2015).

2.2.8 **Strategies for de-biasing**

Mitigating decision-making biases can play a critical role in enhancing decision quality for clinicians. While some biases may be unavoidable, others may be mitigated through techniques such as increasing awareness and utilising decision aids, referred to as de-biasing (Croskerry, 2003).

There are three steps that may help clinicians to mitigate decision-making bias. First, they can build awareness of what may increase their susceptibility to cognitive biases, such as distractions, fatigue, and sleep deprivation (Croskerry et al., 2013a). Second, they can recognise strategies to overcome biases and when necessary. Third, clinicians are suggested to constantly reflect on their thought process before deciding and have the cognitive capacity to decouple from the bias (Stanovich & West, 2008). This can be achieved by switching from the intuitive processing of System 1 to the analytical processing of System 2, allowing for a more thorough examination and verification of the initial intuition (Croskerry, 2000). A range of strategies that may facilitate switching from System 1 to System 2 are presented in Table 2.3 (Croskerry et al., 2013b). Fourth, clinicians may consider obtaining external appraisals from experts to review their methods and approaches in making decisions.

Table 2.3 Strategies and examples for de-biasing

Strategy	**Explanation**	**Examples**
Structured data acquisition	Deliberate data acquisition procedures to ensure adequate information are acquired and minimise blind spots.	Use a differential diagnosis checklist tool to assist clinical reasoning.
Consider alternatives	Establish routine consideration of alternative options.	Seek evidence that may support a RTS decision opposite to the initial impression to force consider other examples.
Group decision strategy	Seek others' opinions and apply crowd wisdom.	Schedule team meetings with other practitioners and design a rehabilitation plan together.
Use of external aid	Improve judgement accuracy by using clinical practice guidelines and algorithms to reduce reliance on memory. Clinicians may also consider the use of clinical decision rules and aids that minimise uncertainty and cognitive load, such as implementing computerised clinical decision support	Visually display a list of clinical tests in the treatment room that clinicians must perform when deciding when an athlete can RTS.
Minimise time pressure	Allow adequate time for thought processes.	Allow enough time for making a diagnosis and planning for RTS.
Supportive environment	Create a supportive environment that encourages high-quality decision making.	Readily availability of rehabilitation protocols, clinical guidelines, RTS criteria to reduce variance. Well-organised working schedule to avoid cognitive overload, fatigue and sleep deprivation (Croskerry et al., 2013a).

2.3 Analysis techniques

Given the challenges in decision making, it may be beneficial to improve data analysis to enhance decision quality. Specifically, clinicians may harness nonlinear analytical methods to address the chaos and complexity inherent in sports. In particular, machine learning techniques have attracted attention for their strength in transforming a large amount of data into practical knowledge and identifying nonlinear patterns (Edouard et al., 2020; Witten et al., 2011). In the context of RTS, the application of machine learning has been growing but is still limited (Albano et al., 2020).

2.3.1 Machine learning

Machine learning is a subfield of artificial intelligence (AI), where the computer system learns from data without being explicitly programmed to do so (Mohammed, 2017; Tibshirani, 2013). Machine learning could recognise correlations, patterns and trends in large datasets (SoleimanianGharehchopogh et al., 2012). Users can also input relevant data into the machine learning model to refine the algorithm and improve the outcome (Mohammed, 2017). Machine learning can be used for predictive and descriptive purposes (Han, 2012). Specifically, clinicians can use predictive modelling for injury diagnosis, prognosis and rehabilitation planning. On the contrary, clinicians can use descriptive modelling to characterise injury profiles and identify the association between the relevant factors.

Machine learning is categorised into *supervised, unsupervised,* and *reinforcement learning* (Jain et al., 1999; Mohammed, 2017). Four main analytical techniques are available within the machine learning umbrella: association, classification, clustering and relationship modelling. Machine learning techniques can search large databases to recognise nonlinear patterns or build models to describe associations and predict outcomes. The use of machine learning has gained momentum in sports injury research, and they have been applied to assess injury risk, analyse movement and predict sports performance (Claudino et al., 2019; Cust et al., 2019; Fältström, Kvist, et al., 2021; Rossi et al., 2019; J. Ruddy et al., 2018).

In supervised machine learning, labelled data is used to train the algorithm. Labelled data refers to a dataset of predictor variables marked with resultant output (Kotsiantis et al., 2006). This training allows the algorithm to learn trends, model relationships and classify groups between inputs and variables (Maymin, 2017). Common relationship-modelling machine learning techniques are regressions and neural networks. In contrast, decision trees and random forests are popular algorithms for classification. The above techniques can be used for continuous and categorical datasets and have been applied in a range of sports domains, for example, in talent identification (Den Hartigh et al., 2018; Maymin, 2017), match outcome prediction (Bunker & Thabtah, 2019; Robertson et al., 2016), movement recognition (Cust et al., 2019), skill analysis (Weigelt et al., 2011) and injury prediction (Rossi et al., 2019).

Contrary to supervised learning, unsupervised learning is trained with unlabelled data. The algorithm finds hidden patterns within the data without prior knowledge of the correct outcomes (Mohammed, 2017). Examples of unsupervised learning techniques are clustering (Jain et al., 1999) and association rule (Agrawal et al., 1993). These techniques have been applied in areas such as player movement analysis (Weigelt et al., 2011), technique analysis (Ball & Best, 2007) and match analysis (Sampaio et al., 2015).

Supervised and unsupervised learning represent most machine learning techniques. Techniques that fall between the two classes may be classified as semi-supervised. Another branch of machine learning is reinforcement, where the algorithm is trained through trial and error (Richard & Andrew, 1998). Reinforcement learning so far has limited application in sports (Ding et al., 2022; Liu & Schulte, 2018).

Limited by human resources, time, bias, uncertainty and complexity, it may be challenging for clinicians to make effective and objective decisions. To this end, clinicians may consider using machine learning to support data analysis and inform decisions. Machine learning is a promising candidate for analysing clinical datasets because of its ability to analyse nonlinear interactions and recognise patterns in large and complex datasets (Dutt-Mazumder et al., 2011). The following subsections outline the two common machine learning techniques (association rule and classification), and which association rule approach is adopted in Chapter Six. Section 4.4.1 also provides examples of how clinicians can frame RTS questions and analyse them with the major machine learning approaches.

2.3.2 Association rule

The association rule is a type of unsupervised learning capable of identifying meaningful patterns between variables in a large dataset (Agrawal & Srikant, 1994). It originated in market-basket analysis, where vendors are interested in the habit of customers, for example, what items customers typically purchase together in a single transaction (e.g., milk, bread and eggs) (Agrawal et al., 1993; Cariñena, 2014). Based on the rules identified, vendors can place frequently co-purchased items on adjacent shelves to increase sales or cross-marketing (e.g., suggest recommended products in online shopping). The output can be expressed in the IF-THEN format. That is, **IF** condition_1 **and** condition_2 **and** … **and** condition_n, **THEN** decision (Daud & Corne, 2009). For example, **if** (the athlete single-leg hops five times without pain) and **if** (the calf strength of the injured leg is 90% of the uninjured side), **THEN** (the athlete could start running). These rules may be generated using association rule mining techniques to conduct large-scale searches within their sports organisation's rehabilitation dataset. Clinicians can then use the rules to guide progression in rehabilitation and minimise maladaptation in training, such as overreaching or excessive muscle soreness. Such approach may fit in clinical settings because of the transparency of the algorithm (Bullock et al., 2022; Muyeba et al., 2013).

Based on the research question, there are a few variations of the association rule approach that clinicians may leverage to increase data resolution. First, users may include temporal attributes in the data mining process to identify an ordered correlation between events (Cariñena, 2014; Pei et al., 2004). As such, the antecedent and consequent rules can exist at different time points. For example, if customers buy pasta this week, they are more likely to buy rice next week (Cariñena, 2014). In the context of RTS, an increase in training workload today may be related to a decrease in running capacity one day later. Second, cyclic association mining can identify rules that exist at regular particular time periods of a dataset (Cariñena, 2014; Özden et al., 1998). In the case of market basket analysis, users can analyse how festive seasons such as Boxing Day sales may observe a higher volume of sales. In sports, researchers may potentially use temporal association mining to explore the association between ACL injury and women's menstruation cycle (Slauterbeck et al., 2002).

The association rule is more suitable for categorical data. When the data set includes continuous data, the data need to be first discretised and presented in interval values, such as “high” and “low” (Stańczyk et al., 2020). Discretising value across a broad spectrum of categories may reduce processing time and increase usability. However, the use of discretisation may introduce sharp boundaries. One of the solutions is to use a fuzzy set (Delgado et al., 2005; Hong & Lee, 2008). Fuzzy sets create soft boundaries boundary to soften the transition between consecutive intervals. For example, a 30-year-old athlete is considered to be “old”, but a 29-year-old athlete is considered “old with a lower degree”. As a result, the transition between being young and old is not sharp, but with a gradual transition. Fuzzy sets may be incorporated in the modelling of quantitative temporal and non-temporal attributes in the event.

In sports performance, the association approach has been used to identify constraints in skill training for kicking training (Browne, Sweeting, et al., 2019; Robertson et al., 2019), talent identification (Robertson et al., 2015) and tactics analysis (Browne, Morgan, et al., 2019). Clinically, the association rule have been used for understanding illness and musculoskeletal disorders (Kanimozhi et al., 2019; Muyeba et al., 2013), but application in RTS is scarce

2.3.3 Classification

Classification is a type of supervised learning, and the most common technique is decision trees (Loh, 2014). Decision trees are nonlinear machine learning techniques that can predict a single outcome using several predictor variables (De'ath & Fabricius, 2000). Decision trees can make predictions based on categorical and continuous data (Loh, 2011), which gives them an advantage over the association rule.

A decision tree algorithm is flow-chart-like, learning from the observation of an item to conclude the item's target class or value. Decision trees work by recursively partitioning the dataset, one variable at a time, into homogenous and mutually exclusive groups (Loh, 2011). In the decision tree, each node denotes a test for each attribute for a particular instance, and each branch represents the test outcome (Figure 2.5). Accordingly, the branches are grown continuously until the predictive power of further splits no longer improves the model (Morgan et al., 2013). A random forest is similar to a decision tree, except that it randomly creates multiple decision trees. Each node in the decision tree works on a random subset of features to calculate the output (Breiman, 2001). The random forest then combines the output of individual decision trees to generate the final output (Breiman, 2001).

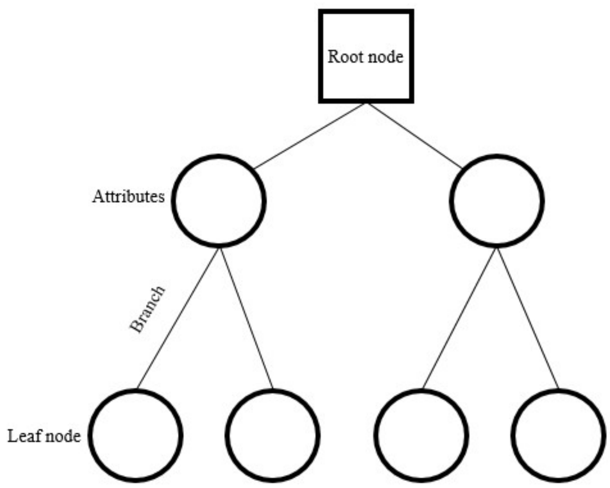

Figure 2.5 Graphical presentation of a standard decision tree

In the design of machine learning models, the choice of attributes is important. Including a small set of relevant and highly predictive attributes in the model-building process can result in a good performance model (Hall & Holmes, 2003). Attribute selection typically involves a combination of search and attribute utility estimation and evaluation concerning the specific learning goal (Hall &

Holmes, 2003). Similar to the association machine learning approach, decision trees are likely to fit in clinical settings because clinicians can assess the output with established evidence and explain the result practically and intuitively (Bullock et al., 2022; Muyeba et al., 2013). For example, if the output from the decision tree suggests an athlete is not ready for RTS, practitioners may backtrack the model and identify the rationale behind it. Users may also refer to the visual output to aid interpretation (Figure 2.5) (Morgan et al., 2013).

Decision trees have been applied in a range of sports settings, for example, to analyse movement (Cust et al., 2019), predict player ratings (McIntosh et al., 2019) and predict shot outcome (Browne et al., 2022). In the field of sports medicine, decision trees have been used to diagnose and predict sports injury (Claudino et al., 2019; Girard et al., 2020; Jauhiainen et al., 2022; Martin et al., 2021; Rossi et al., 2019; J. D. Ruddy et al., 2018), classify knee injury status (Girard et al., 2020) and identify key factors for a better outcome in ACL RTS (Palmieri-Smith et al., 2022). Decision trees may be used to support RTS decisions, however, their application in supporting RTS decisions has been limited (Albano et al., 2020).

Machine learning may be a viable tool for supporting RTS decisions based on its strength in handling complex and nonlinear multivariate data. It may be desirable to research a data-informed system powered by machine learning to analyse high-dimensional datasets. Clinicians may harness data-informed systems and artificial intelligence to increase productivity and accuracy of decisions.

2.3.4 Decision support system

A decision support system (DSS) is a computer technology solution that provides objective evidence to support complex decision making and problem solving (Schelling & Robertson, 2020). These systems typically utilise historical data to assess and analyse current information to form user recommendations (Robertson, Bartlett, et al., 2017). The development and use of DSS have been evolving, from supporting organisational decisions (Shim et al., 2002), to improving sports performance decisions

(Schelling et al., 2021; Schelling & Robertson, 2020; Zeleznikow et al., 2009) and clinical decisions (Hunt et al., 1998; Sutton et al., 2020).

Clinical DSS may aid clinical decision making by matching the patients' characteristics to computerised knowledge. Based on the knowledge base, the DSS can provide individualised assessments or recommendations to clinicians for their consideration (Osheroff et al., 2007). Clinicians may also use DSS to synthesise and integrate information from multiple sources and perform complex evaluations (Garg et al., 2005). In addition, the use of computerised analytics may accommodate the features of the complex systems and assist clinicians in considering the problem holistically (Schelling & Robertson, 2020). Clinically, DSS can be used for various purposes, ranging from improving medical quality, safety and efficiency; and across a range of domains such as screening, diagnosis and treatment (Garg et al., 2005).

Despite clinical DSS having shown great promise in reducing medical error and improving patient care (Hunt et al., 1998), there are limited applications in sports medicine settings. Research has suggested that DSS are more likely to be implemented if the decision makers are willing to make changes and judgements based on the findings from the system (Hunt et al., 1998; McIntosh et al., 2019; Robertson, Bartlett, et al., 2017). Specifically, the following three characteristics have been recommended:

1) The DSS should fit into the workflow of the clinicians (Kawamoto et al., 2005) and optimise the time, cost and burden of using the system (Fernández, 2019; Robertson, Bartlett, et al., 2017).
2) The DSS provides clinicians with actionable recommendations rather than just assessment (Kawamoto et al., 2005). Ideally, the DSS should also allow evaluation and simulation of the decision as a system feedback mechanism (Schelling & Robertson, 2020).

3) The DSS provides timely information to clinicians to provide the most impact (Kawamoto et al., 2005).
4) The output of the DSS should be interpretable by clinicians (Kawamoto et al., 2005). Given that most clinicians may not have formal training in data analytics and interpretation, the display of the clinical DSS output should also be considered.

2.3.5 Visualisation

Output from analytics tools and clinical DSS is only applicable if the results are accessible and interpretable by clinicians. Naturally, users are not motivated to use a DSS if the reporting methods are not interpretable or practical (Green, 1998; S. Liu et al., 2017; Schelling & Robertson, 2020; Thornton et al., 2019). To assist clinicians' interpretation of the findings, the design and style of reporting are critical (Silver, 1991; Thornton et al., 2019).

Appropriate visualisation can translate complex outcomes into interpretable findings and thus reduce the cognitive work and time required to digest the information (Kale et al., 2018). This may aid the uptake of information and encourage users to engage with pleasure (Pinker, 1990). This is especially important to clinicians as they are less likely to have formal analytics training and thus may have difficulty understanding the output from complex analytics. To this end, clinicians can harness visualisations, which require less cognitive load in interpreting than tables and numbers (Green, 1998; Kale et al., 2018). The visualisation may help translate numbers into a more straightforward medium and allows users to effectively gain insight from complex information (Zacks & Tversky, 1999).

In displaying proportional data, the layout and design of graphs are crucial to convey the message (Jordan & Schiano, 1986; Schiano & Tversky, 1992; Tversky & Schiano, 1989). For example, pie charts are not recommended as users judge an area's size less accurately than the length of a line in a bar graph (Spence & Lewandowsky, 1991). Further, the effectiveness of the graph may decrease when the number of components displayed in a bar chart increases (Hollands & Spence, 1998).

2.4 Section summary

RTS decisions are commonly encountered in sports, and clinicians are required to make complex decisions that balance the risks and benefits of athletes and sports organisations. Fortunately, clinicians can utilise the data routinely collected in sports organizations to support their decisions. Clinicians can also use existing theoretical and strategic assessment frameworks to guide the rehabilitation process and consider the relevant factors. However, much is unknown about integrating different data types to make quality decisions.

Within decision making in RTS, there is scope to improve the data quality, data analysis and interpretation to improve efficiency when providing information to clinicians. To appropriately guide the RTS decision-making process, clinicians may evaluate the decision quality (Chapter Three) and view rehabilitation through the lens of the complex systems theory (Chapter Four). Practically, the use of complex systems approach in making decisions remains limited, possibly due to 1) clinicians being unlikely to have formal decision-making training, and 2) the complexity and volume of data available nowadays are more than ever. Clinicians may harness advanced analytical techniques, such as machine learning algorithms, to support RTS decisions with a complex systems approach (Chapters Five and Six).

Part I Frameworks

This section includes Chapters Three and Four, which consist of two peer-reviewed published manuscripts that provide a detailed evaluation of decision-making frameworks and complex systems theory that may improve decision quality. Chapter Three synthesises the available literature in the RTS decision-making framework to provide an overview of the topic and propose a framework for improving decision quality. Chapter Four discusses the hallmark features of complex systems and their relevance to RTS decision making and daily practice.

3 Chapter Three: Study I

Chapter overview

Chapter Three is the first of the four studies contained in this thesis. This study is a narrative review that explores the current decision-making theories and proposes a decision-making framework that may improve the quality of RTS decisions.

The content of this chapter is an accepted manuscript of an article published by Springer Open in Sports Medicine – Open on 13th April, 2022, available at: https://sportsmedicine-open.springeropen.com/articles/10.1186/s40798-022-00440-z

Clinical relevance

With advancements in sports technology and the development of more testing kits and wearables, clinicians nowadays may be overwhelmed with voluminous data. Excessive information may cause clinicians difficulty in consolidating and integrating data collected from different sources and at different time points. As such, there are times when clinicians may “guesstimate”, a combination of guess and estimation, to make a decision. Given that decision-making training is not typically included in a clinician’s education, this narrative review addresses three questions: 1) How to make better decisions? 2) What are the decision-making theories relevant to clinicians’ practice? 3) What are the potential pitfalls that clinicians have to look out for when making decisions?

Yung *et al. Sports Medicine - Open* (2022) 8:52
https://doi.org/10.1186/s40798-022-00440-z

Sports Medicine - Open

REVIEW ARTICLE
Open Access

A Framework for Clinicians to Improve the Decision-Making Process in Return to Sport

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Abstract

Return-to-sport (RTS) decisions are critical to clinical sports medicine and are often characterised by uncertainties, such as re-injury risk, time pressure induced by competition schedule and social stress from coaches, families and supporters. RTS decisions have implications not only for the health and performance of an athlete, but also the sports organisation. RTS decision-making is a complex process, which relies on evaluating multiple biopsychosocial factors, and is influenced by contextual factors. In this narrative review, we outline how RTS decision-making of clinicians could be evaluated from a decision analysis perspective. To begin with, the RTS decision could be explained as a sequence of steps, with a decision basis as the core component. We first elucidate the methodological considerations in gathering information from RTS tests. Second, we identify how decision-making frameworks have evolved and adapt decision-making theories to the RTS context. Third, we discuss the preferences and perspectives of the athlete, performance coach and manager. We conclude by proposing a framework for clinicians to improve the quality of RTS decisions and make recommendations for daily practice and research.

Keywords: Decision-making, Decision, Return to play, Decision analysis, Rehabilitation, RTS, RTP

Key Points

- RTS decisions are complex, nonlinear and multifactorial and thus require external tools to assist practitioners
- To improve the quality of decisions in sports settings, decision-makers could evaluate the following three domains: (1) assess the methodological soundness of the tests chosen, (2) identify potential deviations from normative decision models and (3) implement shared decision-making.

Introduction

Decision-making is a process of weighing the risk(s) and benefit(s) among options to make a choice [1]. In clinical practice, return-to-sport (RTS) decisions can be challenging as they are directly linked to the athlete's well-being and performance. RTS refers to the recovery and rehabilitation continuum: return to participation, return to sport and return to performance [2]. This review focuses on how the quality of RTS decisions could improve.

Premature RTS may risk re-injury [3–5] and subsequently harm the athlete's playing performance [6], financial income [7] and mental health [8, 9]. Yet, if RTS is delayed for a lesser chance of reinjury, it will inevitably reduce a team's player availability. Lower player availability is undesirable as players' match availability is associated with team performance across various sports [10–16]. Consequently, substantial pressure rests on the shoulders of decision-makers to reach a decision that balances the best interest of the athlete's health and performance.

When the context is predictable and routine, for example when managing a tibia fracture on the field, decision-making could be straightforward and relegated to an automated level (i.e., remove from play immediately).

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However, when there is a high level of uncertainty and complexity in the context (e.g., to decide whether an athlete at 95% of recovery should play in the grand final), the ability to make high-quality decisions is less clear, yet potentially even more crucial.

The challenge of complexity and the multifactorial nature of RTS decision-making has been acknowledged for over two decades [17]. A 1998 review by Putukian [17] discussed the concerns and struggles that clinicians have when making RTS decisions, which could be attributed to the multifactorial nature and clinical uncertainty presented in medicine [18, 19]. The majority of the research focus since then has been mostly on developing decision-making frameworks and clinical criteria for RTS. One of the most recognised decision-making frameworks is the Strategic Assessment of Risk and Risk Tolerance (StAART) [20]. The framework, together with the RTS criteria, helps to guide a clinicians' practice. For example, in the management of anterior cruciate ligament (ACL) injury, clinicians may refer to the established RTS criteria [21, 22] and consensus statements [23, 24].

In contrast to the vast literature on RTS criteria, there is less on how clinicians make RTS decisions and how to improve the quality of the decision. This may be because this topic spans at least two distinct fields: sports medicine and decision-making science. We aim to help clinicians conceptualise the decision-making process, increase the thoughtfulness of a decision, identify potential deviations from normative decision models and eventually establish a framework to improve the quality of decision-making.

Disentangling Decisions and Outcomes

The term *decision* refers to the *action* taken to reach a decision, and this is different from the *outcome* of the decision [25, 26]. A high-quality decision refers to a decision that is logical and made based on the uncertainties, values and preferences of the decision-maker [27]. A good *outcome* is an outcome that the decision-maker would wish to have happened and is of high value to them [27].

A high-quality *decision* does not necessarily warrant a good *outcome* due to uncertainties. There are multiple sources of uncertainties, and the two major categories prominent in the medical field are aleatoric uncertainty and epistemic uncertainty [28]. Aleatoric uncertainty is intrinsic to the problem, for example, random variations that arise from observers or instruments. Epistemic uncertainty is extrinsic and comes from limitations in knowledge, such as individual bias [28].

Distinguishing between decision and outcome allows clinicians to separate action from the consequence, so they can focus on improving the quality of the action. Occasionally, clinicians may be disappointed by a bad outcome of a good RTS decision, such as an athlete suffering from a re-injury despite careful medical evaluation. Yet, in the pursuit of a good outcome, there may not be a better way than striving for a high-quality decision. Therefore, in this paper, we focus on evaluating the decision, and not on the outcome.

Evaluating a Decision

There are various ways to evaluate a decision. The first approach is related to the *outcome* of the decision, such as clinical health outcomes (e.g., pain, quality of life), or how regretful or satisfied the patient is with the decision [29–31]. However, there is no consensus on the optimal measurement tool(s) for this purpose. The second approach relates to the *expected value* of the outcome (i.e., expected utility), where probabilistic information about the risk and benefits of personal preferences and values is considered [32]. The third approach is to consider the *decision quality*, which is measured by knowledge of the options and outcomes, realistic perceptions of outcome probabilities, and agreement between patients' values and choices [29].

It may be challenging to measure the quality of a decision with the first two approaches (i.e., outcome and expected utility) due to the complexity of a RTS question. Nevertheless, it may be possible to evaluate the decision with the third approach—decision quality.

Decision analysis is a formal procedure for analysing decision problems by balancing the factors that could influence a decision [27]. To evaluate the decision quality, the decision process could be made transparent by first breaking it down into a sequence of clear steps. We have adapted a decision analysis model from Howard [33] for RTS to systematically evaluate a decision (Fig. 1).

The essence of decision analysis is eliciting the four bases for the decision [33]:

1. *The alternatives* relates to the options that a decision-maker has. In the context of RTS after an injury, it could be whether the athlete could return to full training/competition, modified training or basic rehabilitation training.
2. *The information* refers to knowledge that may be important to formulate the outcome. For example, what information do RTS tests provide to the decision-makers?
3. *The decision models* include models that describe how the decision could be made. That is, on what basis can the decision be made?
4. *The preferences* of a decision-maker could be of multiple dimensions. These include the value (e.g., how much does RTS mean to the athlete or the team?),

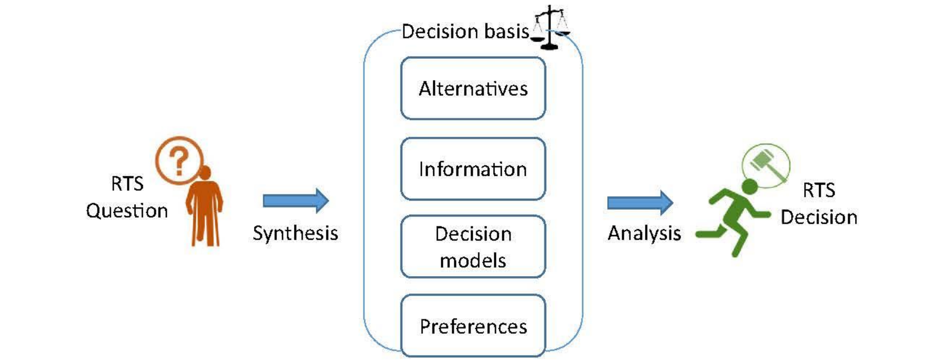

Fig. 1 Steps for evaluating a RTS decision

time preference (e.g., how important is it to play in the upcoming game?) and risk preference (e.g., how much re-injury risk can the team tolerate?).

Among the four key bases for a decision (alternatives, information, decision models and preferences), the alternatives are highly specific to the context and would be difficult to discuss from a broader perspective. Therefore, we have structured this review around the other three bases for a RTS decision: (1) information, (2) decision models and (3) preferences. We first zoom in to the methodological issues of obtaining *information* in the medical room. Second, we zoom out to identify the *decision models* relevant to RTS. Third, we discuss how *preferences* can be addressed with shared decision-making. Finally, we propose a framework to improve RTS decision-making in practice.

To increase the practicability of the framework and to help readers navigate the three bases for the RTS decision, a case scenario describing an ACL injury is used. We use ACL injury because it is a serious injury in sports that may threaten the career of athletes [6, 34]. Multiple clinical and performance tests have been developed to evaluate the readiness of the RTS [35], yet the re-injury risk of ACL remains high [36, 37] and some athletes do not return to sports following the injury [38].

Part 1: Methodological Concerns in Information Gathering

A football player, in her early career, has undergone an ACL reconstruction surgery six months ago and is eager to return to play. She wants to play as soon as possible to gain a contract extension but is also worried about getting reinjured. In the medical room, you sit with the player and decide on what kind of test to perform on-field and off-field.

At the operational level, there are methodological considerations when gathering information for the decision. Below we discuss some of the underlying assumptions and methods concerns.

Number of Criteria Used in RTS

In general, criteria-based RTS (e.g., muscle strength, functional and dynamic stability, and range of motion) have been suggested over a time-frame approach, which is to decide solely based on the athlete's time spent in rehabilitation [39–43]. The ideal number of tests to use for this purpose may vary between cases. There are concerns that an insufficient number of tests may jeopardise the clinician's ability to see the complete profile of an injured athlete. However, too many tests may increase the inherent error (e.g., athlete exhibiting reduced performance due to fatigue or reduced motivation) and exhaust more resources (e.g., staff, time, equipment). Currently, there is no recommendation for the ideal combination and number of tests to provide the most insight into the athlete's readiness for RTS.

Baseline Setting in RTS

Returning to pre-injury levels of health and fitness is often seen as the goal of RTS [2]. Therefore, setting an appropriate baseline provides an ideal foundation for clinicians to monitor progress by comparing the current functional and physical capacity of the athlete with previous preinjury data. However, it is challenging to set a baseline that is objective, replicable and suitable for the setting. For example, currently, there is no guideline on the timing and frequency for performing baseline tests. Adding more complexity to the problem, physiological and performance profiles often fluctuate daily due to periodisation in training and competition schedule (e.g., heart rate variability [44], musculoskeletal screening scores [45], hip strength and flexibility [46] and power (as in countermovement jump) [44].)

Here we used the limb symmetry index (LSI) as an example to illustrate the concerns with baseline setting. LSI is often included in the RTS protocol for ACL injury [22, 47–50]. LSI compares the performance of the involved limb with the uninvolved limb [51]. Often, a 90% side-to-side difference threshold is used as a passing score for RTS [47–50]. However, there is little scientific evidence on the optimal threshold. Even when limb symmetry is achieved, it does not necessarily indicate the athlete has reached a level sufficient for safe sports participation and performance [50, 52]. It is also questionable whether the uninvolved side could be used as the benchmark when pre-injury data are not available. After ACL reconstruction surgery, patients have reduced single-leg hop performance of both the involved and uninvolved sides [52, 53] and for up to 2 years after surgery [54]. This could be attributed to a combination of factors, such as deconditioning, fear or lack of motivation [54]. Consequently, defining the baseline measure for comparison remains a challenge and a suite of RTS tests have been recommended [2].

Validity of RTS Tests

Content Validity

Content validity refers to how well a test protocol reflects what it intends to measure [55, 56]. Selecting measurement tools is important as unnecessary noise may dampen the accuracy of the decision model. If the tests selected are prone to false positives, clinicians may be unnecessarily delaying the rehabilitation process of the athlete [47].

Traditionally, in RTS decisions, clinicians would consider internal athlete data (e.g., physical fitness, strength, well-being, periodic health-screening, body-mass, anthropometric, internal load responses) and external factors such as training loads (e.g., running performance, training and match exposure), the timing in the season, and the importance of the game or training. However, there seems to be a bias towards assessing variables that are easily measured, and missing measures that may be important, but more difficult to measure [57]. For example, in the rehabilitation of an ACL injury, a clinician may assess the hip, knee and ankle joint alignment in jump and land testing to identify the extent of valgus or varus movement. The assessment may provide valuable information regarding movement strategies and physical capabilities of the athlete; however, it may not provide sufficient information regarding the performance in competition. In competition, an athlete may encounter different chaotic and unpredictable scenarios, such as unplanned movement tasks and under high opponent pressure and cognitive load. Despite the best intentions to design testing to be sports specific, the overall physical, psychological and emotional demands of a competitive match could be hard to replicate. Consequently, decision-makers may need to identify the content validity of the test and decide to interpret the test result.

Predictive Validity

Predictive validity is how well a test predicts performance on a criterion that is administered at a later date, such as RTS outcome [56, 58]. Predictive validity is only available for some of the tests such as hop tests [47, 59], single-leg bridge test [60] and psychological readiness test [61]. For most RTS tests, clinicians may not know whether passing the test means the athlete could achieve a satisfactory RTS outcome or not. In a recent study, there was no association between the predetermined functional performance test cut-offs and the risk of a new ACL injury [62]. Similar, the Landing Error Scoring System may not predict the ACL injury risk in a cohort of high school and college athletes [63].

Responsiveness of RTS Test

Responsiveness, or sensitivity, refers to how well a test can detect meaningful changes in skill and functional assessment [55]. While it is important to track progress, recent evidence suggested that some common clinical tests cannot accurately track meaningful gains in biological and functional recovery after injury [64–66]. The time to normalise also differs. For example, in lower-limb injury assessment, 6-m timed hop test returned to normal earlier than the other three single-leg hop tests (single hop for distance, triple hop for distance and crossover hop for distance) [47]. Similarly, in hamstrings strain rehabilitation, straight leg raise returned to full at an early stage as compared to maximum hip flexion with active knee extension [64]. Limited literature is available to inform what tests are most suitable for informing treatment progression and rehabilitation progression [64].

Meaningful Change in RTS Test Result

One of the purposes of conducting RTS tests is to assess the progression made in rehabilitation and to inform the RTS decision [2]. Statistical tests could identify whether the observed change in a particular RTS is due to true difference or the result of chance. The statistical tests, however, in isolation cannot indicate whether the change was clinically meaningful or could be reliably distinguished from random error in the measurement [67]. As such, there is a concept of "clinical significance" to describe whether the change is both noticeable and meaningful to the injured athlete. The clinically important difference refers to the difference in an outcome measure that is clinically meaningful [68]. For example, the smallest change required to detect a meaningful change beyond typical error for 6-m timed hop test is 12.96% [69]. For RTS tests where the data for meaningful change are unavailable, longitudinal tracking may help to identify a trajectory for an informed decision [47].

Unknown Interaction Between Variables

In decision-making, there may be some pieces of information missing, whether known or unknown. For example, little is known about the linearity of soft tissue healing [70] or how compensation movement makes up quantitative symmetry (e.g., reaction and response time). There are also variables that a clinician may have not measured (e.g., knee movement in the worst chaotic scenario) or could not be measured (e.g., knee movement in an unplanned body contact or under extreme fatigue). The lack of measurement of cognitive load and sports-specific stimulus in rehabilitation may also expose a potential flaw in RTS decision-making [57].

Part 2: Zoom Out to Identify the Decision-Making Framework and Theories

You have gathered the information required and are deciding your stance on whether the athlete is suitable to return to play.

After gathering the information, here we zoom out to a broader perspective on decision-making models relevant to RTS. We first discuss a conventional RTS decision-making framework, then introduce the normative and descriptive decision models (Fig. 2). This allows clinicians an opportunity to see how a fully rational person may decide (normative models) and to explain when the decision could deviate from the norm (i.e., descriptive models).

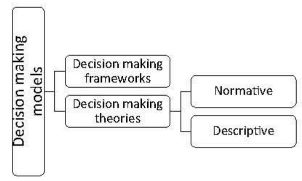

Fig. 2 Overview of decision frameworks and theories

RTS Decision-Making Frameworks

In 2010, Clover and Wall [71] introduced a guideline for RTS decision-making. They proposed considerations for clinical factors and functional athletic ability. Intangible factors for RTS are also included, such as motivation of the athlete, social support, psychological readiness, fear of reinjury, insurance coverage and availability of rehabilitation team [71].

The first formal RTS decision-making guiding framework, a 3-step decision-based model, was proposed by Creighton et al. in 2010 [72]. The framework was designed to guide decisions on when to clear an athlete for full participation in sport without restriction. In 2015, minor revisions were made to the 3-step framework and it was renamed the Strategic Assessment of Risk and Risk Tolerance (StARRT) [20].

The StARRT has been used to clarify the components within and the sequence of decision-making and could help to explain the hidden assumptions that clinicians make in different clinical vignettes.

The process has three steps [72]:

> **Step 1** Evaluating health status. The health status of the athlete is evaluated through medical factors, such as symptoms, medical history, clinical objective tests and severity of the injury.
> **Step 2** Evaluating participation risk. The risk of participation is evaluated through the sport risk modifiers, such as the type of injury or illness, age, types of sports, level of play, the significance of upcoming competition, social factors and financial cost.
> **Step 3** Risk tolerance modifiers. The final step to RTS decision is a risk–benefit assessment by assessing the risk tolerance modifiers. These modifiers can exist at multiple levels (e.g., individual, interpersonal, organisational, community and policy levels) and may shift the decision-makers' priorities and preferences. As a result, RTS decision-making could be more complicated than just a medical case.

The framework has helped make the decision-making process transparent by guiding the key variables that the clinician could consider [73]. However, the StARRT does not intend to define or guide a high-quality decision-making process. In the next section, various decision-making theories are introduced in an attempt to explain the decision-making process. Examples are provided to illustrate some of the methods by which a RTS decision could be reached.

Decision-Making Theories

In decision-making, normative models and descriptive models form the two fundamental branches of decision theory [74]. Normative models are the system of rules and standards for decision-making (i.e., how one should make decisions). They have theoretical value and concerns about how to make the best possible decision when a person is fully rational and informed [74].

In contrast, descriptive models are psychological theory that explains how people actually make judgements and decisions [75]. Due to human behaviour, conflict occurs between how we would like to reason (normative) and our temptation (descriptive) of taking a faster or easier route in cognitive thinking. Descriptive models attempt to understand and explain the deviations from normative models. Here we use an example to illustrate the difference between normative and descriptive approaches: an athlete with an injury may know that alcohol could dampen recovery (a normative model explains what the athlete should do). Despite this, the athlete may still choose to drink at a party due to various reasons (a descriptive model explains why the athlete behaviour deviated from the normative model).

By comparing descriptive models to normative models, decision-makers may identify the potential deviations from normative models and correct the deviations if necessary. The section starts with normative models and is followed by descriptive models.

Normative Models

Common normative models include rule-based theory and explicit utility theory.

Rule-Based Theory The rule-based approach is where a clinician decides based on a set of defined criteria [21, 22]. The assessment could be done on a binary scale (i.e., pass or fail). Table 1 illustrates a hypothetical example using established criteria for ACL injury [22]. Here we assume the relative importance and value assigned for all attributes are the same. The set of criteria includes seven tests, incorporating both function and subjective outcomes to reflect the overall knee performance. The passing criterion for RTS is to score > 90% on the seven tests [22].

Example In scenario 1, the athlete scored above 90% on all tests below and is cleared to RTS. In scenario 2, not all tests are passed and the athlete is not cleared to RTS (see Table 1).

Expected Utility Theory Expected utility theory is a decision model that illustrates how one decides in uncertain conditions, based on the outcomes of different options and the probability of each outcome [76, 77]. It assumes the decision made is rational as it is based on an assessment of the cost and benefit surrounding choices [78, 79]. Under this theory, a clinician makes a decision based on the utility (a subjective value assigned by the decision-makers) of the outcomes of different options and the probability (estimated likelihood) of each outcome [76, 77]. As with other normative models, expected utility theory assumes that decision-makers are fully rational in decision-making and have access to complete information about probabilities and consequences, in terms of time, resources and knowledge [20]. Table 2 shows a hypothetical calculation of weight utility value according to the same ACL RTS guideline as above [22].

Example In Table 2, importance reflects how much the clinician values a specific test, and this is represented

Table 1 Hypothetical example of RTS criteria assessment, with criteria based on Grindem et al. [22] A tick suggests that the athlete has scored > 90% on that test, while a cross represents < 90%

Test	Scenario 1 >90% on all tests	Scenario 2 >90% on some tests only
Knee Outcome Survey—Activities of Daily Living Scale	✔	✔
Global Rating Scale of Function	✔	✔
Quadriceps Strength	✔	✔
Single Hop for Distance	✔	✔
Crossover Hop for Distance	✔	✘
Triple Hop for Distance	✔	✘
6-m Timed Hop	✔	✔
Decision outcome	RTS	Not yet RTS

Table 2 Hypothetical calculation using arbitrary units and utility value in ACL RTS, with criteria based on Grindem et al. [22]. Limb symmetry index (LSI)

Test	Importance (numerical weight)	Scenario 1 >90% on all tests		Scenario 2 >90% on some tests only	
		Utility value (AU)	Weighted utility value (AU)	Utility value (AU)	Weighted utility value (AU)
Knee Outcome Survey—Activities of Daily Living Scale	3	+10 Achieved *0.90 (i.e., 90% of full score)*	3 * 10 =30	+8 Achieved *0.80 (i.e., 80% of full score)*	3 * 8 =24
Global Rating Scale of Function	3	+10 Achieved 0.90	30	+9 Achieved 0.90	27
Quadriceps Strength	5	+10 Achieved 0.90 LSI *(i.e., 90% of LSI)*	50	+8 Achieved 0.80 LSI *(i.e., 90% of LSI)*	40
Single Hop for Distance	4	+10 Achieved 0.90 LSI	40	+8 Achieved 0.80 LSI	32
Crossover Hop for Distance	5	+10 Achieved 0.90 LSI	50	+7 Achieved 0.70 LSI	35
Triple Hop for Distance	5	+10 Achieved 0.90 LSI	50	+7 Achieved 0.70 LSI	35
6-m Timed Hop	2	+10 Achieved 0.90 LSI	20	+10 Achieved 0.90 LSI	20
		Total	270		213
	Decision outcome	RTS		Not yet RTS	

by a numerical weight. Utility value is based on the performance of the test, with 10 the highest score possible and 0 the lowest. In this case, achieving the goal of 90% LSI would correspond to a score of 10. The weight utility value is calculated by multiplying importance (numerical weight) by utility value (AU). For example, an importance of 3 and a utility value of 10 AU will give a weighted utility value of 30 AU (3 × 10AU = 30 AU). The highest possible weighted utility value in this example is 270AU and the decision is made based on the sum of the weighted utility value [80].

In scenario 1, the athlete achieved 90% on all the tests (indicated as "achieved 0.90") and the sum of the weighted utility value is 270AU. The decision is RTS. In scenario 2, some of the tests have not passed the 90% threshold and the sum of the weighted utility value is 213AU. The weighted utility value has not reached the requirement set by the clinician, and the athlete was not cleared to RTS in scenario 2.

Descriptive Models

Because humans are unlikely to be perfectly rational at all times, decisions made could deviate from a normative model. Systematic deviations from normative models are known as biases [75]. By applying normative models to the decisions made, decision-makers could look for possible biases and understand the nature of those biases with descriptive models. Examples of descriptive models include prospect theory, heuristics and bounded rationality [74]. With a better understanding of the biases, decision-makers could develop approaches to correct them (de-bias) and improve the quality of the decisions. The following section describes the common descriptive theories and how a decision may stray from the previous normative models.

Prospect Theory Prospect theory suggested that people consider expected utility relative to a reference point rather than the absolute outcome. It also suggested that future gains and losses are asymmetrical, with losses having a greater emotional impact than gains (i.e., humans dislike losses more than potential gains).

Example In Table 2, the prospect theory would suggest that the decision-maker does not necessarily make decisions based on the absolute weight utility (i.e., 270AU). Instead, they would look at how far the expected utility is relative to a reference point (which is unknown here). If we adopt prospect theory in the context of RTS, a re-injury (loss) may bring a more negative emotional impact than winning (gain). While this may not be true in all cases, it may be worth noting the potential deviations in decision-making due to emotional distress.

Bounded Rationality Bounded rationality describes how humans take reasoning shortcuts and make decisions within the bounds imposed by the environment, ability, information and goal [81]. The decision is rational; however, it is within the limits of information available to the decision-maker. That is, due to the limitation in accessing information, people tend to make sufficient judgements, rather than optimal ones [82, 83]. (For more details, see Gigerenzer and Goldstein [81] and Robertson and Joyce [83].) In RTS, not all meaningful data are collected due to various reasons, such as high cost, a lack of feasibility and time. Therefore, the best outcome for a decision made with unknown factors is not the same as decisions made in the context of transparency [84].

Example In the rehabilitation of an ACL injury, some information will always be unknown due to factors such as limitations in resources. This includes how we can accurately assess the degree of healing of the ACL graft after a reconstruction surgery or measure the loading capacity of the ACL. Consequently, the decision made by the clinician in the vignette is only based on the information available in Tables 1 and 2 and is limited by the cognitive capacity, and the knowledge and choices of the decision-maker.

Heuristic Also known as a cognitive short cut, a heuristic is a decision-making strategy to act more quickly or frugally by ignoring parts of the information [85]. Heuristics allow people to make a rapid, efficient judgement without consuming a substantial amount of time, processing capacity, or when information is incomplete.

Logically, a clinician's decision for RTS would be grounded in a more rational choice as described in normative models due to availability of time and opportunity to gather additional information from test or other staff members (e.g., doctors, coaches, fitness coach). However, RTS decision-making can also be based on heuristic decision-making, as seen when athletes make decisions regarding RTS [86].

There are many types of heuristics that are used in daily life [87]. Tversky and Kahneman [88] proposed three classes of heuristics which people may rely on to assess the probabilities of an uncertain event: availability heuristic, representativeness heuristic and anchoring and adjustment heuristic. In Table 3, we have suggested examples of heuristics that may be of relevance in RTS decisions. Heuristics sometimes may be useful in reducing the complexity of a task in assessing probabilities; however, it may also lead to systematic errors [88].

Part 3: Preferences of the Decision-Makers

You have consolidated the information and have weighed the risk and benefits of the medical clearance. Understanding that you are bounded by the information and knowledge available, you have used the rule-based theory described in Table 1 as the basis for decision-making. Based on scenario 1, where the player has passed all of the tests, you have decided that the player is clinically fit to return to full training. Using the StARRT framework as a reference, you would like to discuss your rationale and other contextual factors with the athlete, coach and manager, to reach a shared decision.

The StARRT framework helps clinicians make RTS decisions based on whether the risk assessment outcome exceeds the decision-maker's risk tolerance[20]. That is, if the risk assessment is lower than the risk tolerance after

Table 3 Definitions and examples of heuristics in RTS

Heuristics	Definition	Example	Possible deviations from normative model
Availability	People infer the probability of an outcome based on how readily it comes to mind [88].	A clinician assesses the risk of injury of an athlete by recalling the recent occurrences within the team.	1. Depending on whether the clinician is familiar with the injury and when it last occurred, there may be recall bias. 2. The subjective probability of an injury may rise temporarily when the clinician sees there are multiple players on the injured list.
Representativeness	People categorise by matching the similarity of an object or incident to an existing one [88].	A clinician has an impression that a female athlete demonstrating knee valgus movement on a jump and land task will sustain a lower limb injury.	Evidence for screening tests in predicting injury is limited [89]. The clinician judgement may be insensitive to the reliability and predictability of the test.
Anchoring-adjustment	People estimate based on an initial value (anchoring) and adjust to yield the final answer (adjustment) [88].	A clinician prioritises information that supports his or her initial judgement of the estimated time to RTS and makes adjustments based on the initial value.	A clinician may stick to the initial hypothesis of the days required for RTS even if new evidence suggested conflicting information. Even if the clinician decides to adjust the estimation, it would be biased toward the initial value.

all factors are considered, the athlete may be cleared to RTS. However, a *low* risk decision may not be synonymous with a *high-quality* decision.

In general medicine, it is recommended that the decision made by the clinician reflects the preferences of a well-informed patient, with consideration of factual and probabilistic health information [32, 90, 91]. There are multiple dimensions to address, including characteristics of the decision, knowledge and expectations of the situation and treatment options and outcomes, personal values and preferences, support and resources needed, personal characteristics and clinical characteristics [29, 91–93].

Practically, there is no optimal measurement tool that can measure the quality of the RTS decision based on the performance outcome or the expected utility of the decision-makers. However, a clinician can improve the decision quality by ensuring the decisions are well-informed and grounded in a shared decision-making approach.

Improving Decision Quality by Shared Decision-Making

Shared decision-making has been a best practice for decision-making in the field of medicine [2, 94, 95]. It respects multiple perspectives and also aims to minimise disagreement due to conflicting interests.

Two phases characterise shared decision-making: 1) *deliberation* (pre-decisional, the process leading to a decision) and 2) *determination* (the act of decision) [96]. Deliberation is where knowledge is searched for, gained and appraised. To improve the quality of the shared decision, both the deliberation and determination could be evaluated [96]. An accurate judgment requires stakeholders to first collaborate to decide on the definition of success [2, 97]. Then decide on which pieces of information to pay attention to, nominate weighting and integrate the information [98]. This information may include the alternatives available, the advantages and disadvantages of the alternatives, the nature of the decision, the associated outcome and its likelihood [94, 96].

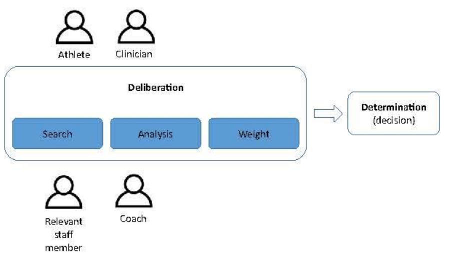

Fig. 3 Shared decision model in sports. Adapted to RTS context from Elwyn et al.[94]

The second phase, determination, is to choose one of the options [96]. The actual decision may occur in a 'black box,' where one combines the available information in their own way without transparency or accountability [99]. The lens decides how one interprets the "real" probabilities, which could be obscured by one's cognitive and emotional influence. For example, how an athlete weighs the importance of his or her sports career may affect how the information is processed (Fig. 3).

Understanding the decision-making theories may allow decision-makers to realise the normative approach and thus engage in a high-quality and rational discussion during deliberation.

The Perspectives of Decision-Makers

The keys to high-quality decision-making include accounting for individual preferences, social and contextual factors (e.g., the type of injury or illness, age, types of sports, level of play, the significance of upcoming competition and social factors and financial cost) [2, 32, 100, 101]. Social and contextual factors also impose constraints at multiple levels and influence the RTS decision, including at individual, interpersonal, organisational, community and policy levels [72, 73, 102]. The factors may shift the athlete's and decision-makers' priorities and preferences, which make decision-making more complicated [20, 72].

Traditionally, clinicians are the gatekeeper of the RTS decision [71, 103–107]. The clinician has skills in assessing the injury-related criteria in RTS, including assessing the state of healing, risk of re-injury and risk of short- or long-term problems [96, 104, 108, 109]. Clinicians also have an overriding duty of care to patients and a legal and ethical obligation to act in a manner that is necessary and appropriate to protect the health of an athlete.

However, with the addition of trainers, rehabilitation coaches and performance coaches, clinicians are no longer the only staff contributing to rehabilitation and RTS decisions. It is questionable whether clinicians should still be the main advisor for RTS decisions, given the numerous non-medical factors to consider [97, 100, 103, 108, 110–113]. In a sports setting, a clinician may even have dual allegiances, as the clinician does not work exclusively for the patient, but also on behalf of the club or organisation. They may experience pressure from their employer (i.e., the sports organisation) to minimise lay-off time and to clear an athlete as soon as possible. As such, an inherent conflict of interest may present in a professional sports team setting [114, 115].

The following section discusses the general concerns and considerations of the athlete and coaches to improve communication transparency and to minimise conflicts.

Athlete

There are internal and external factors influencing how an athlete may view the quality of the decision and listening to their opinions may be beneficial to inform the final decision [101]. Internal factors include perception of body, self-resentment [116, 117] and their emotional tie to their sport [117]. External factors include sociocultural influences, such as financial concerns, expectations from family and friends and their given sport's culture of risk [118, 119]. Some athletes may face social pressure to perform [118]. Social pressure could be the pressure to meet the expectations of peers, fans and coaches [116, 117, 120–122]. Shame and alienation from the team due to injury may lead to low self-esteem and depression [120, 122, 123].

There is limited evidence on how athletes approach decisions about RTS, especially in a complex and risky scenario. 'Playing hurt' is a common phenomenon across different sports, age groups and performance levels [117–119, 124, 125]. However, it is unclear how and when an athlete would choose to play hurt.

In a recent study that investigated how athletes decide on RTS [86], athletes would consider the relevance of the competition (e.g., the importance of the competition), potential sporting consequences (e.g., loss of the starting position) and whether the risk of playing hurt could be offset by some means (e.g., availability of protective gear or possibility of being removed from play if pain increases). If the medically safe alternative (e.g., withdrawal from competition) does not have severe sporting consequences (e.g., loss of starting position), the athlete may opt for it. In contrast, if playing hurt may produce a sporting consequence that the athlete cannot afford but the risk of playing could be subjectively reduced, they may choose to play hurt. Clinicians and coaches can be influential in the athlete's decision-making as clinicians and coaches are likely to know about the sporting consequences and the possibility of risk reduction.

As opposed to the risk analysis suggested in the normative StARRT framework [20], not all athletes attempt to obtain information actively and comprehensively [86]. Therefore, it may be helpful for clinicians and coaches to guide athletes through the information seeking process and provide a full picture of the situation and the sporting consequence.

Performance Coach and Manager

In some settings, coaches and managers could be the decision-makers for RTS, and thus, it is important to have their perspective as well. Coaches and managers are competent in assessing the non-injury-related RTS criteria, such as the athlete's desire to compete, psychological impact, financial consideration and loss of competitive standing [108].

Based on existing literature, some coaches believe they have a responsibility to push the athlete to their limits, mentally and physically to achieve excellence in performance [126]. While some coaches act according to the training restriction implemented to reduce injury risk [122], some perceive prolonged or delayed RTS as harmful to the overall and long-term performance of the athlete [122]. Some coaches also believe clinicians are overly cautious and delay RTS of athletes unnecessarily [122]. However, research is scarce and based on small sample size, thus limiting generalisability.

To facilitate rehabilitation, coaches and managers may help to remove the barriers arising from the social and environmental context [127]. For example, they can ensure that athletes have sufficient resources to access adequate supervised rehabilitation. Coaches and managers can also ensure all relevant personnel are provided with information regarding the injury and the rehabilitation progression. These actions may increase transparency in communication and facilitate the decision to include or exclude from the main training group [127].

There are times when clinicians might miss something important without realising it. Shared decision-making may help to minimise the blind spots by filling the missing gaps and broadening the perspectives.

Practical Implication

Based on a decision analysis model, we have outlined a framework to help clinicians make systematic and objective RTS decisions. The first step is to choose appropriate RTS tests and to synthesise the information in a meaningful way. The second step is to understand the decision-making theories and identify possible deviations from normative models. The third step is using shared decision-making to improve decision quality by eliminating the contextual 'blind spots', such as an individual's expectation, preference and value. We propose a framework that clinicians could refer to when they decide on RTS in a sports organisation (Fig. 4).

Future Research

Currently, there is limited evidence or expert knowledge on how clinical decisions in sports are made, especially for upper-limb injuries. While in principle, the decision-making process of other sports injuries would be similar, future research could also investigate upper-limb injuries, for example, a shoulder dislocation injury. Similarly, there is little attention paid to how heuristics may be present in

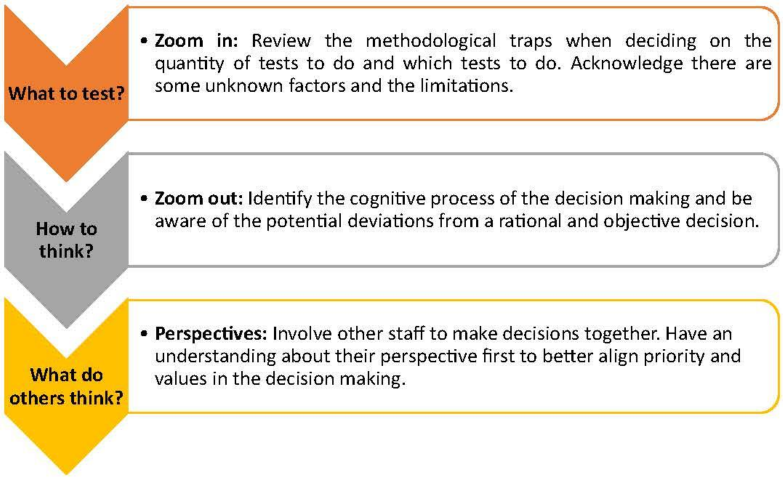

Fig. 4 Three steps to making a high-quality RTS decision

sports medicine practice. Research is needed to identify the heuristics used in clinical practice as limited work has been done in the field. Strategies for better judgment and decisions, such as reducing bias, are also required.

Another concern is the increasing number of data types with the growth of sports technology. There is a certain point where additional information no longer improves a human's ability to make better decisions [128]. The human mind has an upper limit for information processing capacity and is sufficiency sensitive to large inconsistencies, but not small ones [129, 130]. Providing more information than the upper limit would only exhaust one's cognitive information capacity in decision-making, potentially leading to overload, poor decision-making, and dysfunctional performance [131]. Consequently, there is an urge to identify tools that aid human brains in making decisions.

Examples of these decision-making tools could be statistics, mathematical modelling and artificial intelligence (AI) algorithms. In particular, machine learning techniques, a subfield of AI, attracted attention for their strength to transform a large amount of data into useful knowledge and identify nonlinear patterns [132–134]. In many cases, these external aids may complement or be superior to human performance [135–137]. Currently, the application of the above tools mostly remains on the theoretical level. Future research may explore how these tools may be applied on a practical level.

Conclusion

The purpose of this review was to provide an overview of RTS decision frameworks and what constitutes high-quality decision-making. There is a lack of empirical knowledge in RTS decision-making and the potential adaptations within its process; most research focuses on biological and medical factors. One of the strengths of the review is to lay out the decision basis and hence the transparency of a decision. Understanding decision-making theories in the context of RTS and potential deviations from normative decisions may improve the work process and quality of decision-making. More research is required to understand how decisions are made and how to use computation tools to support and improve decision quality.

Abbreviations

AI: Artificial intelligence; ACL: Anterior cruciate ligament; LSI: Limb symmetry index; RTS: Return-to-sport; StARRT: The Strategic Assessment of Risk and Risk Tolerance.

Acknowledgements

KY is supported by the Australian Government Research Training Program Scholarship.

Authors' Contributions

KY and SR provided conceptualisation. KY did writing—original draft preparation. SR, CLA, FS and KY were involved in writing—review and editing. All authors read and approved the final manuscript.

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Funding
Open Access funding enabled and organized by CAUL and its Member Institutions All authors declare that no funding was received for this review.

Availability of Data and Materials
Not applicable.

Declarations

Ethics Approval and Consent to Participate
Not applicable-review article.

Consent for Publication
Not applicable.

Competing interests
Kate Yung, Clare L. Ardern, Fabio R. Serpiello and Sam Robertson declare that they have no conflicts of interest relevant to the content of this review.

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Received: 17 June 2021 Accepted: 23 March 2022
Published online: 13 April 2022

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DECLARATION OF CO-AUTHORSHIP AND CO-CONTRIBUTION: PAPERS INCORPORATED IN THESIS

This declaration is to be completed for each conjointly authored publication and placed at the beginning of the thesis chapter in which the publication appears.

1. PUBLICATION DETAILS (to be completed by the candidate)

Title of Paper/Journal/Book: A framework for clinicians to improve decision making process in return to sport.

https://sportsmedicine-open.springeropen.com/articles/10.1186/s40798-022-00440-z

Surname: Yung First name: Kai Yee (Kate)

Institute: Institute for Health and Sport Candidate's Contribution (%): 80

Status:

Accepted and in press:	☐	Date:	
Published:	☑	Date:	13 Apr 2022

2. CANDIDATE DECLARATION

I declare that the publication above meets the requirements to be included in the thesis as outlined in the HDR Policy and related Procedures – policy.vu.edu.au.

Signature	Date
[redacted]	7 Feb 2023

3. CO-AUTHOR(S) DECLARATION

In the case of the above publication, the following authors contributed to the work as follows:

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4. Potential conflicts of interest have been disclosed to a) granting bodies, b) the editor or publisher of journals or other publications, and c) the head of the responsible academic unit; and

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N/A

Name(s) of Co-Author(s)	Contribution (%)	Nature of Contribution	Signature	Date
Clare Ardern	5	Assisted with methodology, feedback and revisions.	[redacted]	20/1/2023
Fabio Serpiello	5	Assisted with feedback and revisions.	[redacted]	18/1/2023
Sam Robertson	10	Assisted with concept, methodology, feedback and revisions.	[redacted]	17/1/2023

Updated: September 2019

3.1 A framework for clinicians to improve decision making process in return to sport.

3.1.1 Key points

- RTS decisions are complex, nonlinear and multifactorial and thus require external tools to assist practitioners
- To improve the quality of decisions in sports settings, decision makers could evaluate the following three domains: 1) assess the methodological soundness of the tests chosen, 2) identify potential deviations from normative decision models and 3) implement shared decision making.

Keywords: decision making, decision, return to play, decision analysis, rehabilitation, RTS, RTP

3.1.2 Abstract

Return-to-sport (RTS) decisions are critical to clinical sports medicine and are often characterised by uncertainties, such as re-injury risk, time pressure induced by competition schedule and social stress from coaches, families and supporters. RTS decisions have implications not only for the health and performance of an athlete, but also the sports organisation. RTS decision making is a complex process, which relies on evaluating multiple biopsychosocial factors, and is influenced by contextual factors. In this narrative review, we outline how RTS decision making of clinicians could be evaluated from a decision analysis perspective. To begin with, the RTS decision could be explained as a sequence of steps, with a decision basis as the core component. We first elucidate the methodological considerations in gathering information from RTS tests. Second, we identify how decision-making frameworks have evolved and adapt decision making theories to the RTS context. Third, we discuss the preferences and perspectives of the athlete, performance coach and manager. We conclude by proposing a framework for clinicians to improve the quality of RTS decisions and make recommendations for daily practice and research.

3.2 Introduction

Decision making is a process of weighing the risk(s) and benefit(s) among options to make a choice (Burton et al., 2009, p. 301). In clinical practice, return-to-sport (RTS) decisions can be challenging as they are directly linked to the athlete's well-being and performance. RTS refers to the recovery and rehabilitation continuum: return to participation, return to sport and return to performance (Ardern, Glasgow, et al., 2016). This review focuses on how the quality of RTS decisions could improve.

Premature RTS may risk re-injury (Hägglund et al., 2016; Stares et al., 2018; Stares et al., 2019), and subsequently harm the athlete's playing performance (Walden et al., 2016), financial income (Secrist et al., 2016) and mental health (Gouttebarge, Aoki, et al., 2016; Ruddock-Hudson et al., 2012). Yet, if RTS is delayed for a lesser chance of reinjury, it will inevitably reduce a team's player availability. Reduced player availability is undesirable as players' match availability is associated with team performance across various sports (Arnason et al., 2004; Drew et al., 2017; Emery et al., 2011; Hägglund et al., 2013; Hoffman et al., 2019; L. Podlog et al., 2015; Waldén et al., 2007). Consequently, substantial pressure rests on the shoulders of decision makers to reach a decision that balances the best interest of the athlete's health and team performance.

When the context is predictable and routine, for example, when managing a tibia fracture on the field, decision making could be straightforward and relegated to an automated level (i.e., remove from play immediately). However, when there is a high level of uncertainty and complexity in the context (e.g., to decide whether an athlete at 95% of recovery should play in the grand final), the ability to make high-quality decisions is less clear, yet potentially even more crucial.

The challenge of complexity and the multifactorial nature of RTS decision making has been acknowledged for over two decades (Putukian, 1998). A 1998 review by Putukian (1998) discussed the concerns and struggles that clinicians have when making RTS decisions, which could be attributed to the multifactorial nature and clinical uncertainty presented in medicine (Malcolm, 2009; Shrier et al., 2010). The majority of the research focus since then has been mostly on developing decision-making frameworks and clinical criteria for RTS. One of the most recognised decision-making frameworks is the Strategic Assessment of Risk and Risk Tolerance (StAART) (Shrier, 2015). The framework, together with the RTS criteria, help to guide the clinician's practice. For example, in the management of anterior cruciate ligament (ACL) injury, clinicians may refer to the established RTS criteria (Grindem et al., 2016; Kyritsis et al., 2016) and consensus statements (Meredith et al., 2020; Rothrauff et al., 2020).

In contrast to the vast literature on RTS criteria, there is less on how clinicians make RTS decisions and how to improve the quality of the decision. This may be because this topic spans at least two distinct fields: sports medicine and decision-making science. We aim to help clinicians conceptualise the decision-making process, increase the thoughtfulness of a decision, identify potential deviations from normative decision models, and eventually establish a framework to improve the quality of decision making.

3.2.1 Disentangling decisions and outcomes

The term *decision* refers to the *action* taken to reach a decision, and this is different from the *outcome* of the decision (Gass, 1983; Vlek, 1984). A high-quality decision refers to a decision that is logical and made based on the uncertainties, values and preferences of the decision maker (Howard, 2007). A good *outcome* is an outcome that the decision maker would wish to have happened and is of high value to them (Howard, 2007).

A high-quality *decision* does not necessarily warrant a good *outcome* due to uncertainties. There are multiple sources of uncertainties, and the two major categories prominent in the medical field are aleatoric uncertainty and epistemic uncertainty (Indrayan, 2020). Aleatoric uncertainty is intrinsic to the problem, for example, random variations that arise from observers or instruments. Epistemic uncertainty is extrinsic and comes from limitations in knowledge, such as individual bias (Indrayan, 2020).

Distinguishing between *decision* and *outcome* allows clinicians to separate action from the consequence, so they can focus on improving the quality of the action. Occasionally, clinicians may be disappointed by a bad outcome in a good RTS decision, such as an athlete suffering from a re-injury despite careful medical evaluation. Yet, in the pursuit of a good outcome, there may not be a better way than striving for a high-quality decision. Therefore, in this paper, we focus on evaluating the decision, and not on the outcome.

3.2.2 Evaluating a decision

There are various ways to evaluate a decision. The first approach is related to the *outcome* of the decision, such as clinical health outcomes (e.g., pain, quality of life), or how regretful or satisfied the patient is with the decision (Holmes-Rovner et al., 2007; Sepucha et al., 2013; Stacey et al., 2017).

However, there is no consensus on the optimal measurement tool(s) for this purpose. The second approach relates to the *expected value* of the outcome (i.e., expected utility), where probabilistic information about the risk and benefits of personal preferences and values are considered (Hamilton et al., 2017). The third approach is to consider the *decision quality*, which is measured by knowledge of the options and outcomes, realistic perceptions of outcome probabilities, and agreement between patients' values and choices (Stacey et al., 2017). It may be challenging to measure the quality of a decision with the first two approaches (i.e., outcome and expected utility) due to the complexity of a RTS question. Nevertheless, evaluating the decision with the third approach – decision quality- may be possible.

Decision analysis is a formal procedure for analysing decision problems by balancing the factors that could influence a decision (Howard, 2007). To evaluate the decision quality, the decision process could be made transparent by first breaking it down into a sequence of clear steps. We have adapted a decision analysis model from Howard (Howard, 1988) to RTS to systematically evaluate a decision (Figure 3.1).

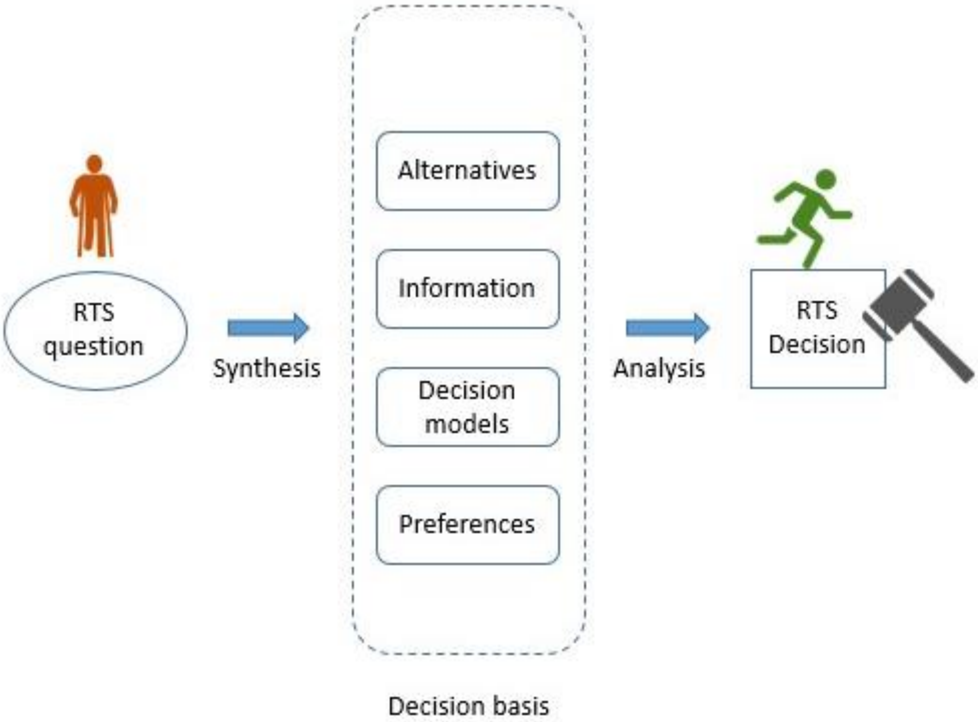

Figure 3.1 Steps for evaluating a RTS decision

The essence of decision analysis is eliciting the four bases for the decision (Howard, 1988):

1) The alternatives: relates to the options that a decision maker has. In the context of RTS after an injury, it could be whether the athlete could return to full training/competition, modified training or basic rehabilitation training.

2) The information: refers to knowledge that may be important to formulate the outcome. For example, what information do RTS tests provide to the decision makers?

3) The decision models: includes models that describe how the decision could be made. That is, on what basis can the decision be made?

4) The preferences: preferences of a decision maker could be of multiple dimensions. These include the value (e.g., how much does RTS mean to the athlete or the team?), time preference (e.g., how important is it to play in the upcoming game?) and risk preference (e.g., how much re-injury risk can the team tolerate?).

Among the four key bases for a decision (alternatives, information, decision models and preferences), the alternatives are highly specific to the context and would be difficult to discuss from a broader perspective. Therefore, we have structured this review around the other three bases for a RTS decision: 1) information, 2) decision models and 3) preferences. We first zoom in on the methodological issues of obtaining *information* in the medical room. Second, we zoom out to identify the *decision models* relevant to RTS. Third, we discuss how *preferences* can be addressed with shared decision-making. Finally, we propose a framework to improve RTS decision making in practice.

To increase the practicability of the framework and to help readers navigate the three bases for the RTS decision, a case scenario describing an ACL injury is used. We use ACL injury because it is a serious injury in sports that may threaten the career of athletes (Ekstrand, 2019; Walden et al., 2016). Multiple clinical and performance tests have been developed to evaluate the readiness of the RTS (Webster & Hewett, 2022), yet the re-injury risk of ACL remains high (Della Villa et al., 2021; Paterno et al., 2014) and some athletes do not return to sports following the injury (Lai et al., 2018).

3.3 Part 1: Methodological concerns in information gathering

A football player, in her early career, has undergone an ACL reconstruction surgery six months ago and is eager to return to play. She wants to play as soon as possible to gain a contract extension but is also worried about getting reinjured. In the medical room, you sit with the player and decide on what kind of test to perform on-field and off-field.

At the operational level, there are methodological considerations when gathering information for the decision. Below we discuss some of the underlying assumptions and methods concerns.

3.3.1 **Number of criteria used in RTS**

In general, criteria-based RTS (e.g., muscle strength, functional and dynamic stability, and range of motion) have been suggested over a time-frame approach, which is to decide solely based on the athlete’s time spent in rehabilitation (Hickey et al., 2017; Serner et al., 2020; Tassignon et al., 2019; van der Horst et al., 2016; Zambaldi et al., 2017). The ideal number of tests to use for this purpose may vary between cases. There are concerns that an insufficient number of tests may jeopardise the clinician’s ability to see the complete profile of an injured athlete. However, too many tests may increase the inherent error (e.g., athlete exhibiting reduced performance due to fatigue or reduced motivation) and exhaust more resources (e.g., staff, time, equipment). Currently, there is no recommendation for the ideal combination and number of tests to provide the most insight into the athlete’s readiness for RTS.

3.3.2 Baseline setting in RTS

Returning to pre-injury levels of health and fitness is often seen as the goal of RTS (Ardern, Glasgow, et al., 2016). Therefore, setting an appropriate baseline provides an ideal foundation for clinicians to monitor progress by comparing the athlete's current functional and physical capacity with previous preinjury data. However, it is challenging to set an objective, replicable and suitable baseline for the setting. For example, currently, there is no guideline on the timing and frequency for performing baseline tests. Adding more complexity to the problem, physiological and performance profiles often fluctuate daily due to periodisation in training and competition schedule (e.g., heart rate variability (Thorpe et al., 2015), musculoskeletal screening scores (Esmaeili, 2018), hip strength and flexibility (Paul et al., 2014) and power (as in countermovement jump) (Thorpe et al., 2015).)

Here we used the limb symmetry index (LSI) as an example to illustrate the concerns with baseline setting. LSI is often included in the RTS protocol for ACL injury (Davies et al., 2019; Fitzgerald et al., 2000; Grindem et al., 2016; Munro & Herrington, 2011; Wellsandt et al., 2017). LSI compares the performance of the involved limb with the uninvolved limb (Petschnig et al., 1998). Often, a 90% side-to-side difference threshold is used as a passing score for RTS (Davies et al., 2019; Fitzgerald et al., 2000; Munro & Herrington, 2011; Wellsandt et al., 2017). However, there is little scientific evidence on the optimal threshold. Even when limb symmetry is achieved, it does not necessarily indicate the athlete has reached a level sufficient for safe sports participation and performance (Wellsandt et al., 2017; Wren et al., 2018). It is also questionable whether the uninvolved side could be used as the benchmark when pre-injury data are unavailable. After ACL reconstruction surgery, patients have reduced single-leg hop performance of both the involved and uninvolved side (Gokeler et al., 2017; Wren et al., 2018) and for up to 2 years after surgery (Chung et al., 2015). This could be attributed to a combination of factors, such as deconditioning, fear or lack of motivation (Chung et al., 2015). Consequently, defining the baseline measure for comparison remains challenging and a suite of RTS tests have been recommended (Ardern, Glasgow, et al., 2016).

3.3.3 Validity of RTS tests

3.3.3.1 Content validity

Content validity refers to how well a test protocol reflects what it intends to measure (Robertson, Kremer, et al., 2017; Robertson et al., 2014). Selecting measurement tools is important as unnecessary noise may dampen the accuracy of the decision model. If the selected tests are prone to false positives, clinicians may unnecessarily delay the athlete's rehabilitation process (Davies et al., 2019).

Traditionally, in RTS decisions, clinicians would consider internal athlete data (e.g., physical fitness, strength, well-being, periodic health screening, body mass, anthropometric, internal load responses) and external factors such as training loads (e.g., running performance, training and match exposure), the timing in the season, the importance of the game or training. However, there seems to be a bias towards assessing variables that are easily measured, and missing measures that may be important but more difficult to measure (Paul, 2020). For example, in rehabilitating an ACL injury, a clinician may assess the hip, knee and ankle joint alignment in jump and land testing to identify the extent of valgus or varus movement. The assessment may provide valuable information regarding the athlete's movement strategies and physical capabilities; however, it may not provide sufficient information regarding the performance in competition. In competition, an athlete may encounter different chaotic and unpredictable scenarios, such as unplanned movement tasks and under high opponent pressure and cognitive load. Despite the best intentions to design sports-specific tests, the overall physical, psychological and emotional demands of a competitive match could be hard to replicate. Consequently, decision makers may need to identify the content validity of the test and decide to interpret the test result.

3.3.3.2 Predictive validity

Predictive validity is how well a test predicts performance on a criterion that is administered at a later date, such as RTS outcome (Ardern et al., 2013; Robertson, Kremer, et al., 2017). Predictive validity is only available for some of the tests, such as hop tests (Davies et al., 2019; Paterno et al., 2017), single leg bridge test (Freckleton et al., 2014) and psychological readiness test (Webster & Feller, 2018). For most RTS tests, clinicians may not know whether passing the test means the athlete could achieve a satisfactory RTS outcome or not. A recent study found no association between the predetermined functional performance test cut-offs and the risk of a new ACL injury (Fältström, Hägglund, et al.). Similarly, the Landing Error Scoring System may not predict the ACL injury risk in a cohort of high school and college athletes (Smith et al., 2011).

3.3.4 **Responsiveness of RTS test**

Responsiveness, or sensitivity, refers to how well a test can detect meaningful changes in skill and functional assessment (Robertson et al., 2014). While it is important to track progress, recent evidence suggested that some common clinical tests cannot accurately track meaningful gains in biological and functional recovery after injury (Hegedus, McDonough, Bleakley, Cook, et al., 2015; Hegedus, McDonough, Bleakley, Baxter, et al., 2015; Whiteley et al., 2018). The time to normalise also differs. For example, in the lower limb injury assessment, the 6-m timed hop test returned to normal earlier than the other three single-leg hop tests (single-hop for distance, triple hop for distance and cross-over hop for distance) (Davies et al., 2019). Similarly, in hamstrings strain rehabilitation, straight leg raise returned to normal much earlier than the maximum hip flexion with active knee extension (Whiteley et al., 2018). Limited literature is available to inform what tests are most suitable for reporting treatment progression and rehabilitation progression (Whiteley et al., 2018).

3.3.5 Meaningful change in RTS test result

One of the purposes of conducting RTS tests is to assess the progression made in rehabilitation and to inform the RTS decision (Ardern, Glasgow, et al., 2016). Statistical tests could identify whether the observed change in a particular RTS is due to a true difference or the result of chance. The statistical tests, however, in isolation cannot indicate whether the change was clinically meaningful or could be reliably distinguished from random error in the measurement (Mann et al., 2012). As such, there is a "clinical significance" concept to describe whether the change is noticeable and meaningful to the injured athlete. The clinical significance refers to the difference in an outcome measure that is clinically meaningful (Katz et al., 2015). For example, the smallest change required to detect a meaningful change beyond typical error for 6-m timed hop test is 12.96% (Noyes et al., 1991). For RTS tests where the data for meaningful change are unavailable, longitudinal tracking may help to identify a trajectory for an informed decision (Davies et al., 2019).

3.3.6 Unknown interaction between variables

In decision making, some pieces of information may be missing, whether known or unknown. For example, little is known about the linearity of soft tissue healing (Järvinen et al., 2014) or how compensation movement makes up quantitative symmetry (e.g., reaction and response time). There are also variables that a clinician may not have measured (e.g., knee movement in the worst chaotic scenario) or could not be measured (e.g., knee movement in an unplanned body contact or under extreme fatigue). The lack of measurement of cognitive load and sports-specific stimulus in rehabilitation may also expose a potential flaw in RTS decision making (Paul, 2020).

3.4 Part 2: Zoom out to identify the decision-making framework and theories

You have gathered the information required and are deciding your stance on whether the athlete is ready to return to play.

After gathering the information, we zoom out to a broader perspective on decision-making models relevant to RTS. We first discuss a conventional RTS decision-making framework, then introduce the normative and descriptive decision models (Figure 3.2). This allows clinicians to see how a fully rational person may decide (normative models) and to explain when the decision could deviate from the norm (i.e., descriptive models).

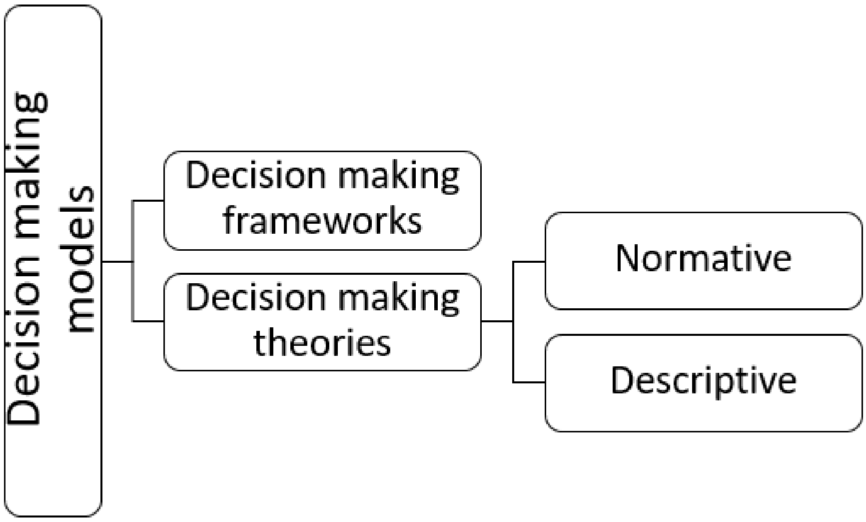

Figure 3.2 Overview of decision frameworks and theories

3.4.1 RTS Decision-making frameworks

In 2010, Clover and Wall (2010) introduced a guideline for RTS decision making. They proposed considerations for clinical factors and functional athletic ability. Intangible factors for RTS are also included, such as the athlete's motivation, social support, psychological readiness, fear of reinjury, insurance coverage and availability of rehabilitation staff members (Clover & Wall, 2010).

The first formal RTS decision-making guiding framework, a 3-step decision-based model, was proposed by Creighton et al. in 2010 (Creighton et al., 2010). The framework was designed to guide decisions on when to clear an athlete for full participation in sport without restriction. In 2015, minor revisions were made to the 3-step framework and it was renamed the Strategic Assessment of Risk and Risk Tolerance (StARRT) (Shrier, 2015). The StARRT has been used to clarify the components within and the sequence of decision making, and could help to explain the hidden assumptions that clinicians make in different clinical vignettes.

The process has three steps (Creighton et al., 2010):

Step 1: Evaluating health status. The athlete's health status is evaluated through medical factors, such as symptoms, medical history, clinical tests and injury severity.

Step 2: Evaluating participation risk. The risk of participation is evaluated through the sport risk modifiers, such as the type of injury or illness, age, types of sports, level of play, the significance of upcoming competition, social factors and financial cost.

Step 3: Risk tolerance modifiers. The final step to RTS decision is a risk-benefit assessment by assessing the risk tolerance modifiers. These modifiers can exist at multiple levels (e.g., individual, interpersonal, organisational, community and policy levels) and may shift the decision makers' priorities and preferences. As a result, RTS decision making could be more complicated than just a medical case.

The framework has helped make the decision-making process transparent by guiding the key variables that the clinician could consider (Shrier et al., 2015). However, the StARRT does not intend to define or guide a high-quality decision-making process. In the next section, various decision-making theories are introduced in an attempt to explain the decision-making process. Examples are provided to illustrate some of the methods to reach a RTS decision.

3.4.2 **Decision-making theories**

In decision making, normative models and descriptive models form the two fundamental branches of decision theory (Bell et al., 1988). Normative models are the system of rules and standards for decision-making (i.e., how one should make decisions). They have theoretical value and concerns about how to make the best possible decision when a person is fully rational and informed (Bell et al., 1988).

In contrast, descriptive models are psychological theories explaining how people make judgements and decisions (Baron, 2012). Due to human behaviour, conflict occurs between how we would like to reason (normative) and our temptation (descriptive) to take a faster or easier route in cognitive thinking. Descriptive models attempt to understand and explain the deviations from normative models. Here we use an example to illustrate the difference between the normative and descriptive approaches: an athlete with an injury may know that alcohol could dampen recovery (a normative model explains what the athlete should do). Despite this, the athlete may still choose to drink at a party due to various reasons (a descriptive model explains why the athlete's behaviour deviates from the normative model). By comparing descriptive models to normative models, decision makers may identify the potential deviations from normative models and correct the deviations if necessary. The section starts with normative models and is followed by descriptive models. Common normative models include rule-based theory and explicit utility theory.

3.4.2.1 Rule-based theory

The rule-based approach is where a clinician decides based on a set of defined criteria (Grindem et al., 2016; Kyritsis et al., 2016). The assessment could be done on a binary scale (i.e., pass or fail). Table 3.1 illustrates a hypothetical example using established criteria for ACL injury (Grindem et al., 2016).

Table 3.1 Hypothetical example of RTS criteria assessment, with criteria based on Grindem et al. (2016). A tick suggests that the athlete has scored >90% on that test, while a cross represents <90%.

Test	**Scenario 1** **>90% on all tests**	**Scenario 2** **>90% on some tests only**
Knee Outcome Survey—Activities of Daily Living Scale	✓	✓
Global Rating Scale of Function	✓	✓
Quadriceps Strength	✓	✓
Single Hop for Distance	✓	✓
Crossover Hop for Distance	✓	×
Triple Hop for Distance	✓	×
6-m Timed Hop	✓	✓
Decision outcome	**RTS**	**Not yet RTS**

Here we assume the relative importance and value assigned for all attributes are the same. The set of criteria includes seven tests, incorporating both function and subjective outcomes to reflect the overall knee performance. The passing criterion for RTS is to score >90% on the seven tests (Grindem et al., 2016).

Example: Based on the rule-based theory, in scenario 1, the athlete scored above 90% on all tests below and is cleared to RTS. In scenario 2, not all tests are passed and the athlete is not cleared to RTS (See Table 3.1).

3.4.2.2 *Expected utility theory*

Expected utility theory is a decision model that illustrates how one decides in uncertain conditions, based on the outcomes of different options and the probability of each outcome (Connolly et al., 1999; Edwards, 1977). It assumes the decision made is rational as it is based on an assessment of the cost and benefit surrounding choices (Ashby & Smith, 2000; Reyna & Rivers, 2008). Under this theory, a clinician makes a decision based on the utility (a subjective value assigned by the decision makers) of the outcomes of different options and the probability (estimated likelihood) of each outcome (Connolly et al., 1999; Edwards, 1977). As with other normative models, expected utility theory assumes that decision makers are fully rational in decision making and have access to complete information about probabilities and consequences (Shrier, 2015). Table 3.2 shows a hypothetical calculation of weight utility value according to the same ACL RTS guideline as above (Grindem et al., 2016).

Table 3.2 Hypothetical calculation using arbitrary units and utility value in ACL RTS, with criteria based on Grindem et al. (2016). Limb symmetry index (LSI).

Test	**Importance (numerical weight)**	**Scenario 1 >90% on all tests**		**Scenario 2 >90% on some tests only**	
		Utility value (AU)	**Weighted utility value (AU)**	**Utility value (AU)**	**Weighted utility value (AU)**
Knee Outcome Survey—Activities of Daily Living Scale	**3**	+10 Achieved *0.90* *(i.e., 90% of full score)*	3 * 10 =30	+8 Achieved *0.80* *(i.e., 80% of full score)*	3 * 8 =24

Global Rating Scale of Function	**3**	+10 Achieved 0.90	30	+9 Achieved 0.90	27
Quadriceps Strength	**5**	+10 Achieved 0.90 LSI *(i.e., 90% of LSI)*	50	+8 Achieved 0.80 LSI *(i.e., 90% of LSI)*	40
Single Hop for Distance	**4**	+10 Achieved 0.90 LSI	40	+8 Achieved 0.80 LSI	32
Crossover Hop for Distance	**5**	+10 Achieved 0.90 LSI	50	+7 Achieved 0.70 LSI	35
Triple Hop for Distance	**5**	+10 Achieved 0.90 LSI	50	+7 Achieved 0.70 LSI	35
6-m Timed Hop	**2**	+10 Achieved 0.90 LSI	20	+10 Achieved 0.90 LSI	20
		Total	270		213
	Decision outcome	**RTS**		**Not yet RTS**	

Example: In Table 3.2, importance reflects how much the clinician values a specific test, and this is represented by a numerical weight. Utility value is based on the performance of the test, with 10 the highest score possible and 0 the lowest. In this case, achieving the goal of 90% LSI would correspond to a score of 10. The weight utility value is calculated by multiplying *importance* (numerical weight) by *utility value* . For example, an importance of 3 and a utility value of 10 will give a weighted utility value of 30 arbitrary unit (AU) (3 x 10AU = 30 AU). The highest possible weighted utility value in this example is 270AU (scenario 1) and the decision is made based on the sum of the weighted utility value (Barber-Westin & Noyes, 2011).

In scenario 1, the athlete achieved 90% on all the tests (indicated as “achieved 0.90”) and the sum of the weighted utility value is 270AU. The decision is for the athlete to RTS. In scenario 2, some of the tests have not passed the 90% threshold and the sum of the weighted utility value is 213AU. The weighted utility value has not reached the requirement set by the clinician, and the athlete was not cleared to RTS in scenario 2.

3.4.2.3 Descriptive models

Because humans are unlikely to be perfectly rational at all times, decisions made could deviate from a normative model. Systematic deviations from normative models are known as biases (Baron, 2012). By applying normative models to the decisions made, decision makers could look for possible biases and understand the nature of those biases with descriptive models. Examples of descriptive models include prospect theory, heuristics and bounded rationality (Bell et al., 1988). With a better understanding of the biases, decision makers could develop approaches to correct them (de-bias) and improve the quality of the decisions. The following section describes the common descriptive theories and how a decision may stray from the previous normative models.

3.4.2.4 Prospect theory

Prospect theory suggests that people consider expected utility relative to a reference point rather than the absolute outcome. It also suggests future gains and losses are asymmetrical, with losses having a greater emotional impact than gains (i.e., humans dislike losses more than potential gains).

Example

In Table 3.2, the Prospect theory would suggest that the decision maker does not necessarily make decisions based on the absolute weight utility (i.e., 270AU). Instead, they would look at how far the expected utility is relative to a reference point (which is unknown here). In the context of RTS, a re-injury (loss) may bring a more negative emotional impact than winning (gain). While this may not be true in all cases, it may be worth noting how emotional distress affects decision making.

3.4.2.5 Bounded rationality

Bounded rationality describes how humans take reasoning shortcuts and make decisions within the bounds imposed by the environment, ability, information and goal (Gigerenzer & Goldstein, 1996). The decision is rational, however, it is within the limits of information available to the decision maker. That is, due to the limitation in accessing information and resources, people tend to make sufficient judgements, rather than optimal ones (Robertson & Joyce, 2019; Simon, 1955). (For more details, see Gigerenzer and Goldstein (1996) and Robertson and Joyce (2019)). In RTS, not all meaningful data are collected due to various reasons, such as high cost, a lack of feasibility and time. Therefore, the best outcome for a decision made with unknown factors is not the same as decisions made in the context of transparency (Gigerenzer, 1999).

Example

In the rehabilitation of an ACL injury, some information will always be unknown due to factors such as limitations in knowledge and resources. This includes how we can accurately assess the degree of healing of the ACL graft after a reconstruction surgery or measure the loading capacity of the ACL. Consequently, the decision made by the clinician in the above vignette is only based on the information available in Table 3.1 and Table 3.2, and is limited by the decision maker's cognitive capacity, knowledge and preference.

3.4.2.6 Heuristic

Also known as a cognitive short-cut, a heuristic is a decision making strategy to act more quickly or frugally by ignoring parts of the information (Gigerenzer et al., 2011). Heuristics allow people to make a rapid, efficient judgement without consuming a substantial amount of time, processing capacity, and when information is incomplete. Logically, a clinician's decision for RTS would be grounded in a more rational choice as described in normative models due to the availability of time and opportunity to gather additional information from tests or other staff members (e.g., doctors, coaches, fitness coach).

However, RTS decision making can also be based on heuristic decision making, as seen when athletes make decisions regarding RTS (Mayer et al., 2020).

There are many types of heuristics that are used in daily life (Gigerenzer & Gaissmaier, 2011). Tversky and Kahneman (Tversky & Kahneman, 1974) proposed three classes of heuristics that people may rely on to assess the probabilities of an uncertain event: availability heuristic, representativeness heuristic and anchoring and adjustment heuristic. In Table 3.3, we have suggested examples of heuristics that may be of relevance in RTS decisions. Heuristics may sometimes be useful in reducing the complexity of a task in assessing probabilities, however, it may also lead to systematic errors (Tversky & Kahneman, 1974).

Table 3.3 Definitions and examples of heuristics in RTS.

Heuristics	Definition	Example	Possible deviations from the normative model
Availability	People infer the probability of an based on how readily it comes to mind (Tversky & Kahneman, 1974)	A clinician assesses the risk of injury of an athlete by recalling the recent occurrences within the team.	- Depending on whether the clinician is familiar with the injury and when it last occurred, there may be recall bias. - The subjective injury risk may rise temporarily when the clinician sees there are multiple players on the injured list.
Representativeness	People categorise by matching the similarity of an object or incident to	A clinician has an impression that a female athlete demonstrating	- Evidence for screening tests in predicting injury is limited (Nilstad et al., 2021). The

	an existing one that has already existed in our minds (Tversky & Kahneman, 1974).	knee valgus movement on a jump and land task would suffer from lower limb injury.	clinician's judgement may be insensitive to the reliability and predictability of the test.
Anchoring-adjustment	People estimate based on an initial value (anchoring) and adjust to yield the final answer (adjustment) (Tversky & Kahneman, 1974).	A clinician prioritises information that supports his or her initial judgement of the estimated time to RTS and makes adjustments based on the initial value.	- A clinician may stick to the initial hypothesis of the days required for RTS even if new evidence suggests conflicting information. - Even if the clinician decides to adjust the estimation, it would be biased toward the initial value.

3.5 Part 3: Preferences of the decision makers

You have consolidated the information and weighed the risk and benefits of the medical clearance. Understanding that you are bounded by the information and knowledge available, you have used the rule-based theory described in Table 3.1 as the basis for decision making. Based on scenario 1, where the player has passed all of the tests, you have decided that the player is clinically fit to return to full training. Using the StARRT framework as a reference, you would like to discuss your rationale and other contextual factors with the athlete, coach and manager, to reach a shared decision.

The StARRT framework helps clinicians make RTS decisions based on whether the risk assessment outcome exceeds the decision maker's risk tolerance (Shrier, 2015). That is, if the risk assessment is lower than the risk tolerance after all factors are considered, the athlete may be cleared to RTS. However, a *low* risk decision may not be synonymous with a *high-quality* decision.

In general medicine, it is recommended that the decision made by the clinician reflects the preferences of a well-informed patient, with consideration of factual and probabilistic health information (Hamilton et al., 2017; Marteau et al., 2001; Sepucha et al., 2007). There are multiple dimensions to address, including characteristics of the decision, knowledge and expectations of the situation and treatment options and outcomes, personal values and preferences, support and resources needed, personal characteristics and clinical characteristics (Jaffray & Wakker, 1993; Marteau et al., 2001; O'Connor et al., 1998; Stacey et al., 2017).

Practically, no optimal measurement tool can measure the quality of the RTS decision based on the performance outcome or the expected utility of the decision makers. However, a clinician can improve the decision quality by ensuring the decisions are well-informed and grounded in a shared decision-making approach.

3.5.1 Improving decision quality by shared decision making

Shared decision-making has been a best practice for decision making in the field of medicine (Ardern, Glasgow, et al., 2016; Barry & Edgman-Levitan, 2012; Elwyn et al., 2012). It respects multiple perspectives and also aims to minimise disagreement due to conflicting interests.

There are two phases in shared decision-making: 1) *deliberation* (pre-decisional, the process leading to a decision) and 2) *determination* (the act of decision) (Elwyn & Miron-Shatz, 2010) (see Figure 3.3). Deliberation is where knowledge is searched, gained, and appraised. To improve the shared decision's quality, deliberation and determination could be evaluated (Elwyn & Miron-Shatz, 2010). An accurate judgment requires stakeholders to first collaborate to decide on the definition of success (Ardern, Glasgow, et al., 2016; Dijkstra et al., 2017). Then, they can decide on which pieces of information to pay attention to, nominate weighting and integrate the information (Montazemi et al., 1996). This information may include the alternatives available, the advantage and disadvantages of the alternatives, the nature of the decision, the associated outcome and its likelihood (Elwyn et al., 2012; Elwyn & Miron-Shatz, 2010).

The second phase, determination, is to choose one of the options (Elwyn & Miron-Shatz, 2010). The actual decision may occur in a 'black box', where one combines the available information in their own way without transparency or accountability (2014a). The lens decides how one interprets the "real" probabilities, which could be obscured by one's cognitive and emotional influence. For example, how an athlete weighs the importance of his or her sports career may affect how the information is processed. Understanding the decision-making theories may allow decision makers to realise the normative approach and thus engage in a high-quality and rational discussion during deliberation.

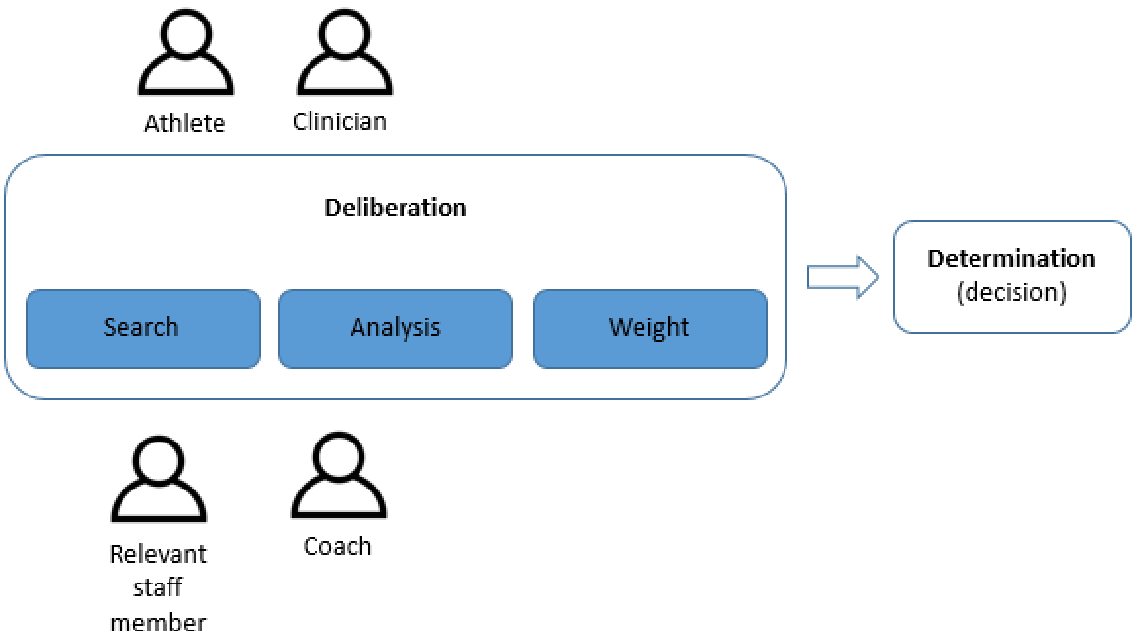

Figure 3.3 Shared decision model in sports. Adapted to RTS context from Elwyn et al. (2012).

3.5.2 The perspectives of decision makers

The keys to high-quality decision making include accounting for individual preferences, social and contextual factors (e.g., the type of injury or illness, age, types of sports, level of play, the significance of upcoming competition and social factors and financial cost) (Ardern, Glasgow, et al., 2016; Bolling et al., 2018; Hamilton et al., 2017; McCall et al., 2017). Social and contextual factors also impose constraints at multiple levels and influence the RTS decision, including at individual, interpersonal, organisational, community and policy levels (Creighton et al., 2010; Gruskin et al., 2013; Shrier et al., 2015). The factors may shift the athlete's and decision makers' priorities and preferences, which make decision making more complicated (Creighton et al., 2010; Shrier, 2015).

Traditionally, clinicians are the gatekeeper of the RTS decision (Clover & Wall, 2010; Ekstrand et al., 2019; Gabbett & Whiteley, 2017; Herring et al., 2012; Gordon O Matheson et al., 2011; McCall et al., 2016). The clinician has skills in assessing the injury-related criteria in RTS, including assessing the state of healing, risk of re-injury and risk of short- or long-term problems (Elwyn & Miron-Shatz, 2010; Herring et al., 2012; Shrier et al., 2014; Shultz et al., 2013). Clinicians also have an overriding duty of care to patients and a legal and ethical obligation to act in a manner that is necessary and appropriate to protect the health of an athlete.

However, with the addition of trainers, rehabilitation coaches, and performance coaches, clinicians are no longer the only staff contributing to rehabilitation and RTS decisions. It is questionable whether clinicians should still be the main advisor for RTS decisions, given the numerous non-medical factors to consider (Ardern, Bizzini, et al., 2016; Creighton et al., 2012; Dijkstra et al., 2017; Dunlop et al., 2019; Gordon O Matheson et al., 2011; Gordon O. Matheson et al., 2011; McCall et al., 2017; Shrier et al., 2014). In a sports setting, a clinician may even have dual allegiances, as the clinician does not work exclusively for the injured athlete, but also on behalf of the club or organisation. They may experience pressure from their employer (i.e., the sports organisation) to minimise lay-off time and to clear an athlete as soon as possible. As such, an inherent conflict of interest may present in a professional sports team setting (Stovitz & Satin, 2006; Testoni et al., 2013).

The following section discusses the general concerns and considerations of the athlete and coaches to improve communication transparency and minimise conflicts.

3.5.2.1 Athlete

Internal and external factors influence how an athlete may view the quality of the decision, and listening to their opinions may be beneficial to inform the final decision (Bolling et al., 2018). Internal factors include perception of the body, self-resentment (Podlog & Eklund, 2006; Young et al., 1994) and their emotional tie to their sport (Podlog & Eklund, 2006). External factors include sociocultural influences, such as financial concerns, expectations from family and friends and their given sport's culture of risk (Mayer et al., 2018; Mayer & Thiel, 2018). Some athletes may face social pressure to perform (Mayer & Thiel, 2018). Social pressure could be the pressure to meet the expectations of peers, fans and coaches (Podlog & Eklund, 2006; Podlog & Eklund, 2007; Leslie Podlog et al., 2015; Wiese-bjornstal et al., 1998; Young et al., 1994). Shame and alienation from the team due to injury may lead to low self-esteem and depression (Nixon, 1993; Podlog & Eklund, 2007; Wiese-bjornstal et al., 1998).

There is limited evidence on how athletes approach decisions about RTS, especially in a complex and risky scenario. 'Playing hurt' is a common phenomenon across different sports, age groups and performance levels (Mayer et al., 2018; Mayer & Thiel, 2018; Podlog & Eklund, 2006; Roderick et al., 2000; Schubring & Thiel, 2014). In a recent study that investigated how athletes decide on RTS (Mayer et al., 2020), athletes would consider the relevance of the competition (e.g., the importance of the competition), potential sporting consequences (e.g., loss of the starting position) and whether the risk of playing hurt could be offset by some means (e.g., availability of protective gears or possibility to be removed from play if pain increases). If the medically safe alternative (e.g., withdrawal from competition) does not have severe sporting consequences (e.g., loss of starting position), the athlete may opt for it. In contrast, if playing hurt may produce a sporting consequence that the athlete cannot afford, but the risk of playing could be subjectively reduced, they may choose to play hurt. Clinicians and coaches can influence the athlete's decision making as clinicians and coaches are likely to know about the sporting consequences and the possibility of risk reduction.

As opposed to the risk analysis suggested in the normative StARRT framework (Shrier, 2015), not all athletes attempt to obtain information actively and comprehensively (Mayer et al., 2020). Therefore, it may be helpful for clinicians and coaches to guide athletes through the information-seeking process and provide a full picture of the situation and the sporting consequence.

3.5.2.2 Performance coach and manager

In some settings, coaches and managers could be the decision makers for RTS and thus it is important to have their perspective as well. Coaches and managers are competent in assessing the non-injury related RTS criteria, such as athlete's desire to compete, psychological impact, financial consideration and loss of competitive standing (Shrier et al., 2014).

Based on existing literature, some coaches believe they are responsible for pushing the athlete to their limits, mentally and physically, to achieve excellence in performance (Nixon, 1994). While some coaches act according to the training restriction implemented to reduce injury risk (Podlog & Eklund, 2007), some perceive prolonged or delayed RTS as harmful to the athlete's overall and long-term performance (Podlog & Eklund, 2007). Some coaches also believe clinicians are overly cautious and delay RTS of athletes unnecessarily (Podlog & Eklund, 2007). However, research is scarce and based on a small sample size, thus limiting generalisability.

To facilitate rehabilitation, coaches and managers may help to remove the barriers arising from the social and environmental context (Walker et al., 2020). For example, ensuring athletes have sufficient resources to access adequate supervised rehabilitation. Coaches and managers can also ensure all relevant personnel are provided with information regarding the injury and the rehabilitation progression. These may increase transparency in communication and facilitate the decision to include or exclude from the main training group (Walker et al., 2020). There are times when clinicians might miss something important without realising it. Shared decision-making may help to minimise the blind spots by filling the missing gaps and broadening the perspectives.

3.6 Practical implication

Based on a decision analysis model, we have outlined a framework to help clinicians make systematic and objective RTS decisions. The first step is to choose appropriate RTS tests and to synthesise the information in a meaningful way. The second step is to understand the decision-making theories and identify possible deviations from normative models. The third step is using shared decision-making to improve decision quality by eliminating the contextual 'blind spots', such as individual's expectations, preferences and values. We propose a framework that clinicians could refer to when they decide on RTS in a sports organisation (Figure 3.4).

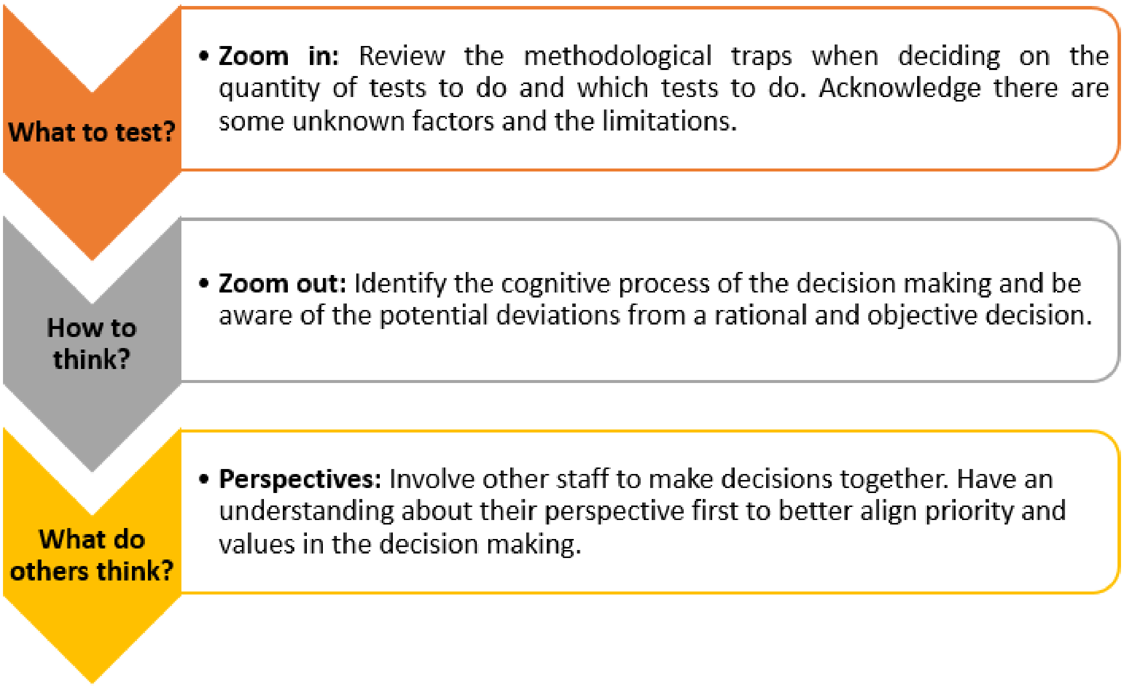

Figure 3.4 Three steps to making a high-quality RTS decision

3.6.1 Future research

Currently, there is limited evidence or expert knowledge on how clinical decisions in sports are made, especially for upper limb injuries. While in principle, the decision-making process of other sports injuries would be similar, future research could also investigate upper limb injuries, for example, a shoulder dislocation injury. Similarly, there is little attention paid to how heuristics may be present in sports medicine practice. Research is needed to identify the heuristics used in clinical practice, as limited work has been done in the field. Strategies for better judgment and decisions, such as reducing bias are also required.

Another concern is the increasing number of data types with the growth of sports technology. At a certain point, additional information no longer improves a human's ability to make better decisions (Glöckner et al., 2012). The human mind has an upper limit for information processing capacity and is sufficiently sensitive to large inconsistencies, but not small ones (Saaty & Ozdemir, 2003; Simon, 1957). Providing more information than the upper limit would only exhaust one's cognitive information capacity in decision-making, potentially leading to overload, poor decision-making, and dysfunctional performance (Cowan, 2001). Consequently, there is an urge to identify tools that aid human brains in making decisions.

These decision-making tools include statistics, mathematical modelling and artificial intelligence (AI) algorithms. In particular, machine learning techniques, a subfield of AI, attracted attention for their strength in transforming a large amount of data into useful knowledge and identifying nonlinear patterns (Bittencourt et al., 2016; Edouard et al., 2020; Witten et al., 2011). In many cases, these external aids may complement or be superior to human performance (Bate et al., 2012; Grove et al., 2000; Maymin, 2017). Currently, applying the above tools mostly remains on the theoretical level. Future research may explore how these tools may be applied on a practical level.

3.7 Conclusion

The purpose of this review was to provide an overview of RTS decision frameworks and what constitutes high-quality decision making. There is a lack of empirical knowledge in RTS decision making and the potential adaptations within its process; most research focuses on biological and medical factors. One of the strengths of the review is to lay out the decision basis and hence the transparency of a decision. Understanding decision-making theories in the context of RTS and potential deviations from normative decisions may improve the work process and quality of decision making. More research is required to understand how decisions are made and how to use computation tools to support and improve decision quality.

4 Chapter Four: Study II

Chapter overview

Chapter Four is the second of the four studies contained in this thesis. This study is a narrative review that provides an overview of the hallmark features of complex systems and their relevance to RTS research and daily practice.

The content of this chapter is an accepted manuscript of an article published by Springer Open in Sports Medicine – Open on 22nd February, 2022, available at: https://sportsmedicine-open.springeropen.com/articles/10.1186/s40798-021-00405-8.

Clinical relevance

There is a growing recognition that most sporting environments are complex adaptive systems and this acknowledgement extends to sports injury, rehabilitation and RTS decisions. Through the complex systems lens, clinicians may have a broader perspective of the overall picture and acknowledge the potential linear and nonlinear interaction between the variables. The increased awareness of complex systems and its relevance to RTS may help clinicians improve decision quality

Sports Medicine - Open

REVIEW ARTICLE

Open Access

Characteristics of Complex Systems in Sports Injury Rehabilitation: Examples and Implications for Practice

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Abstract

Complex systems are open systems consisting of many components that can interact among themselves and the environment. New forms of behaviours and patterns often emerge as a result. There is a growing recognition that most sporting environments are complex adaptive systems. This acknowledgement extends to sports injury and is reflected in the individual responses of athletes to both injury and rehabilitation protocols. Consequently, practitioners involved in return to sport decision making (RTS) are encouraged to view return to sport decisions through the complex systems lens to improve decision-making in rehabilitation. It is important to clarify the characteristics of this theoretical framework and provide concrete examples to which practitioners can easily relate. This review builds on previous literature by providing an overview of the hallmark features of complex systems and their relevance to RTS research and daily practice. An example of how characteristics of complex systems are exhibited is provided through a case of anterior cruciate ligament injury rehabilitation. Alternative forms of scientific inquiry, such as the use of computational and simulation-based techniques, are also discussed—to move the complex systems approach from the theoretical to the practical level.

Keywords: Complexity, Return to sport, Return to play, Decision making, Machine learning, Bayesian network

Key Points

- Complex systems have distinct properties, such as nonlinearity, emergence and adaptation. Sixteen features of complex systems have been identified in sports injury rehabilitation.
- Rehabilitation practitioners may connect complex systems theory with their operations in the sports setting.

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Challenges in Return to Sport Decision Making

Return-to-sport (RTS) can challenge health professionals, coaches (i.e., practitioners) and athletes. In competitive sports, where marginal gains in performance are sought, athletes and practitioners often weigh risks and benefits when making the RTS decisions. In a team sports setting, full availability of players allows greater flexibility in tactical planning, such as deciding the best team formation based on the opponent's playing style. Player availability is linked to performance [1–3] and could reduce the financial burden on the team [4, 5].

Research on RTS decision making largely focuses on identifying a criteria list based on biological factors and on whether the athlete has returned to baseline performance level (e.g., Grindem et al. [6], Stares et al. [7], and Kyritsis et al. [8]). This approach has assisted practitioners in being transparent in the decision process, for instance, to grant a medical clearance. However,

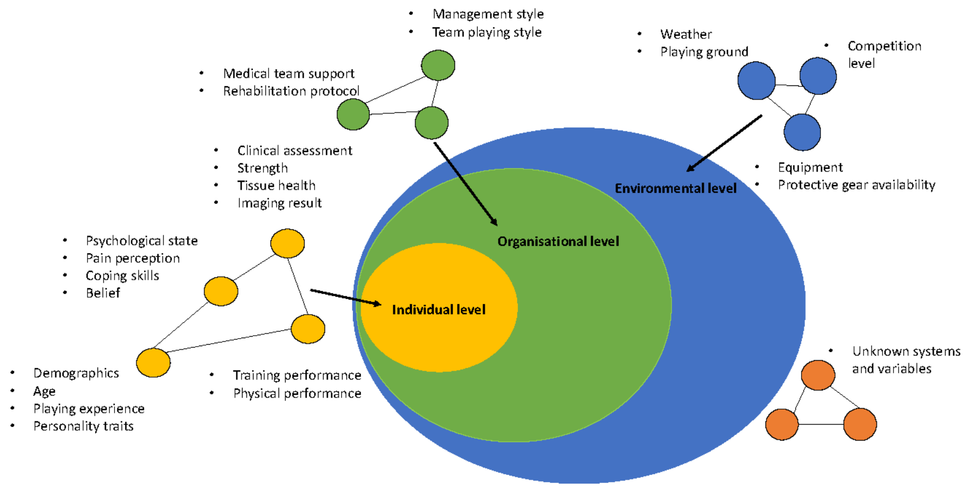


Fig. 1 A multilevel system map with factors related to return to sport decision in anterior cruciate ligament injury

underlying complexity and the high degree of interlinks, independencies, and temporal components also need consideration. For example, the same criteria may not apply to athletes of a different mental state, age group or playing level. Furthermore, non-linearity is commonly seen in the context of sports. As an example, most football fans would know that a team composed of the best-skilled players, does not necessarily produce the best performance. Instead, the outcome is highly dependent on the interplay of tactical, physiological, social and even emotional factors. Similarly, it may be beneficial to view RTS more than simply addressing a set of predefined RTS criteria, or achieving an arbitrary numerical change in a performance test.

To address these limitations and objectives, we propose an approach using the complex systems theory. Recent work from Bittencourt et al. [9] has raised awareness of the theory and more could be done to clarify the characteristics of complex systems and to increase the practical utility of the complex systems approach. Consequently, this paper builds on the work of Bittencourt et al. [9] and aims to (1) clarify the terminologies in the complex systems approach and adapt them for sports, (2) provide examples relevant to rehabilitation and (3) introduce tools that can model the complexity and increase practical utility in applied settings.

What is a Complex Systems Approach?

A Complex Systems Approach to Decision Making in Sports Medicine

The complex systems theory, with more than 50 years of history [10], acknowledges the multifaceted nature of sports and seeks to understand the interactions among different factors and the outcomes of the systems [9, 11]. Complex systems are dynamic, open systems [12]. They are characterised by non-linearity due to feedback loops and interaction among the factors. This means that outputs are not always proportional to the inputs, and a small adjustment may lead to a large change in the systems and vice versa [13].

In complex systems, factors that interact with each other to form the systems are known as units [12]. In the context of RTS, these units could include age, wellness, biological healing of injured tissue, stress, external pressure and injury history. The units interact and define the space and dimension of the systems [14]. Consequently, different systems within systems emerge. These systems may be categorised based on their nature, for example, biomechanical, physiological and psychological. They may also be hierarchical and of multiple levels, namely individual, organisational and environmental (see Fig. 1). The individual level represents factors related to the individual athlete, from tissue healing to personal traits. The organisational level represents external factors related to the sporting club, organisation and support team, e.g., the coaching and medical team. The environmental level covers factors beyond the organisational level, such as the weather, playing schedule and competition level.

In recent years, the complex systems approach has gained momentum and has been used to understand sports injury occurrence [9, 15] and behaviour in sports performance [16–19]. However, the terminologies used in complex systems are often less familiar to practitioners and could be easily confused with merely *complicated* or *multifactorial*. Most studies recognize the importance of considering multiple factors in determining readiness for RTS or in the context of injury recognition [6, 8, 9, 20–26], but more work is required to raise awareness on why the lens of complex systems approach should be adopted by practitioners in rehabilitation.

Applying a Complex Systems Model for ACL rehabilitation

This paper provides examples based on the 16 common features of complex systems recently illustrated by Boehnert et al. [27]. They are adapted for the context of sports in Table 1, with examples illustrated mainly from an anterior cruciate ligament (ACL) injury.

An ACL injury is used here as the case illustration as it is a serious injury that may threaten the career of an athlete [28, 29]. The estimated annual medical cost associated with ACL reconstruction surgery in Australia was over A$75 million per year [30]. Currently, there is no consensus regarding the optimal functional rehabilitation criteria [20] and objective physiological RTS criteria [31]. Despite ACL injuries being one of the most researched topics in the sports medicine literature [32], the re-injury risk of ACL remains high [33, 34]. The complexity within ACL RTS may be explained at the individual, organisational and environmental levels.

Implications for Practice and Future Research

By illustrating the features of complex systems with a common sports injury, we highlight their practical utility in RTS. The complex systems approach provides a theoretical framework for interpreting the patterns that emerge from biopsychosocial and other external factors. In ACL rehabilitation, conducting independent clinical tests and functional assessments may provide useful information regarding the athletes' physical and mental status. However, a complex systems approach facilitates a more complete picture of the problem and an increased awareness of how different factors may interact.

There are two challenges on using the complex systems approach: (1) the high degree of complexity may deter practitioners who do not have formal training in handling large and complex datasets from using this approach, (2) Unlike studying in a controlled laboratory environment, it is near impossible to isolate a portion of the larger systems (i.e., isolation of the biological healing process from broader biopsychosocial factors). Fortunately, many computer-based decision support systems now have the capability of incorporating features of complex systems in their design and utility. For example, to operationalise one of the above features, "change over time", the working model can allow flexibility in updating the baseline and encourage repeated testing at multiple time points during the rehabilitation. We believe practitioners who develop an understanding of complex systems will be well-positioned to efficiently articulate their needs with analysts and ultimately develop decision support systems that inform best practices (e.g., RTS decision making).

Computer simulation (e.g., agent-based modelling), machine learning and Bayesian network (BN) analyses are all potential tools for analysing both non-complex or complex systems [35]. These methods can consider the dynamic interaction at multiple levels simultaneously, consequently viewing RTS more completely and supporting decision making. These analytical tools may help to achieve the following: (1) allow practitioners to study and compare the potential outcome (e.g., likelihood of reinjury) of different decisions that are otherwise almost impossible to test safely in real life, (2) increase the decision efficiency by learning from previous experience and streamlining data from multiple sources and formats, (3) identify patterns in data that may cause a certain outcome.

These techniques can be used to construct clinical decision support systems, which may complement or be superior to human decisions. In a review of seventy studies, a decision support system improved clinical practice in 68% of trials [36]. These decision support systems have also provided more accurate diagnoses than human experts in some medical fields [37, 38]. Yet, the application of these approaches in RTS is still scarce in the literature. As such, we have provided a vignette here to outline how machine learning techniques and Bayesian networks could be applied to support RTS decision making: a 30-year-old professional female football player tore her hamstring 10 days ago during the season and a grade II hamstring strain was diagnosed. There is an important match in 2 weeks and there are six relevant questions, as covered in the below sections, which the practitioners and the coach would like to ask. Ultimately, the coach would like to know as early as possible about

Table 1 The 16 common features of complex systems adapted for return-for-sport

Characteristics	Definition	Example
1. Feedback	Units in a complex system are mutually interacting and output is fed back and becomes a new input [70]. The feedback could be positive or negative. For example, positive feedback increases the rate of change while negative feedback works by reversing the direction of change.	Rehabilitation training leads to tissue adaptations, which improves physical fitness and performance (positive feedback). However, maladaptation can occur (e.g., alteration in neuromuscular control and muscle damage), leading to suboptimal response which may delay progress (e.g., delayed onset of muscle soreness). This acts as negative feedback for the systems, signalling the training intensity was too high.
2. Emergence	Emergent properties arise from the interactions of its units. The units serve as the building blocks for patterns to arise at higher levels [71].	After an ACL injury, injured athletes often train separately from the squad and have a different training regime. During this time of relative isolation and hardship, the athlete may build up a high level of resilience.
3. Self-organisation	Systems may order themselves spontaneously to form patterns and achieve an optimal or stable state [14].	ACL is a key sensorimotor system for postural control, which helps to maintain and control upright posture [72]. Following an ACL injury, the brain activation profile will be affected and shifts toward a visual-motor strategy, as opposed to a sensory-motor strategy. Instead of relying on movement and spatial awareness, people with ACL deficiency may rely more on the visual system, especially under challenging dynamic task constraints [73]. This is an example of how the sensorimotor system self-organises to compensate for the loss of ACL.
4. Levers and hubs	Levers and hubs are key structures in the systems that play a crucial role in how the systems will behave. Identifying them could allow interventions in the systems effectively [27].	There are exceptional factors that are influential in the RTS process and altering them may lead to rapid gain. In ACL rehabilitation, intense rehabilitation and patient motivation are established levers and hubs that may underpin a positive outcome following ACL rehabilitation [74].
5. Non-linearity	Outputs are not always proportional to the inputs. Small changes may lead to a large change in the systems and vice versa [14].	The same training stimulus can create a large recovery response (e.g., delayed onset of muscle soreness) on the first training session, but not subsequent training. This is because the body can non-linearly adjust to the training stimulus after the first session. The response exhibits a non-linear behaviour where the outcome (i.e., training response) is not proportional to the input (i.e., training stimulus).
6. Domains of stability	Many systems are dynamic however may eventually converge to a stable state. This stability will be maintained unless there is a significant perturbation [70].	Balance and proprioceptive training are often included in the ACL rehabilitation protocol. However, balance and technique training may not be effective in changing an athlete's knee joint kinematics or decreasing external knee moments during pre-planned and unplanned side-stepping [75]. Similarly, gait mechanics are also difficult to modify even after completion of rehabilitation training and restoration of muscle strength [76]. This may be because the systems have achieved a domain of stability and the parts of the systems are well-entrenched, making it very difficult or near impossible to change. Once the systems have achieved a state of stability, they could only be altered when the stimulus is strong enough to push them through the tipping point [70].
7. Adaptation	Components or actors within the systems are capable of learning and evolving in response to the changes in the environment [70].	Some people with ACL deficiency may exhibit increased knee flexion at early stance and reduced extension in mid to late stance [77]. This is an adaptation that allows hamstrings to be efficient synergists to the ACL in walking [78, 79] and to reduce the anterior translation force of the tibia [77]. This represents how the body adapts to ACL deficiency by bringing changes within the systems. The adaptation appears to happen autonomously, unconsciously, and without explicit programming.

Table 1 (continued)

Characteristics	Definition	Example
8. Path dependency	Events and actions that occurred previously influence future states and decisions [27].	ACL rehabilitation usually follows a path and one can only progress to the next stage by meeting a set of criteria. For example, in the early rehabilitation phase, progressive weight-bearing allows the knee joints to acclimatise to increased load and assist in the development of a normal gait pattern [80, 81]. Plyometric training is only incorporated if full range of motion (ROM), sufficient strength base, and flexibility are demonstrated. For on-pitch rehabilitation, activities should begin with simple drills and advance to more complex exercises [80]. A control-chaos continuum (CCC) could be followed on-field, where rehabilitation training constraints progress from high control to high chaos [82].
9. Tipping point	If the perturbation of a system goes beyond a certain threshold, there will be a phase transition in the system's behaviour which may not be reversible [70].	In ACL rehabilitation, one of the early goals is to strengthen lower limb muscles to minimise muscle atrophy [83]. Squat exercise may be used as a training stimulus (perturbation) and it may cause micro-tears and inflammation of the muscle fibres (system deviates from the stable state). The neuromuscular system will repair and adapt (system returns to a stable state), leading to muscle hypertrophy [84]. However, if the intensity and volume exceed the capacity of the soft tissue, there will be a loss in stability (e.g., quadriceps muscle strain) and an inability to relax back to the previous stable state automatically. There will be a change in system behaviour (i.e., re-injury [85]).
10. Change over time	Systems are dynamic and can evolve over time. This is because they constantly interact and negotiate with the environment, leading to continuous change [70].	Psychological characteristics of athletes can change during the ACL rehabilitation process and affect how they cope with RTS and future injury [86]. In the physical performance aspect, training capacity evolves and generally declines with age [87]. For example, the heart rate maximum during exercise declines with age [88]. Maximal oxygen consumption is inversely and strongly related to age for active and endurance-trained populations [89].
11. Open system	Complex systems are considered open as it is difficult to define their boundary. The systems interact with the environment and are also being influenced by the environment continuously. In contrast, closed systems are systems where the influence of the environment on them is negligible [14].	The size of the systems could hardly be defined, as things in the environment that are seemingly small may also influence them. For example, a wet training ground affects the ground reaction force and movement strategy for athletes during running [90]. Shoe designs and types of playing surfaces are related to ACL injury risk due to the shoe-surface friction [91]. Playing music during rehabilitation training may reduce the perception of physical effort during training and improve physical performance by delaying fatigue or increasing work capacity [92, 93].
12. Unpredictability	Due to non-linearity and emergence properties, it is difficult to predict how the systems will evolve [9].	Precise forecasting of when an athlete should RTS is challenging. It is difficult to predict the estimated time for recovery as there is unpredictability on how the systems evolve. For example, how will the motivation of the athlete change throughout rehabilitation? How will the change in a personal relationship affect the performance of the athlete? In some cases, it is impossible to gather, store, and use all of the information about the state of complex systems at one point to predict the outcome.
13. Unknowns	There are always units that influence the systems which are either unknown or could not be observed or measured. Therefore, it may seem that the systems evolved unpredictably [9].	There are factors that decisions makers may not be aware of during the ACL rehabilitation due to different reasons, for example, limited knowledge (e.g., how a genetic variant is associated with ACL rehabilitation and injury risk?), technology constraints (e.g., how reliable are the measurement tools?), insufficient resources (e.g., is it possible to measure everything?), bias and issues that stakeholders have been unaware of.

Table 1 (continued)

Characteristics	Definition	Example
14. Distributed control	Control of a system is distributed across different parties and no one has complete control over the systems [9]. There is no top-down control approach as the process is not controlled by a single factor at a superior level.	The success of ACL rehabilitation is determined by all interacting units, from biological graft healing at the microscopic level, to intra-personal factors (clinical assessment, functional test, and biopsychosocial factors), and inter-personal factors at the macroscopic level. No single factor in isolation could determine the success of the outcome.
15. Nested system	There are nested hierarchies within the complex systems, forming systems within systems [27].	ACL rehabilitation itself exhibits nest hierarchies in the following order: Cell > muscle > brain > inter-personal > family and friends > organization > environment. At the cell level, shortly after graft implantation, fibrous scar tissue will be formed between the graft and host bone [94], followed by ligamentization [95]. At the muscular system level, quadriceps muscle atrophy and dysfunction are commonly observed after ACL reconstruction and are often associated with altered movement pattern [96, 97], possibly due to alterations at the brain (motor cortex) level and neurophysiological changes in muscles [98–101]. At the intrapersonal level, physiological cardiac adaptation [102] and aerobic fitness [103] are all substantially reduced after an ACL injury. At the interpersonal level, social support plays a key role in regaining confidence and eradicating fear of re-injury throughout rehabilitation [104–106].
16. Multiple scales and levels	Multiple perspectives are required when viewing complex systems. The systems are three dimensional and interactions within the systems often occur at different scales and levels [27].	Rehabilitation can be considered on the biological level, psychosocial level or performance level. There is more than one domain involved and often the systems have to be understood from multiple perspectives.

the availability of the player so that they could plan the players' list and hence the game strategy.

Machine Learning Techniques

As a subfield of artificial intelligence (AI), machine learning focuses on the use of data to train algorithms that can make classifications or predictions [39, 40]. That is, it could recognise new meaningful correlations, patterns and trends in a large amount of data [41]. Not only are machine learning techniques suitable for non-complex analysis, but they can also accommodate multi-dimensional analysis in sport [42, 43]. New data could also be input into the model for it to learn and improve the task, leading to refinement of skills [40].

The goals of machine learning techniques in sports medicine setting can be divided into predictive and descriptive modelling [44]. Specifically, predictive modelling can be used for injury prognosis, diagnosis, and rehabilitation planning. Descriptive modelling can be used to characterize the general property of an injury, such as its severity, as well as include hypotheses of causality. However, as with traditional statistical approaches, machine learning techniques are simply a method for analysing the data, providing a prescriptive or descriptive output. For understanding and estimating causal relationships, appropriate study designs are required, for example, randomised controlled trials. Machine learning is often characterised by five major approaches (i.e., association, classification, clustering, relationship modelling and reinforcement learning), each having already been applied for injury risk assessment and/or performance prediction in sports [45–49]. Each of these approaches could serve as the methods to answer questions relevant to RTS.

Question 1: Should the Athlete Progress to Full Training?

Scenario The athlete has completed 10 days of rehabilitation training. The practitioners would like to assess whether the athlete is ready to progress to full training. An association approach could be used here, using the rule-based system (Table 2).

Rule-based approaches identify meaningful and frequent patterns between variables in a large dataset [50]. Often less identifiable by the practitioner, the rules may help them identify patterns that indicate optimal rehabilitation combinations of variables by flagging both commonly occurring and meaningful patterns in data.

In the above hypothetical example, a multivariate analysis of rules associated with a rehabilitation outcome is conducted. The model was set to only produce 3 categories of rules that contained the rehabilitation outcome as a result (i.e., ready for full training, not yet ready and unchanged). These could be the three rules most strongly associated with the rehabilitation outcome. A tick represents the presence of the context within the rule. The system could identify the number of rules required based on previous rehabilitation experience and to implement the rules when the complexity of the content is beyond human brain capacity. An increased number of rules may better represent complexity; however, it may potentially make the solution more difficult to operationalize practically.

Question 2: What is the Likelihood that the Athlete Could Return to the Pre-injury Level Given the Current Level of Training?

Scenario There are only 2 weeks until an important match. The coach would like to know the likelihood that the athlete could return to pre-injury level by then. Given the volume of high-speed running training that the athlete has completed, a classification method could be used to identify the likelihood (Table 3).

A decision tree uses dichotomous divisions to create the classification algorithm. Representing the rules, the decision tree could be used to develop a clinical decision algorithm for RTS [49, 51]. Each node denotes a test on an attribute value and each branch represents an outcome of the test, with the leaves representing the class.

The above is a graphical representation of the decision tree that used a classification algorithm to identify the probability of RTS from a hamstring injury. Each node is associated with a rule condition, which branches off to the child node. In this example, the outcome of RTS is likely a non-linear relationship with the training volume and mental readiness, which is a characteristic of the complex systems approach (see Table 1, example 5). Using the classification approach may help to include non-linearity into analyses.

Question 3: When is the Athlete Expected to Return to Sport?

Scenario The coach would like to know when the athlete is expected to RTS based on the experience of the clinician and also accounting for the athlete's age. Clustering technique could be used to analyse the past data.

Clustering allocates data points into groups that share similar or dissimilar features [52]. In RTS, this may be useful in the allocation of multiple athletes to training groups. This could be done for clinical presentation, playing position, demographics, or inter-and intra-personal factors.

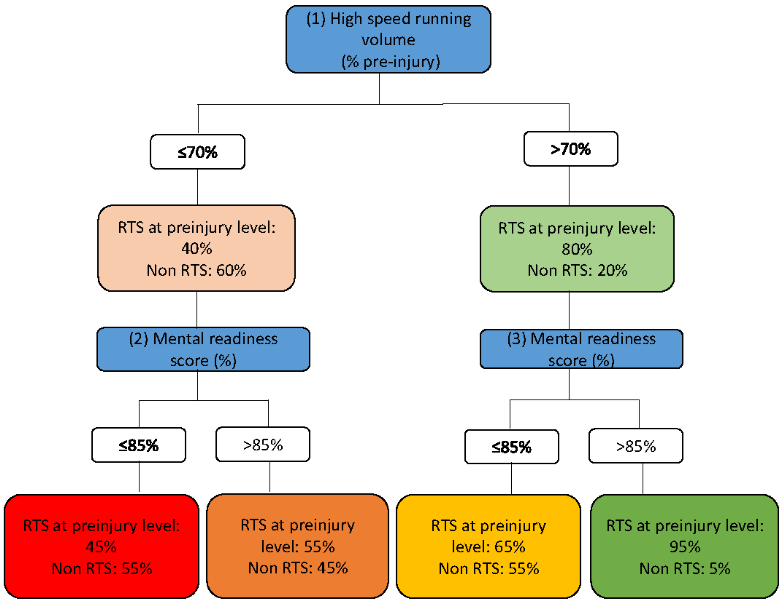
Table 4 visualizes one of the multiple approaches to which injured athletes could be clustered. Each dot represents an injured athlete and is coloured based on their severity. Size represents a measure of each athlete's age, with a larger size representing older age. They are further

Table 2 The association approach to determine should the athlete progress to full training

Rule 1 Range of motion full	Rule 2 Limb asymmetry index 100%	Rule 3 Training load >100% match requirement	Rule...	Decision
✓	✓	✓		✓Ready for full training. progress
✓	✖	✖		✖ Not ready for full training
✓	✓	✖		- Continue current rehabilitation

Table 3 The classification approach to identify the likelihood for an athlete to RTS

Approach	Classification
Task	Supervised
Technique	Decision tree and random forest
Output type	Categorical or continuous Examples: ready to compete, not yet ready to compete
Application example	

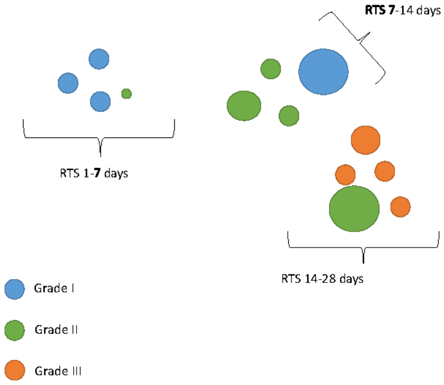


grouped into three different clusters, representing the severity and time to RTS. In this hypothetical example, the model output is the predicted days to RTS. However, it could also be designed to produce categorical outputs such as being ready to train or not yet ready to train.

Question 4: The Athlete has a High Level of Mental Readiness. Would that Change the Level of Confidence About the Athlete's Readiness to Play in an Important Game?

Scenario From the clustering approach, the coach has considered that the athlete may require at least 2 weeks to return to competition at pre-injury level. However, the

Table 4 The clustering approach to identify when the athlete may return to sport

Approach	Clustering
Task	Unsupervised
Technique	K-nearest neighbours
Output type	Categorical Examples: RTS grade, days to RTS
Application example	

coach noticed that the athlete had a high level of mental readiness, as reflected by relevant measures (e.g., Injury-Psychological Readiness to Return to Sport scale [53]). The coach would like to know how this new information, combined with the previous knowledge, may change the practitioner's judgement. A relalationship modelling approach described below is used.

Relationship modelling involves estimating relationships between a dependent variable and one or more independent variables. Regression analysis, commonly used in the analysis, is also a type of relationship modelling technique and could be used with the complex systems approach. For example, it could be used for modelling the relationship between outcomes, such as match results [54] and injury incidence [45].

Table 5 shows a hypothetical example of how the confidence to RTS (y-axis) may be associated with the volume of high-speed running done (x-axis) and the mental-readiness score (size of the bubble). The level of mental readiness is denoted by the size of the bubble. A higher level of mental readiness is indicated with a larger size bubble and is in green colour. A lower level is indicated with a smaller size and is in red. The association could be multi-dimensional and could be constructed based on the number of inputs available, e.g., running speed, load accumulation, psychological readiness.

Question 5: What is the Optimal Sequence of Rehabilitation in a Case of Hamstring Injury Rehabilitation?

Scenario After reviewing the dataset, the coach and the clinician would like to explore how to further leverage the available data and identify adaptive personalized treatment plans in the future. Reinforcement learning may help to optimize the sequence of decisions that favour a long-term outcome. Reinforcement learning is described below.

Unlike supervised or unsupervised learning, reinforcement learning trains itself through trial and error to explore behaviours in the system that could maximize the reward [55]. This feature makes it suitable for solving sequential decision problems. In this clinical vignette, reinforcement learning could help to identify a personalized rehabilitation pathway for maximizing the reward (i.e., managing the injury or reaching the rehabilitation goal).

In the context of a hamstring injury (see Table 6), a practitioner has to decide when to initiate and adjust rehabilitation training, such as jogging, eccentric hamstring exercise, and high-speed running. Each decision affects the athlete's rehabilitation outcome at the end of the program and the total days of absence. The rewards require practitioners' input, such as comparing the intensity and volume of high-speed running to the pre-injury. The reliability of the treatment-quality estimate depends

Table 5 The relationship modelling approach to identify the effect of mental readiness

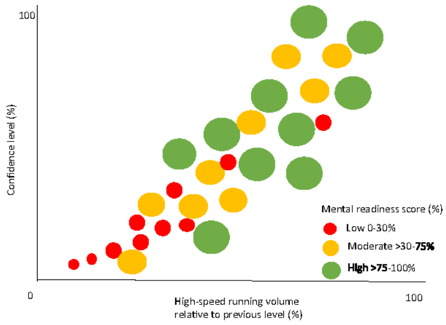
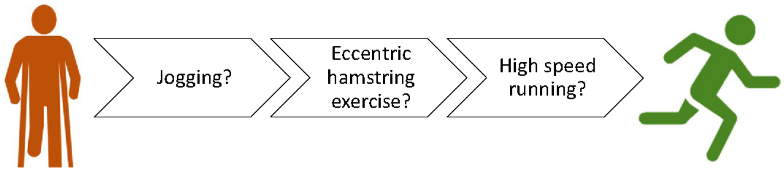
Approach	Relationship modelling
Task	Supervised
Technique	Regression and neural networks
Output type	Continuous
Application example	

Table 6 Use of reinforcement learning to optimise the sequence of rehabilitation

Approach	Reinforcement learning
Task	Not applicable
Technique	Markov decision process
Output type	No output variable
Application example	

heavily on the amount of data that were used to train the algorithm used in the reinforced learning, and the extent to which the proposed and observed treatment policies agree.

Bayesian Network

Besides the machine learning approach, Bayesian methods are becoming increasingly popular in the study of sports [56] and may contribute to RTS. Various forms of BN have been applied across different sectors, including medical [57–61], ecology [62–64] and transportation [65].

BN uses Bayesian inference for probability computations and can be visually presented using directed acyclic graphs. Arrows on the BN, known as directed arcs, indicate the direction of the influence [66]. These show how various discrete or continuous factors in RTS influence one another and the outcome in a graphical presentation [66]. BN allows calculation of the conditional probabilities of the outcome of a decision when the value of some of the factors has been observed. As new evidence is revealed, changes are brought to the conditional probability of the decision outcome [67].

Question 6: How Would the Sex of the Athlete Affect the Perceived ACL Injury Risk?

Scenario The athlete has now recovered from the hamstring injury but is worried about the potential ACL injury risk. The coach wants to know how the sex of the athlete (prior) [as female] would affect how one perceives the ACL injury risk (outcome) [higher risk of ACL injury]

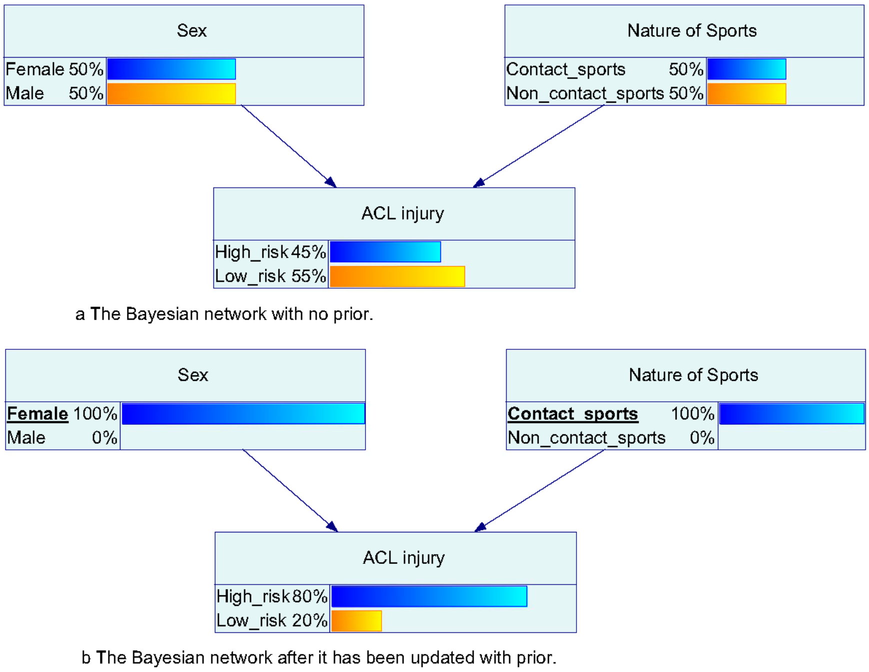


Fig. 2 Illustration of a Bayesian network before (**a**) and after it has been updated with a prior (sex or/and nature of sport) (**b**). The outcome of the prediction (ACL injury risk) has changed as a result

(Fig. 2) [68], and how it may inform the potential consequence of a RTS decision.

Only one prior is used here to explain the application for easier understanding. However, a BN can account for multiple variables to increase the accuracy of the model and to acknowledge the complex systems approach, as seen from a hypothetical example here in Fig. 3.

A BN could be operated in both directions, performing both predictive and diagnostic inference. As an example, a BN may provide the following information to support RTS decisions: (1) given the observation of the athlete's rehabilitation markers, what is the likelihood for the athlete to perform at pre-injury level upon RTS? (2) to increase the likelihood to achieve certain outcomes of RTS, what is the combination of test results and/or observations required?

Logically, BN seems to fit into the requirement of RTS decisions, as often multiple unknown factors are involved in the process (e.g., how wellness may be associated with the injury risk). Although these unknown parameters are uncertain, they could be described by a probability distribution table, with information supplied by a domain expert or relevant literature.

Establishing a BN requires data and could be complemented by expert knowledge [66]. Expert knowledge allows the model to specify the decision options available and the utilities that the user is after. For example, decision-makers may decide if the utility (degree of satisfaction) of the RTS outcome is based on either maximising the team performance, minimising the risk of subsequent injury, or equilibrium between the two. However, this also implies that the quality of the model output would rely on the quality of the existing evidence and expert's knowledge, which may be flawed or biased.

Future Research

A shift towards a complex systems approach may help to view RTS more realistically. Future research should be mindful of the following issues:

(1) The complex systems approach and the machine learning techniques cannot necessarily elucidate the

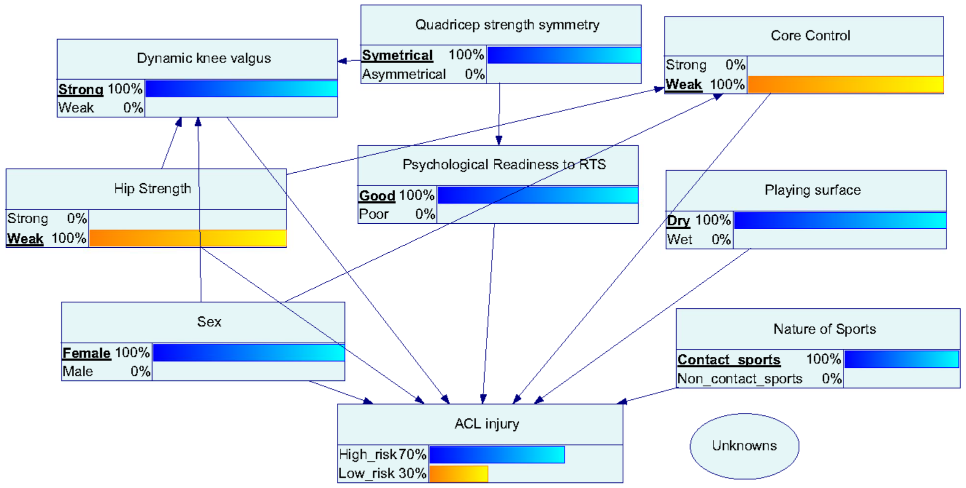


Fig. 3 A hypothetical example of a Bayesian network with multiple priors for ACL injury risk

causal mechanism. Based on Table 1, the characteristics of complex systems do not permit cause and effect relationships to be determined. However, that does not imply they are inappropriate for understanding a problem nor they are of low practical utility.

(2) The accuracy of the computation relies heavily on the quality of the dataset and previous knowledge. For example, what is the association between different variables (e.g., age, playing style, previous injury history, culture, and lifestyle)? What is the potential effect of external factors (e.g., stress, financial pressure, lack of social support) on RTS progress and decision making? Currently, there is insufficient evidence on these aspects. High quality randomized controlled trials and longitudinal research that acknowledges the complex systems approach are required to observe regularities that are antecedent to the success of a rehabilitation program.

(3) The RTS systems that researchers could construct would consist of what is available and known, rather than what is important. Some factors may be difficult to measure due to the availability of time, resources and their non-deterministic or qualitative nature [69]. For example, motivation for RTS during rehabilitation is important but often not measured due to difficulty obtaining accurate feedback. However, this is inevitable, as unknowns and unpredictability are characteristics of complex systems. Nevertheless, if possible, real data should be applied to prove the concept and provide useful output for practitioners, as the ultimate goal of embracing complex systems approaches in RTS is to produce findings closer to the real world.

Conclusion

The complex systems approach has been applied to understand different aspects of sports science and medicine. This review has highlighted the characteristics and terminologies of complex systems, as exhibited by a case of ACL rehabilitation. When assessing the test result for clinical and functional tests, practitioners should also be aware of the dynamic systems evolving around the injury rehabilitation (refer to the examples in Table 1) and endeavour to understand the full picture. Future research may make use of computational modelling and machine learning techniques to identify the regularities of the pattern that emerges as a whole. A paradigm shift that results in the application of complex systems approach to understanding the RTS process and decision making should be encouraged.

Abbreviations

ACL: Anterior cruciate ligament; AI: Artificial intelligence; BDN: Bayesian decision network; BN: Bayesian network; RTS: Return-to-sport.

Acknowledgements

KY is supported by the Australian Government Research Training Program Scholarship. Our Bayesian network model was built using GeNIE Modeler (BayesFusion) from https://www.bayesfusion.com/.

Authors' contributions
Conceptualization: KY and SR. Writing- original draft preparation: KY. Writing- review and editing: SR, CA, FS and KY. All authors read and approved the final manuscript.

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Funding
Open Access funding enabled and organized by CAUL and its Member Institutions. The authors declare that no funding was received for this review.

Availability of data and materials
Not applicable.

Declarations

Ethics approval and consent to participate
Not applicable- review article.

Consent for publication
Not applicable.

Competing interests
Kate Yung, Clare Ardern, Fabio Serpiello and Sam Robertson declare that they have no conflict of interest relevant to the content of this review.

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Received: 8 June 2021 Accepted: 29 December 2021
Published online: 22 February 2022

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This declaration is to be completed for each conjointly authored publication and placed at the beginning of the thesis chapter in which the publication appears.

1. PUBLICATION DETAILS (to be completed by the candidate)

Title of Paper/Journal/Book: Characteristics of complex systems in sports injury rehabilitation: examples and implications for practice.

https://sportsmedicine-open.springeropen.com/articles/10.1186/s40798-021-00405-8

Surname: Yung First name: Kai Yee (Kate)

Institute: Institute for Health and Sport Candidate's Contribution (%): 80

Status:

Accepted and in press: ☐ Date:

Published: ☑ Date: 22 Feb 2022

2. CANDIDATE DECLARATION

I declare that the publication above meets the requirements to be included in the thesis as outlined in the HDR Policy and related Procedures – policy.vu.edu.au.

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3. CO-AUTHOR(S) DECLARATION

In the case of the above publication, the following authors contributed to the work as follows:

The undersigned certify that:

1. They meet criteria for authorship in that they have participated in the conception, execution or interpretation of at least that part of the publication in their field of expertise;
2. They take public responsibility for their part of the publication, except for the responsible author who accepts overall responsibility for the publication;

3. There are no other authors of the publication according to these criteria;

4. Potential conflicts of interest have been disclosed to a) granting bodies, b) the editor or publisher of journals or other publications, and c) the head of the responsible academic unit; and

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N/A

Name(s) of Co-Author(s)	Contribution (%)	Nature of Contribution	Signature	Date
Clare Ardern	5	Assisted with methodology, feedback and revisions.	[redacted]	20/1/2023
Fabio Serpiello	5	Assisted with feedback and revisions.	[redacted]	18/1/2023
Sam Robertson	10	Assisted with concept, methodology, feedback and revisions.	[redacted]	17/1/2023

Updated: September 2019

4.1 Characteristics of complex systems in sports injury rehabilitation: examples and implications for practice.

4.1.1 Key Points

- Complex systems have distinct properties, such as nonlinearity, emergence and adaptation. 16 features of complex systems have been identified in sports injury rehabilitation.
- Rehabilitation practitioners may connect the complex systems theory with their operations in the sports setting.

4.1.2 Abstract

Complex systems are open systems consisting of many components that can interact among themselves and the environment. As a result, new forms of behaviours and patterns often emerge. There is a growing recognition that most sporting environments are complex adaptive systems and this acknowledgement extends to sports injury. Consequently, practitioners involved in return-to-sport decision making are encouraged to view the decisions through the complex systems lens to improve decision quality in rehabilitation. This review builds on previous literature by providing an overview of the hallmark features of complex systems and their relevance to RTS research and daily practice. An example of how characteristics of complex systems are exhibited is provided through a case of anterior cruciate ligament (ACL) injury rehabilitation. Alternative forms of scientific inquiry, such as the use of computational and simulation-based techniques, are also discussed—to move the complex systems approach from the theoretical to the practical level.

4.2 Challenges in return to sport decision making

Return-to-sport (RTS) decisions can be challenging for health professionals, coaches (i.e., practitioners) and athletes. In competitive sports, where marginal gains in performance are sought, athletes and practitioners often weigh risks and benefits when making the RTS decisions. In a team sports setting, full availability of players allows greater flexibility in tactical planning, such as deciding the best team formation based on the opponent's playing style. Player availability is linked to performance (Drew et al., 2017; Hägglund et al., 2013; Williams et al., 2016) and could reduce the financial burden on the team (Hickey et al., 2014; Mather et al., 2013).

Research on RTS decision making largely focuses on identifying a criteria list based on biological factors and on whether the athlete has returned to baseline performance level (e.g., Grindem et al. (Grindem et al., 2016), Stares et al. (Stares et al., 2018), and Kyritsis et al. (Kyritsis et al., 2016)). This approach has assisted practitioners in being transparent in the decision process, for instance, granting a medical clearance to RTS. However, underlying complexity and the high degree of interlinks, independencies, and temporal components also need consideration. For example, the same criteria may not apply to athletes of a different mental state, age group or playing level. Furthermore, non-linearity is commonly seen in the context of sports. For example, most football fans would know that a team composed of the best-skilled players does not necessarily produce the best performance. Instead, the outcome depends on the interplay of tactical, physiological, social and even emotional factors. Similarly, viewing RTS more than simply addressing a set of predefined RTS criteria or achieving an arbitrary numerical change in a performance test may be beneficial.

We propose an approach using the complex systems theory to address these limitations and objectives. Recent work from Bittencourt et al. (Bittencourt et al., 2016) has raised awareness of the theory. More could be done to clarify the characteristics of complex systems and increase the practical utility of the complex systems approach. Consequently, this paper builds on the work of Bittencourt et al. (Bittencourt et al., 2016) and aims to 1) clarify the terminologies in the complex systems approach and adapt them for sports, 2) provide examples relevant to rehabilitation and 3) introduce tools that can model the complexity and increase practical utility in applied settings.

4.3 What is a complex systems approach?

4.3.1 A Complex systems approach to decision making in sports medicine

The complex systems theory, with more than 50 years of history (Bertalanffy, 1969), acknowledges the multifaceted nature of sports and seeks to understand the interactions among different factors and the outcomes of the systems (Bittencourt et al., 2016; Philippe & Mansi, 1998). Complex systems are dynamic, open systems (Von Bertalanffy, 1950). They are characterised by non-linearity due to feedback loops and interaction among the factors. This means that outputs are not always proportional to the inputs, and a small adjustment may lead to a large change in the systems and *vice versa* (Philippe et al., 2004).

In complex systems, factors that interact with each other to form the systems are known as units (Von Bertalanffy, 1950). In the context of RTS, these units could include age, wellness, biological healing of injured tissue, stress, external pressure and injury history. The units interact and define the space and dimension of the systems (Rickles et al., 2007). Consequently, different systems within systems emerge. These systems may be categorised based on their nature, for example, biomechanical, physiological and psychological. They may also be hierarchical and of multiple levels, namely individual, organisational and environmental (see Figure 1). The individual level represents factors related to the individual athlete, from tissue healing to personal traits. The organisational level represents external factors related to the sporting club, organisation and support team, e.g., the coaching and medical team. The environmental level covers factors beyond the organisational level, such as the weather, playing schedule and competition level.

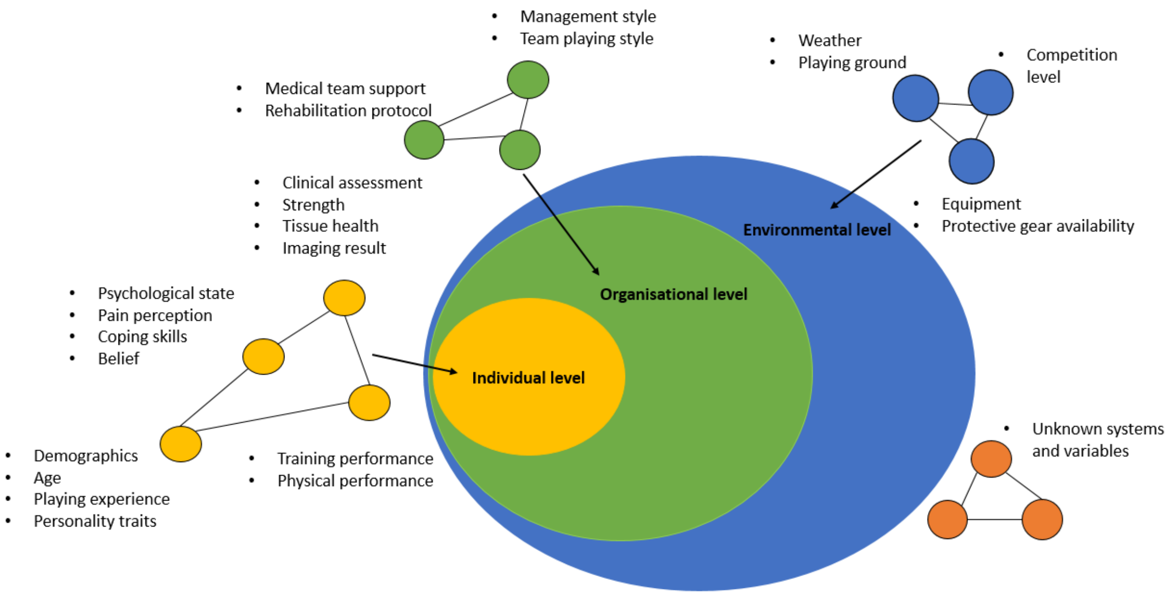


Figure 4.1 A multilevel system map with factors related to return to sport decision in anterior cruciate ligament injury.

In recent years, the complex systems approach has gained momentum and has been used to understand sports injury occurrence (Bittencourt et al., 2016; Hulme et al., 2017) and behaviour in sports performance (Dalton-Barron et al., 2020; Duarte et al., 2013; Mclean et al., 2019; Salmon & McLean, 2019). However, the terminologies used in complex systems are often less familiar to practitioners and could be easily confused with merely *complicated* or *multifactorial.* Most studies recognise the importance of considering multiple factors in determining readiness for RTS or in the context of injury recognition (Barber-Westin & Noyes, 2011; Bittencourt et al., 2016; Creighton et al., 2010; Grindem et al., 2016; Hartigan et al., 2010; Kyritsis et al., 2016; Logerstedt et al., 2014; Lynch et al., 2015; Gordon O Matheson et al., 2011; Shrier, 2015), but more work is required to raise awareness and explain why practitioners should adopt the lens of complex systems approach in rehabilitation.

4.3.2 Applying a complex systems model for ACL

This paper provides examples based on the 16 common features of complex systems recently illustrated by Boehnert et al. (Joanna et al., 2018). They are adapted for the context of sports in Table 4.1, with examples illustrated mainly from an anterior cruciate ligament (ACL) injury.

An ACL injury is used here as the case illustration as it is a serious injury that may threaten an athlete's career (Ekstrand, 2019; Walden et al., 2016). The estimated annual medical cost associated with ACL reconstruction surgery in Australia was over AUD$75 million per year (Janssen et al., 2012). Currently, there is no consensus regarding the optimal functional rehabilitation criteria (Lynch et al., 2015) and objective physiological RTS criteria (van Melick et al., 2016). Despite ACL injuries being one of the most researched topics in the sports medicine literature (Anderson et al., 2016), the re-injury risk of ACL remains high (Della Villa et al., 2021; Paterno et al., 2014). The complexity within ACL RTS may be explained at the individual, organisational and environmental levels.

Table 4.1 The 16 common features of complex systems adapted for return-to-sport

Characteristics	Definition	Example
1. Feedback	Units in a complex system are mutually interacting and output is fed back and becomes a new input (Davids et al., 2014). The feedback could be positive or negative. For example, positive feedback increases the rate of change while negative feedback works by reversing the direction of change.	Rehabilitation training leads to tissue adaptations, which improves physical fitness and performance (positive feedback). However, maladaptation can occur (e.g., alteration in neuromuscular control and muscle damage), leading to suboptimal response, which may delay progress (e.g., delayed onset of muscle soreness). This acts as negative feedback for the systems, signalling the training intensity was too high.
2. Emergence	Emergent properties arise from the interactions of its units. The units serve as the building blocks for patterns to arise at higher levels (Holland, 2014).	After an ACL injury, injured athletes often train separately from the squad and have a different training regime. During this time of relative isolation and hardship, the athletes may build up a high level of resilience.
3. Self-organisation	Systems may order themselves spontaneously to form patterns and achieve an optimal or stable state (Rickles et al., 2007).	ACL is a key sensorimotor system for postural control, which helps to maintain and control upright posture (Grooms et al., 2016). Following an ACL injury, the brain activation profile will be affected and shift toward a visual-motor strategy, as opposed to a sensory-motor strategy. Instead of

		relying on movement and spatial awareness, people with ACL deficiency may rely more on the visual system, especially under challenging dynamic task constraints (Davids et al., 1999). This is an example of how the sensorimotor system self-organises to compensate for the loss of ACL.
4. Levers and hubs	Lever and hubs are key structures in the systems that play a crucial role in how the systems will behave. Identifying them could intervene in the systems effectively (Joanna et al., 2018).	There are exceptional factors that are influential in the RTS process and altering them may lead to rapid gain. In ACL rehabilitation, intense rehabilitation and patient motivation are established lever and hubs that may underpin a positive outcome following ACL rehabilitation (Grindem et al., 2015).
5. Non-linearity	Outputs are not always proportional to the inputs. Small changes may lead to a large change in the systems and vice versa (Rickles et al., 2007).	The same training stimulus can create a large recovery response (e.g., delayed onset of muscle soreness) on the first training session, but not subsequent training. This is because the body can non-linearly adjust to the training stimulus after the first session. The response exhibits a non-linear behaviour where the outcome (i.e., training response) is not proportional to the input (i.e., training stimulus).
6. Domains of stability	Many systems are dynamic however may eventually converge to a stable state. This stability will be maintained unless there is a significant perturbation (Davids et al., 2014).	Balance and proprioceptive training are often included in the ACL rehabilitation protocol. However, balance and technique training may not be effective in changing an athlete's knee joint kinematics or decreasing external knee moments during pre-planned and unplanned side-stepping (Donnelly et al., 2012). Similarly, gait mechanics are difficult to modify even after rehabilitation training and restoring muscle strength (Arhos et al., 2021). This may be because the systems have achieved a domain of stability and the parts of the systems are well-entrenched, making it very difficult or

		near impossible to change. Once the systems have achieved a state of stability, they can only be altered when the stimulus is strong enough to push them through the tipping point (Davids et al., 2014).
7. Adaptation	Components or actors within the systems can learn and evolve in response to the changes in the environment (Davids et al., 2014).	Some people with ACL deficiency may exhibit increased knee flexion at early stance and reduced extension in the mid to late stance (Roberts et al., 1999). This is an adaptation that allows hamstrings to be efficient synergists to ACL in walking (Li et al., 1999; Pandy & Shelburne, 1997) and to reduce the anterior translation force of the tibia (Roberts et al., 1999). This represents how the body adapts to ACL deficiency by bringing changes within the systems. The adaptation appears to happen autonomously, unconsciously, and without explicit programming.
8. Path dependency	Events and actions that occurred previously influence future states and decisions (Joanna et al., 2018).	ACL rehabilitation usually follows a path and one can only progress to the next stage by meeting a set of criteria. For example, in the early rehabilitation phase, progressive weight-bearing allows the knee joints to acclimate to increased load and assist in developing a normal gait pattern (Bousquet et al., 2018; Cavanaugh & Powers, 2017). Plyometric training is only incorporated if a full range of motion (ROM), sufficient strength base, and flexibility are demonstrated. For on-pitch rehabilitation, activities should begin with simple drills and advance to more complex exercises (Cavanaugh & Powers, 2017). A control-chaos continuum could be followed on-field, where rehabilitation training constraints progress from high control to high chaos (Taberner et al., 2020).

9. Tipping point	If the perturbation of a system goes beyond a certain threshold, there will be a phase transition in the system's behaviour which may not be reversible (Davids et al., 2014).	In ACL rehabilitation, one of the early goals is to strengthen lower limb muscles to minimise muscle atrophy (Gokeler et al., 2014). Squat exercise may be used as a training stimulus (perturbation) and may cause micro-tears and inflammation of the muscle fibres (the system deviates from the stable state). The neuromuscular system will repair and adapt (the system returns to a stable state), leading to muscle hypertrophy (Kraemer & Ratamess, 2005). However, if the intensity and volume exceed the capacity of the soft tissue, there will be a loss in stability (e.g., quadriceps muscle strain) and it could not relax back to the previous stable state automatically. There will be a change in system behaviour (i.e., re-injury (Kibler et al., 1992)).
10. Change over time	Systems are dynamic and can evolve over time. This is because they constantly interact and negotiate with the environment, leading to continuous change (Davids et al., 2014).	The psychological characteristics of athletes can change during the ACL rehabilitation process and affect how they cope with RTS and future injury (Langford et al., 2009). In the physical performance aspect, training capacity evolves and generally declines with age (Faulkner et al., 2008). For example, the heart rate maximum during exercise declines with age (Gellish et al., 2007); maximal oxygen consumption is inversely and strongly related to age for active and endurance-trained populations (Wilson & Tanaka, 2000).
11. Open system	Complex systems are considered open, as it is difficult to define their boundary. The systems interact with the environment and are continuously influenced by the environment. In contrast, closed systems are systems where the influence of the	The size of the systems could hardly be defined, as things in the environment that are seemingly small may also influence them. For example, wet training ground affects athletes' ground reaction force and movement strategy during running (Dowling et al., 2010). Shoe designs and types of playing surfaces are related to ACL injury risk due to shoe-surface

	environment on it is negligible (Rickles et al., 2007).	friction (Thomson et al., 2015). Playing music during rehabilitation training may reduce the perception of physical effort during training and improve physical performance by delaying fatigue or increasing work capacity (Gabana et al., 2015; Karageorghis et al., 2013).
12. Unpredict-ability	Due to non-linearity and emergence properties, it is difficult to predict how the systems will evolve (Bittencourt et al., 2016).	Precise forecasting when an athlete can RTS is challenging. It is difficult to predict the estimated time for recovery as there is unpredictability in how the systems evolve. For example, how will the motivation of an athlete change throughout rehabilitation? How will the change in a personal relationship affect the athlete's performance? In some cases, gathering, storing, and using all of the information about the state of complex systems at one point to predict the outcome is impossible.
13. Unknowns	There are always units that influence the systems which are either unknown or could not be observed or measured. Therefore, it may seem that the systems evolved unpredictably (Bittencourt et al., 2016).	There are factors that decisions makers may not be aware of during the ACL rehabilitation due to different reasons, for example, limited knowledge (e.g., how genetic variant is associated with ACL rehabilitation and injury risk?), technology constraints (e.g., how reliable are the measurement tools?), insufficient resources (e.g., is it possible to measure everything?), bias and issues that stakeholders have been unaware of.

14. Distributed control	Control of a system is distributed across different parties and no one has complete control over the systems (Bittencourt et al., 2016). There is no top-down control approach as a single factor does not control the process at a superior level.	The success of ACL rehabilitation is determined by all interacting units, from biological graft healing at the microscopic level to intra-personal factors (clinical assessment, functional test, and biopsychosocial factor) and inter-personal factors at the macroscopic level. No single factor in isolation could determine the success of the outcome.
15. Nested system	There are nested hierarchies within the complex systems, forming systems within systems (Joanna et al., 2018).	ACL rehabilitation itself exhibits nest hierarchies in the following order: Cell> muscle> brain> inter-personal> family and friends> organization> environment At the cell level, shortly after graft implantation, fibrous scar tissue will be formed between the graft and host bone (Kawamura et al., 2005), followed by ligamentisation (Arnoczky et al., 1982). At the muscular system level, quadriceps muscle atrophy and dysfunction are commonly observed after ACL reconstruction and is often associated with altered movement pattern (Ithurburn et al., 2015; Lewek et al., 2002), possibly due to alterations in the brain (motor cortex) level and neurophysiological changes in muscles (Kuenze et al., 2015; Lepley et al., 2015; Luc-Harkey et al., 2017; Zarzycki et al., 2018). At the intrapersonal level, physiological cardiac adaptation (Steding-Ehrenborg et al., 2013), and aerobic fitness (Almeida et al., 2018) are all substantially reduced after an ACL injury. At the interpersonal level, social support plays a key role in regaining confidence and eradicating the fear of re-injury throughout rehabilitation (Carson & Polman, 2008; Magyar & Duda, 2000; Podlog & Eklund, 2006).

16. Multiple scales and levels	Multiple perspectives are required when viewing complex systems. The systems are three-dimensional and interactions within the systems often occur at different scales and levels (Joanna et al., 2018).	Rehabilitation can be considered on biological, psychosocial, or performance levels. There is more than one domain involved, and the systems must be understood from multiple perspectives.

4.4 Implications for practice and future research

By illustrating the features of complex systems with a common sports injury, we highlight its practical utility in RTS. The complex systems approach provides a theoretical framework for interpreting the patterns that emerged from biopsychosocial and other external factors. In ACL rehabilitation, conducting independent clinical tests and functional assessments may provide useful information regarding the athletes' physical and mental status. However, a complex systems approach facilitates a more complete picture of the problem and an increased awareness of how different factors may interact.

There are two challenges to using the complex systems approach: 1) The high degree of complexity may deter practitioners who do not have formal training in handling large and complex datasets from using this approach, 2) Unlike studying in a controlled laboratory environment, it is near impossible to isolate a portion of the larger systems (i.e., isolation of the biological healing process from broader biopsychosocial factors). Fortunately, many computer-based decision support systems can now incorporate features of complex systems in their design and utility. For example, to operationalise one of the above features, "change over time", the working model can allow flexibility in updating the baseline and encourage repeated testing at multiple time points during the rehabilitation. We believe practitioners who understand complex systems will be well-positioned to efficiently articulate their needs with analysts and ultimately develop decision support systems that inform best practices (e.g., RTS decision making).

Computer simulation (e.g., agent-based modelling), machine learning and Bayesian network (BN) analyses are all potential tools for analysing both non-complex or complex systems (Peterson & Evans, 2019). These methods can consider the dynamic interaction at multiple levels simultaneously, consequently viewing RTS more completely and supporting decision making. These analytical tools may help to achieve the following: 1) Allow practitioners to study and compare the potential outcome (e.g., the likelihood of reinjury) of different decisions that are otherwise almost impossible to test safely in real life, 2) Increase the decision efficiency by learning from previous experience and streamlining data from multiple sources and formats, 3) Identify patterns in data that may cause a certain outcome.

These techniques can be used to construct clinical decision support systems, which may complement or be superior to human decisions. In a review of seventy studies, a decision support system improved clinical practice in 68% of trials (Kawamoto et al., 2005). These decision support systems have also provided more accurate diagnoses than human experts in some medical fields (Kunhimangalam et al., 2014; Martinez-Franco et al., 2018). Yet, applying these approaches in RTS is still scarce in the literature. As such, we have provided a vignette here to outline how machine learning and Bayesian network could be applied to support RTS decision making:

A 30-year-old professional female football player tore her hamstring ten days ago during the season and a grade II hamstring strain was diagnosed. There is an important match in two weeks' time. The practitioners and the coach would like to ask six relevant questions, as covered in the below sections. Ultimately, the coach would like to know as early as possible about the availability of the player such that they could plan for the player's list and hence the game strategy.

4.4.1 Machine learning techniques

As a subfield of artificial intelligence (AI), machine learning focuses on the use of data to train algorithms that can make classifications or predictions (Mohammed, 2017; Tibshirani, 2013). That is, it could recognise new meaningful correlations, patterns and trends in a large amount of data (SoleimanianGharehchopogh et al., 2012). Machine learning techniques are suitable for non-complex analysis and can also accommodate multi-dimensional analysis in sport (Edouard et al., 2020; Witten et al., 2011). New data could also be input into the model for it to learn and improve the task, leading to the refinement of skills (Mohammed, 2017).

The goals of machine learning techniques in sports medicine settings can be divided into predictive and descriptive modelling (Han, 2012). Specifically, predictive modelling can be used for injury prognosis, diagnosis, and rehabilitation planning. Descriptive modelling can be used to characterise the general property of an injury, such as its severity, as well as include hypotheses of causality. However, as with traditional statistical approaches, machine learning techniques are simply a data analysis method, providing a prescriptive or descriptive output. Appropriate study designs are required to understand and estimate causal relationships, such as randomised controlled trials. Machine learning is often characterised by five major approaches (i.e., association, classification, clustering, relationship modelling and reinforcement learning), each having already been applied for injury risk assessment and/or performance prediction in sports (Claudino et al., 2019; Cust et al., 2019; Fältström, Kvist, et al., 2021; Rossi et al., 2019; J. Ruddy et al., 2018). Each of these approaches could serve as a method to answer questions relevant to RTS.

Question 1: Should the athlete progress to full training?

Scenario: The athlete has completed ten days of rehabilitation training. The practitioners would like to assess whether the athlete is ready to progress to full training. An association approach could be used here, using the rule-based system.

Table 4.2 The association rule approach to determine should the athlete progress to full training.

<table>
<tr><td>Approach</td><td>Association rule</td></tr>
<tr><td>Task</td><td>Supervised or Unsupervised</td></tr>
<tr><td>Technique</td><td>Association rule (arules)</td></tr>
<tr><td>Output type</td><td>Categorical
Examples: Ready for full training, not ready for full training, continue rehabilitation.</td></tr>
<tr><td>Application example</td><td>
<table>
<tr><td><u>Rule 1</u>
Range of motion full</td><td><u>Rule 2</u>
Limb asymmetry index 100%</td><td><u>Rule 3</u>
Training load >100% match requirement</td><td><u>Rule ….</u></td><td><u>Decision</u></td></tr>
<tr><td>✓</td><td>✓</td><td>✓</td><td></td><td>✓Ready for full training.
progress</td></tr>
</table>
</td></tr>
</table>

	✓	✗	✗		✗ Not Ready for full training
	✓	✓	✗		- Continue current rehabilitation

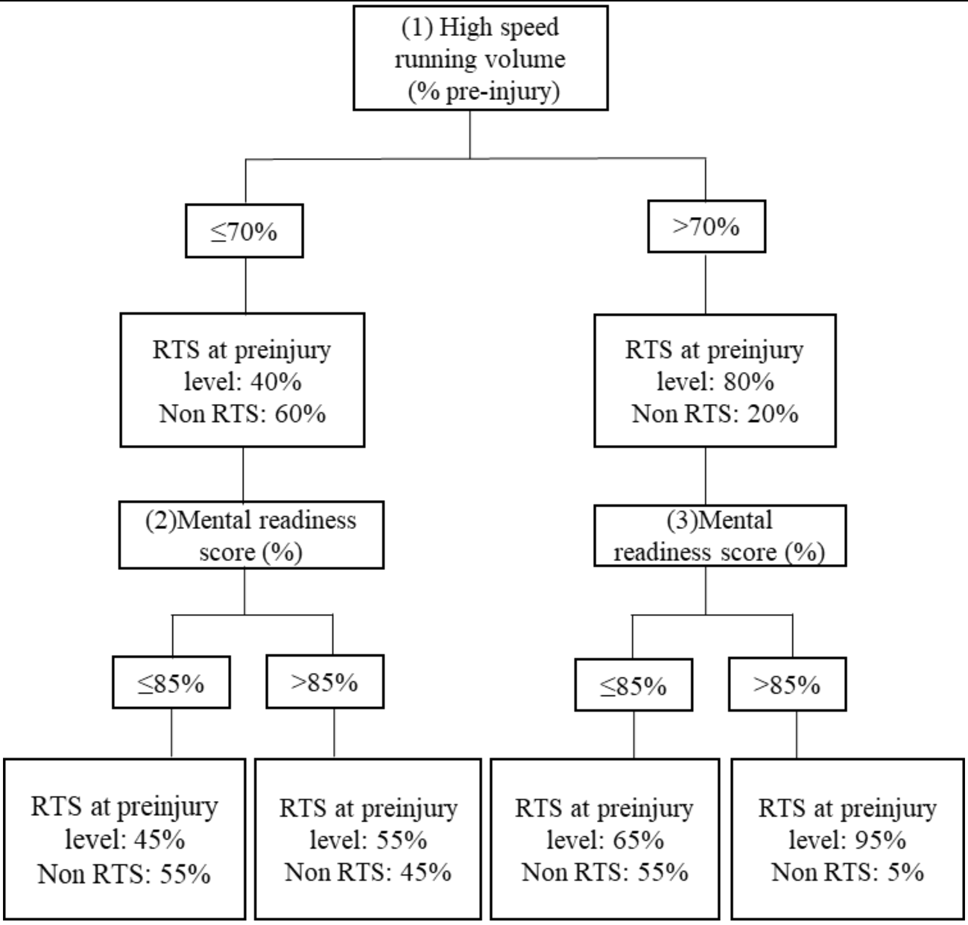
Association rules are used to uncover hidden patterns or relationships (Agrawal & Srikant, 1994). Often less identifiable by the clinicians, the rules identified may help them formulate optimal rehabilitation program. This is typically done using data mining techniques, where large amounts of data are analysed to identify interesting patterns and relationships. One popular algorithm for generating association rules is the Apriori algorithm. This algorithm works by first identifying frequent itemsets (i.e., sets of items that occur together frequently), and then generating association rules based on these itemsets. Agrawal et al. (1993) provides additional information on the underlying methodology.

In the above hypothetical example, a multivariate analysis of rules associated with a rehabilitation outcome is conducted. The model was set to only produce three categories of rules that contained the rehabilitation outcome as a result (i.e., ready for full training, not yet ready and unchanged). These could be the three rules most strongly associated with the rehabilitation outcome. A tick represents the presence of the context within the rule. The system could identify the number of rules required based on previous rehabilitation experience and implement the rules when the complexity of the content are beyond human brain capacity. An increased number of rules may better represent complexity, however, it may potentially make the solution more difficult to operationalise practically.

<u>Question 2: What is the likelihood that the athlete could return to the pre-injury level, given the current level of training?</u>

Scenario: There are only two weeks until an important match. The coach would like to know the likelihood that the athlete could return to pre-injury level by then. Given the volume of high-speed *running training that the athlete has completed, a classification method could be used to identify the likelihood.*

Table 4.3 The classification approach to identify the likelihood for an athlete to RTS.

Approach	Classification
Task	Supervised
Technique	Decision tree and Random forest
Output type	Categorical or Continuous Examples: Ready to compete, not yet ready to compete.
Application example	

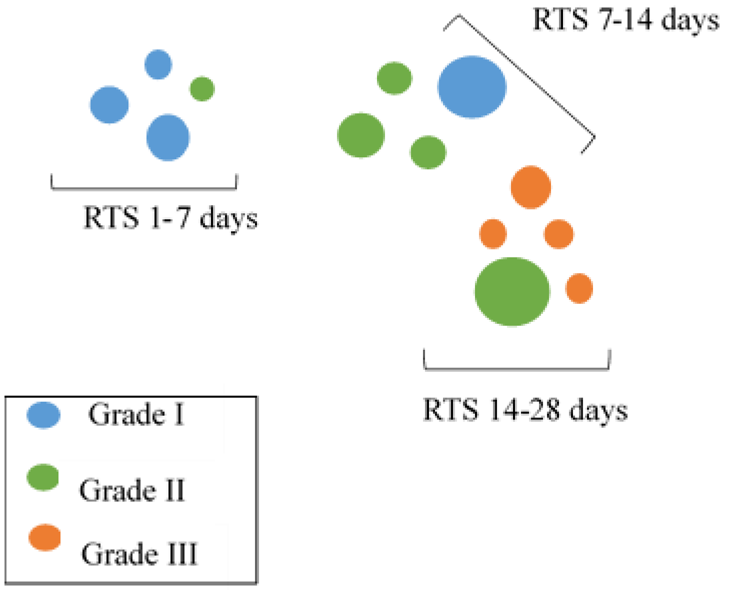
Classification is a type of supervised learning in machine learning that involves predicting a categorical label or class for a given input. In classification, a machine learning algorithm is trained on a labelled dataset, where each data point is associated with a specific class or label. The goal of the algorithm is to learn a mapping between the input features and the corresponding output label, so that it can accurately classify new, unseen data. Some common classification algorithms include decision trees, logistic regression, support vector machines (SVM), k-nearest neighbours (KNN), and naive Bayes. These algorithms use different mathematical techniques and assumptions to learn the mapping between input features and output labels, and they have different strengths and weaknesses depending on the specific task and dataset. Table 4.3 shows a graphical representation of the decision tree that used a classification algorithm to identify the probability of RTS from a hamstring injury. A decision tree uses dichotomous divisions to create the classification algorithm and can be used to develop a clinical decision algorithm for RTS (Albano et al., 2020; Fältström, Kvist, et al., 2021). Each node denotes a test on an attribute value and each branch represents an outcome of the test, with the leaves representing the class. In Table 4.3, each node is associated with a rule condition, which branches off to the child node. In this example, the outcome of RTS is likely a nonlinear relationship with the training volume and mental readiness, which is a characteristic of the complex systems approach (see Table 4.1, example 5). Using the classification approach may help to include non-linearity in analyses and readers who are unfamiliar with the methodology can refer to a comprehensive review chapter (Kotsiantis et al., 2007).

Question 3: When is the athlete expected to return to sport?

Scenario: The coach would like to know when the athlete is expected to RTS based on the experience of the clinician and also accounting for the athlete's age. A clustering technique could be used to analyse the past data.

Table 4.4 The clustering approach to identify when the athlete may return to sport.

Approach	Clustering
Task	Unsupervised
Technique	K-nearest neighbours
Output type	Categorical

<table>
<tr><td></td><td>Examples: RTS Grade, days to RTS.</td></tr>
<tr><td>Application example</td><td>
</td></tr>
</table>

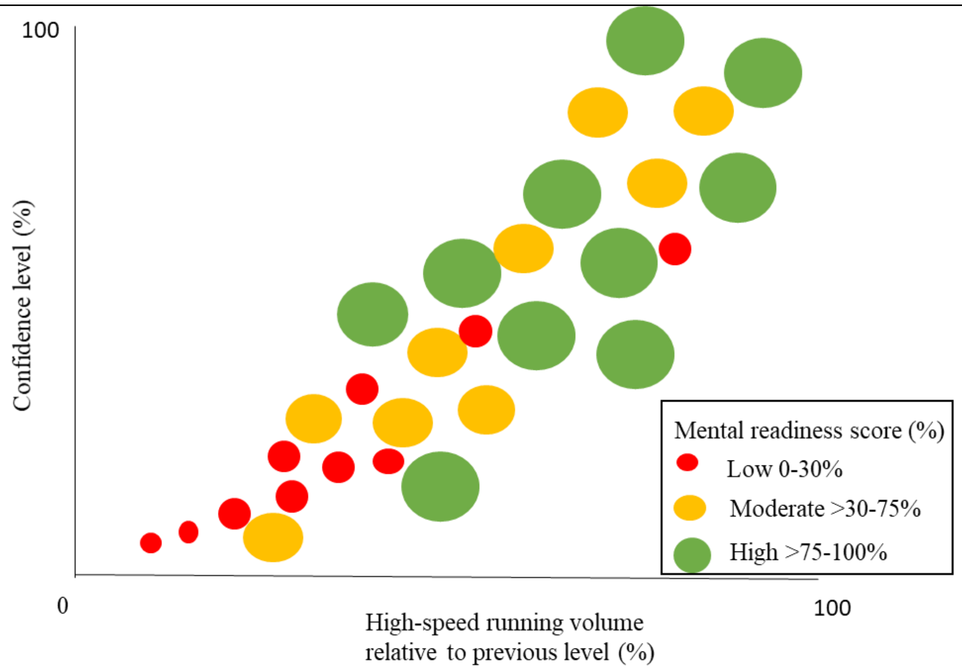
Clustering is a machine learning technique that involves grouping similar data points into groups based on their features (Jain & Dubes, 1988). The goal of clustering is to partition a dataset into subsets, or clusters, in such a way that data points within the same cluster are more similar to each other than to those in other clusters. Clustering is an unsupervised learning method, meaning it does not require labelled data or predefined categories. The main objectives include data exploration, data segmentation, anomaly detection, customer segmentation, image and object recognition and document classification. In sports, this may be useful in allocating multiple athletes to training groups. This could be done for clinical presentation, playing position, demographics, or inter-and intra-personal factors. Jain et al. (1999) provide more in-depth knowledge of clustering methodology.

Table 4.4 visualises one of the multiple approaches to which injured athletes could be clustered. Each dot represents an injured athlete and is coloured based on their severity. Size represents a measure of each athlete’s age, with a larger size representing older age. They are further grouped into three different clusters, representing the severity and time to RTS. In this hypothetical example, the model output is the predicted days to RTS. However, it could also be designed to produce categorical outputs such as being ready to train or not yet ready to train.

<u>Question 4: The athlete has a high level of mental readiness. Would that change the confidence level of the athlete's readiness to play an important game?</u>

Scenario: From the clustering approach, the coach has considered that the athlete may require at least two weeks to return to competition at pre-injury level. However, the coach noticed that the athlete had a high level of mental readiness, as reflected by relevant measures (e.g., the Injury-Psychological Readiness to Return to Sport scale (Glazer, 2009)). The coach would like to know how this new information, combined with the previous knowledge, may change the practitioner's judgement. A relationship modelling approach described below is used.

Table 4.5 The relationship modelling approach to identify the effect of mental readiness.

Approach	Relationship modelling
Task	Supervised
Technique	Regression
Output type	Continuous
Application example	

Relationship modelling is a statistical technique that relates a dependent variable to one or more independent (explanatory) variables. They can show whether changes observed in the dependent variable are associated with changes in one or more of the explanatory variables. Relationship modelling involves estimating relationships between a dependent variable and one or more independent variables. Regression analysis, commonly used in the analysis, is also a type of relationship modelling technique and could be used with the complex systems approach. For example, it could be used for modelling the relationship between outcomes, such as match results (Robertson et al., 2016) and injury incidence (Ruddy et al., 2018). There are various types of regression models, depending on the nature of the data and the relationship between the variable, such as multiple linear regression, logistic regression and Bayesian time series regression model. Readers interested in the details of the methodology refer to Vittinghoff et al. (1999).

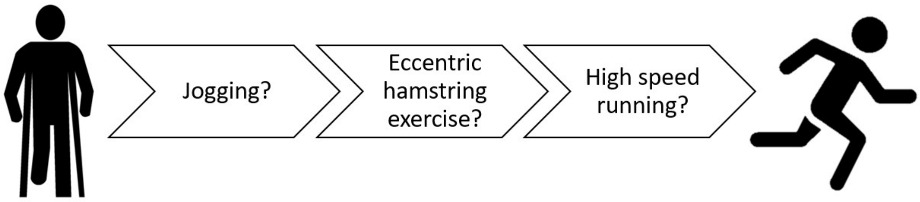
Table 4.5 shows a hypothetical example of how the confidence to RTS (y-axis) may be associated with the volume of high-speed running done (x-axis) and the mental-readiness score (size of the bubble). The size of the bubble denotes the level of mental readiness. A higher level of mental readiness is indicated with a larger size bubble and is in green colour. A lower level is indicated with a smaller size and is in red. The association could be multi-dimensional and could be constructed based on the number of inputs available, e.g., running speed, load accumulation, and psychological readiness.

Question 5: What is the optimal sequence of rehabilitation in a case of hamstring injury rehabilitation?

Scenario: After reviewing the dataset, the coach and the clinician would like to explore how to leverage the available data further and identify adaptive, personalised treatment plans in the future. Reinforcement learning may help optimise the decisions that favour a long-term outcome. Reinforcement learning is described below.

Table 4.6 Use of reinforcement learning to optimise the sequence of rehabilitation.

Approach	Reinforcement learning
Task	Not applicable
Technique	Markov decision process

Output type	No output variable
Application example	

Reinforcement learning is a type of machine learning where an agent learns to make decisions by interacting with an environment to maximise a cumulative reward. Unlike supervised or unsupervised learning, reinforcement learning trains itself through trial and error to explore behaviours in the system that could maximise the expected cumulative reward over time. (Richard & Andrew, 1998). The agent uses this learned policy to decide what actions to take in various states of the environment. This feature made it suitable for solving sequential decision problems. In this clinical vignette (Table 4.6), reinforcement learning could help to identify a personalized rehabilitation pathway for maximising the reward (i.e., managing the injury or reaching the rehabilitation goal). A recent review is available for readers unfamiliar with the background and use (Gottesman et al., 2019).

In the context of a hamstring injury (see Table 4.6), a practitioner has to decide when to initiate and adjust rehabilitation training, such as jogging, eccentric hamstring exercise, and high-speed running. Each decision affects the athlete’s rehabilitation outcome at the end of the program and the total days of absence. The rewards require practitioners’ input, such as comparing the intensity and volume of high-speed running to the pre-injury. The reliability of the model’s outcome depends heavily on the data used to train the algorithm used in the reinforced learning, and the extent to which the proposed and observed treatment policies agree.

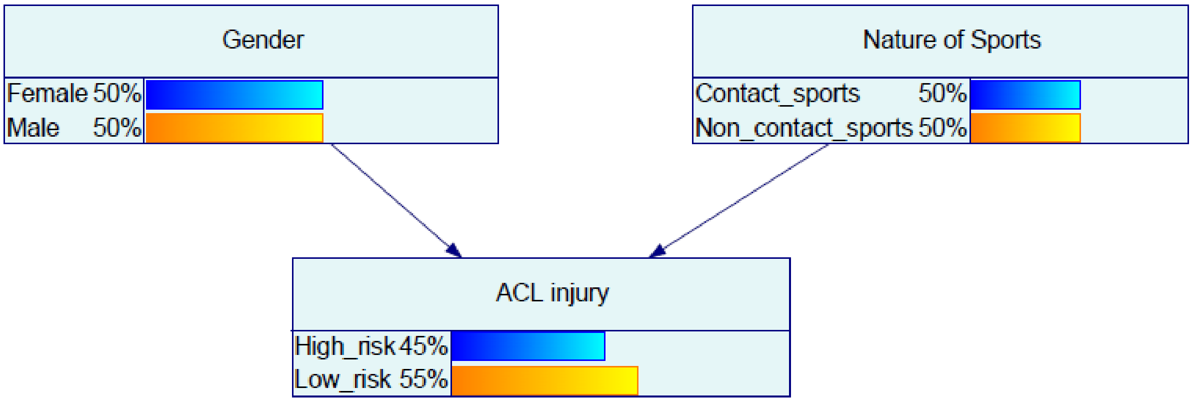
4.4.2 Bayesian network

Besides the machine learning approach, Bayesian methods are becoming increasingly popular in the study of sports (Santos-Fernández et al., 2019) and may contribute to RTS. Various forms of Bayesian network (BN) have been applied across different sectors, including medical (Fenton et al., 2020; McLachlan et al., 2020; Seixas et al., 2014; Yet et al., 2013; Yet et al., 2017), ecology (Johnson et al., 2010; Wu et al., 2018; Wu et al., 2017) and transportation (Wu et al., 2014).

BN uses Bayesian inference for probability computations and can be visually presented using directed acyclic graphs. Arrows on the BN, known as directed arcs, indicate the direction of the influence (Constantinou & Fenton, 2018). These show how various discrete or continuous factors in RTS influence one another and the outcome through a graphical presentation (Constantinou & Fenton, 2018). BN calculates the conditional probabilities of the outcome of a decision when the value of some of the factors has been observed. As new evidence is revealed, changes are brought to the conditional probability of the decision outcome (Eugene, 1991).

Question 6: How would the sex of the athlete affect the perceived ACL injury risk?

Scenario: The athlete has now recovered from the hamstring injury but is worried about the potential ACL injury risk. The coach wants to know how the sex of the athlete (prior) [as female] would affect the ACL injury risk (outcome) [higher risk of ACL injury] (Fig.4.2) (Montalvo et al., 2019), and how it may inform the potential consequence of a RTS decision.



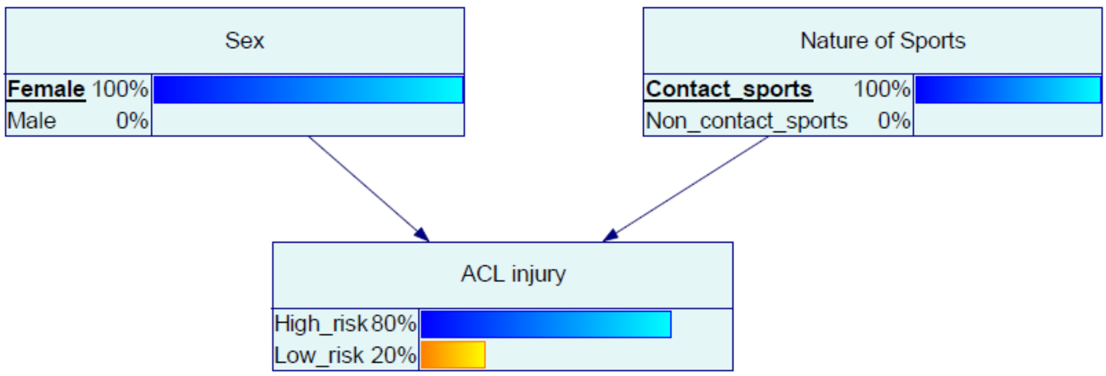


Figure 4.2 Illustration of a Bayesian network before (top) and after it has been updated with a prior (sex or/and nature of sport) (bottom). The outcome of the prediction (ACL injury risk) has changed as a result.

Only one prior is used here to explain the application for easier understanding. However, a BN can account for multiple variables to increase the model's accuracy and acknowledge the complex systems approach, as seen from a hypothetical example in Figure 4.3.

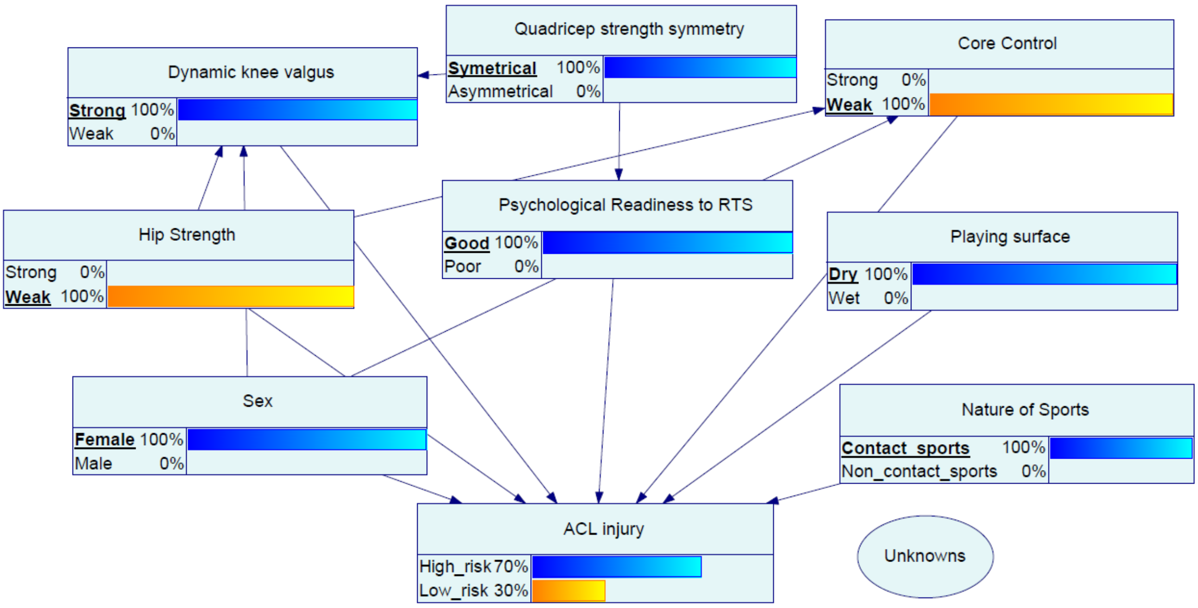


Figure 4.3 A hypothetical example of a Bayesian network with multiple priors for ACL injury risk.

A BN could be operated in both directions, performing both predictive and diagnostic inference. As an example, a BN may provide the following information to support RTS decisions: 1) Given the observation of the athlete's rehabilitation markers, what is the likelihood for the athlete to perform at pre-injury level upon RTS? 2) To increase the likelihood of achieving certain outcomes of RTS, what is the combination of test results and/or observations required?

Logically, BN seems to fit into the requirement of RTS decisions, as often multiple unknown factors are involved in the process (e.g., how wellness may be associated with the injury risk). Although these unknown parameters are uncertain, they could be described by a probability distribution table, with information supplied by a domain expert or relevant literature.

Establishing a BN requires data and could be complemented by expert knowledge (Constantinou & Fenton, 2018). Expert knowledge allows the model to specify the available decision options and the utilities the user is after. For example, decision makers may decide if the utility (degree of satisfaction) of the RTS outcome is based on either maximising the team performance, minimising the risk of subsequent injury, or equilibrium between the two. However, this also implies that the quality of the model output would rely on the quality of the existing evidence and expert knowledge, which may be flawed or biased.

4.5 Future research

A shift towards a complex systems approach may help to view RTS more realistically. Future research should be mindful of the following issues:

1) The complex systems approach and machine learning techniques cannot necessarily elucidate the causal mechanism. Based on Table 4.1, the characteristics of the complex systems do not permit the ability for cause-and-effect relationships to be determined. However, that does not imply they are inappropriate for understanding a problem nor are they of low practical utility.

2) The computation accuracy relies heavily on the dataset's quality and previous knowledge. For example, what is the association between different variables (e.g., age, playing style, previous injury history, culture, and lifestyle)? What is the potential effect of external factors (e.g., stress, financial pressure, lack of social support) on RTS progress and decision making? Currently, there is insufficient evidence on these aspects. High-quality randomised controlled trials and longitudinal research that acknowledges the complex systems approach is required to observe regularities that are antecedent to the success of a rehabilitation program.

3) The RTS systems that researchers could construct consist of what is available and known, rather than what is important. Some factors may be difficult to measure due to the availability of time,

and resources and its non-deterministic or qualitative nature (Bourne et al., 2003). For example, motivation for RTS during rehabilitation is important but often not measured due to difficulty in obtaining accurate feedback. However, this is inevitable, as unknowns and unpredictability are characteristics of complex systems. Nevertheless, real data should be applied if possible to prove the concept and provide useful output for practitioners. The ultimate goal of embracing complex systems approaches in RTS research is to resemble findings closer to the real world.

4.6 Conclusion

The complex systems approach has been applied to understand different aspects of sports science and medicine. This review has highlighted the characteristics and terminologies of complex systems, as exhibited by a case of ACL rehabilitation. When assessing the test result for clinical and functional tests, practitioners should also be aware of the dynamic systems evolving around the injury rehabilitation (refer to the examples in Table 4.1) and endeavour to understand the full picture. Future research may make use of computational modelling and machine learning techniques to identify the regularities of the pattern that emerged as a whole. A paradigm shift that results in applying a complex systems approach to understanding the RTS process and decision making should be encouraged.

Part 2 Practical applications

This section includes Chapters Five and Six, which consist of two original studies that adopt two different analytical methods. Part 2 builds on Part 1 and adopts techniques that are congruent with a complex systems approach. Making decisions with a complex systems approach is challenging because it may be nearly impossible for clinicians to integrate multiple data types and consolidate them quickly due to their limited short-term memory and cognitive processing power. To complement the frameworks in Part 1, Chapters Five and Six adopt two analytical methods that allow clinicians to 1) integrate multiple data types, 2) consolidate a high volume of data and 3) accommodate the characteristics of the complex systems, such as non-linearity and emergence.

5 Chapter Five: Study III

Chapter overview

Chapter Five is the third of the four studies contained in this thesis. It consists of an original case study that uses a change point approach to identify meaningful changes in the RTS continuum. Clinicians can apply the change point analysis to any other injuries to identify meaningful changes in RTS progression and make informed decisions.

The content of this chapter was submitted to the Science and Medicine in Football (Taylor and Francis) on 12th September, 2022. It is currently in resubmission stage, and the first revision was submitted on 10th January, 2023.

Clinical relevance

Clinicians often collect multiple rehabilitation data at regular time points during the entire RTS period to monitor the RTS process. While these longitudinal datasets may help clinicians evaluate the rehabilitation progress, there are challenges for clinicians to 1) integrate the multiple data types, 2) analyse the overall change and 3) accommodate the characteristics of complex systems. To support clinicians in evaluating their past practice and improving future decision quality, Chapter Five adopts an analytical method (change point method) to overcome the above challenges.

5.1 A change point method to detect meaningful changes in return to sport progression in athletes.

5.1.1 Key points

- Univariate change point analysis can determine the change point of a single measurement and provide information specific to each performance metric, which informs the rehabilitation progress based on a single metric.
- Multivariate change point analysis identifies a common change point across multiple sets of longitudinal data, giving an overall impression of the progression of the rehabilitation.
- Clinicians may further explore analytics tools to handle large complex datasets in rehabilitation.

5.1.2 Abstract

Return-to-sport (RTS) decision making is often challenging, as rehabilitation is complex and non-linear. With improvements to sports technology, clinicians are collecting more data and at more regular time points during rehabilitation to gauge the progression in their RTS. Analytical methods, such as change point detection, may leverage complex longitudinal data to detect when meaningful changes (change points) have occurred. To explore how the change point approach may be used in RTS, we present a single case study of a professional football player who sustained a lower-limb muscle injury during training. Four wellness metrics and five running performance metrics were collected over 124 days. In the univariate analysis, the change points for stress, sleep, mood and soreness were located on days 30, 47, 50 and 50, respectively. The change points for total distance, acceleration, maximum speed, deceleration and high-speed running were located on days 32, 34, 37, 41 and 41, respectively. The multivariate analysis resulted in a single change point for the wellness metrics and running performance metrics, on days 50 and 67, respectively. Clinicians can use similar techniques to integrate data from multiple sources, identify meaningful change points and evaluate athletes' progression along the RTS continuum.

5.2 Introduction

In competitive sports, clinicians often track rehabilitation progression to estimate when an athlete could return to full training and competitions. RTS decisions can be challenging as they are often characterised by uncertainties, such as re-injury risk, time pressure induced by competition schedule and social stress from coaches, families and supporters. In addition, the outcome of the RTS decisions pertains to the athletes' well-being (Leslie Podlog et al., 2015) and team performance (Hägglund et al., 2013).

In football, on-field rehabilitation typically comprises four stages (Dunlop et al., 2019): 1) return-to-running (clearance to train on-field), 2) return-to-modified training (clearance to train with the team in a modified capacity), 3) return-to-play (clearance to be selected for competition) and 4) return-to-performance (returns to pre-injury performance level). Clinicians typically decide when injured athletes can progress to the next phase by consolidating information from clinical and functional assessments and comparing the results to pre-injury level and/or different time points of rehabilitation. For example, in hamstring injury rehabilitation, clinicians may measure palpation pain, flexibility and outer range strength daily to inform rehabilitation progression (Whiteley et al., 2018). The test results, complemented by the clinician's experience, are sometimes used as a proxy to gauge the readiness of an athlete to progress in rehabilitation (Whiteley et al., 2018).

Much of RTS research has focused on establishing criteria for clearing the athlete to return to unrestricted sports (Ardern, Glasgow, et al., 2016). However, these criteria are outcome-oriented and intended to help clinicians determine the endpoint of rehabilitation. There is value in exploring methodology that can leverage longitudinal data and evaluate the progression along the RTS continuum.

Developing a methodology to inform the rate of progression requires consideration of rehabilitation as a dynamic, complex process — an environment constantly changing due to the interaction of multiple factors (Yung et al., 2022a). The constantly changing environment leads to the emergence of non-linear behaviours, which means that the outcome is not always proportional to the input. For example, the same rehabilitation training program will not always produce the same training response because the body adapts to the stimulus after the first few sessions (Yung et al., 2022a). New behaviours may also emerge as a result of individual rehabilitation, such as an athlete exhibiting an increased level of stamina and resilience. This may subsequently change the athlete’s perception towards the level of training intensity. As a result, clinicians may have difficulty forming the whole picture of the rehabilitation progress by tracking the rehabilitation metrics separately and then combining the partial results (Yung et al., 2022a). Furthermore, due to the characteristics of complex systems, merely tracking the change in one (or multiple) metrics is unlikely to reflect the overall shift within the systems.

It is impossible for clinicians to keep direct track of all the changes within the systems because humans have limited cognitive power in analysing and consolidating complex information (Miller, 1956; Yung et al., 2022b). When the information becomes too complex to understand, humans may be reluctant to make important decisions, and resort to actions such as procrastination and endless pursuit of better information (Sarma, 1994). Fortunately, clinicians can leverage machine learning techniques to handle large and complex datasets systematically (Yung et al., 2022a). Machine learning can analyse both data from non-complex and complex systems (Peterson & Evans, 2019) and could be potentially used to describe the complexity inherent in sports environments (Yung et al., 2022a). In sports medicine, analytics and machine learning techniques have been used in the area of injury prevention and prediction (de Leeuw et al., 2022; Karnuta et al., 2020; Rommers et al., 2020; Van Eetvelde et al., 2021) but have been rarely used to evaluate progression in RTS.

To evaluate the progression of training, clinicians can use a range of data types to quantify the internal (e.g., via subjective wellness scores (Impellizzeri et al., 2004)) and external workload (e.g., via global navigation satellite systems (GNSS) (Cummins et al., 2013)). In particular, GNSS devices are common in football and other field-based sports to measure the volume and intensity of on-field rehabilitation running performance (Stares et al., 2018; Taberner & Cohen, 2018). Based on the metrics derived from GNSS devices, clinicians can plan progressive loading and management throughout the stages of rehabilitation, for example, a gradual increment in total distance, high-speed running distance, acceleration and deceleration (Buckthorpe, 2019; Taberner & Cohen, 2018). In addition, clinicians may monitor athletes' wellness regarding their mental health and their subjective feeling towards the training intensity (Gastin et al., 2013; Taylor et al., 2012; Thorpe et al., 2017; Thorpe et al., 2015). With technological improvements, many of the above aspects can now be feasibly, conveniently, and routinely measured in many sports organisations. However, the complex dataset presents a new challenge: how can clinicians integrate, understand and visualise multiple data types simultaneously?

To explore methods that may support clinicians in decision making, this study aimed to explore an analytical approach known as the change point method. The change point method may help clinicians analyse longitudinal data collected during RTS and retrospectively evaluate the progression along the RTS continuum.

5.3 Methods

5.3.1 Design

We have registered this protocol in the Open Science Framework (OSF.IO/4P76B). This design is a prospective single case observational study of an athlete in a professional football club. Such study design may direct focus on the features and the methodology of the change point method. Ethics approval was obtained from the Victoria University Human Research Ethics Committee (HRE22-071).

5.3.2 Participant

The case was a football player who sustained an acute lower limb muscle injury during high-speed running in football training and returned to play at the pre-injury level as determined by the club's coaching staff. There was no interruption (e.g., COVID-19 isolation, personal leave) during the rehabilitation period. The rehabilitation program was entirely completed in the football club under the supervision of the club's medical team.

5.3.3 Data Collection

Data were prospectively collected during training sessions and competitions of the 2021/2022 Australian A-League season. The data consisted of two parts: 1) the pre-injury period, starting from the beginning of preseason to the day before the injury, and 2) the rehabilitation period, starting from the day of injury to the day when the athlete returned to play at the pre-injury level, as determined by coaching staff. The day when the injury occurred and the player was removed from training is denoted as day 0.

The four key stages of the RTS continuum in this study are defined as:

1. Straight-line running: The day when the athlete began basic running drills in a straight line. Training sessions were completed individually with the rehabilitation trainer.
2. Change of direction running: The day when the athlete began curve running, change of direction and agility training. The training may involve some ball work. Training sessions were completed individually with the trainer.
3. Modified training: The day when the athlete integrated with the main squad training for some training drills in a modified capacity. There were still some restrictions regarding the training intensity, movement and volume.
4. Full training: The day when the athlete was medically cleared to train with the main squad with no restrictions.

To determine the running performance in rehabilitation, the athlete wore a 10 Hz GNSS device (Apex Pro Series, STATSports, Newry, Ireland) placed on the back between the scapulae. Each unit included a 100-Hz accelerometer, magnetometer, gyroscope and 10 Hz GPS. The GNSS, which is certified by FIFA for use both in training and matches (FIFA, 2023), is validated to quantify running activities. The reliability and validity of these units have been previously reported. They display a high level of validity in total distance and maximal velocity team sport settings (Beato et al., 2018), as well as excellent inter and intra-unit reliability (Beato & Keijzer 2019). The device used has good inter-device reliability for the measurement of total distance and maximal velocity (Beato et al., 2018). These devices also possess suitable reliability and consistency for threshold-based accelerations and accelerations (Crang et al., 2021; Comier et al., 2023). The athlete wore the same device during all activities to reduce inter-unit error (Beato et al., 2018; Cummins et al., 2013) and no additional analysis was used to account for the variations within the data. Upon completion of each training session, all tracking data were downloaded using the proprietary software (Sonra 3.0, STATSports, Newry, Ireland). Among the metrics derived from the GNSS system, five metrics were selected after consulting the club's high-performance staff:

1. Total distance (m): Total distance covered in the session.
2. Maximum speed (km.h^{-1}): Maximum running speed attained in the session.
3. High-speed running (m): Distance covered above 5.5 m.s^{-1}
4. Accelerations: number of accelerations between 3.0 and 10 m.s^{-2} with a minimum duration of 0.5 s.
5. Decelerations: number of decelerations between -3.0 and -10 m.s^{-2} with a minimum duration of 0.5 s.

As part of the pre-training routine of the football club, the athlete also reported daily wellness scores on the mornings of the training days. The athlete rated sleep quality, mood, stress and overall soreness using a mobile phone application, on a scale 0-10 (10 being the best).

5.3.4 Change point analysis

Change point analysis is an analytical method to identify change points that segment a set of longitudinal data (e.g., the rehabilitation process) based on statistical features, such as the mean (Aminikhanghahi & Cook, 2017). As such, the behaviour of the subsequent segment is inherently different to the segment before the change point (Cho & Fryzlewicz, 2015). Univariate change point indicates when a meaningful change has occurred in a sequence value, implying a marked improvement or deterioration in a metric. In a multivariate change point analysis approach, a common change point is detected across multiple metrics (Bardwell et al., 2019). Change point analysis has been previously applied in medicine (Hall et al., 2000) and sports science (Corbett et al., 2019; Teune et al., 2022b) to detect the onset of illness or overall change in sports performance. In the context of RTS, clinicians can use it to detect meaningful changes in various clinical markers and determine when an athlete can progress in rehabilitation.

5.3.5 Statistical Analysis

The athlete's identifiers were removed before proceeding to statistical analysis. All data analysis was completed in *RStudio* software (version 1.3.1093) (R Core Team, 2019), using the R (version 4.03) programming language. The *cpt.mean()* function from the *changepoint* package was used to identify the time point during the rehabilitation period where there was a meaningful change in the sequence mean (Killick & Eckley, 2014). In applying a univariate change point analysis with one change point, each of the nine metrics in physical performance and wellness was analysed separately. To find one change point, the parameters set were AMOC (at most one change), which limited the algorithm to only search for a maximum of one change point in a segment. The minimum segment length was set to seven days, which means the shortest duration between the change points must be at least seven days. This parameter was set based on the practice at the club, where high-performance staff consider seven days as a training block. Setting the above parameters based on our research question and the context may minimise the inherent noise from the data and identify change points that may be practical and coherent. The metrics recorded in the pre-injury period formed a baseline for pre- and post-injury comparison.

To match the four phases of the RTS continuum, we identified three change points to compare with the three transitional points, that is, 1) return to change of direction running, 2) return to modified training and 3) return to full training. Similarly, *cpt.mean()* function was used. The method was set to binary segmentation to search for a maximum of three change points to align with the three transition points. Similar to one change point, we set the minimum segment length to seven days for the same reason outlined above.

A multivariate change point analysis was performed to determine a common change point across multiple metrics during rehabilitation (Bardwell et al., 2019). The *mrc* function from the *Change point.mv* package (Killick & Eckley, 2014) was applied across the four wellness metrics and the five performance metrics. This function identified a common and most recent change point across the groups of time series data (Bardwell et al., 2019). The parameters of the functions were set to search for a maximum of one change point and a penalty value of 100 was arbitrarily applied.

5.4 Results

A total of 124 days were included in the analysis. The pre-injury period consisted of 33 days, including 17 training sessions; the rehabilitation period consisted of 97 days, including 60 training sessions and 3 competitions. The means and standard deviations recorded in the pre-injury period and used as the baseline are as follows: For the wellness scores, sleep was 8.5 ± 0.7, mood was 9.1 ± 0.4, stress was 8.5 ± 1.0, and soreness was 8.0 ± 0.5. For pre-injury performance metrics, total distance was 7057 ± 1694 m, high-speed running was 588 ± 387 m, maximum speed was 28.1 ± 3.3 km.h^{-1}, the number of accelerations was 101 ± 36.1, and the number of decelerations was 72 ± 31.5.

5.4.1 Univariate analysis change point locations

Univariate analysis with one change point is shown in Figure 5.1 and the distribution of values within each segment is shown in Figure 5.2. The change points for stress, sleep, mood and soreness were located on days 30, 47, 50 and 50, respectively. The change points for total distance, accelerations, maximum speed, decelerations and high-speed running were located on days 32, 34, 37, 41 and 41, respectively.

In applying univariate change point analysis with a maximum of three change points, the result is reported in Figure 5.4. Across all metrics, three change points were identified, except for mood, where the change point algorithm could detect only two change points. The change points were located between days 27-54 (Figure 5.4). The distribution of values within each segment is shown in Figure 5.3.

5.4.2 Multivariate analysis change point locations

The multivariate analysis identified a single change point for wellness metrics and running performance metrics on days 50 and 67, respectively (Figure 5.5). The metric distribution before and after the change point was reported in Figure 5.6.

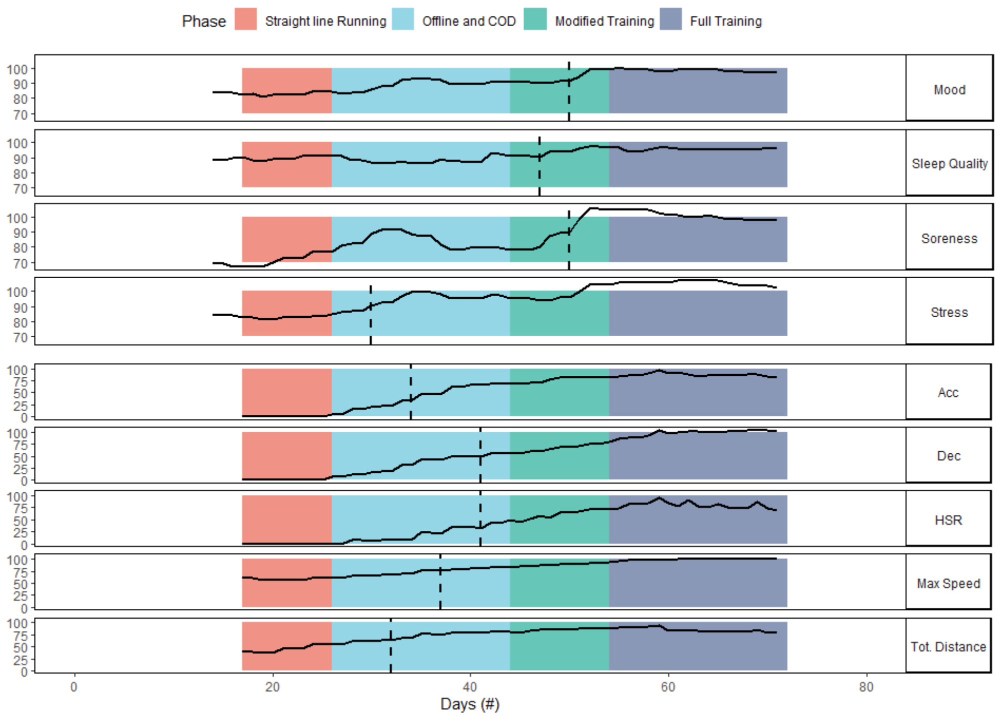


Figure 5.1 A univariate change point analysis of each metric, with one change point each. Data normalised to the percentage of pre-injury level. COD: Change of direction. Acc: number of acceleration; Dec: number of deceleration; HSR: high-speed running; Max Speed: maximum running speed; Tot. Distance: total distance.

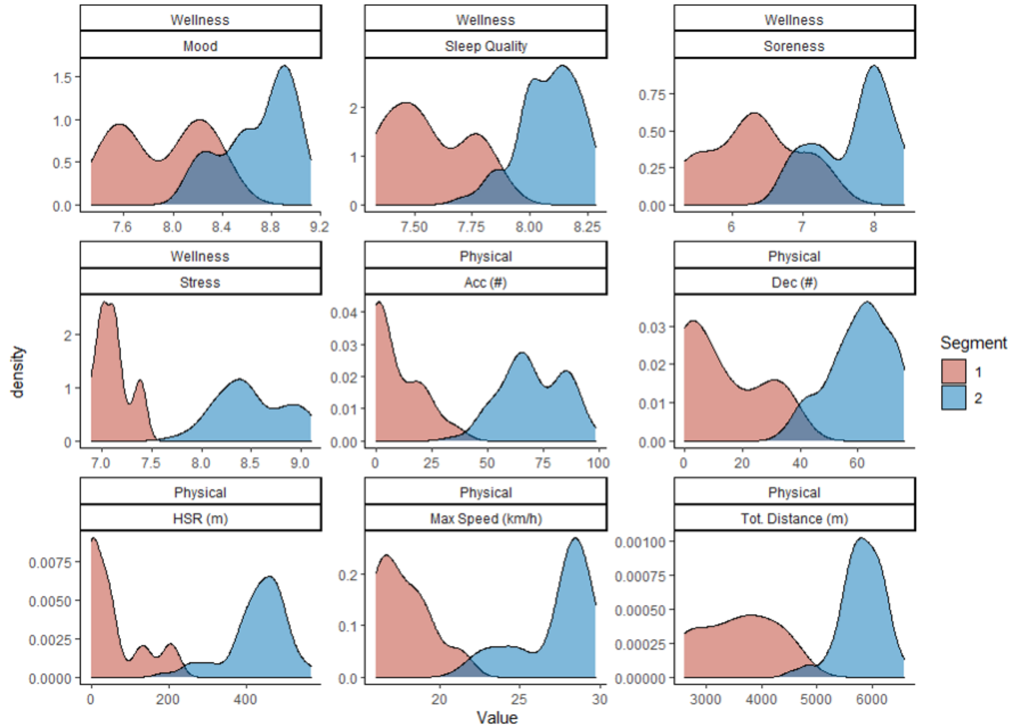


Figure 5.2 Distribution of the metrics in each segment of univariate analysis, before and after the change point. Acc (#): Number of accelerations; Dec (#): number of decelerations; HSR (m): High-speed running (m); Max. Speed (km/h): maximum running speed (km•h^{-1})

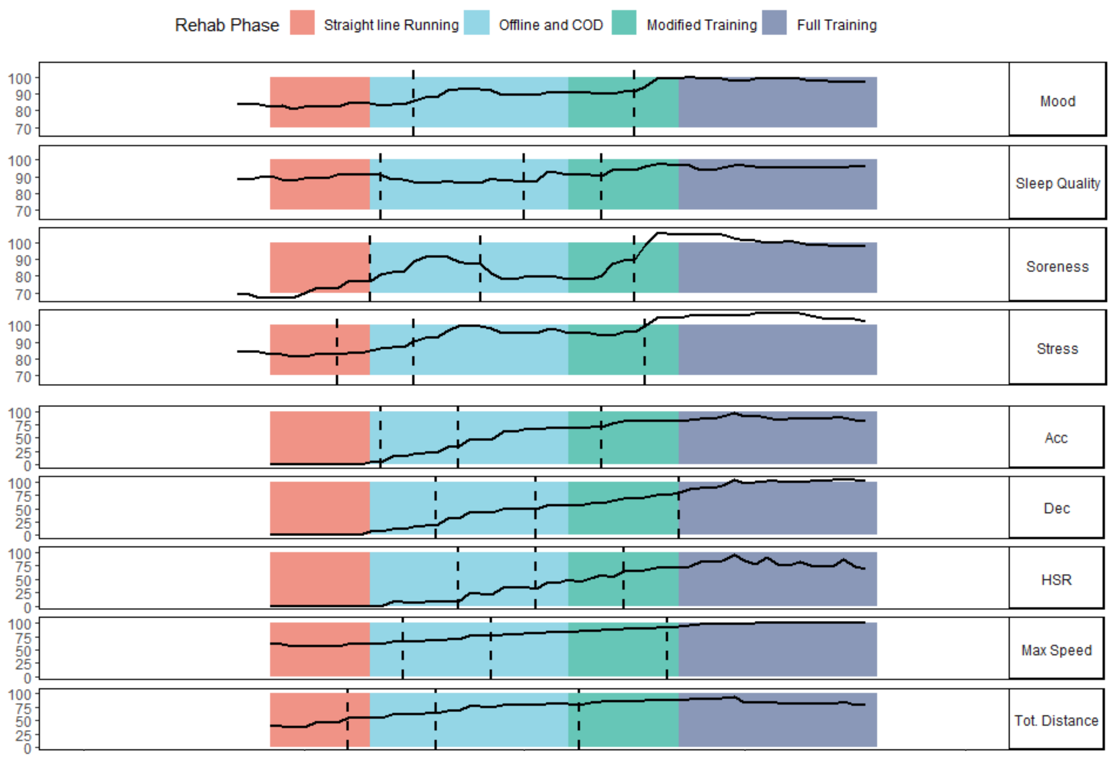


Figure 5.4 A univariate change point analysis of each metric, with three change points each (only two change points for Mood). Data normalised to the percentage of pre-injury level. COD: Change of direction. Acc: number of acceleration; Dec: number of deceleration; HSR: high-speed running; Max Speed: maximum running speed; Tot. Distance: total distance.

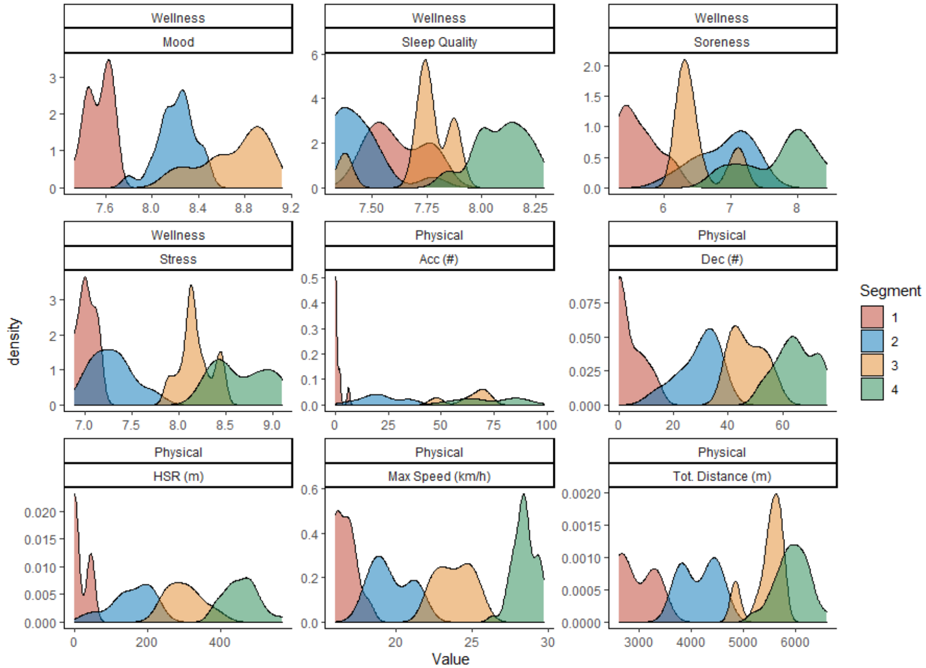
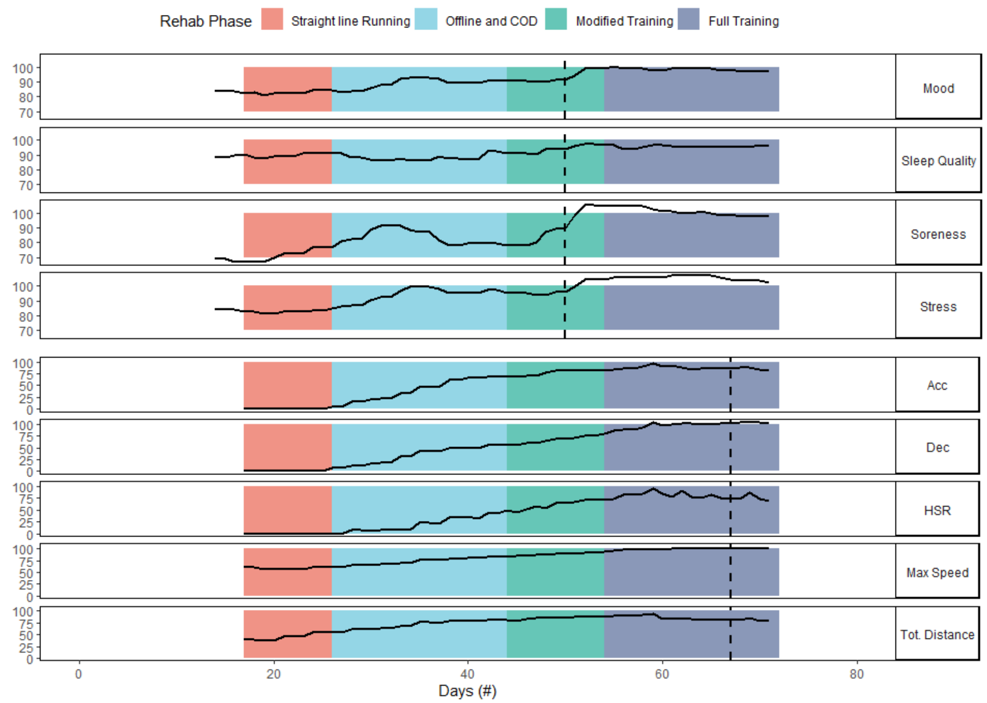


Figure 5.3 Distribution of the metrics in each segments of univariate analysis, before and after the multiple change points. Acc (#): Number of accelerations; Dec (#): number of decelerations; HSR (m): High-speed running (m); Max. Speed (km/h): maximum running speed (km•h^{-1})



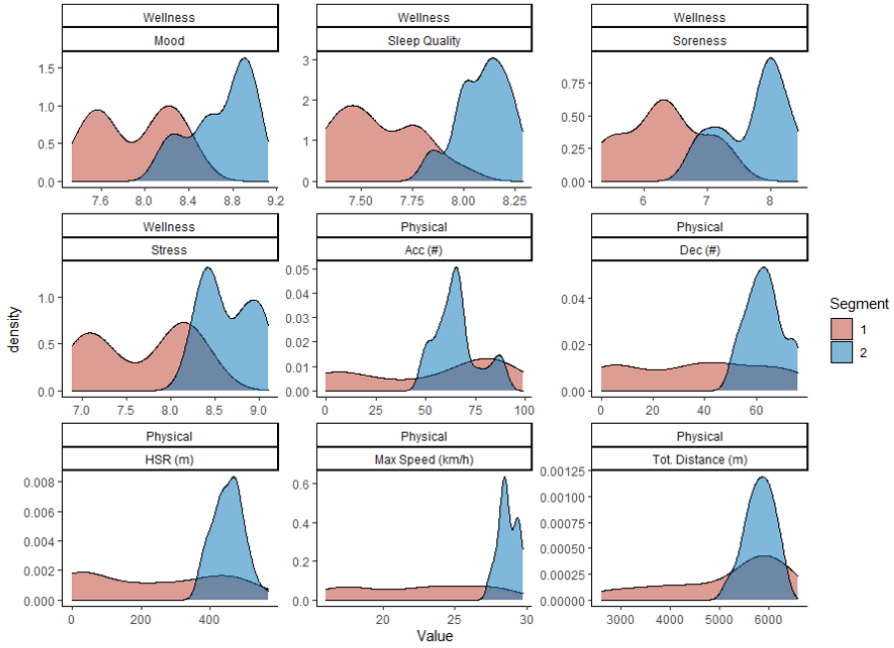


Figure 5.5 A multivariate change point analysis for wellness and running performance metrics. Data normalised to the percentage of pre-injury level. COD: Change of direction. Acc: number of acceleration; Dec: number of deceleration; HSR: high-speed running; Max Speed: maximum running speed; Tot. Distance: total distance.

Figure 5.6 Distribution of the metrics in each segments of multivariate analysis, before and after the common change point. Acc (#): Number of accelerations; Dec (#): number of decelerations; HSR (m): High-speed running (m); Max. Speed (km/h): maximum running speed (km•h^{-1})

5.5 Discussion

This is a single case study to highlight the methodology and the features of the change point method. To exemplify the change point method, we present the univariate and multivariate approaches to determine the change points during the rehabilitation of a lower limb muscle injury in football. The specific practical implications of each approach are discussed below.

5.5.1 Practical implications for one change point

The change points indicate to users when a meaningful change occurs for each metric. In Figure 5.1, the change points for total distance occurred first (day 32), followed by acceleration (day 34), deceleration (day 37), high-speed running (day 41) and maximum speed (day 41). The clinician can identify when meaningful changes occur and evaluate if this sequence aligns with the intended rehabilitation protocol. In particular, the change point for high-speed running occurred during the change of direction running phase. This change point could be used as a proxy of the phase of the rehabilitation (i.e., the phase where meaningful change is expected for high-speed running) and could be used to manage the expectation of the athletes and coaches regarding the progression of rehabilitation along the RTS continuum.

Another practical example is knowing that the sleep quality takes longer than stress to reach the change points (days 47 vs 30), clinicians may choose to monitor the athlete's sleep quality closely during the early rehabilitation phases and work with the athlete to remove any potential barriers to sleep. This may be beneficial to the overall rehabilitation because sleep quality is vital for athletic wellness, performance and recovery (Halson, 2008).

5.5.2 Practical implications of three change points

In Figure 5.4, we segmented the RTS with a maximum of three change points to compare with the three major planned transitions before return to full training (i.e., 1) return to straight-line running, 2) change of direction running, and 3) modified training). Our results indicated that the change points detected did not align closely with individual rehabilitation stages. However, the last change points of all metrics occurred during the modified training phase, which indicated all meaningful changes occurred before proceeding to full training. This pattern may be used as a proxy to support the decision for athlete to return to full training.

The disadvantage of the current approach is the detection of two to three change points for each of the nine metrics resulting in 26 change points. This amount of information is beyond what most adults could only store in short-term memory (4-7 items) (Cowan, 2001; Saaty & Ozdemir, 2003) and therefore can overload clinicians' cognitive processing capacity. For that reason, the multivariate approach may be more appropriate for monitoring the changes in the metrics.

5.5.3 Practical implication for multivariate analysis

When clinicians want to use more than one metric to determine the RTS progression, the multivariate approach can aggregate the change points of multiple metrics and simplify them into a common change point. For example, to know when there were overall changes in the four wellness metrics and the five running performance metrics, clinicians can simply refer to two common change points: day 50 for wellness and day 67 for running performance (Figure 5.5). Here, the multivariate analysis identified the time when the data sequence levelled out together, which may imply the metrics have stabilised and reached a steady state. It may appear intuitive when there are nine metrics to monitor. However, with technological development and the use of a complex systems approach, clinicians may want to include more data in their analysis, such as isometric strength, resting heart rate and heart rate variability. Due to the rich amount of information and the inherent complexity of rehabilitation, closely monitoring all the RTS data would be nearly impossible. While the clinicians first have to determine and select which metrics should be included in the analysis, the multivariate analysis aids clinicians by consolidating the information and presenting an overall result. Having these change point models in place may help clinicians avoid over-emphasising the importance of metrics that are easily available or interpretable while neglecting the others.

5.5.4 Advantages of change point analysis

Methods that can capture and analyse multiple metrics simultaneously and efficiently are much needed in sports medicine (Yung et al., 2022a). By using change point analysis, clinicians can simultaneously identify the meaningful change(s) in one or multiple metrics. Clinicians can also visualise the data together even though the data come from different sources and formats. Our model's capacity to integrate multiple types of data may increase the usability of the analytical method (Silver, 1991) and bring benefits to the decision analysis (Yung et al., 2022b). The exploration of the change point approach attempts to shift toward complex systems approach when analysing complex data.

Change point analysis is intuitive and likely to be understood by clinicians with little or no experience in analytics. This feature is crucial because analysis techniques are more likely to be implemented in applied sports settings if their efficiency, interpretability and functionality fit with the operational framework of a sports organisation (Schelling & Robertson, 2020). In our study, Figures 5.1, 5.3 and 5.5 allow clinicians to visualise the process and summarise the location of the change points in the context of the rehabilitation continuum intuitively. Specifically, we present the the graphs using a percentage of pre-injury level so clinicians can visualise the overall rehabilitation outcome compared to the baseline. This is also particularly helpful when comparing data from multiple athletes. The density plots (Figures 5.2, 5.4 and 5.6) are presented using raw values to inform clinicians of the actual metrics. We aim to produce visualisations that require less cognitive work to understand and allow clinicians to digest the information effectively (Dadzie & Rowe, 2011; Kale et al., 2018).

5.5.5 Limitations and future applications

There are at least four limitations of the change point approach. First, change points are detected based on the duration of the longitudinal data. Therefore, at this stage, it is more suitable for evaluating past practices and is not intended for live monitoring and making instant decisions. However, as technology and analysis in sports rehabilitation advances, future work may implement live change point analysis, where clinicians can receive up-to-date information to inform their decision making. Second, the *changepoint.mv* package only permits detection of one change point for the multivariate change point analysis. As such, we did not perform a multivariate change point analysis with three change points. Future work may look to implement this function as it becomes available. Third, as with most analytics systems, there is some inherent bias relevant to the algorithm. The current approach is limited by the information available within the elite sports setting, i.e., metrics derived from the GNSS devices and wellness scores. Beyond these two data types, there may be other data types relevant to RTS progression. Fourth, clinicians need to adjust the parameters of the change point algorithm based on the context and the purpose. The number and the location of change points discovered depend highly on the parameters of 1) the maximum number of change points and 2) the minimum length of the segment.

A future application of the change point approach is to establish a change point profile for different injuries. Each type of injury has unique considerations in the RTS progression (Taberner et al., 2019). For example, the load planning sequence for hamstring injuries is running speed, and acceleration/deceleration magnitudes. In contrast, the load planning sequence for adductor injuries is the change of direction, and technical actions such as passing, crossing and shooting (Taberner et al., 2019). Clinicians may use the change point profiles to evaluate RTS progression objectively. Furthermore, this procedure can be part of the reflective observation in transforming the clinician's experience to conceptualise the rehabilitation lesson learnt. Actively reflecting on previous experience is paramount for learning (Kolb & Kolb, 2018) and improving decision making in complex systems (Bennet & Bennet, 2008)

5.6 Conclusion

We have outlined a change point approach to identify meaningful changes in the RTS continuum. The univariate approach provided information regarding the sequence and time point of the change points. The multivariate approach provided a common change point for multiple metrics, information that would benefit clinicians to have a broad overview of the changes in the rehabilitation process. Clinicians can apply the change point analysis to any other injuries to identify meaningful changes in RTS progression and make informed decisions.

6 Chapter Six: Study IV

Chapter overview

Chapter Six is the final study in this thesis. This original case study uses an association rule approach to develop IF-THEN rules to represent the relationship between rehabilitation and physiological adaptions (muscle soreness post-training). These findings may inform decisions in rehabilitation training and design. Clinicians can adopt these methods to conduct large-scale searches for seemingly random, yet important and frequently occurring patterns to discover rules that may support their rehabilitation training design and recovery planning.

The content of this chapter has been submitted to the Journal of Sports Sciences (Taylor and Francis) on 29th January, 2023. It is currently under review.

Clinical relevance

Understanding the interactions between variables through a complex systems approach may help clinicians better address the dynamic nature of rehabilitation and improve decision quality. To identify the interactions within the complex systems, clinicians may explore the regularities of the emerging behaviour through pattern recognition. However, hidden patterns and unexpected patterns within large complex datasets are often not obvious to human eyes. There is a need to explore analytical methods that may assist clinicians in revealing patterns within a large RTS dataset and help improve future RTS decisions.

6.1 Application of association rule to rehabilitation training design: a football exemplar.

6.1.1 Key points

- This study used an association rule approach to discover combinations of variables frequently associated with a low score of muscle soreness on the next day or two days after training.
- The rules can condense a large volume of data and translate it into interpretable rules for clinicians to act on.
- The method may reduce a large dataset's complexity without comprising the non-linearity structure.

6.1.2 Abstract

The sheer volume of data derived from sports technologies and clinical tools may challenge clinicians' information processing capacity and hinder them from making effective decisions. Machine learning approaches, such as the association rule method, can evaluate the nonlinear relationship between voluminous wellness and physical performance data. This study uses an association rule method to discover rules that can classify the level of muscle soreness the next day (T+1) and two days after training (T+2). To exemplify the approach, six wellness metrics and eight physical performance metrics were collected over one season from a professional football player who sustained a lower-limb muscle injury. The Apriori algorithm was implemented. A total of 3356 and 1876 rules were discovered for T+1 and T+2, respectively. An exemplar rule with three explanatory variables is that when metre per minute = high, decelerations = medium and sleep = low, the player is likely to give a low score for muscle soreness on T+1. The results may inform clinicians how to manipulate the rehabilitation program design to achieve the desired level of training adaptations. Clinicians can also adapt similar methods to conduct large-scale searches for frequent patterns and rules that may support their training design and recovery planning.

6.2 Introduction

To inform training and return-to-sport (RTS) decisions, clinicians first need to determine which tests to perform and the metrics to be tracked. For instance, clinicians can quantify the physical output of an athlete and compare the result with a benchmark, such as the pre-injury level or competition level (e.g., 5 km represents 80% of the pre-injury game load). Clinicians may also refer to the internal load to understand the physiological and psychological stress imposed by a given external load on the injured athlete, for example, heart rate, subjective perception of the effort and subjective wellness (Foster et al., 2001; Halson, 2014; Taylor et al., 2012). In particular, wellness questionnaires (sleep, energy, stress and muscle soreness) have been widely adopted to quantify an athlete's subjective response to exercise stress on the training day (T) (Gallo et al., 2016; Taylor et al., 2012; Thornton et al., 2016; Thorpe et al., 2017; Thorpe et al., 2015).

Integrating data from multiple sources into structured decision-making processes can be challenging for multiple reasons. First, depending on the number of tests required, the volume and complexity of data may exceed human information processing capacity (Yung et al., 2022b). When clinicians have access to a high volume of data, they may not be able to process or consider it all, potentially leading to slow or compromised decision-making (Cowan, 2001). Second, a challenge for decision makers are the linear, and often nonlinear, relationships between variables required to predict future states (Yung et al., 2022a). Identifying such relationships without the use of external aids, such as computing, is extremely difficult (Bache-Mathiesen et al., 2021).

This study adopts an association rule methodology to assist clinicians in integrating multiple data types and consolidating complex data into interpretable information. The association rule method is a classic method that finds relationships among a large set of variables (Agrawal & Srikant, 1994). The output can be expressed in the IF-THEN format: **IF** $condition_1$ **and** $condition_2$ **and** … **and** $condition_n$, **THEN** decision (Daud & Corne, 2009). The association rule methodology has been employed in sports analysis (Browne, Morgan, et al., 2019; Browne, Sweeting, et al., 2019; Robertson et al., 2019) and talent identification (Robertson et al., 2015). Specifically, in identifying talents in the

Australian Football League, three simple rules formed based on physical performance and anthropometric attributes may discriminate players who are more likely to be drafted (Robertson et al., 2015). For example, **IF** 20m sprint ≤ 2.99s, **THEN** Australian Football League drafted (Robertson et al., 2015). Using simple heuristic rules helps retain some complexity while reducing the number of variables that practitioners need to focus on. Similarly, the association rule method may also fit into RTS, helping clinicians to integrate physical performance and wellness data and estimate the post-training muscle soreness level.

The primary aim of this study was to discover rules for classifying the level of muscle soreness post-training and their accuracy (confidence). Muscle soreness was selected as the exemplary target outcome (consequent) because it reflects the intensity of the training program and the adaptations of the athletes. The rules discovered may help clinicians to manipulate the rehabilitation program to achieve the desired level of post-training muscle soreness, such as creating a higher level of stimulus for positive adaptations or a lower level for recovery. The secondary aim was to evaluate the relationship between the number of variables included in the model and the confidence of the rules.

6.3 Methods

6.3.1 Design

This was a prospective observational case study of one professional athlete from an Australian A-League football club. Ethical approval to conduct the study was obtained from the Victoria University Human Research Ethics Committee (HRE22-071).

6.3.2 Participant

The participant sustained an acute lower limb muscle injury during high-speed running in football training. The athlete returned to play at the pre-injury level, as determined by the coach. The rehabilitation program was completed in the football club under the supervision of the club's medical team.

6.3.3 Data collection

Data were collected during training sessions and competitions of the 2021/2022 Australian A-League season, from pre-season training until the end of the season. To determine the running performance in rehabilitation, the athlete wore a 10 Hz GNSS device (Apex Pro Series, STATSports, Newry, Ireland) placed on the back between the scapulae. Each unit included a 100-Hz accelerometer, magnetometer, gyroscope and 10 Hz GPS. The GNSS, which is certified by FIFA for use both in training and matches (FIFA, 2021), is validated to quantify running activities. The reliability and validity of these units have been previously reported. They display a high level of validity in total distance and maximal velocity team sport settings (Beato et al., 2018), as well as excellent inter and intra-unit reliability (Beato & Keijzer 2019). The device used has good inter-device reliability for the measurement of total distance and maximal velocity (Beato et al., 2018). These devices also possess suitable reliability and consistency for threshold-based accelerations and accelerations (Crang et al., 2021; Comier et al., 2023). The athlete wore the same device during all activities to reduce inter-unit error (Beato et al., 2018; Cummins et al., 2013) and no additional analysis was used to account for the variations within the data.

Upon completion of each training session, all tracking data were downloaded using the proprietary software (Sonra 3.0, STATSports, Newry, Ireland). Among the metrics derived from the GNSS system, eight physical performance metrics were selected after consulting the club's high-performance staff:

1. Total distance (TD) (m): Total distance covered in the session.
2. Metre per min ($m.min^{-1}$): Total distance covered in a minute.
3. Maximum speed ($km.h^{-1}$): Maximum running speed attained in the session.
4. High-speed running (HSR) (m): Distance covered above 5.5 $m.s^{-1}$
5. Zone 5 (Z5) distance: Distance covered in speed zone 5.5-7 $m.s^{-1}$.
6. Zone 6 (Z6) distance: Distance covered in speed zone 7-11 $m.s^{-1}$.
7. Accelerations (Acc): number of accelerations between 3.0 and 10 $m.s^{-2}$ with a minimum duration of 0.5 s.

8. Decelerations (Dec): number of decelerations between -3.0 and -10 $m.s^{-2}$ with a minimum duration of 0.5 s.

On the morning of the training days, the athlete rated sleep quality, mood, stress, energy, diet and overall muscle soreness on a scale 0-10 (0 – worst, 10 – better) using a mobile phone application.

6.3.4 Association rule

The association rule method is used to discover knowledge and present them in the form A=> B, where A and B represent *itemsets*. The implication symbol (=>) denotes that if a *transaction* in the database contains A, it also satisfies the conditions in B. As such, *A* is referred to as the *antecedent* and *B* the *consequent.* Each transaction includes a set of variables (*items*) that occurred together.

In the context of rehabilitation, each training day represents a transaction. As an example, the rule $\{high - speed\ running > 500m,\ poor\ sleep\ quality\} \Rightarrow \{high\ soreness\}$ would indicate that when the high-speed running performed is more than 500m and the sleep quality in the previous night was poor (antecedents (A)), the soreness after training would be high (consequent (B)).

To further evaluate the validity of the rules, we can refer to two measurements: *Confidence* (Eq.1) and *Support* (Eq. 2). Confidence measures how often the rule is true and can be expressed as:

$$confidence\ (A \rightarrow B) = \frac{Number\ of\ transactions\ containing\ A\ and\ B}{Total\ number\ of\ transactions\ containing\ A} \qquad \textit{Eq.1}$$

Support refers to how frequently an association rule occurs in the entire set of transactions and is defined as:

$$support\ (A \rightarrow B) = \frac{Number\ of\ transactions\ containing\ A\ and\ B}{Total\ number\ of\ transactions\ (N)} \qquad \textit{Eq.2}$$

6.3.5 Statistical Analysis

The athlete's identifiers were removed before proceeding to statistical analysis. All analysis was completed in *RStudio* software (version 1.3.1093) (R Core Team, 2019), using the R (version 4.03) programming language. Mean and standard deviation were calculated for soreness scores and each of the eight training metrics.

To apply the association rule algorithm, each variable was first discretised based on frequency. Discretising the data based on frequency allowed each bin to contain a similar amount of data, which may better reflect the underlying distribution and the common practice in applied settings which some clinicians routinely discretise continuous variables to aid decision making. Performance running metrics (except Z6 distance) were discretised into three bins (low, medium and high). The distribution of wellness and Z6 variables were narrower and would not permit frequency discretisation into three bins, hence two were used.

The *Apriori* algorithm from the *arules package* was used to explore frequent combinations of variables co-occurring in the dataset (Agrawal & Srikant, 1994). In the general form of the association rule methodology, there is no restriction on whether a variable appears as the antecedent and consequent. However, to discover rules relevant for clinicians, the consequent was restricted to one variable. In our example, a lower score in muscle soreness reported on the next day (T+1) and two days after (T+2), respectively, were used as the consequents of the two models. A lower score indicates more muscle soreness.

Muscle soreness was selected as the consequent, while all other variables were used as antecedents to characterise the training sessions. The parameters set for the *Apriori* algorithm were a minimum support of 0.06, a minimum confidence set of 0.2, a minimum and maximum rule length of 3 and 11 variables, respectively. These parameters captured a wide range of rules for the purpose of the example and were applied to the *Apriori* algorithm to T+1 and T+2 transactions to search for rules resulting in a lower score for muscle soreness.

6.4 Results

A total of 115 training sessions with complete data were included in the analysis. The distribution of each variable is displayed in Figure 6.1. The mean and standard deviation of the items and the resulting cut-off value of discretisation are shown in Table 6.1.

Figure 6.1 Histogram for included variables. m/min: metre per minute; Max speed (km/h): maximum running speed (kilometre per hour).

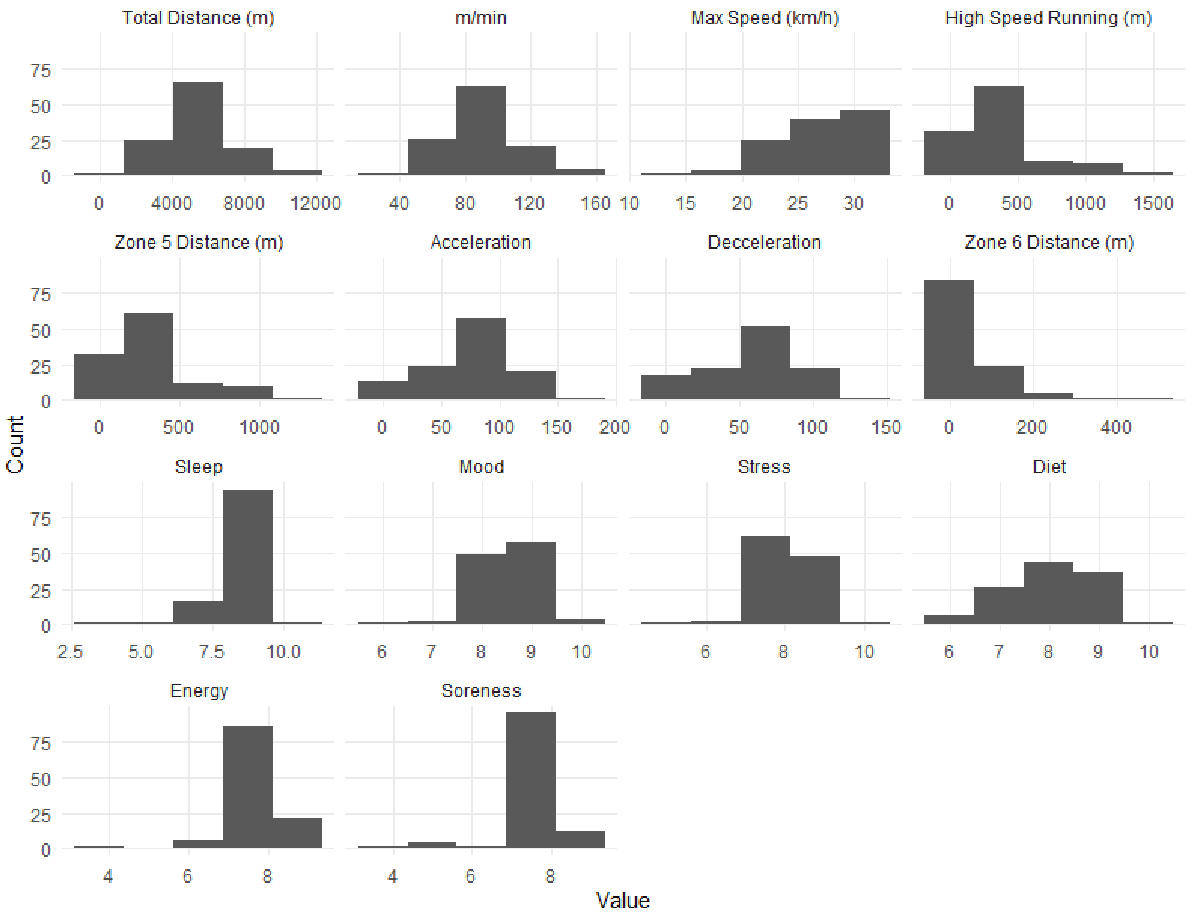


Table 6.1 Mean (SD) and cuff-off values used to discretise each variable.

Variable	Mean (SD)	Low	Med	High
Total distance (m)	5217 ± 2079	≤ 4420	4421 - 5630	≥ 5631
Metre per min ($m.min^{-1}$)	91.2 ± 22.9	≤ 81.9	82 - 96.5	≥ 96.6
Maximum speed ($km.h^{-1}$)	26.9 ± 3.9	≤ 25.1	25.2 - 29.3	≥ 29.4
High-speed running (m)	390 ± 335	≤ 226	227-429	≥ 430
Z5 distance (m)	338 ± 271	≤ 208	209 - 404	≥ 405
Accelerations	75 ± 37	≤ 65	66 - 88	≥ 89
Decelerations	58 ± 32	≤ 50	51 - 73	≥ 74
Muscle Soreness	8 ± 1	≤ 7	8	≥ 9
		Low	**High**	
Z6 distance (m)	53 ± 85	≤ 19	≥ 20	
Sleep quality	8 ± 1	≤ 8	≥ 9	
Mood	9 ± 1	≤ 9	10	
Stress	8 ± 1	≤ 8	≥ 9	
Energy	8 ± 1	≤ 8	≥ 9	
Diet	8 ± 1	≤ 8	≥ 10	

Figure 6.2 Six exemplary rules with three, five and eight explanatory variables are displayed. The rules are associated with a low score in muscle soreness on the next day after training (T+1), and are ordered by confidence. Each discretised variable is colour coded according to its category for visual interpretability.

	Physical performance								Wellness							
	Total distance	Metre per minute	Maximum speed	High speed running	Zone 5 distance	Zone 6 distance	Accelerations	Decelerations	Sleep	Mood	Stress	Energy	Diet	Confidence	Support	Explanatory variables (n)
1		High						Med	Low					1	0.0645	3
2		High						Low	High					1	0.0645	3
3		High						Med	Low		Low		Low	1	0.0645	5
4	Med					Low	Med		Low		Low			1	0.0645	5
5	Low	High	Low			Low	Low	Low			High		Low	1	0.0645	8
6	Low	High				Low		Low		Low	High	Low	Low	1	0.0645	8

Legend		
Low	Medium	High

Figure 6.3 Six exemplary rules with three, five and eight explanatory variables are displayed. The rules are associated with a low score in muscle soreness on two days after training (T+2) and are ordered by confidence. Each discretised variable is colour coded according to its category for visual interpretability.

	Physical performance								Wellness							
	Total distance	Metre per minute	Maximum speed	High speed running	Zone 5 distance	Zone 6 distance	Accelerations	Decelerations	Sleep	Mood	Stress	Energy	Diet	Confidence	Support (%)	Explanatory variables (n)
1			Med			Low					Low			1	0.0755	3
2						Low		Med	Low					1	0.0755	3
3	Med				High					Low	Low		Low	1	0.0755	5
4				High				Med	Low		Low	Low		1	0.0755	5
5		High		High	High				Low	Low	Low	Low	Low	1	0.0755	8
6	High	High		High	High				Low	Low		Low	Low	0.8	0.0943	8

Legend		
Low	Medium	High

Figure 6.4 Level of rules' confidence based on the number of explanatory variables included in the T+1 and T+2 models.

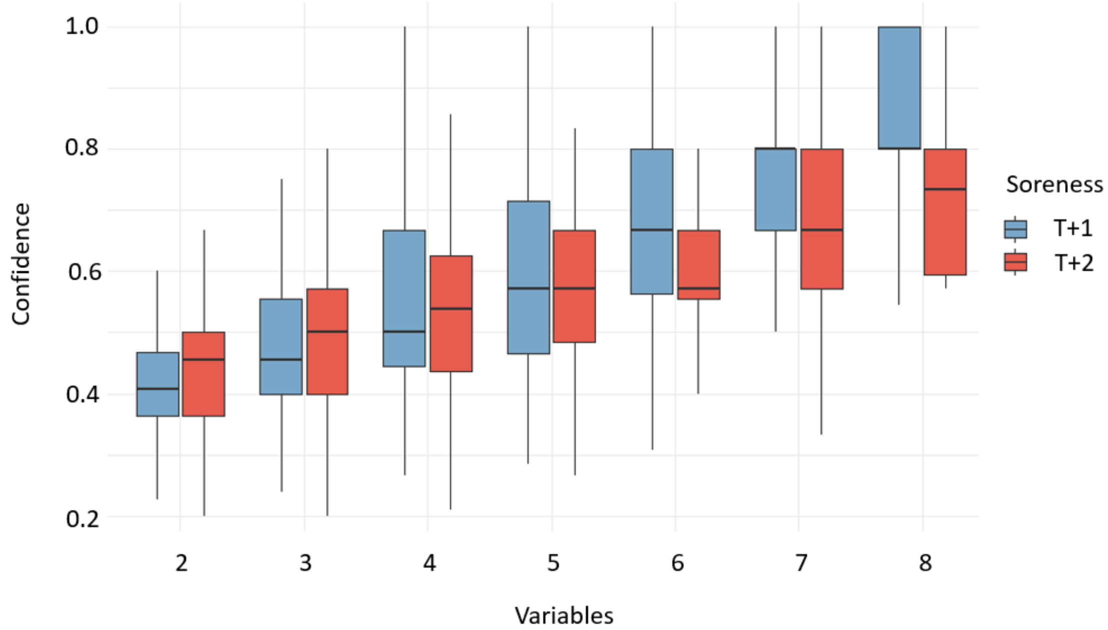
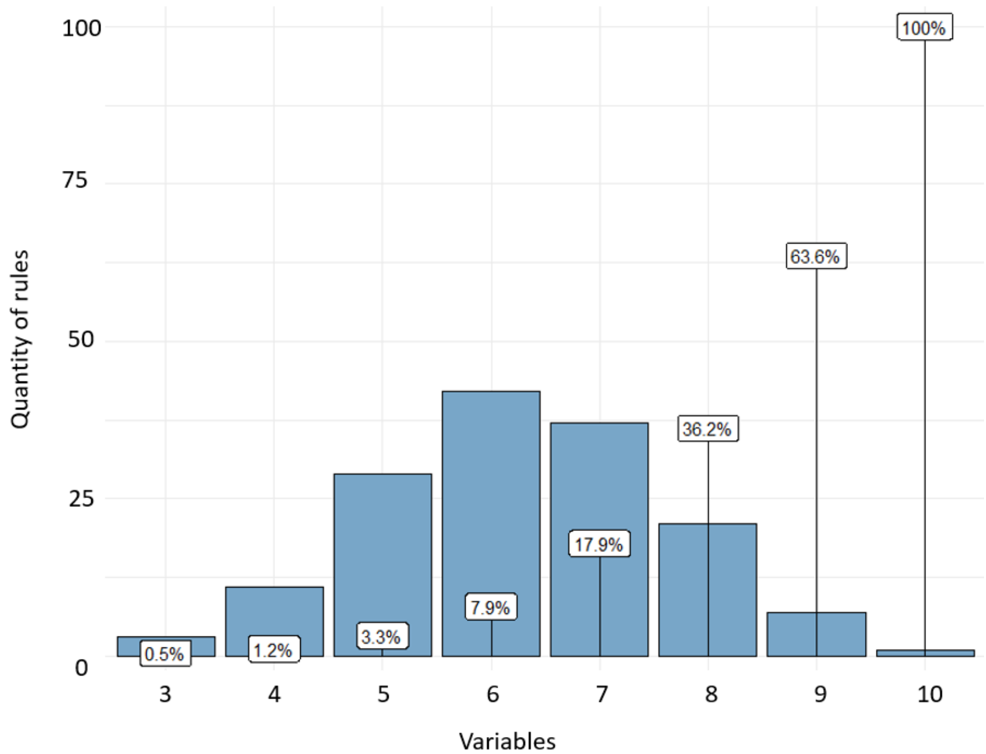


Figure 6.5 The quantity of rules according to the number of explanatory variables included in the T+1 association rule model. Labels indicate the proportion of rules where confidence = 1.



6.5 Discussion

This study aimed to evaluate the use of association rule among a complex dataset relating to a professional footballer's rehabilitation. As an exemplar, we generated rules that may help clinicians manipulate the rehabilitation program to achieve the desired level of post-training muscle soreness. The target consequent is a lower score of muscle soreness (i.e., more muscle soreness) on the day after training (T+1) and two days after (T+2).

First, multiple combinations of variables led to the target consequent. As an example from the T+1 model (Figure 6.2), rule #1 indicate *high* metre per minute, *medium* decelerations, *low* sleep led to a lower score of muscle scores (consequent). Other rules with high accuracy (confidence) are displayed in Figure 6.2 and Figure 6.3 as examples. Next, we investigated the relationships between the number of variables included in the model and the accuracy of the rules to discuss the trade-off between data input and models' accuracy. The methodology used here may help clinicians establish simple, intuitive rules to guide their decisions in manipulating the level of post-training muscle soreness. From a broader methodological perspective, clinicians may use the association rule method to integrate multiple data types and condense complex information into simple rules to support other decisions. For example, to identify the relationships between wellness, training load, mood states (antecedents) and player availability (consequent).

Accuracy, efficiency and interpretability are important considerations when using machine learning models in applied settings, as with most modelling approaches (H. Liu et al., 2017). In terms of accuracy, with the same dataset, more complex models usually have lower accuracy than simpler models (Halilaj et al., 2018). As shown in Figure 6.4, the rule's confidence level increased when more variables were added to the T+1 model. However, this is more likely to apply when the variables are valid and relevant to the model. For example, adding more variables to the T+2 model did not improve the model's performance as apparent as the T+1 model (Figure 6.4). It is possible that the level of muscle soreness on T+2 was not closely associated with variables included in the T+2 model. Other factors, such as events occurring on T+1, may have a considerable effect on the muscle soreness on T+2.

Although models with more variables generally have higher accuracy, there is a trade-off between accuracy, efficiency and interpretability. First, a complex model with more variables requires clinicians to spend more resources (e.g., staffing, time and equipment) to collect and clean the required data. This may generally couple with a longer computation processing time. Second, complex models are usually less interpretable and readable, as humans have limited information processing capacity (Miller, 1956). Often, users may prefer extracting the rules from the model to see any relationships between the inputs and the outputs (H. Liu et al., 2017). Therefore, a complex model with complicated rules may be difficult and cumbersome to follow. In contrast, rules containing fewer variables are easier to read and interpret. For example, in Figure 6.2, some clinicians may find models with three explanatory variables (rules #1 and #2) easier to read and interpret than eight (rules #5 and #6). Third, rules with higher confidence often come with a lower support value, meaning the model has less extrapolation ability in other unseen data. This is commonly known as over-fitting (Daud & Corne, 2009). Since the utility of the model depends highly on the user's preference, available resources and working style, there may not be a one-size-fits-all approach.

To choose a model that balances accuracy, efficiency and interpretability, clinicians may consider the principle of parsimony, which suggests that models with fewer variables are preferred if they do not meaningfully deteriorate accuracy (Stubbe et al., 2005). A parsimonious model achieves the desired level of goodness of fit using the minimum number of explanatory variables. In our analysis, six variables gave the highest number of rules with a confidence of 1.0 (n = 42) in the T+1 model, accounting for 7.9% of all the rules discovered with six variables (Figure 6.5). The percentage of rules having a confidence = 1.0 increases nonlinearly with the number of variables (Figure 6.5). With supporting information from Figure 6.4 and Figure 6.5, clinicians can choose their preferred number of explanatory variables based on their available resources, operation style, personal preference and the level of confidence they are willing to accept. Ultimately, the decisions on the number of variables in the model should be aimed at improving the clinicians' ease of use and increasing the speed of their decision making, which again, may vary among users. For example, given the confidence of the models and the data input required for this case, some clinicians may find six variables appropriate. However, when using the association rule approach for investigating other research questions, such as the relationship between an injury diagnosis and the expected time to RTS, more variables may be required to capture the details of the injury. While more variables may capture more information and lead to a more accurate model, users may expect a diminishing return on accuracy. For example, the accuracy of T+1 model levels out when six variables are included (Figure 6.4). To strike a balance between the accuracy, efficiency and interpretability of the model, clinicians may also consider controlling the model complexity such that the generated model will not be very complex. Model complexity can be controlled by using different methods, such as feature extraction (e.g., Principal Component Analysis) (Jolliffe, 2002). The aim is to transform the dataset to a lower dimensional space by combining existing attributes and thus reduce model complexity.

When analysing large datasets relating to apparently complex phenomena, a nonlinear analysis may provide greater insight into the characteristics of the behaviour compared to a linear approach (Robertson et al., 2015). The association rule algorithm utilised here integrated data from physical performance and wellness to highlight combinations of variables that may lead to a lower score of muscle soreness on T+1 (Figure 6.2) and T+2 (Figure 6.3). For example, when considering five explanatory variables in the T+1 model (Figure 6.2), rule #3 indicates that if the player has completed a training session with *high* metres per minute, *medium* decelerations, and subjectively-rated *low* for the sleep, stress and diet score, the player is likely to have a *low* score for muscle soreness on T+1. Not only might the association rule methodology help reduce clinicians' time and mental burden in eyeballing or analysing datasets from different sources (e.g., wellness questionnaire and GNSS database) within a limited timeframe, it may also uncover nuanced patterns that are not easily perceived by humans.

As required by the association rule approach, the continuous values in this study are discretised into two or three categories (bins) based on frequency. The bins are then presented in linguistic terms, such as low, medium and high, for simplicity and to fit into applied settings. The categories, however, can also be set using other rationales, such as data distribution or practical requirements of the sports organisation. For example, a sports organisation may set their metres per minute categories based on the performance goal of the organisation. The ideal model for a sports organisation may require trial and error and be determined based on model performance.

Clinicians can acquire knowledge from books, orally transmitted learning, practical experience and common sense. However, clinicians may be subjected to biases due to various reasons. For example, bias may be introduced during clinician training (e.g., a heavy emphasis on specific musculoskeletal factors only) or by practice (e.g., clinicians accustomed to a particular routine). As such, the knowledge acquired could also be constrained by social context and sometimes biased towards conventional practice. In contrast, a machine learning system can gain knowledge by performing exhaustive searches through large data sets and through statistical analysis. It may find rules that are consciously or unconsciously implemented by clinicians and help systematically structure the knowledge. Clinicians can integrate and complement their knowledge with that elicited from the association rule (Webb, 1996).

However, as promising as machine learning is in analysing data and driving informed decision making, it can also be susceptible to unintended biases (Mehrabi et al., 2021). For example, the machine learning system learns to make decisions based on historical (training) data, which can include biased human decisions. To address potential machine learning bias, clinicians may first need to honestly and openly question if best evidence practice is used in the current workflow, and actively hunt for biases that may manifest themselves in data. Furthermore, due diligence, such as externally validating the model in the target population for which they are intended, is also recommended prior to using any model in a clinical setting (Bullock et al., 2022). Ultimately, at the current development stage, machine learning models are not intended to replace human decisions. Instead, they are tools that may supplement subjective assessment and allow a deeper understanding of complex human behaviour, and hence improving decision quality (Gamble et al., 2020).

This example model has several limitations. First, the data only included supervised training conducted at the club. Activities conducted outside formal sessions were not included in our analysis but may contribute to the reported subjective wellness, for example, walking the dog longer than usual. Second, the initial off-feet rehabilitation training was not included in our analysis because we could not capture the external workload of the upper body during this period. Third, the reliability of the self-reported wellness information depends on different factors, such as the athlete's honesty and familiarity with the questionnaire. Fourth, in our model, muscle soreness was the proxy for training intensity and the athlete's response. However, muscle soreness may be biased towards gym-based eccentric exercises (Cheung et al., 2003; Cleak & Eston, 1992). Fifth, although discretising data can condense the data and keep broader categories (Stańczyk et al., 2020), it introduces sharp boundaries and may lead to data loss (Hong & Lee, 2008).

6.6 Conclusion

This study used an association rule methodology to explore and discover combinations of variables frequently associated with a low score of muscle soreness on the next day or two days after a training session. The rules can condense a large volume of data and translate them into interpretable rules for clinicians to act on. This approach may reduce the complexity of large datasets without comprising the nonlinearity structure.

7 Chapter seven: General discussion and conclusion

Chapter Overview

This chapter consolidates the key findings and implications of this thesis and discusses how these can be implemented in the applied setting. This chapter contains a general discussion, industry implementations, future directions and conclusions.

7.1 General discussion

This thesis aimed to provide tools to support clinicians in RTS decision making by adopting the complex systems theory as its major theoretical framework. Collectively, the four studies discussed frameworks (Part 1) and their practical applications (Part 2) to improve RTS decisions by using a complex systems approach and advanced analytical tools[1].

First, Chapter Three discussed how clinicians can evaluate a decision based on a decision analysis perspective and what factors constitute a good decision. Making RTS decisions is challenging because injury cases are often complex and unique. Due to the linearity and emergence behaviour, it is also hard to predict the outcome from a few clinical tests alone. As such, the decision-making framework in Chapter Three outlined critical considerations for clinicians to observe, evaluate and interpret the RTS question. This also formed the basis of the thesis, including defining a *good* decision. To improve decision quality, clinicians may view rehabilitation from multiple perspectives and harness the complex systems theory.

The complex systems theory, a well-recognised approach to conceptualising sports injury and rehabilitation, can be used as the theoretical framework to understand sports injury and rehabilitation (Bittencourt et al., 2016). Complex systems theory guides clinicians in defining and interpreting systems from multiple perspectives, thus providing them with a better opportunity to understand and explain complex decisions. Chapter Four explained the concepts of the complex systems theory and complemented them with clinically relevant examples. Complex systems have distinctive characteristics, for instance, emergence, feedback loops and dynamics shaped by nonlinear interaction. Complex systems, however, may be challenging to apply in practice because it requires clinicians to

[1] In the beginning of this doctoral investigation, I initially proposed to collect data across multiple seasons. However, when professional sports were highly disrupted by COVID-19 pandemic, it was difficult to conduct large scale studies. As a result, this thesis included two review studies and two case studies that compared the analytical techniques using data from the same player.

move from finding “causes” to finding “relationships” within the system (Bittencourt et al., 2016). Clinicians are also often presented with a high volume of complex data, which may overwhelm their information processing capacity. With the digitisation of health care and the development of sports technology, there are opportunities to harness and capitalise on the information being captured to improve RTS decisions with the use of analytical methods and through a complex systems approach.

In Part 2, Chapters Five and Six adopted analytical methods that can accommodate the characteristics of the complex systems and potentially improve RTS decisions in applied settings. In planning a rehabilitation program, depending on the number and types of tests and/or monitoring required, clinicians can be challenged by 1) a large volume of data and 2) multiple data types and formats (e.g., longitudinal and discrete datasets). Meanwhile, clinicians only have limited time and mental capacity to analyse, consolidate, interpret and report the findings. To develop methodologies that may improve clinicians’ decision quality and accommodate the characteristics of complex systems, Part 2 adopted analytical methods that may fit into applied settings. Specifically, Part 2 contributed to resolving two common types of data problems in applied clinical settings:

1) Clinicians often collect multiple data types during the RTS process at regular time points. Specifically, longitudinal data are commonly found in clinical settings as clinicians track the rehabilitation progression. How can clinicians integrate and analyse the longitudinal data?
2) What are the hidden and unexpected patterns in a large rehabilitation dataset? How to exploit them and structure the knowledge?

For question 1, Chapter Five adopted the change point method. The change point method was selected for its advantage in finding meaningful change(s) in a longitudinal dataset. In particular, an important practical aspect of the change point method is that it accepts various continuous metric representations, such as physical performance data from GNSS devices or wellness monitoring data. This increases versatility in the rehabilitation environment, where multiple data types are often presented. For example, clinicians may want to continuously track the hamstring isometric strength and high-speed running distance after a hamstring injury. In addition, clinicians can compare the location and sequence of the change points with their clinical judgement and past practice. For example, what is the preferred sequence of change points after a groin injury? In addition, univariate and multivariate approaches were also investigated to explore how the change point method can integrate and visualise multiple longitudinal data types.

For Question 2, Chapter Six adopted the association rule method. The association rule method was selected because it can integrate multiple data types and condense complex information into simple and intuitive rules. Consequently, clinicians can use the rules to identify the interaction between multiple variables and guide their decisions in clinical practice. In Chapter Six, clinicians can find rules that were associated with the level of post-training adaptations. Using the same method, clinicians may discover frequently occurring patterns in different aspects, for example, the combination of variables that may maximise the RTS outcome, or minimise injury risk. Furthermore, both the change point and association rule methods provide simple visualisations whereby clinicians can track the rehabilitation process (change point method) and identify the associations between aspects of athlete behaviours (association rule method).

While this thesis only explored the change point and association rule methods, other machine learning methods, such as classification (e.g., decision tree), may also fit into the clinical setting. Similar to the association rule method, the classification approach may explain the reasoning behind the output and is intuitive. In contrast with the association rule, the classification approach could be advantageous by enabling data to be modelled in its original format (e.g., continuous) and not needing data to be discretised. Discretising data may improve clinicians' ease of use and increase the speed of interpreting data, but it may also reduce the explanatory power of continuous variables. However, this thesis has not included classification in the studies because change point and association rule methods are relatively more intuitive and easier for clinicians to understand and apply. This may increase the work's applicability in sports medicine and encourage clinicians to explore and uptake analytics in their practice. However, it is still worthwhile to investigate classification and other analytics methods in the future and compare them regarding their functions, applicability and feasibility in applied settings.

Both change point and association rule methods are post-hoc analyses and intend to evaluate past practice. These methods may help clinicians systematically structure existing knowledge and complement it with empirical evidence and clinical experience. Clinicians’ experiences, despite their importance, are sometimes poorly articulated and may create challenges in structuring the knowledge. The methodologies proposed in Part 2 may help to structure the knowledge and help develop consistency in clinical practice and decision quality within a sports club or an organisation. For example, sometimes clinicians may find it hard to articulate their experience, such as when they think an athlete is safe to RTS. In this case, clinicians can elicit knowledge from the rehabilitation dataset using the association rule method, consolidate their clinical experience into rules and use the rules to support their decision making. The rules may also help the less experienced staff make decisions and align the sports organisation’s practice. Overall, structuring knowledge with analytical methods may also help clinicians consistently apply the best possible knowledge, reduce unwanted variability, and ultimately improve decision quality.

The results from Chapters Five and Six demonstrated the strength of using descriptive and associative analysis in complex systems. Specifically, Chapter Five analysed longitudinal data trends and identified when meaningful changes occured. Chapter Six delved into the discovery of rules that are associated with increased levels of muscle soreness post-training. The rules may serve as beacons for clinicians, aiding them to foresee scenarios that may predict athletes' responses after training. In practice, the patterns and trends identified can aid clinicians in manipulating rehabilitation programs and influencing outcomes. Descriptive and associative analyses, with their expediency and practicality, may operate harmoniously with the complex systems approach. In complex systems, causes and effects often interlace in complex choreography, rendering the task of unpacking the latent forces guiding system behavior profoundly challenging and time-consuming. To this end, descriptive and associative analyses provide insights and actionable information to clinicians with efficacy and without the need for an exhaustive understanding of the complex causal relationships within.

While this thesis encourages clinicians to adopt a complex systems approach for decision-making, there are associated pitfalls when employing this approach to data analysis: 1) Complex systems analysis often involves integrating and analysing multiple types of data; however, it is not merely about indiscriminately incorporating all data into models without filtering for relevance. The initial thought process should encompass clinical reasoning, such as selecting the relevant metrics, choosing the most appropriate tests and determining the frequency of data collection. Furthermore, the quality of data is as important as the quantity. Inadequate or poor-quality data can lead to misleading patterns and therefore inaccurate conclusions. 2) While complex or advanced modelling might be imperative for analysing complex systems, excessively complex models can prove challenging for clinicians to interpret. In addition, they might not consistently outperform simpler models, despite their complexity. Striking a balance between model complexity and interpretability is crucial. 3) It is challenging to determine the causality within complex systems due to the intricate interdependencies and feedback loops, as mentioned earlier. However, relying solely on correlations, such as descriptive and associative analyses, may not adequately aid clinicians in comprehending the underlying mechanisms behind a clinical presentation. Within a sports organisation, researchers and clinicians can perform descriptive, associative and causative analyses coherently: Descriptive and associative analyses provide the operational foresight, while causal analysis probes deeper to unravel the root causes. This helps clinicians navigate the complexities of sports rehabilitation with a comprehensive perspective, while bridging timely interventions and foundational understanding. 4) Validating complex systems models can be difficult due to the unique and dynamic nature of the phenomena involved. However, expert knowledge may enhance the robustness of complex systems analyses by refining and validating the model against real-world observations. To navigate the above features and pitfalls of the complex systems, a multidisciplinary approach that combines expertise in statistics, data science and domain knowledge, are strongly encouraged.

Both Chapters Five and Six used a single case study design to exemplify the analytical methodologies. Case study research has sometimes been criticised for lacking scientific rigour and having limited generalisability to other subjects (Yin, 2009). While there are limitations to a single case study design, such an approach is advantageous when exploring a complex issue in-depth in applied settings (Crowe et al., 2011). The current single case design may direct readers' focus to the analytical methodologies and how the exemplars used them to integrate, analyse and visualise multiple data types simultaneously. Furthermore, the context and dynamics of most sports injuries and RTS processes are different and seldom repeat. For example, a similar hamstring injury may occur at various stages of the tournament; the mentality and personality of athletes differ. Clinicians may apply the methods in Chapters Five and Six to evaluate the RTS decisions on a case-by-case basis and structure the knowledge based on clinical experience. To systematically structure the knowledge to inform practice, it is also possible to consolidate the results of multiple case reports within the same sports organisation. For example, clinicians can try to discover rules that may produce the desired RTS outcome after a specific injury. While aggregating the results of case reports do not replace meta-analysis nor provide a statistically significant cross-section view of rehabilitation, they may provide crucial insight into the rehabilitation trajectory and identify if any common patterns are arising throughout RTS.

7.2 Implications for the sports industry

Effective rehabilitation program design, implementation and evaluation require consideration of the whole rehabilitation system. To this end, using a complex systems approach has been recommended in sports medicine (Bittencourt et al., 2016). Specifically, studying complex systems provides compelling concepts for capturing useful information about the world, including rehabilitation and sports injuries (Bittencourt et al., 2016).

To encourage clinicians to use the complex systems approach, Chapter Four translated the concepts and jargon of the complex systems theory into common languages and supplemented them with relevant clinical examples. Analysing data with a complex systems approach offers valuable insights into rehabilitation, and Chapter Four presented several key aspects to consider, such as emergence, non-linearity, tipping point, adaptation and feedback. Understanding these features is essential to predict and describe the behaviours of complex systems, which may aid decision making.

Chapter Five then proposed a new framework for RTS decisions which suggests clinicians 1) zoom into the methodological traps in clinical testing, 2) zoom out to identify the cognitive process, and 3) gain a perspective of the rehabilitation systems and align priority with other relevant stakeholders *(athlete, coach, management*). This framework encourages clinicians to harness the complex systems approach and look at the broader rehabilitation system from a "big picture" perspective (Hulme et al., 2017). This may help clinicians re-think the array of contributory factors that impact the rehabilitation outcome and progress. Sometimes, reforming and enhancing systems may be more effective than modifying the determinants of performance at the individual (Hulme et al., 2017). As an example, in Chapter Five, the change point univariate method indicated that most wellness variables (mood, sleep and soreness) reached their change points during the modified training session, which was when the athlete integrated with the main squad training in a modified capacity. Based on this finding and through the lens of the complex systems, clinicians may investigate the factors associated with the meaningful change points and develop protocols at the team or organisational level to facilitate rehabilitation. For instance, allowing injured players to get involved with some form of main squad activities (e.g., ball or non-ball training and team building activities) as early as possible.

Part 2 of this thesis aimed to improve data analysis to inform decisions. While the use of complex systems approach has been recognised as theoretically important to sports medicine, it remains challenging to implement these concepts in applied sports for multiple reasons. First, the sheer volume of data from different sources increased the complexity of the decision. Second, conventional analysis methods often assume linearity and focus on identifying one or more risk factors in isolation (van Dyk et al., 2016). Assuming linearity between factors and outcomes, and not accounting for the complexity rooted within findings may produce contradicting results (van Dyk & Witvrouw, 2020). To this end, the analytical methods presented in Part 2 may contribute by better capturing the multi-component patterns of human biopsychosocial behaviours and the dynamics of injury and rehabilitation with a multivariate approach.

A multivariate approach is preferable when examining the nonlinear relationships between variables because it allows clinicians to consolidate multiple data from different sources. By analysing multiple data types simultaneously, it may help to increase work efficiency and reduce the cognitive workload of interpreting. As demonstrated in Chapter Five, a multivariate change point method can aggregate the change points of multiple metrics and simplify them into a common change point.

Therefore, the clinician could refer to two common change points to summarise the overall changes in the four wellness metrics and the five running performance metrics.

These analytical methods are used to complement clinicians' existing clinical knowledge. For example, clinicians are generally aware of the principles of progressive loading on a hamstring muscle after injury. However, it can be challenging for them to analyse the nonlinear relationship between variables without the use of analytical methods (e.g., hamstring strength, the number of accelerations performed during training, and subjective stress levels). To this end, the association rule method (Chapter Six) provided another means of aggregating multivariate information. These rules are simple, intuitive and human-readable, meaning that they are user-friendly to clinicians who may have less training in computer-based analytics. Furthermore, clinicians can modify the content and length of the rules to suit their operational needs and preferences. Specifically, clinicians can choose to include information they believe to be valuable in the rules and decide how many pieces of information they would like to include. For example, some clinicians may prefer excluding the wellness information, while others may prefer including heart rate variability as a mean to assess stress levels. In addition, some clinicians may choose longer rules with more comprehensive information, while some prefer shorter rules for better applicability.

The exponential growth in data collected through advancements in sports technology presents exciting opportunities for improved analysis and understanding of complex systems in sports medicine. While univariate and linear approaches to data analysis may have been sufficient in the past, the increasing size and complexity of datasets necessitate the adoption of multivariate analytical methods, such as the change point and association rule methods. These techniques have the potential to uncover crucial combinations of variables that may impact outcomes, providing a deeper understanding of the system than previously possible. As demonstrated in Chapter Six, the use of analytical methods can reveal underlying relationships between variables that may contribute to increased muscle soreness post-training, offering valuable insights for the planning and design of rehabilitation programs.

The change point and association rule methods provide versatile solutions for analysing high-order interactions and nonlinear relationships presented in sports medicine. When using the analytical methods, it is advisable for practitioners to adjust the parameters of the algorithms based on the specific context and research question, in order to optimise their results and ensure the validity of the analysis. For example, in Chapter Five, clinicians were recommended to adjust the parameters of the change point algorithm based on the context and the purpose. The number and the location of change points discovered depend highly on the parameters of 1) the maximum number of change points and 2) the minimum length of the segment. Similarly, for the association rule approach in Chapter Six, clinicians also need to adjust the parameters based on their preference for 1) minimum support, 2) minimum confidence, and 3) the rule length.

Of paramount importance within this thesis is not only the theoretical understanding of the complex systems and machine learning techniques, but the practical “how-to” aspect of integrating the above knowledge into daily operations. To help clinicians consolidate the knowledge acquired and apply them effectively in practice, clinicians can use the Cynefin framework as a reference guide (Snowden & Boone, 2007). The Cynefin framework was developed to help leaders understand their challenges and to make decisions based on the context, which includes clear, complicated, complex, chaotic and a centre of confusion. Readers may refer to Snowden & Boone (2007) for further details. Based on the Cynefin framework, when clinicians make decisions with a complex systems approach, they may consider using the "probe-sense-respond" strategy: Clinicians can first *probe* the system by implementing a rehabilitation program based on the injury, RTP goals and timeline. Subsequently, clinicians can *sense* athletes’ performance progress by collecting data from clinical assessments (e.g., range of motion), and physical performance tests (e.g., leg strength). Moreover, clinicians can gather feedback from the athletes regarding their pain levels and perceived wellness. Clinicians can then *respond* to the data collected by analysing the datasets to identify patterns that are most effective in reducing pain and promoting recovery. Machine learning, through data analysis and descriptive and associative modelling, can find hidden patterns, predict recovery trajectories, and provide timely feedback to athletes and clinicians during rehabilitation sessions, as discussed earlier. For example, in Chapter Five, the change points suggested clinicians to monitor the athlete’s athlete’s sleep quality closely during the early rehabilitation phases because sleep quality takes longer than stress to reach the change points. In Chapter Six, the association rule approach suggested that when the athlete had poor sleep the previous night, clinicians may manipulate the muscle soreness post-training by adjusting the running intensity (metre per minute) and the number of decelerations in the training session. If certain rehabilitation program or strategies consistently lead to better outcomes or patterns, clinicians can prioritise and emphasis them. The "probe-sense-respond" approach is particularly suited for complex systems because it encourages adaptive response based on the patterns and rules discovered. This methodology encourages continual adjustments, which resonate with the inherent dynamism characteristic of complex systems.

7.3 Developing decision support systems

Data-informed decision support systems may enhance the accuracy and speed of clinicians' decision-making processes, provided that these systems can access sufficient high-quality data and employ the most appropriate methodology (Robertson, 2020; Robertson, Bartlett, et al., 2017). Building on this notion, there are two key advantages to consider: First, objective data analysis may provide an unbiased evaluation of the high volume of complex data, which can help overcome human cognitive limitations, heuristics or biases (Schelling & Robertson, 2020). Second, data analysis techniques can determine complex nonlinear interactions within large datasets over a period of time. This may be attractive for clinicians working in professional sports because large, multivariate datasets are increasingly common due to the rapid development of sports technology. By leveraging these data analysis techniques, clinicians can not only make more informed decisions but also transcend the limitations that human cognition can impose (Robertson & Joyce, 2019).

The two methods introduced in Part 2 are likely to fit in clinical settings as decision support aids because both approaches can explain the reasoning behind the output and are intuitive. The success of a decision support aid hinges on the transparency of the algorithm, that is, whether the clinician can understand and explain the verdict generated by the algorithm (Lipton, 2017; Watson et al., 2019). If the clinician does not understand the rationale behind the system's output, they may be skeptical of the result and, therefore, reluctant to adopt the system in practice (Schelling & Robertson, 2020). For a decision support aid to be used in a clinical setting, quality, practicability and interpretability are essential (Bullock et al., 2021). There is value in developing decision aids because decisions made using decision aid are generally more systematic and less prone to human cognitive bias (Sutton et al., 2020).

Importantly, the key essence of this thesis is not to remove the role of humans in the decision-making process but to be better supported and complemented by computational tools. Complex systems allow clinicians to view rehabilitation with a broader perspective. However, this would be extremely difficult to achieve without the support of computational analytical tools. This thesis emphasised the supporting role of analytical tools in consolidating rehabilitation data and presented clinicians with user-friendly visualisations that may support their clinical judgement. In addition, the tools and techniques presented in Part 2 of this thesis carry the overarching objective of innovating and creating novel solutions to improve RTS decision. Sporting organisations may consider adopting these analytical methods to gain a performance edge over their competitors. In short, the implementation of this thesis is intended to call for a paradigm shift towards the complex systems approach, followed by providing tools that may support, but not replace, clinicians' decisions.

7.4 Broader applications

Football (soccer) was used as an exemplar sport to demonstrate the applications of methods (change point and association rule). The framework and methodologies throughout this thesis, however, can be extended to other sports. Similar data capture techniques, such as GNSS tracking devices and athletes' monitoring tools, are commonly used across other field sports, such as Australian Football (Teune et al., 2022a) and field hockey (Jennings et al., 2012). Thus, the framework and methodologies may be extended to these sports. Adjustments to methodologies are required when working with sports that involve more upper limbs, such as baseball. In this case, clinicians may measure the pitching velocity and the number of pitches performed instead of the running performance metrics (Dowling et al., 2020).

Although a case of lower limb injury of a football player was used throughout Part 2, the methodologies described can be applied to most lower limbs and upper limbs injuries. Clinicians are encouraged to use their experiential knowledge to guide adaptions of the framework and methodologies within this thesis. For example, when managing a shoulder injury, clinicians may perform the Athletic Shoulder test and monitor the change in upper body isometric strength throughout RTS (Ashworth et al., 2018).

With the development of sports technology and wearable technology, clinicians can integrate more data types relating to other aspects of health and performance into these analyses. For example, data from wearables (e.g., heart rate variability and joint kinematics) and other questionnaires (e.g., personality and mental health) could also be included. These data may be measured and included within the same models and permit a deeper understanding of the interactions between variables. For example, clinicians may track the athlete's mental health throughout the RTS process and identify how it may be associated with performance output. This knowledge may also inform session design, such as how to modify the training sessions and better support the athlete when the athlete is mentally stressed. Furthermore, these data may provide additional contextual information when evaluating the athlete's readiness for RTS. This kind of analysis may become more feasible as sports technology that facilitates automatic data collection continues to evolve and implement widely.

The analytical techniques presented within this thesis allow more data types to be analysed together. As such, it may encourage collaboration between sports disciplines, which is advantageous in sports science and medicine (Browne et al., 2021; Dijkstra et al., 2014; Woods et al., 2021). To RTPerf after injury, athletes need to undergo rehabilitation and develop athletic qualities, including physical, mental, technical and tactical skills. In this process, the close collaboration between multiple high-performance staff is highly desirable, including but not limited to technical and tactical coaches, physiotherapists, sports scientists, strength and conditioning coaches, psychologists and nutritionists. One way to facilitate collaboration and communication is to integrate relevant data and present them together. Part 2 demonstrates how physical performance and wellness data can be combined and analysed to inform RTS decisions. Exemplar visualisations of the results may be used as a platform for high-performance staff to visualise data and discuss the appropriate management for RTS. In summary, many opportunities exist to adapt this thesis's decision-making framework and analytical techniques to elevate RTS decision quality.

Future directions

The use of complex systems approach as the theoretical lens in RTS is still in its infancy and requires time to mature. This thesis has presented multiple avenues for future research. There is scope to investigate further how these tools and frameworks may be transferred to the applied setting and their effect. First, future work can compare the clinicians' decisions with and without analytical tools to examine the efficacy of analytical tools. If clinicians demonstrate superior performance compared to decision-supporting systems, researchers need to further improve the methodology. Nevertheless, the call for methodological improvement is constantly required, especially in light of the continuous influx of higher-quality data as a result of technological development. As better and more data becomes available, it will become increasingly challenging for clinicians to outperform the analytical tools. A research design using randomised control trials may be conducted to compare the outcomes. However, the feasibility of this type of study may be limited in applied settings, for example, in high-performance sports. Consequentially, qualitative studies may also be considered. Second, future research may also build on current work and harness real-time information feedback to further increase the analytical tools' functions. For example, real-time feedback may be included in the change point analysis in Chapter Five. This real-time feedback may signal to clinicians when an athlete's rehabilitation behaviour is critically drifting from expectation and requires adjustment to the program. As technology and analysis in sports rehabilitation advance, there may be metrics (maybe other than physical performance and wellness) or algorithms that can support real-time decision making.

The analytical techniques within this thesis only represented two of the many other types of analytics. They may serve as a catalyst to generate and support novel approaches to RTS decisions. However, the applicability and practicability of using other analytical techniques remain largely unexplored in sports medicine, such as classification, agent-based modelling, network analyses and dynamic systems analyses (Peterson & Evans, 2019). Researchers may continue to explore other innovative methods that can simultaneously analyse the dynamic interaction at multiple levels and among variables of different groups.

In preparing a sports organisation and clinicians to be comfortable making RTS decisions with a complex systems approach, several competencies may be helpful. For example, it may be ideal for clinicians to have some basic understanding of analytics, including the theoretical knowledge of machine learning techniques (Rein & Memmert, 2016). These skills are often not a regular part of professional discipline training and education, but the knowledge may support clinicians to use advanced tools in applied settings and be aware of the limitations (Bullock et al., 2022). However, it is also crucial to recognise that clinicians alone are not sufficient for conducting these analyses effectively. It is strongly advisable to engage experts who possess specialised knowledge in areas such as data science, statistics and mathematics. These experts can play a pivotal role in bridging the gap between various disciplines and devising innovative research methodologies, particularly through collaborative endeavours. To foster these advancements, I strongly encourage future research teams to adopt a robust multi-disciplinary approach, with clinicians, high-performance staff, and data scientists, collectively working in synergy to derive meaningful insights from complex datasets (Casals & Finch, 2018).

7.5 Conclusions

This thesis may provide clinicians with methodologies to improve decision-making quality and analysis. The specific conclusions of this thesis are:

1. Clinicians may improve RTS decisions from two perspectives: improving decision-making process and data analysis.
2. There are different decision-making frameworks, and they are associated with various potential biases. Based on the decision-making framework used, there are strategies to help clinicians mitigate biases and potentially improve decision-making process.
3. Clinicians are recommended to view athletes with a complex systems approach, recognise the complex nature of rehabilitation and identify the interaction between various variables. This may help clinicians to understand the "big picture" of the problem.

4. Analytical methods congruent with a complex systems approach may help clinicians identify the interaction between variables and exploit unobvious patterns within a large dataset.
5. The application of analytical methods proposed in this thesis may help clinicians aggregate multiple data types, accommodate complex systems and present them in intuitive visual graphs.
6. These analytical methods can help clinicians move to multivariate nonlinear analysis, which may better represent the complex systems in sport and rehabilitation.
7. Future work could focus on examining the effect of the decision-making framework and the use of various analytics methods in daily operations.

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9 Appendices

Figure 9.1 Infographics for decision-making framework 1

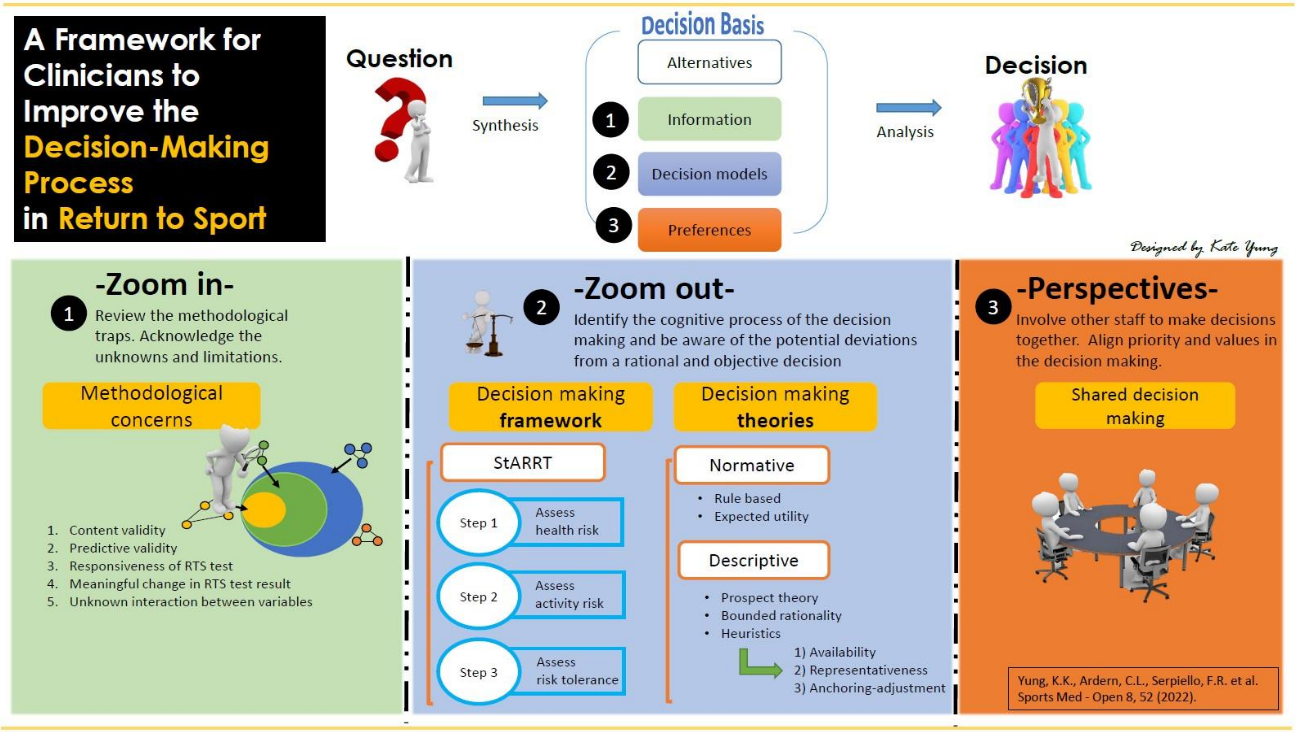


Figure 9.2 Infographics for decision-making framework 1 (continue)

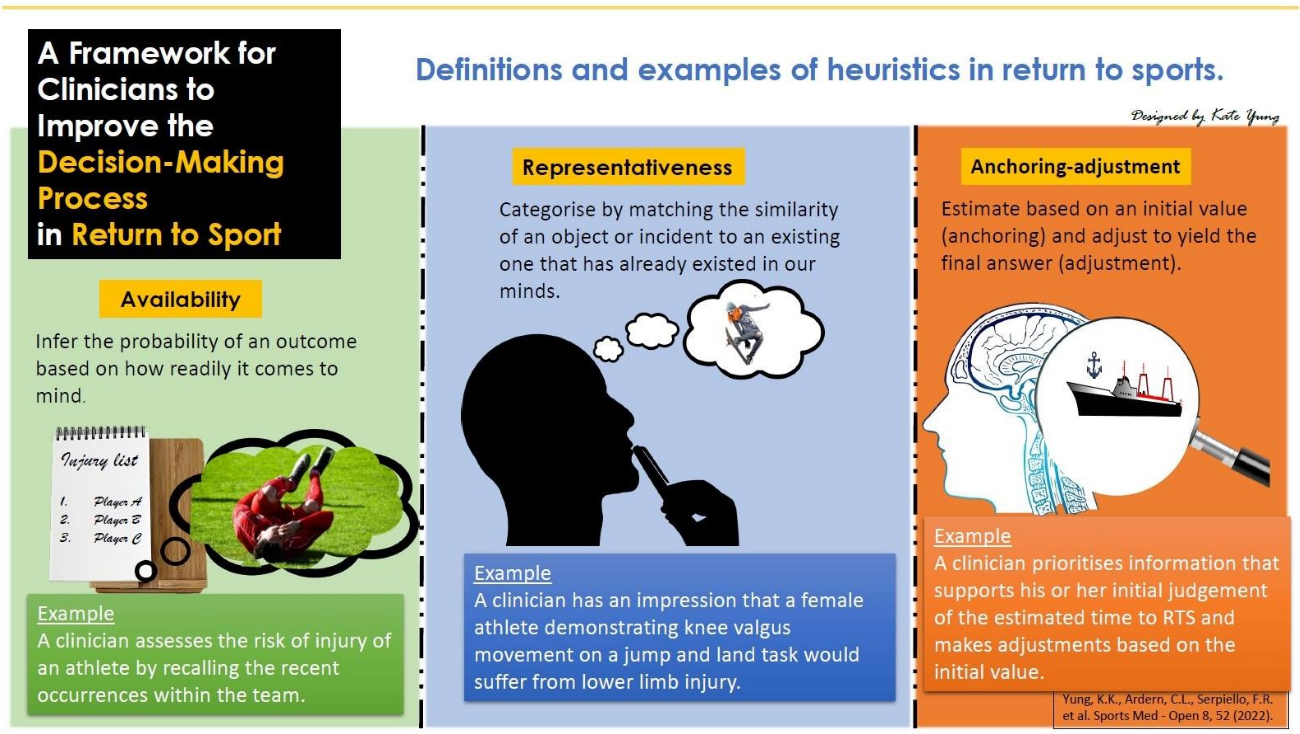


Figure 9.3 Study 2 featured in Football Medicine and Performance issue 38, pg 10-11

feature

A FLOCK OF BIRDS AND THE COMPLEX SYSTEMS: UNFOLDING THE CHARACTERISTICS OF COMPLEX SYSTEMS IN SPORTS INJURY REHABILITATION

FEATURE / KATE YUNG

Introduction

Since the development of the injury prevention model with the complex systems model [1], there has been increasing interest in the complex systems theory. Practitioners have been trying to understand how the model is relevant to their practice and how will it change their practice. The article aims to explain what the complex systems theory is and how it is relevant to the daily practice and operation in football.

What is the complex systems theory?

- The complex systems theory, with more than 50 years of history [2], acknowledges the multifaceted nature of sports and seeks to understand the interactions among different factors and the outcomes of the systems [1, 3].
- Complex systems are dynamic, open systems [4]. They are characterised by non-linearity due to feedback loops and interaction among the factors. This means that outputs are not always proportional to the inputs, and a small adjustment may lead to a large change in the systems and vice versa [5].
- Complex systems are composed of a large number of interacting components which give rise to global behaviour and make up a system that exhibits novel characteristics [4].
- In the context of return to sport (RTS), these units could include age, wellness, biological healing of injured tissue, stress, external pressure and injury history. The units interact and define the space and dimension of the systems [6].
- This means that complex systems can not be understood by studying their parts. Instead, it may be better to be studied from multiple perspectives.
- Examples of complex systems are flocks of birds, ecosystems and immune systems.

Complex systems explained with a flock of birds

- All individual birds follow a simple rule: maintain proximity without bumping into each other. That results in emergent behaviour known as flocking (Figure 1).

Complex systems ≠ Complicated & multifactorial only.

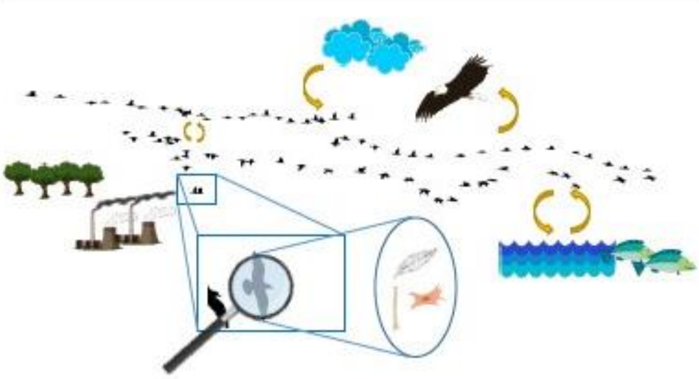


Figure 1. A flock of birds and the complex systems

- The flock emerged without any lead bird directing each bird's action.
- Multiple perspectives are required when viewing complex systems. The systems are three dimensional and interactions within the systems often occur at different scales and levels [7]. These include the environment, ecosystem and human activity (Figure 1).

Complex systems in rehabilitation

- Human systems, like a flock of birds, are also complex systems with distinctive characteristics. Using anterior cruciate ligament (ACL) rehabilitation as an example, we have described the characteristics of complex systems in our paper "Characteristics of Complex Systems in Sports Injury Rehabilitation: Examples and Implications for Practice" [8].
- In the context of RTS, the interacting factors could include age, wellness, biological healing of injured tissue, stress, external pressure and injury history. The factors will interact with the environment and other factors and consequently, different systems within systems emerge.
- These systems may be categorised based on their nature, for example, biomechanical, physiological and psychological.
- They are also of multiple levels, namely individual, organisational and environmental. The individual level represents factors related to the individual athlete, from tissue healing to personal traits. The organisational level represents external factors related to the sporting club, organisation and support team, e.g., the coaching and medical team. The environmental level covers factors beyond the organisational level, such as the weather, playing schedule and competition level.

FAQ 1: I know rehabilitation is complex and multifactorial, why do I have to bother about complex systems?

- The complex systems approach provides a theoretical framework for interpreting the patterns that emerged from biopsychosocial and other external factors. It is a tool for analyzing a problem more thoughtfully and efficiently.

- In ACL rehabilitation, conducting independent clinical tests and functional assessments may provide useful information regarding the athletes' physical and mental status. However, a complex systems approach facilitates a more complete picture of the problem and increased awareness of how different factors may interact.
- We encourage practitioners to consider multiple perspectives and come up with a solution or protocol that is broad and may address the root cause of a problem.

FAQ 2: If return to sport is so complex, is there anything we can do?

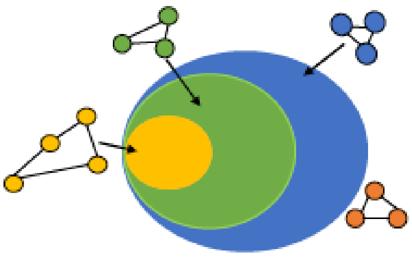
- When assessing the test result for clinical and functional tests, practitioners should also be aware of the dynamic systems evolving around injury rehabilitation and endeavour to understand the full picture.
- There are at least two challenges in understanding and explaining the behaviour of systems: 1) The high degree of complexity and 2) it is nearly impossible to isolate a portion of the larger systems (i.e., isolation of the biological healing process from broader biopsychosocial factors).
- We may have to rely on computer-based decision support systems that have the capacity of incorporating features of complex systems in their design and utility. For example, the use of machine learning techniques that could accommodate non-linearity association.
- Machine learning is often characterised by five major approaches (i.e., association, classification, clustering, relationship modelling and reinforcement learning), each having already been applied for injury risk assessment and/or performance prediction in sports [9-13].

Conclusion

- Complex systems are dynamic, open systems with distinctive characteristics.
- We encourage a shift in paradigm to a complex systems approach when making decisions regarding return to play.
- The use of computational modelling and machine learning techniques may have the capacity to identify the regularities of the pattern that emerged as a whole.

Figure 2. *Major approaches of machine learning techniques*

IMPORTANT POINTS ABOUT COMPLEX SYSTEMS



- Complex systems is a theory in general science and has been applied in other fields as well.
- They are dynamic, open systems with distinctive characteristics.
- It is more than complicated or complex. It is a way of thinking and understanding the systems that we are living in.
- It is challenging to analysis using a complex systems approach. Analytical techniques and machine learning model may be helpful in solving the problems.

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Figure 9.4 Infographics for Characteristics of Complex Systems in Sports Injury Rehabilitation