Man & machine: Adaptive tools for the contemporary performance analyst

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Abstract

Sport, like many industries, is experiencing growth in resources, professionalism and data generation. An understanding of how humans can effectively and efficiently interact with technology, computers and other machines to improve sports performance is still being developed. As a consequence, the landscape in which the performance analyst now finds themselves has fundamentally changed. New, improved and different skill sets are now required in order to be impactful and experience sustained success. However, this growth also presents new opportunities to address difficult problems, including many that were previously considered intractable. This article lists ten essential adaptive tools for the contemporary performance analyst, many of which are useful in both research and applied sporting environments. A rationale for each is proposed, with an emphasis on ensuring that the performance analyst will be equipped to thrive in both current and future sport environments.

Introduction

Sport, like many industries, is currently experiencing considerable growth. In sports science disciplines specifically, university enrolments are at an all-time high, whilst adoption of new technologies by sporting organisations combined with greater financial resources is producing data at record rates. Faster, cheaper and increased access to this data means that the manner in which decisions can now be made compared to previously is vastly different.

Fundamentally, these drivers of growth have increased the flexibility afforded to users with respect to decision-making processes. Decision-makers can choose to consider different volumes and quality of data, multiple types of analyses and various amounts of time before determining an appropriate course of action. However, these drivers have also created new challenges such as how to handle incompatible data formatting, understanding the increased complexity of applied environments, as well as developing methods to integrate humans and machines in decision-making processes.

In performance analysis specifically, many of these developments were foreshadowed. For instance, Bartlett (2001), noted the divergence of sports disciplines such as notational analysis and biomechanics based on their shared use of data and video. The rise of automated coding, the consideration of sporting competitions as complex systems, as well as the harnessing of spatiotemporal data to develop coaching insights were all forecasted by McGarry (2009). Glazier (2010) lamented many related issues that remain unresolved today, such as adoption of an appropriate theoretical framework on which to both base and connect sports performance research and practice.

Whilst some gains have been made in the abovementioned areas, the number and variety of challenges facing the contemporary performance analyst are higher than ever before. Primarily, this article aims to provide a current perspective of these challenges as they pertain to performance analysis in the field. Tools that the contemporary performance analyst can adopt to develop more accurate and efficient solutions to the challenges faced in sporting environment are identified, promoted and discussed.

1. Decision support systems

"By their very nature, complex adaptive systems are difficult to analyse and their behaviour is difficult to predict. It is hoped that intricate computer simulations will provide useful tools for accurately forecasting the behaviour of systems governed by the interactions of hundreds, or possibly thousands, of purposive agents acting to achieve goals in chaotic, dynamic environments (Fogel, Chellapilla & Angeline, 1999)"

Competitive sport can undoubtedly be a chaotic, dynamic environment. In order to better understand these environments, humans are increasingly seeking the assistance of external aides, such as decision support systems. These systems provide objective evidence to decision-making (Spraque, 1980), typically using historical data to generate a recommendation or assessment based on output generated by statistical analysis or a machine learning algorithm (Kawamoto, Houlihan, Balas & Lobach, 2005). They also tend to incorporate back-end databases where information can be not only accessed and queried, but also reformatted for multiple purposes.

Decision support systems have become increasingly common in performance sport and have been reported in the literature for purposes such as player performance evaluation (Calder & Durbach, 2015), competition planning (Ofoghi, Zeleznikow, MacMahon & Raab, 2013) and athlete monitoring (Robertson, Bartlett & Gastin, 2017). Despite considerable successes, in some environments they have experienced limited uptake (Robertson, Bartlett & Gastin, 2017; Kayande De Bruyn, Lilien, Rangaswamy, & Van Bruggen, 2009). Reasons for this include a 'handing over' of responsibility to computers, or a fear of people's jobs being replaced. Those in positions of authority may also see decision support systems as a threat to their own power and responsibilities.

So why are decision support systems so important to the contemporary performance analyst? Well firstly, their efficacy. The superior performance of decision support systems on a range of tasks comparative to humans has been well-established. Such findings are particularly prevalent whereby multiple potential options exist, the data are complex, or there is disagreement amongst stakeholders as to what constitutes best practice (Bate, Hutchinson, Underhill, & Maskrey, 2012; Hoch & Schkade, 1996). A second consideration relates to necessity. Global data volume is growing at an exponential rate and expected to hit 175 zettabytes in 2025, over half of which will be generated by IoT devices (International Data Corporation, 2020) and over 80% of which will be unstructured (Data Management Solutions Review, 2019). Continued increases in the volume of data generated from vision, wearable sensors, human self-report and third-party sources will likely mean that organisations will not be able to organise or make use of data without the adoption of decision support systems. Thus, in addition to performance benefits, they can also substantially improve the efficiency of both the individual and organisation by automating repetitive processes, as well as storing and allowing rapid access to data obtained from multiple sources. A good system may even facilitate easy querying across different areas of a sporting organisation; for instance, exploration of relationships between performance data and membership, marketing or social media content. For a broader breakdown of the factors warranting consideration in the development and evaluation of decision support systems in sport, see (Schelling & Robertson, 2019).

2. Human & machine interaction

"A considerable fraction of (human) clinical time is being irrationally expended in the attempt to do…prognostic jobs that could be done more efficiently…through the systematic cultivation of complex statistical methods" (Meehl, 1954)"

Much has been written about the differences between recommendations or decisions made by humans and those of algorithm-informed machines, such as those often utilised by decision support systems. These writings have typically emphasised the limitations of humans, tending to focus on how the abovementioned systems consistently better human judgement across a range of tasks and questions.

Despite this, the performance analyst may be required to develop clever strategies in order to facilitate stakeholder adoption of decision-support systems. Developing an understanding of both *where* and *why* humans and machines differ in their processing of various problems is of particular value and can serve to alleviate any potential angst of machines 'taking over'. Obviously, most humans do not like their limitations to be constantly highlighted. Thus, machine-based recommendations should be seen as a supplementary resource – at least initially – in order for stakeholders to first see them as an opportunity rather than a threat to their own judgements.

So how can the performance analyst best identify the questions and processes in their workflow that are most suitable for decision support? One method is to define each process based on its corresponding constraints and characteristics, thus constituting its *decision support readiness*. Figure 1 provides an example template of this approach. Common constraints and characteristics may include the frequency of the process (i.e., daily), its relative importance to the organisation (measured qualitatively or for example based on financial implications), its complexity (computationally or based on stakeholder feedback) and the time required/afforded in which to undertake the given process. Other characteristics also exist and can be considered depending on the requirements or emphasis of the organisation. Processes experiencing the strongest influence of certain constraints may represent those most suitable for decision support system adoption.

****** INSERT FIGURE 1 ABOUT HERE ******

It is also important to note that although staff working in sport are expected to be experts in their given domain, very rarely does their expertise include formal training in decision-making. Thus, decision support adoption provides a means by which complex decisions and processes can be offloaded to semi- or even full-automation. From both a decision accuracy and operational efficiency standpoint, doing so will provide both these individuals and the organisation a favour.

3. Perspective

‘All models are wrong but some are useful’ (Box, 1976)

Combining sport’s inherent complexity with the abovementioned rapid increase in data, it is not surprising that considerable disagreement exists with respect to many of the industry’s most important problems. Common perspectives into topics such as quantifying team sport athlete performance, or defining tactical behaviour represent pervasive examples. Whilst disagreements across research and the industry are somewhat inevitable and perhaps even desirable, understanding the underlying theoretical underpinnings as to why they exist is of benefit.

The theory of bounded rationality provides us with a means by which to further this understanding (see Robertson & Joyce, 2019 for a sport example). The theory holds that the decision-making of individuals is influenced by the information to which they have access, the cognitive limitations of their minds, and the finite time in which they have in which to act (Simon, 1957; Kahneman, 2003). Bounded rationality posits that in complex situations, individuals who intend to make rational decisions are bound to make satisfactory choices, rather than maximizing or optimising ones (Gama, 2013; Gigerenzer & Selten, 2002). Consequently, it helps to explain how two individuals can arrive at different conclusions on a given problem, even when accessing the same information. Perhaps even more importantly, it advocates the importance of admitting that we ‘know what we don’t know’ in complex scenarios.

So what does this mean for the contemporary performance analyst? In the event that a contrasting view is presented on a certain problem, the other individual may well be wrong – but they may also simply be considering the same problem in a different way, or utilising different information. Because no individual will ever consider all of the relevant information to a specific problem, an optimal solution will never be arrived at. Further, what represents an appropriate solution today, may no longer be accurate or sufficient in future - particularly as technology improves and data volume grows. Thus, it is important that the performance analyst has an awareness that they do not, and will likely never, have access to all relevant information on a given problem. Acknowledging this can render them more likely to adopt a growth mentality with respect to their knowledge base, as well as potentially develop an open-mind with respect to networking and developing new skill sets. This is crucial in the performance analyst understanding their place as a member of an interdisciplinary, high performance team, who coordinate activity through unifying principles, language and behaviours.

4. Innovation

(Innovation can be) "a new idea, creative thoughts, new imaginations in form of device or method"

(Merriam-Webster, 2016)

Assuming the performance analyst has adopted decision-support systems into some of their work processes, a concomitant improvement in work efficiency should ensue. An additional benefit of this adoption is a subsequent increase in time availability. Some of this time should be spent on identifying and implementing new innovation. Sporting clubs have long turned to innovation in order to obtain new insights and gain an advantage over their competitors. But how does the performance analyst decide as to which innovation areas to focus on? To help guide the performance analyst, a range of factors should be considered. For instance, does the initiative have the potential to meaningfully improve outcomes for the organisation? How much does it need to do so, in order for it to be considered a success? Is the initiative likely to experience ongoing and sustainable adoption by stakeholders?

Considering existing questions and processes on a 'priority continuum' can identify those innovation areas most appropriate to target (Figure 2). Each can be rated quantitatively (i.e., 'the question is addressed on a weekly basis and costs) or qualitatively (i.e., 'the process is of a high priority to the organisation and ready for further investigation').

****** INSERT FIGURE 2 ABOUT HERE ******

Typically, questions and processes which feature at the *Reluctance* end of the priority continuum experience high exposure to many of the constraints discussed in Section 2. Examples may include limited access to high quality data, or high investment by stakeholders in their own subjectively-informed decisions, thus resulting in a reluctance to alter existing practice. They may feature no standardised method of data collection or reporting, which can lead to the possibility of perceived conflicting/contradictory conclusions drawn from objective data vs humans (although this may also be a feature of questions located on the higher end of the continuum).

Those featured near the *Curiosity* mid-point of the continuum are typically characterised by a level of openness on behalf of the organisation. There will typically be a short to medium amount of time available in which to address the questions. Common examples of such questions for the performance analyst include player evaluation in team sports or in-game coaching decisions. Accordingly, these questions also tend to facilitate opportunities for comparison of human vs machine recommendations.

Questions and processes at the *Necessity* point of the continuum typically feature access to data of both a high volume and quality, as well as high complexity. Importantly, they also tend to feature low affordance of time, thus innovation may potentially be required by necessity. New and challenging problems such as interpreting team sport movement patterns using computer vision (Thomas, Gade, Moeslund, Carr & Hilton, 2017), or determining the expected value of a possession in team sport (Spencer et al., 2019; Cervone, D'Amour, Bornn & Goldsberry, 2016) represent examples. Obtaining solutions to these questions can result in meaningful gains to organisations by indirectly improving outcomes through obtaining insights not available to competitors. Equally importantly, they may meaningfully improve time efficiency and workflow, such as reducing excessively manual time spent coding vision in professional team sports.

5. Versatility

'A problem well stated is a problem half solved' (Charles Kettering)

Many of the questions faced by performance analysts can be posited in multiple ways. Developing abilities by which they can express, analyse and communicate data in various formats is one such manner that performance analysts can display versatility and increase their value to an organisation.

In the literature, applied research into injury presents a good example of one topic that has been investigated in a variety of ways. It has been addressed by considering changes in odds ratios (Colby, Dawson, Heasman, Rogalski & Gabbett, 2014), modelling injury likelihood (Carey, Blanch, Ong, Crossley, Crow & Morris, 2017), and as a machine learning forecasting problem (Rossi, Pappalardo, Cintia, Iaia, Fernàndez, & Medina, 2018), to name a few. Each of these approaches have respective strengths and weaknesses, depending on the application context and intended user. The influence of framing the training availability problem in different ways on resultant interpretation and action has not gone unnoticed in the literature. Limitations on the utility of common screening tests for injury modelling have been detailed (Bahr, 2016), whereas the influence of the arbitrary discretisation of continuous data on altered interpretation of injury models has also been discussed (Carey, Crossley, Whiteley, Mosler, Ong, Crow & Morris, 2018).

Principles of versatility can be applied to many other common problems faced by performance analysts. Typically, organisations tend to utilise methods and frame questions in ways that either meet their prior expectations (see confirmation bias (Nickerson, 1998)), or are 'operationally compatible'. The latter term refers to the adoption of an approach that produces insights which are most actionable in practice; thus is compatible with the operational processes of a given organisation. Again, an awareness of how similar problems are faced in other industries can help to allow the performance analyst to draw on this experience when required to act rapidly and produce multiple potential solutions to a problem for key stakeholders.

Application of different types of analytical approaches to the same data set is another way in which the performance analyst can display versatility (Witten, Frank, Hall & Pal, 2016; Ofoghi, Zeleznikow, MacMahon & Raab, 2013). Many success stories relating to applications of machine learning in sport have more to do with the flexibility of these algorithms in handling the same problem in different ways, than solely their ability to accurately predict outcomes from large data sets. For instance, consideration of a question as a classification problem rather than regression may cause the end-user to alter the way in which they view the scenario altogether. Thus, developing a working knowledge of various analysis methodologies is a useful trait for the contemporary performance analyst to possess, irrespective of whether they ever intend to become highly proficient in data science or not.

The continued utility of computing in performance analysis has also allowed for greater reproducibility, automation and transparency of workflows (see Ram, 2013). Open source programming languages such as R and Python have been at the forefront of this. In addition to technical computational skills, many of the hallmarks of adaptability can also be developed by the performance analyst through adopting computational thinking. This refers to the "thought processes involved in formulating a problem and expressing its solution(s) in such a way that a computer—human or machine—can effectively carry out" (Wing, 2014). It encourages logical organisation of data, abstractions and pattern recognition, reformulating problems, process efficiency and automation. In doing so, one of its major benefits is that the method typically provides a multitude of solutions to the same problem. In a society increasingly utilising computation in so many of its daily functions, it is not surprising that computation has joined theory and experimentation as the third recognised pillar of science (United States President's Information Technology Advisory Committee, 2005). Thus, a key challenge of organisations moving forwards will be to recruit appropriate teams of individuals skilled in computational thinking, irrespective of whether they possess formal training in the area.

6. Visualisation

'There is no such thing as information overload, just bad design' (Edward Tufte)

A picture really can be worth a thousand words. Attention spans are getting shorter, whilst athletes and coaches expect ever-stimulating presentations to help prepare and review competition. Communicating complex information via visualisations offloads cognitive work to automatic perceptual processing (Kale, Nguyen, Kay & Hullman, 2018). Thus, a good visualisation can save time, as it may only require the act of recognition on behalf of the user, as opposed to the searching and conscious processing potentially required when reading written reports. Consequently, recommendations outputted from visualisations can be interpreted and actioned more quickly than those obtained via written reports (Larkin & Simon, 1987). This is of particular importance in time-poor decision-making processes, such as tactical coaching during competition or consideration of the health status of a large group of athletes prior to commencement of a training session. Other useful features of a good visualisation may include interactivity, animation, context, storytelling and its ability to stimulate creativity in the viewer.

Of course, a need will always exist for raw data and written reports. Visualisations also have the potential to mislead; this can occur even unintentionally on behalf of the analyst. The contemporary performance analyst should develop qualities such as interchangeability and flexibility with respect to how they present various output. Concepts such as informational and computational equivalence are important considerations in this respect. An example of informational equivalence relates to two visualisations or reports whereby all information contained in one is inferable from the other, and vice versa (Larkin & Simon, 1987). Some of the best visualisations in terms of facilitating fast operational decision-making can allow the user to obtain as much relevant insight as a written report or data table. Computational equivalence relates to the extent to which the visualisation can be generated comparative to a written report using a similar rate of processing. In a landscape that is utilising increasingly larger types of data, in particular various forms of multimedia, computational equivalence has never been more important for sports organisations than it is right now.

Visualisations should also be able to illustrate uncertainty in predictions or recommendations. It is well established that they can help to facilitate this comparative to written reports (Kay, Kola, Hullman & Munson, 2016). This is more important than often realised; when people don't understand uncertainty in a recommendation they don't tend to trust it – consider the weather forecast as an example. Fundamentally, when dealing with a human interpreter and decision-maker, a poor visualisation may be the defining reason as to why a certain course of action is taken or not, even if a high-performing analytical model underlies it. With so many open-access, easy-to-use visualisation software available, this area is a valuable yet easy area for the performance analyst to upskill in.

7. Evaluation

If you judge, investigate (Seneca)

Evaluation seems like a basic and obvious exercise to undertake. However, in practice it is often overlooked. The systematic assessment of models, recommendations or reports provided to stakeholders is beneficial on multiple levels for the performance analyst. Most simply, evaluation facilitates their longitudinal refinement. For models and quantitative reports, evaluation is often achieved through cross-validation – comparing the performance of an established model on new data once it becomes available. However, this is not always possible, as often small datasets exist within sporting organisations. Further, although developing an accurate report or model is paramount, such evaluation does not provide insights into how it was received by the end user, or relevant stakeholders (discussed below in 'Feedback'). Again, the utility of decision support systems for the purpose of evaluation can provide access to quantitative data almost instantaneously, thus allowing the performance analyst to provide an evaluation or justification of their work performance on demand.

Reference points are another important consideration to be aware of for the purposes of evaluation. One such reference point is *existing practice*. For instance, a solution or recommendation may often be benchmarked against an existing approach or practice in the short term in order to determine whether it warrants ongoing adoption by the organisation. A decision on how much better the newly proposed solution is required to be in order for it to replace existing practice may be required (see Kay, Patel & Kientz, 2015). Often this decision will be affected by factors such as the extent to which the new solution reduces cost or saves time. Consideration of contextual variables can also alter these evaluation reference points. In a decision-making problem, one such contextual variable may be the number of *potential options available*. In a scenario whereby only two options exist, there is a higher likelihood of making a correct, enhanced, or more satisfactory decision solely by chance. In relatively more complex questions entailing multiple potential options, this likelihood is comparatively lower.

Another common reference point is *expectation;* that is, how the performance of the solution or recommendation compares to the ex-ante expectation of either a model/recommendation or a human user. With respect to the latter, expectation helps to explain why a team having a poor year following a championship winning season is typically viewed as more of a failure than it would have been had they been mid-table in the year prior. In this scenario, expectation of an organisation may be artificially high based on past performance, thus anything other than a repeat performance in subsequent seasons may be viewed as a disappointment. Through systematic measurement of the longitudinal influence of factors such as the schedule and the number of injured players, reference points can also be objectively adjusted dynamically, thus facilitating more informed evaluations of player or team performance (Robertson & Joyce, 2018; Robertson & Joyce, 2015). Thus, expectations may be fixed, as is often the case in modelling, or dynamic and subject to change on a weekly or daily basis. Of course, expectations can be dangerous reference points. For instance, it may sometimes be considered worse to perform badly when there is pressure, compared to when there is none. Expectations may also cause changes to behaviour, sometimes inadvertently. For instance, a single bad loss for a coach of a team expected to win a championship may lead to the knee-jerk decision for them to be fired. Research in football has shown that players are more likely commit more fouls and receive more cards after falling behind in a match that they are expected to win (Bartling, Brandes & Schunk, 2015). Thus evaluation, whilst important, is more than solely the performance of a solution or recommendation – it is multi-faceted and requires input from multiple stakeholders.

8. Feedback

The single biggest problem in communication is the illusion that it has taken place (George Bernard Shaw)

For the contemporary performance analyst, feedback may be required on the utility of a given process, a model implementation, or their broader work output as an individual or team. Politically speaking, it also makes sense to seek feedback; a willingness to seek this out can illustrate ambition and an appetite for personal development.

For automated or semi-automated reporting and processes, a good decision support system should facilitate feedback - ideally in a manner that does not encumber the stakeholder unnecessarily. Constant demands for feedback can become tedious; thus, a balance should be struck between obtaining this formally and informally. Development of bespoke evaluation frameworks, that can incorporate both quantitative and qualitative values is of particular benefit. Such frameworks should be intuitive in their design, optional and potentially semi-automated in order to maximise stakeholder engagement.

****** INSERT FIGURE 3 ABOUT HERE ******

Figure 3 illustrates how such a framework can be developed, using the example of obtaining feedback on a visualisation. Five example items by which feedback may be sought on the visualisation are shown, however more or less could be included. The intended outcomes of maximising the feedback on each item are also shown. For instance, receiving a high feedback score on the aesthetics of a visualisation is likely to be an indicator of user enjoyment, thus is also likely to enhance regularity of use. Further, a visualisation which affords flexibility at the user-end is likely to facilitate innovation through allowing the user to explore multiple solutions to a particular problem. The framework can display flexibility in and of itself; items can be switched 'on' or 'off' on the feedback framework (see the Applicability column), depending on their relevance to the particular visualisation, report or recommendation.

Analytically speaking, typically well-performing 'black-box' algorithms such as neural networks may suffer from limited adoption given that the user may not be provided a clear understanding as to how a recommendation has been formulated (Kayande, De Bruyn, Lilien, Rangaswamy & van Bruggen, 2009; Umanath & Vessey, 1994). Thus, a question arises with respect to weighting the feedback received on various items for a given process or individual. Perhaps surprisingly, in many models or reports, feasibility (cost, time) and interpretability are often considered as equally as important as its accuracy (Robertson, Bartlett & Gastin, 2017; Sanders & Mandrodt, 2003)

Feedback is often considered after processes have been implemented or decisions have been made, however can be equally or even more useful when obtained beforehand. Activities such as 'pre-mortems' (Kahneman & Klein, 2009) consist of group settings to brainstorm all potential factors relating to a problem, prior to it being systematically addressed. Following briefing, respondents are then asked to envisage a scenario whereby a solution to the problem has failed. This allows for stakeholders to voice concerns or highlight weaknesses about a specific project during the planning phase (Klein, 2007). Potential failure points can then be identified before they occur, helping to create a culture of feedback within an organisation, as well as identify strong decision-makers. This process works most effectively in scenarios whereby participants are provided an opportunity to receive feedback on their judgments, so that they can strengthen them and gain expertise. Without this exercise it can be difficult to determine the mechanisms behind why a decision was correct or not.

9. Generalise

The challenge we all face is how to maintain the benefits of breadth, diverse experience, interdisciplinary thinking, and delayed concentration in a world that increasingly incentivises, even demands, hyperspecialisation (David Epstein)

Contemporary performance analysts face a dilemma. A generalist skill set is becoming increasingly required, however specific aptitudes remain essential. In following a generalist path at the expense of a specialist approach, one also runs the risk of potentially becoming neither. Fundamentally, whether the field likes it or not, performance analysts are now required to be technologists as well. Analytical prowess is not far behind in terms of its importance. This increased dependency on technology for not only many of the performance analyst's functions but also other sports practitioners, is unlikely to abate any time soon.

In high performance sport more broadly, collective generalist skill sets are also becoming more common. This is evidenced by the state of the workforce. People from video analysis, biomechanics, statistics, and even physics hold performance analysis roles with various organisations. But it is not just their background that is important. An ongoing skill set in complementary areas is now more important than ever. Displaying an aptitude for coaching, scouting, skill acquisition, training design, analytics and even 'story-telling' are all of use and when developed at a baseline skill level can further support the hard skills displayed by the performance analyst.

To the ‘one-dimensional’ performance analyst, a clear message emerges – develop a generalist skill set, but cultivate a point of difference. Attend conferences and speak with people in other disciplines. People often talk about the importance of doing this, but don’t follow through. If you are working with spatiotemporal data, talk to someone in criminology. If wanting to evaluate outcomes made by human decision-makers, talk to a behaviourial economist. If implementing data infrastructure, talk to a data engineer who has done this for a large multinational organisation. Although innovation is important, adaptation of methods and processes utilised elsewhere can be easily transferred and often be sufficient without recreating the wheel.

A range of other skills and qualities are also relevant, many of which are often incorrectly assumed as inherent in scientifically trained individuals. For example, the importance of maintaining a healthy level of scepticism to new claims, understanding principles of measurement such as validity and reliability and making appropriate inferences from simple observations compared to structured experiments. The challenge for the education provider is to ensure that these cornerstones of scientific training are produced in their graduates, yet the content delivered to students is contemporary and relevant. Hyper-specialised education offerings are also likely to be more susceptible to becoming outdated, whereas the development of traits that are transferable as well as promoting collaboration will always be valuable. These generalist traits can also tend to promote a keenness to pursue inter and transdisciplinary approaches to tackling some of sports most challenging problems.

10. Future planning

It is better to foresee even without certainty than not to foresee at all (Henri Poincare)

To this point of the paper, it should be apparent that rapid rate of development in technology and sport as a whole means that the future for the performance analyst will look very different to the present.

The skillsets of performance analysts will need to change; in fact, as we’ve discussed - they already have in many ways. Technological and computational literacy are now more important than ever before. As new data types emerge, the performance analyst will also have a responsibility to maintain the ethical and integrity demands of utilising such data. This includes considerations such as which third parties have access to player information, as well as ensuring that it isn't used to create false narratives around an athlete's performance.

Adopting a theoretical framework (i.e., complex systems) helps to maintain consistency throughout workflows, and optimise communication strategies within an organisation. Whilst not always possible, when this simple unification is lacking from sporting organisations it may result in an overemphasis on *what* is occurring than focussing on the underlying drivers (*why*). Without the latter, it isn't possible to design interventions directly capable of changing those areas of in need of improvement. Having the same theoretical underpinnings across departments also helps to break down silos within an organisation. For instance, if an athlete is struggling to maintain technique when executing a given skill, this allows for a conversation between the physiologist, coach, psychologist and performance analyst to occur using the same lens. The performance analyst should aspire to be the conduit for many of these conversations due to their management of corresponding data, further increasing their value to the organisation.

This increased responsibility that is likely to be placed on performance analysts also provides further opportunities. As new and better types of data continue to become available, then data from the past are going to be even less useful when making predictions about the future. Thus, exercises such as future scenarios planning, particularly as it pertains to adoption of new technologies, may also fall under the remit of the performance analyst. These exercises typically consist of collective, systematic planning for a future situation 5-10 years ahead (i.e., developing a new practice facility) in order to ensure it will be suitable for the expected changes to the environment.

In order to be truly forward-thinking, the performance analyst needs to set aside to do just that – think[1]. Opportunities to utilise some of the tools mentioned earlier, such as innovation, cannot be explored without dedicated time away from normal operational processes of high-performance sport. Growing a strong network both within and outside of sporting circles will continue to be useful for informing this innovation. The education sector, in particular universities, need to become more responsive in providing relevant training for such future environments. Academics who have spent time working in the field (sometimes colloquially referred to as 'pracademics') shape as important leaders in this area. Innovators and entrepreneurially minded individuals can also influence the nature of this training in profoundly different ways comparative to the traditional academic. This relevant training is important not only to appropriately prepare graduates for their careers, but also to ensure the long-term viability of the universities themselves.

Conclusion

This article has discussed and advocated ten tools for the contemporary performance analyst. These tools provide not only a prescription of activities that the analyst should emphasise in their ongoing development, but also areas for further brainstorming and expansion. The individuals and organisations that are able to address some of the conceptual and operational considerations discussed in this article will be amongst those best placed to obtain competitive advantage in their endeavours of relevance – regardless of what the future may hold.

Footnote: [1] The reader is directed to a short video featuring Bill Gates and Warren Buffet on the importance of taking time out from a crowded schedule in order to think and be creative https://www.youtube.com/watch?v=nH5K0yo-o1A

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Figure captions

Figure 1.

Decision support readiness for a given question or process faced by the performance analyst. Each process can be defined by multiple characteristics and constraints, with the coloured bars representing the typical range expected in each.

Figure 2.

An innovation priority continuum for performance analysis.

Figure 3.

A user feedback framework, using the example of visualisation. The visualisation can be evaluated based on multiple items, either qualitatively or using a form or rating scale. The intended outcome of maximising user feedback on each item is displayed.

Figure 1

Time
Short
Long
Frequency
Often
Rare
Importance
Low
High
Complexity
Simple
Complex
Bias prevalence
Weak
Strong

Figure 2

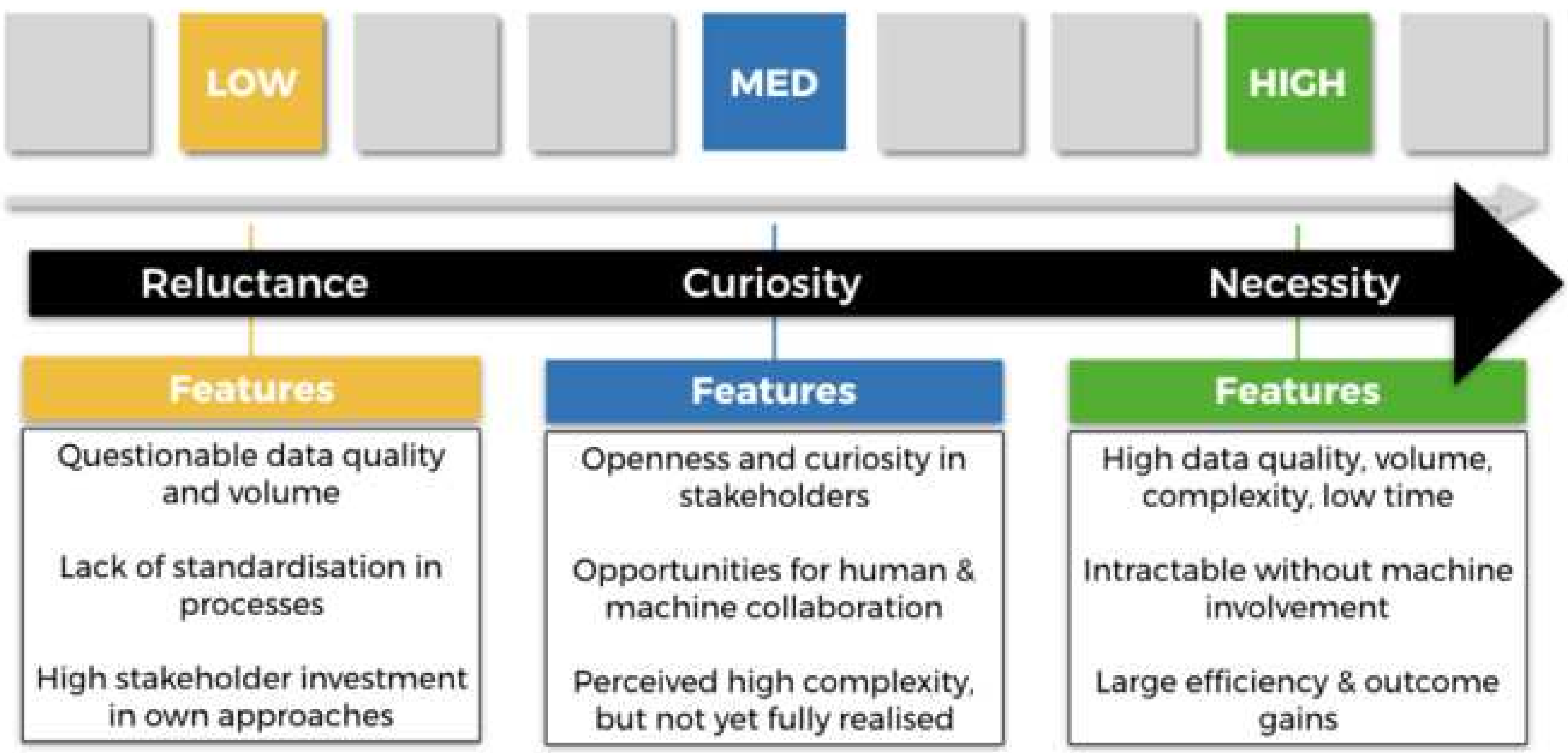
LOW
MED
HIGH
Reluctance
Curiosity
Necessity
Features
Questionable data quality and volume
Lack of standardisation in processes
High stakeholder investment in own approaches
Features
Openness and curiosity in stakeholders
Opportunities for human & machine collaboration
Perceived high complexity, but not yet fully realised
Features
High data quality, volume, complexity, low time
Intractable without machine involvement
Large efficiency & outcome gains

Figure 3

Applicability
Item
Outcome
Aesthetics
User enjoyment
Informational equivalence
Efficiency
Flexibility
Innovation
Uncertainty
Accuracy
Impact
Behaviour change