Introduction to football analytics 2021

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INTRODUCTION

The incorporation of new technology into sport has resulted in an increase in both the volume of data and the variety of its types. This has led to a need for completely new areas of expertise (such as that provided by data analysts, computer scientists and mathematicians) in organisational departments, as well as adaptation by those already holding established roles, such as sport scientists, strength and conditioning coaches and performance analysts. The link between sports and computer sciences is now well established, and few top-level professional structures resist its integration. However, despite the interdisciplinarity of many staff teams, the knowledge and linguistic barriers between different scientific fields mean that interaction between professionals can often be difficult. One way to help address this problem is for experiential and scientific knowledge, historically based on reductionism, to move towards an understanding of sport as a complex phenomenon.

The complexity of football lies mainly in the number of interactions between teammates and their environment, in particular their opponents, but is also found in the context of the game as a whole. Traditionally, performance has been evaluated by isolating system components including the physical and physiological; the technical (derived from the players' on-ball events); or tactical aspects (the relationship between teammates and opponents). These "performance components" cannot be seen at the same level but instead in a nested way, because the inherent processes within them emerge on different timescales (figure 1). It is in a competitive environment, evolving over several years, where cooperative processes are situated. The team cooperates at the timescale of weeks and months as well as more immediately at the timescale of the match's 90-plus minutes to achieve the main objective of winning. Interpersonal synergies between players are then formed and dissolved on a scale of seconds and tens of seconds on the pitch, allowing them to score a goal or avoid conceding (Ric et al. 2016). These team patterns then make the context for the individual actions that emerge in a smaller timescale (seconds or milliseconds). Therefore, context must be understood as the environment for an organism-environment relationship at all scales and in performance analysis, from seeing the team as an organism (Duarte et al. 2012), through to the player himself within the team, and even down to the organs or systems within the athlete (Pol et al. 2020).

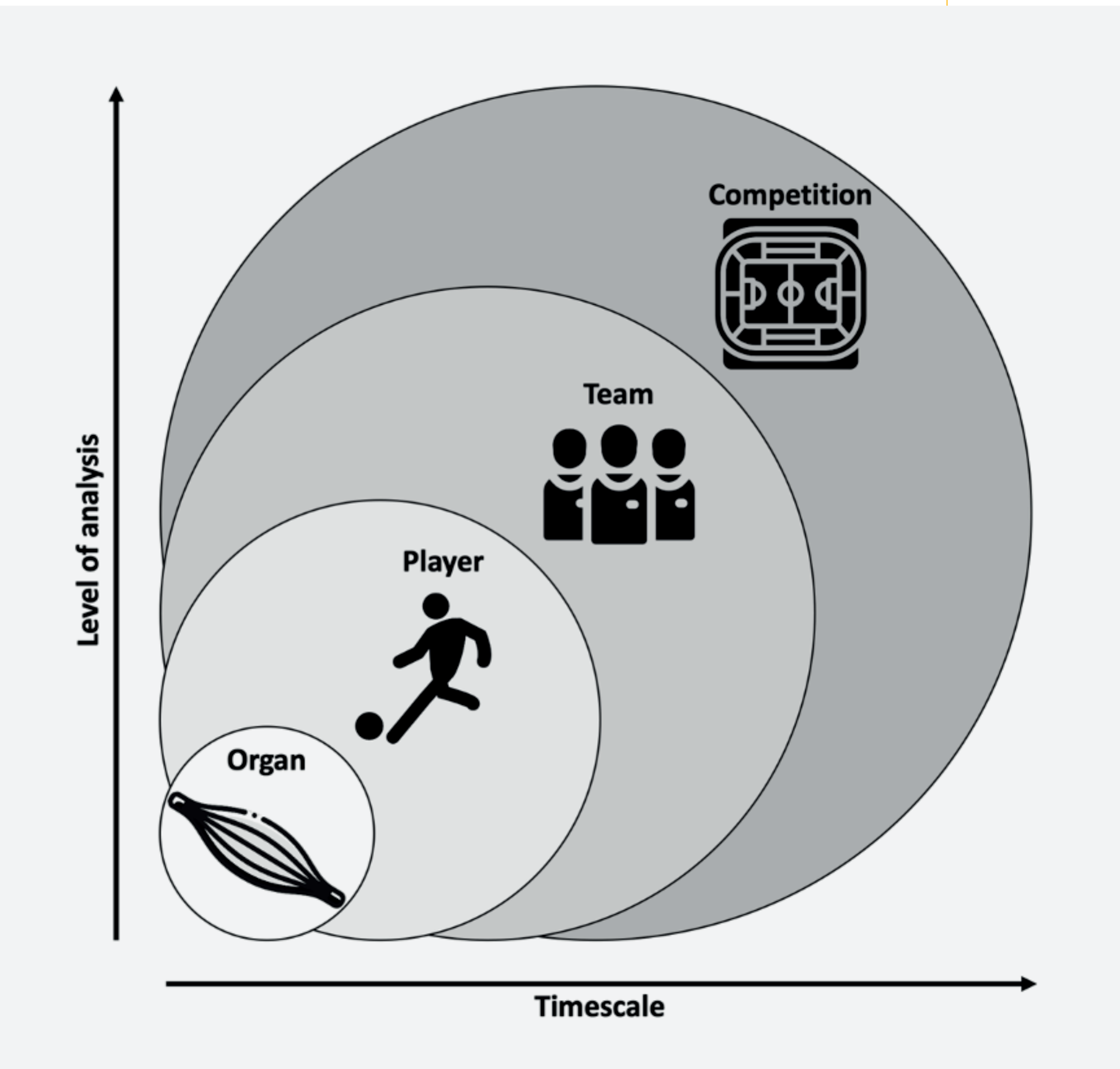

Figure 1. Nested levels and scales of performance analysis.

For these levels of performance analysis, tracking data (team), event data (player) and biometric data (organ) is collected systematically. The integration of many of these data sets is essential and has been recommended within clubs or institutions for proper data management (Linke et al. 2018). FIFA, in its aim to assist associate members or other stakeholders, is developing standards for the unification of these data sources. Related to this, the assignment of unique player IDs aims to avoid duplication and incompatibility between different data sources and competitions, thus providing simplicity for joint data analysis at all levels of performance. At a higher level, where performance is affected by competition (e.g. the league), the effects of situational or contextual variables on the behaviour of players and teams should be considered (Gómez et al. 2013). In fact, during FIFA competitions, performance can be affected by macro-considerations such as the location and climate of where the competition takes place. However, variables that influence at shorter time scales (e.g. match location, half, score, team formation, etc.) have also been extensively studied. Traditionally, these variables have been represented as frequencies of individual actions or aggregations of collective behaviour derived from event and tracking data respectively. However, this type of analysis makes it difficult to consider the context in the description of the results. Consequently, recent statistical models have emphasised estimating the value of those actions (Decroos et al. 2019), as well as the behaviour of the team's performance in relation to the opponent's disposition and the ball (Fernández & Bornn, 2020). The value of these behaviours (individual or collective) derives from the context in which they take place. For example, the value of actions-decisions with or without a ball has been quantified according to variables such as location, distance to the goal or the angle, that vary in tens of second. On the other hand, the effect of the style and system of play, or the number of players on each line of pressure and defensive organisation, implies contextual changes on a larger scale of seconds or tens of seconds. Furthermore, changes in situational variables, already noted above, play an important role in the effects they can have on mental or emotional pressure (Bransen et al. 2019).

It is common for media and fans to consider players in a position within a system of play or team formation. However, within the same position(s), different roles exist. Because of the dynamism of the game, these positions are not static and depend on specific contexts that can be identified within the game. Among them, moments in which a team has the ball and others in which it tries to recover it can be differentiated. Similarly, playing strategies such as pressure or withdrawal to recover the ball or more elaborate direct play when possessing the ball can also be identified (Castellano & Pic, 2019).

Furthermore, the ball location between the different confrontation lines (Castellano et al. 2007) and the depth of these lines will also determine more specific contexts of interaction. These structures can be practised and learnt over the time scale of months, but can change in the blink of an eye.

Identifying the most common formations during these game contests, and the changes derived from the transitions between them, are some of the challenges that some researchers are already beginning to address. The stability of these formations, and also derived from the values of width and depth of the team, dispersion of the players respect to their team centroid and the depth of the rear line, characterise its organisation. In turn, this definition makes possible to characterise defensive disruption as a function of the variation from the previous set of variables, allowing players' performance to be classified according to the impact that their passes have on the opponent's defensive (dis) organisation (Goes et al. 2019). Most football teams are organised according to the location of the goals, because of two main objectives: to score a goal and protect their own goal. However, the location of the ball is essential to define the context of the game and, in some cases, it is the element that determines the organisation of the players, regardless of the team that is in possession of the ball. So much so that FC Barcelona has been clearly differentiated from other teams (Gyarmati et al. 2014) because of how the team makes use of it through passing, as an action by which the players relate and interact. Although the Barça style of play has been characterised by high passing percentages, this is not an end in itself, but a means through which the players organise themselves around the ball.

It is precisely this organisation that defines one of the most common drills during the club's team training sessions, the "rondo". Despite the extensive research on the use of small-sided games (Clemente et al. 2020), the effects from rondos or other common training drills such as positional games (Casamichana Gómez et al. 2018) on player behaviour or the dynamics of the coordination between them are still unknown. Little research has addressed the need to identify values, parameters or patterns of play that allow the design of training scenarios that are representative of the game. There are already some publications which, through the identification of physical demands (e.g. distance covered) according to the game context, help to design drills that fit with the identified demands (Bradley & Ade, 2018). However, making training drills that meet not only physical but also behavioural demands is still a challenge for both data and sports scientists. This will be best achieved through collaborative efforts.

In summary, one of the challenges for researchers and practitioners is to break down the linguistic barriers between the areas of knowledge or fields of science in order to allow better and more efficient information transmission. The adoption of a transdisciplinary theoretical approach will allow a better understanding of all scales of the emergent processes arising from football environments (e.g. talent identification and development, performance analysis, injury risk assessment, etc.). The identification of essential variables through current analytical techniques (e.g. machine learning) from the inductive approach would allow the modelling of simulations derived from those variables (deductive approach) to capture the system's performance/intelligence (Hristovski & Balagué, 2020). The conceptualisation, quantification and modelling, through entropy, could one day elucidate a paradigm shift in sports performance that might allow its unification at all levels of analysis. Under the nested relationship between levels, the context-dependent analysis of performance will be presented in the following chapters by offering to the reader a wide view of the research carried out by some of the most renowned experts from that topic.

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Always think before computing!

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INTRODUCTION

What could we tell analysts to help them better connect theory and practice? Let's start from the beginning: why do we analyse the game?

R: There are three types of analysis that practically all professional clubs apply today. The first is oriented toward the scouting of talented players that the club may want to sign. This entails analysing the market to gain insight and decide whether or not players might be an attractive choice for certain positions. The second is analysis of opponents (teams or players), which is aimed at understanding the characteristics and weaknesses of rivals to prepare for competition against them. The third is player performance analysis, which is currently focused on kinematic variables (e.g. total distance covered, velocity, etc.). I am not aware of any elite club in the world that does not use this level of analysis.

N: This means that there are three organisational levels (club, team and player) that are involved in such performance analysis. Any decision made at a higher level (club), such as signing new players, affect those made at lower levels (e.g. team strategies, players actions) and vice versa. That is, the composition of the roster will impact playing systems and competitive strategies, which, in turn, bind the performance and actions of individual players (Balagué et al. 2019); Pol et al. 2020). Likewise, lower-level events (e.g. an injured or underperforming player) shape higher-level ones (change of playing strategies, signing of new players). It is important to take into account that these three levels cannot

be understood in isolation when thinking about performance analysis.

R: In fact, these three levels share a common limitation, inherited from an overly reductionist brand of sports science: they underestimate context.

a. Club level: When signing players, we often forget that some of them perform better in certain clubs and worse in others. Big data and statistics are used to confirm that a player is good at performing certain actions; it is then inferred that s/he will perform other actions equally well. But we must also examine the context in which s/he is performing these actions exceptionally well. There are also other areas outside the context of the match that allow us to predict whether or not a player will adapt well to the club. A fast and skilled dribbler may be invaluable in a team that covers a lot of distance due to its playing style. However, if we put that same player in a team that spends a lot of time in possession of the ball and that generally forces the opponent to retreat, s/he will lose that running space and, suddenly, no longer seem like such a skilled dribbler. Likewise, we might say that a player is the best centre-back without specifying that his or her team plays close to its own goal, leaving little space behind them. This player might be very good at confrontation but might not be a very fast runner. If s/he is signed by a team that plays in possession of the ball in the opponent's half, s/he will be forced to run long distances, face multiple players at once in a larger space and enjoy fewer one-on-one challenges in her/his territory. As a result, he or she won't just lose her/his reputation as the best centre-back but will come off as a shoddy defender. In contrast, consider a fast and small centre-back, such as Javier Mascherano, who played with Barça. In the context of that team, he was undoubtedly one of the best centre-backs in the world. However, he probably would have had more difficulty performing at that level had he been on a team that played defence closer to its own goal. In fact, when playing with Argentina, which does indeed play defence closer to their own goal, he was more of a midfielder than a centre-back. Players who are deemed the best in their position may end up seeming second-rate when the context is changed.

b. Team: When analysing an opponent, there is a general tendency to make statements such as "this team usually presses in this way" or "they play with the ball like this". The idea is to offer an average, or a general rule, of how the team plays. But "this is how they press" can only be confirmed when the opponent does not force them to play differently. For example, this statement will no longer hold true when playing against a team with the resources to resist such pressure. Identifying an "average" or a "summary" in this way does not provide information about what a team will do in a context in which their standard playing style is no longer effective. This analysis, therefore, becomes useless if, as a team, we manage to overcome our rival. And since that is the general objective, it is useless all around. Nevertheless, averages are compiled for teams to identify their characteristics and label them, despite the fact that these characteristics will disappear as soon as the context of the game changes.

c. Player: When analysing the performance of individual players, we once again seek out these averages and compare them with the team average, sometimes with the player averages and sometimes with what is typical in that level of competition. These averages offer little information about whether or not a player is capable of adapting to the demands arising from the context of the match.

At all three levels of analysis there is an attempt to extract quantitative data and little emphasis on the context.

Absolute, decontextualised quantification is very uninformative. For example, the simplest way to objectify perceived exertion (PE) is with the Borg scale (RPE 6-20 or CR-10) (Borg, 1998). Based on my experience in different situations and with different teams, the information obtained from PE ratings means very little if the players do not value this type of monitoring and if it is not adequately contextualised. We must encourage and harness athletes' ability to perceive and integrate information and put it at the service of monitoring. These are exceptional means of injury prevention and promote autonomy and self-management of workloads (Pol et al. 2018).

We can gather a great deal of information through conversations with athletes about how they feel in similar situations. This also may help the player become more aware of her/his condition and learn to express it as a comparison to her/himself and not to an external scale. But I think that if I wanted to publish these data I would be required to quantify them based on an external universal reference to objectify the differences between performance on different days and across different weeks. That would be difficult to publish, don't you think, Natalia?

N: Right, sports sciences place a greater emphasis on quantitative research, easier to objectify, and relies too heavily on group data averages.

However, it is possible to operationalise psychological or sociological information extracted from interviews and focus on individual data obtained from time series (Molenaar, 2004; Nesselroade and Molenaar, 2010: Rose et al. 2013). The main experimental model used to test research hypotheses in sports sciences is the comparison of group data means through inferential statistics. The fact that the averages obtained do not correspond to any specific individual is generally not taken into account when interpreting and applying research results. In fact, neglecting the idiosyncrasy of the structure of time-dependent variations within a single individual and assuming the equivalence between inter- and intra-individual variability is a common mistake of this type of research that leads to erroneous interpretations and inadequate practical applications (Rose, 2016, Balagué et al. in press).

Ignoring the context in which complex adaptive systems interact can be very misleading. In particular, when such context is non-stationary and fast changing, as during sports games. For example, the total distance covered by a player or her/his running velocity may be functional or un-functional depending on the context. Since every competition and every rival is different, it would be a mistake to compare kinematic information, obtained either at individual or collective level, without an adequate contextualisation and interpretation. In this sense, examining the dynamics of change of the variables under study is more informative to recognise whether performance stagnation or deterioration is taking place. This is applicable to all the aforementioned levels and requires updated assumptions and deep theoretical understanding of the examined processes.

R: Most clubs have entire departments devoted to generating analysis tools that, in practice, add no value to the work of the coaches. The problem lies in developing applications or reports without first thinking about the underlying theoretical assumptions. If the phenomena to be analysed are not properly understood, it is difficult to create effective applications. The first thing to do is to improve our understanding about the principles that lead the behaviour of the systems we deal with: the game, the team, the players. Only then a right answer to the question “what do we need to analyse?” will emerge. With the current approach, countless resources are being wasted.

N: Years ago, we published an article titled “Thinking Before Computing: Changing Perspectives in Sport Performance,” (Balagué y Torrents, 2005). It might be useful to look back on its message to clarify what it means performance analysis from a complex perspective. Certain study variables such as entropy, big data or more advanced processing techniques (e.g. deep learning) are generally associated with the analysis of the game as a complex phenomenon. However, processing large volumes of data and variables compiled from these techniques is of little use if there is not accompanied by a deep understanding of the process under study. It must also be noted that merely processing common variables in the study of complex systems does not necessarily mean that a complex analysis of the game is performed. For example, the entropy measures, usually associated with the study of complex systems, can be used to answer a very simple question about cause and effect relationships that has nothing to do with a complex perspective. Essentially, in this perspective, we are not just changing the type of data analysis or study variables but the type of questions, assumptions and research interpretations. This is something we need to emphasise so that resources are not wasted. Otherwise, the same mistake will be made over and over, just with more sophisticated technology and more data or new variables, but still without improving the understanding of the phenomena

> **“Statistics itself, which does have clear limitations, is not the main problem”**

under study.

R: In fact, this lack of reasoning is more common in science than you might think. The journal Nature recently published an article signed by 850 scholars of different academic ranks that denounces the misuse of statistics in research. Specifically, it calls for the retirement of statistical significance to put an end to publications that report “hyped” results and dismiss crucial effects (Amrhein et al. 2019). Even the American Statistical Association has spoken out against the misuse of inferential statistics and its role in promoting erroneous and biased findings (Wasserstein et al. 2016; McShane et al. 2019). This tendency is not exclusive to performance analysis, but pervasive throughout sports science.

N: Statistics itself, which does have clear limitations, is not the main problem. It is the misuse and misinterpretation of statistics in an oversimplified research context. There is a general belief that exceeding a threshold for statistical significance means a result is real (Wasserstein et al. 2016; Amrhein et al. 2019, McShane et al. 2019). Without a deep understanding of the assumptions behind the research hypotheses, methodological decisions, data analysis and interpretation, the research is no longer practical but rather may add to the confusion and harm the advance of knowledge. If we do not understand the theory, we cannot propose useful practical applications. We need to be aware of the norm in sports science: isolating variables, comparing group averages, obtaining results based on statistical significance and putting them into practice as general truths. All this represents a significant bias for the advancement of knowledge. The reductionist tendency, inherited from medicine and psychology, and over-simplified theoretical assumptions limit the evolution of our understanding of complex phenomena linked to sports performance.

It is possible, however, to turn away from tradition and opt for other models, such as those of complex systems, widely applied in several emerging branches of biology. Of course, this option does mean overcoming the resistance and difficulties that come with any paradigm shift. We now find ourselves in the midst of that transition, forcing models that are to some extent incompatible to coexist. However, the difficulties associated with such paradigm shifts should not discourage the pioneers because they are on the right track. Interdisciplinary work is being encouraged in many scientific branches and the contributions of physicists, mathematicians and computer scientists, collaborating with sports scientists, are key in performance analysis.

R: However, it is important to highlight that merely creating multidisciplinary teams will not overcome the obstacles of studying a phenomenon that belongs to no specific discipline: neither the game nor the player fit within these disciplines. Therefore, it is not just about adding new professionals and perspectives from different branches, but about sharing a common approach to how the systems that we work with function – whether players or teams – and making contributions from that common vision.

N: Right, there are transdisciplinary initiatives that pursue real knowledge integration, but multidisciplinarity is in fact non integrative (Balagué et al. 2017). It is necessary to clarify what a real integration means, and which type of approaches may satisfy it. Some authors suggest that training-methodology departments should integrate knowledge on the basis of an ecological dynamics approach (Rothwell et al. 2020). This perspective, however, focuses on the level of perception and action, while neglecting other relevant levels related to strength and conditioning (e.g., biochemical and physiological). In line with trans- or cross-disciplinarity, some authors sustain that integration requires a common scientific vocabulary shared across disciplines (Balagué et al. 2017); Hristovski et al. 2017). In this direction, Glazier (2017) proposes the unification of knowledge based on the concept of constraints and Balagué et al. (2017) suggest the Dynamic Systems Theory as an ideal integrative framework. DST does not limit the common vocabulary to the concept of constraints but to all the DST concepts; valid for all levels of analysis (see Fig. 1).

However, despite having powerful tools such as Dynamic Systems Theory, it is quite challenging to evaluate the dynamics of change in collaborative and competitive processes in which rivals never behave in exactly the same way and there are no static situations, as in football.

R: Perhaps we should change the type of question or the objective of performance analysis. If we have a deep understanding of the dynamic mechanisms of players/teams to adapt to the context of a match or training session, and develop them during training sessions, we could even forget about analysing the opponent. The issue is that training sessions are often focused on the rival, on their weaknesses and strengths as detected from analysing their game. In response, optimal, predetermined solutions are prepared. But if we changed the objective from having the team or player learn specific solutions to improving their potential for adaptation and diversity (Pol et al. 2020) and their ability to resolve unpredictable situations – such as those that happen regardless of how we train – we would not even need to analyse the opponent or, at least, not in the way we currently do. We could focus instead on analysing the state of our team and deciding whether we should generate new training challenges or a sense of confidence by strengthening scenarios already under control. But, of course, for that we would need the deep understanding of the theoretical foundations of performance that we mentioned earlier.

N: Even separating training and competition would no longer make sense. There is training in competition and competition in training, so why shouldn't we view them as continuous, adaptive processes with disturbances and constraints that are more or less intense and/or global?

R: In fact, training while competing is the best type of training; this becomes very clear in teams that play every three days. One of the main problems that usually crop up after a team that is not accustomed to competing at a high frequency qualifies for a European competition, is that the coaches underestimate that they can no longer train as much as they used to. If they do not address the process as a whole, understand that competition is part of the process, and eliminate a significant part of the training, they end up overwhelming the team. Even if the coach is changed, it becomes very difficult to revive the team. This situation repeats itself every year.

N: There is a fundamental problem in our understanding about the systems we deal with: it is generally assumed that they are dominated by

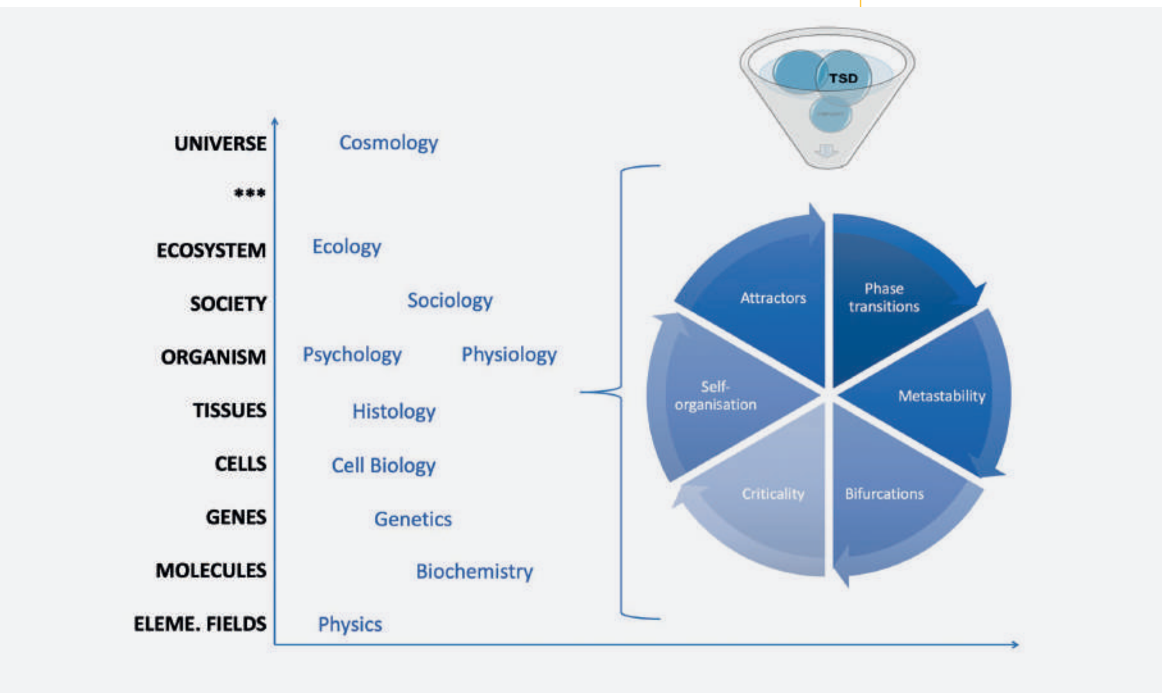

Figure 1.
Structure and organisation of scientific fields sharing the same concepts and principles from Dynamic Systems Theory.
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> **“More information does not mean more knowledge”**

the dynamics of their components, instead of being dominated by the dynamics of the interactions among such components, as occurs in complex systems (Delignières and Marmelat, 2012). This explains why training focuses on components and underestimates the counterproductive effects this may have on competition. For example, fragmenting and stabilising excessively positional play in attack and defence (separately) during trainings may harm the transitions during competitions. Moreover, there is a crucial training goal in team sports that is often underestimated by this component-dominant approach: developing interpersonal synergies among players. These synergies, which are the basis of the team's functional diversity potential and competitiveness (Pol et al. 2020), require collective challenges and constant interaction between players to overcome them. If training objectives change their focus, the line between training and competition will be blurred. Technology must serve that understanding, not the other way around. Different departments of the club, even members of the coaching staff, often analyse competition and training separately. That is, the performance department and the physical trainers focus on analysing players and their physical and physiological response during training through GPS data, and analysis departments focus on the competition (event data and movement tracking) through video analysis. Perhaps this fragmentation should also be put into question. These common and artificially built barriers can be reduced under the proposed paradigm shift, and specifically, under the umbrella offered by the Dynamic Systems Theory.

R: The key to knowledge integration is a shared understanding of the phenomenon to be studied. You can have a team comprising professionals from different disciplines working on an integrated job, but if the biomechanist tells you that a player missed a pass because s/he shot from the wrong angle, while the physical trainer says that s/he was worn out by the end of the game because s/he played for too many minutes and did not rest enough, and the physiologist agrees with the physical trainer and adds that the results of the last blood analysis were not good enough, what do you do? You say you are doing multidisciplinary and integrated work because every specialist provides their view on the phenomenon, but if all these specialists understand it differently, and look at it from their own perspective, it becomes very difficult to generate new knowledge. In such cases, a multidisciplinary team is of little or no use and may even detract from the work. If we do not change our understanding, any other efforts we make are useless.

N: More information does not mean more knowledge. Scientific specialisation has provided a lot of detailed information, but this does not necessarily imply greater comprehension and knowledge. For example, specialisation does not encompass the fact that the levels of analysis previously mentioned – club, team and player – do not exist independently of each other but are related by circular causality (Balagué et al. 2019). In cooperative and competitive environments, maintaining and developing the potential for functional diversity/unpredictability – also defined as intelligent cooperative-competitive behaviour – at different levels is crucial (Hristovski and Balagué, 2020). In other words, having a smart club, a smart team, and smart players means evading and escaping situations of reduced possibilities of goal achievement in different contexts. Opponents try to reduce that diversity potential intervening at all levels, and the goal is to maintain and develop it despite these disruptions. Functional players are those that contribute to the collective goal, and functional teams are those that escape and quickly regain the diversity potential despite their opponents' actions. One fundamental advantage is that this potential can be measured using a common variable: information entropy.

R: In conclusion, to improve the methodologies of game analysis we must start by improving our understanding of the phenomena under study. When our understanding changes, the questions we ask ourselves change; and when the questions change, the way we analyse phenomena necessarily changes as well.

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