Performance indicators are a selection or combination of action variables that describe some or all aspects of sports performance (Hughes and Bartlett, 2002). They are demonstrated to be valid measures of performance, possessing the metric properties of an objective measurement procedure, a known scale of measurement and a valid way of interpretation (O’Donoghue, 2010). Performance analysts and coaches use them in order to describe or compare positive or negative aspects of performance within or between competitions. This chapter covers theoretical background on performance indicators and describes possible processes of improving validity. A review of several applied research studies addressing procedures for normalizing performance indicators is presented. Also, there is a brief discussion of how some recent studies are addressing some of the issues outlined in this chapter for several game sports (see Table 10.1, Appendix).

Sports performance and the performance indicators
Performance analysis is used to help sports organizations align activities with short-, mid- and long-term strategic objectives. In pursuit of this aim, there is a clear need to develop and implement the use of adequate performance measures. It is a fact that substantial amounts of data are gathered and analysed within these organizations; however, most of the time there is no certainty that these measures are linked with success factors and the process consumes too many resources for such limited usefulness. This issue demonstrates the need for valid indicators of sports performance.

The term performance indicator is not another designation for ‘variable’ because not all variables are valid measures of important aspects of sports performance, whereas performance indicators are, by definition (O’Donoghue, 2010). Performance indicators are single or combined action variables that describe some or all aspects of sports performance (Hughes and Bartlett, 2002). Therefore, they represent valid measures of performance and possess the metric properties of an objective measurement procedure, a known scale of measurement and a valid means of interpretation (O’Donoghue, 2010). From a theoretical and applied perspective, a performance indicator should help explain the game outcome and thus advance understanding, providing for
meaningful understandings of game behaviour that are also useful in sports practice (McGarry, 2009). Naturally, performance indicators may be associated with the process of performance only and not necessarily with regard to outcomes. For example, the style of play, whether net play in tennis or directness of possession in soccer, may not ultimately be associated with player ranking or match outcome. There may be successful baseline players as well as net players in all areas of the world tennis rankings, just as there may be teams with slow build-up style and teams with direct counter-attacking styles in all areas of the FIFA world soccer rankings.

The framework presented in Figure 10.1 requires data processing if valid performance indicators are to be used in sports performance profiling. The substantial amount of data currently gathered by sports organizations needs to be transformed to performance indicators, with the aim of producing measures linked to performance processes. Performance indicators may be single or combined variables adequately normalized within and/or between sports contests to ensure that they can be compared. Particularly in game sports, they should also be able to capture global or partial aspects of complex, dynamic and non-linear properties of performance. Therefore, potential sources of variability and the criteria used to address validity should be considered carefully. Following this process, performance indicators may be suitable for use in profiling (see Figure 10.1).

There are several characteristics that seem to describe adequately the nature of game sports and, consequently, can be attended when performance is to be studied (Davids et al., 2003; Glazier, 2010; Lames and MacGarry, 2007). Performance is complex in that interactions between players and opponents allow for emergent behaviour to occur. Performance is also dynamic, meaning that all interactions are time dependent and, finally, performance is non-linear because the output is almost never directly proportional to its input. Having these concepts in mind, theoretically, performance indicators should be able to capture global or partial aspects of these complex, dynamic and non-linear properties as required. However, these are non-simple tasks and require continuing development from scientific research in forthcoming years. Nevertheless, available research in performance analysis is already substantial and, importantly, has allowed knowledge of performance in sports to improve significantly.
Several approaches have been followed to explore the validity of performance indicators, such as expert opinion (Hraste et al., 2008; Tminic et al., 2000), expert–novice paradigms (Araújo et al., 2005), contrast between winners and losers (Ibáñez et al., 2003; Ortega et al., 2007) and contrast between successful and unsuccessful performances (Ibáñez et al., 2008; Koh et al., 2011). The main goals here are to associate behaviours (actions) in lawful ways with outcomes (e.g. point/goal scored, game won, etc.). However, the meaningful drawing of inferences from sports behaviour to sports outcomes remains an open challenge for sports scientists (McGarry, 2009).

In general, quality of data can be described in terms of objectivity, reliability and validity. Sports scientists often have to deal with noisy data; thus, these concepts play a vital role in research and have motivated the development of a substantial body of methodological literature, reported in both journal articles (Atkinson and Nevill, 1998; Hopkins, 2000; Jeukendrup and Currell, 2008) and books (Berg and Latin, 2007; Morrow et al., 2011; Thomas et al., 2011). These references are able to clarify basic concepts and techniques, addressing all the main problems when dealing with data gathering and analysis. Performance analysis in sports is furthermore the unique focus of literature that, for example, addresses the statistical procedures to measure data reliability (Hughes and Bartlett, 2002; Hughes and Franks, 2004, 2008; O’Donoghue, 2010). The use of adequate operational definitions and the validity of performance indicators are related to reliability of data collection in performance analysis and therefore have a strong impact (O’Donoghue, 2007).

Research in sports performance analysis using performance indicators aims to document performance behaviour. In this regard, performance analysis systems should attend to the fact that performance in many sports is variable and, therefore, performance indicators should be analysed under the influence of several constraints. These constraints can exist as a characteristic of an individual (height, weight, speed, strength), as an element of the environment (weather, surface, importance of the competition, quality of opposition, location, match status) or as part of the task that the individual or the team is trying to perform (executing a pass, zone defence in basketball) (Davids et al., 2003; Newell, 1986). Consequently, sports behaviour emerges under the interaction of these constraints and variability is an essential feature for understanding how to operate efficiently in a variety of performing contexts. For example, available research in performance analysis has recognized opposition effects as one of the most important factors of variability (McGarry and Franks, 1994; O’Donoghue, 2009) and, particularly, how performance indicator values can be evaluated against the corresponding values for the opponent within a game (Hughes and Bartlett, 2002). In sum, it seems clear that most performance indicators are context- and time-dependent and therefore unreliable (Lames and MacGarry, 2007), unless adequate procedures are taken.

**Normalizing the performance indicators**

In performance analysis, the data are collected using mainly ratio (e.g. duration of ball possession measured in seconds) or nominal scales (e.g. categorizations of football passes as successful or unsuccessful). Afterwards, the data may be normalized according to adequate game criterions to allow for meaningful within- and between-game comparisons (Kubatko et al., 2007; Sampaio and Janeira, 2003). The resulting performance indicators, expressed as non-dimensional ratios, have the advantage of being independent units of analysis (Hughes, 2004). For example, basketball game-related statistics are useful for analysing performance, but may lack validity when performance needs to be analysed across a season due to game rhythm contamination (i.e. the presence of faster- and slower-paced games throughout the season). For example, the perform-
ance of a team that makes 35 field goals in an 80-possession game is different to the performance of another team that makes 35 field goals in a 90-possession game, other things being equal. These facts point to the imperative for normalizing the data using adequate criterions according to game specificities (Sampaio and Janeira, 2003). Usually, these criterions would be score, time and innings dependent (Hughes and Franks, 2004, 2008). Several examples can be found using ball possessions in basketball or football (Hughes and Franks, 2005; Kubatko et al., 2007; Sampaio and Janeira, 2003) or time in rugby union (Eaves et al., 2005), but, surprisingly, the available research is not as systematized as might be expected.

Using criteria to improve validity

Available research has used several criteria to approach validity of performance indicators. One of the most common is the contrast between game outcomes (winning, losing and drawing teams) and has been carried out in several sports, such as basketball (Gomez et al., 2008a, 2008b; Ibáñez et al., 2003; Lorenzo et al., 2010; Ortega et al., 2007; Sampaio and Janeira, 2003; Toro et al., 2007), football (Lago-Peñas et al., 2010, 2011a, 2011b), rugby (Jones et al., 2004; Vaz et al., 2010) and water polo (Escalante et al., 2011; Lupo et al., 2011; Platanou, 2004). In general, research with these aims has tested these hypotheses either by identifying differences between group scores using univariate parametric/non-parametric techniques or by identifying relationships using bivariate or multiple regression models. However, performance in game sports often requires analysis of several sets of (dependent) variables simultaneously and, therefore, the use of statistical procedures such as MANOVA, principal components analysis, discriminant analysis, clustering systems or artificial neural networks and other non-linear procedures may be appropriate (Bracewell, 2003; Puterman and Wittman, 2009). For example, most of the available research hypothesizes predictive variables for discriminating different outcomes. For example, higher values in basketball defensive rebounding (Gomez et al., 2008b), football crosses (Lago-Peñas et al., 2010) or water polo goalkeeper-blocked shots (Escalante et al., 2011) are traits of winning teams and, therefore, performance indicators that coaches might want to monitor closely.

It has been suggested that contrasting performances of winners and losers can only provide a measure of team success at a given instant because successful teams can lose some games and unsuccessful teams can win some games (Ibáñez et al., 2008; Madrigal and James, 1999). Therefore, other authors have tried to measure the team’s season-long success by contrasting performances from higher and lower classification ranks (Ibáñez et al., 2008; Oberstone, 2009; Rampinini et al., 2009). Often times the selected cut-off points for ranking (discriminating) teams for classification purposes are quite arbitrary. For example, research undertaken in the English Football Premier League has divided the clubs into three groups: higher rank – the UEFA Champions League-qualified teams; lower rank – the teams relegated to the lower-division Championship; and middle rank – the remaining teams (Oberstone, 2009). Conversely, research in basketball divided the teams into higher and lower ranks according to their qualification (or not) to the playoff series (Ibáñez et al., 2008). Although these cut-off points might represent natural divisions, they frequently might lack accuracy. In the previous examples, a football team might be performing as well as the qualified teams for the UEFA Champions League and, yet, are assigned to a lower-ranked group. Two basketball teams can have similar performances across the season, and even might end with the same number of wins, but only one of them reaches playoff qualification. In order to classify these cases more accurately, some research used clustering techniques performed with either a single or a combined group of variables. In volleyball, for example, a cluster analysis was used to group national teams that
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participated in a World Cup into competitive levels using a combined group of variables, such as: points at the end of competition, ratio of total number of points won and lost, ratio of sets won and lost, and the percentage of sets won (Marcelino et al., 2011). The authors predefined three clusters that were labelled as ‘high quality’, which included the first four ranked teams, ‘intermediate quality’, which included the fifth, sixth and seventh ranked teams, and ‘low quality’, which included the five lowest-ranked teams. Afterwards, only high- and low-quality teams were compared for the purposes of maximizing contrasts in the statistical analysis.

There are occasions when clustering may helping improve validity of the performance indicators. In high-scoring sports such as basketball, volleyball or rugby, the contrast between winners and losers can be analysed according to game score differences. In general, research has considered a priori two (balanced and unbalanced) or three (close, balanced and unbalanced) groups for analysis. The results seem to demonstrate that the importance of performance indicators changes with game score differences. For example, basketball free-throw shooting and volleyball effectiveness of attack are important performance indicators, particularly when the differences in score are tightest (Drikos and Vagenas, 2011; Sampaio and Janeira, 2003). In squash, the percentage of rally time spent in the T area differentiates better the less-balanced confrontations (Vučković et al., 2009).

Data reduction is a useful technique for processing data gathered in performance analysis. The main goal here is to identify from a smaller data set fewer performance indicators that might be used to provide accurate feedback to coaches and players, thereby avoiding presentation of redundant information (O’Donoghue, 2008). In football, Gómez et al. (2012) analysed 36 variables related to game actions that occurred in several pitch locations. The authors performed factor analysis in a database of 1,900 games from the Spanish Professional Football League and the principal components method reduced the data to a representative smaller set of four factors: Factor 1 – turnovers in zone 5.2 and crosses in zone 4; Factor 2 – goals and shots in zone 5.1, turnovers in zone 4 and ball recover in zone 2; Factor 3 – goals and shots in zone 5.2; and Factor 4 – turnovers in zone 5.1 (Gómez et al., 2012). As expected in a highly unpredictable game like football, the obtained model only accounted for 22.3 per cent of total variance. The models obtained in less unpredictable games, as, for example, basketball or tennis, seem more representative. With similar goals, Sampaio et al. (2010) analysed a database containing 5,309 records from 198 basketball players and factor analysis reduced 11 variables to five factors (free throws, two and three-point field goals, passes and errors), accounting for 82 per cent of total variance. O’Donoghue (2008) gathered data from 24 variables by analysing 146 completed tennis matches from the women’s singles events. Factor analysis reduced the data to eight factors while accounting for 72.7 per cent of variance (serving to the left on first serve; winning points; serving to the right to the advantage court; service speed; serving to the left on second serve to adversary court; service faults; unforced errors; serving to the left on second serve to deuce criteria). These data reduction techniques can be seen as a first step towards identifying factors that may act as performance indicators. Afterwards, these performance indicators can be contrasted, for example, according to quality of opposition or game outcome (Gómez et al., 2012; Sampaio et al., 2010).

Game time is an important source of variability of performance indicators, although research is generally scarce on this topic. ‘Early success’ models (Isoahola and Blanchard, 1986) suggested that strong initial performances may increase psychological momentum, increasing the prospect of winning outcomes, although it would appear that the latter moments of game time may be the most important determining feature (Bar-Eli and Tenenbaum, 1988a, 1988b). Thus, consensus is not yet reached regarding the hierarchical importance of game periods. Nevertheless, there is sufficient evidence to support the idea that some game periods are more important for
game outcome than others. It is difficult to understand this effect in isolation of other considerations, however. For example, basketball teams’ field goal percentages may be lower in the last five minutes of the game due to interaction with a favourable score more so than to game time itself. Game time is usually included in time motion analysis research, probably more with the intention of identifying periods of increased fatigue, in each game half, for example (Rampinini et al., 2007, 2009) or each 15-minute period of a football game (Mohr et al., 2003). Curiously, research has not yet explored in depth the dynamics of performance indicators. Possibly, the initial and final periods of games require analysis of different performance indicators or, at least, need to be considered using different normative values. For example, basketball free-throw performance indicators acquire much higher importance in the final moments of balanced games, where the game is yet to be decided and the frequency of fouling increases (Kozar et al., 1994). Therefore, all information about performing on the free throw under uncertain game outcomes is probably obscured when data are averaged on total game time.

Performance indicators often exhibit substantial within-game variability but results may be different when it comes to variability between games. In game sports, the available research on seasonal variations is often centred on anthropometric and physiological variables (Drinkwater et al., 2005; Metaxas et al., 2006), with tenuous differences identified during the season and across seasons. Research on seasonal variation of performance indicators, in contrast, is scarce. Sampaio et al. (2010) undertook such investigation using professional basketball players’ game-related statistics according to team quality and playing time. Seasonal variation was analysed over eight-month periods in a sample of 5,309 records from 198 players, and analysis was performed on stronger, intermediate and weaker teams and, also, on more and less important players. Although there were several team quality and playing time effects, no differences were found within season periods. Therefore, the results seem to suggest that those performance indicators are stable enough for use across the season.

Concluding remarks

The framework presented in Table 10.1 summarizes this chapter using examples from recent literature. The substantial amounts of data that are currently gathered by sports organizations need to be transformed to performance indicators that serve as valid performance metrics. Performance indicators may be single or combined variables adequately normalized within and/or between games to ensure that they can be compared. Particularly in game sports, they should also be able to capture global or partial aspects of complex, dynamic and non-linear properties of performance. Therefore, the potential sources of variability and the criteria used to address validity should be considered carefully. Only then might the performance indicators be viewed as appropriate for use in the profiling of sports performance.
### Table 10.1 Overview of recent studies carried out in different sports for approaching the validity of performance indicators

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<td>Point difference in scores</td>
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