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THE SELECTION OF HUMAN RESOURCES IN SOCCER

A weighted plus/minus metric for individual soccer player performance

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ABSTRACT (ENGLISH)

Human resource management is a component of the general management of an entity and has become, in recent decades, an ever-expanding area of theoretical, methodological and applicative research, this being one of the direct consequences of the evolution of managerial practice and thinking.

Specifically, the thesis will focus on the most popular sport in Italy, soccer, and the way of selecting and choosing the best and most effective human resources to achieve the best results on the field and consequently economically.

The first chapter focuses on the 'investments' of a football club, i.e., its youth sector, and the methods of selection and contact that have been created in recent years, dislodging the traditional approach and proposing a multidisciplinary and global one. This is because nowadays the technical aspect is no longer sufficient but must be integrated with other motor and athletic aspects as well as the mental health of the footballer, which is becoming an increasingly noisy topic.

The second part, on the other hand, focuses on the selection of the adult footballer, i.e., already a professional, and on modern data and metrics applicable to players from all over the planet that allow for an initial and useful data-based selection process.

Finally, the paper concludes with a part analysing the performance of Ascoli Calcio's players, based on a plus/minus metric applied to football that evaluates the contribution, positive or negative, of each player to the team's total performance.

ABSTRACT (ITALIANO)

La gestione delle risorse umane è una componente della gestione generale di un'azienda ed è diventata, negli ultimi decenni, un'area di ricerca teorica, metodologica e applicativa in continua espansione, essendo questa una delle dirette conseguenze dell'evoluzione della pratica e del pensiero manageriale.

Nello specifico, la tesi si concentrerà sullo sport più popolare in Italia, il calcio, e sulle modalità di selezione e scelta delle risorse umane migliori e più efficaci per ottenere i migliori risultati in campo e di conseguenza economici.

Il primo capitolo si concentra sugli "investimenti" di una società calcistica, ovvero il suo settore giovanile, e sui metodi di selezione e contatto che sono stati creati negli ultimi anni, abbandonando l'approccio tradizionale e proponendone uno multidisciplinare e globale. Questo perché oggi l'aspetto tecnico non è più sufficiente, ma deve essere integrato con altri aspetti motori e atletici, nonché con la salute mentale del calciatore, che sta diventando un argomento sempre più rumoroso.

La seconda parte, invece, si concentra sulla selezione del calciatore adulto, cioè già professionista, e sui moderni dati e metriche applicabili ai calciatori di tutto il pianeta che permettono un primo e utile processo di selezione basato sui dati.
Infine, il documento si conclude con una parte che analizza la performance dei giocatori dell'Ascoli Calcio, basata su una metrica plus/minus applicata al calcio che valuta il contributo, positivo o negativo, di ciascun giocatore alla performance totale della squadra.

INTRODUCTION

Soccer sport in recent years has transformed into something that is no longer just about the mere outcome of the game but is now commonly treated as a business and not just a passion.

Soccer is more than just what spectators and television audiences see in stadiums. They can know the names of players, they can watch and appreciate their performances, but often they know nothing about people and processes outside the field of play that are responsible for selecting, training, and managing the activities of a soccer team.

In the increasingly entrepreneurial and corporatist view of the sport, family ownership has disappeared and large corporations that acquire clubs where the owners aim to achieve one result, the economic one, have become more and more predominant.

According to this view, the selection and enhancement of the most remunerative human resources, the footballers, have become a crucial aspect from the earliest years of age and raise in importance when referring to professional footballers worth millions of euros.

Throughout the chapters it will be shown how human resource selection in soccer is changing from the past and follows an age-based path.

The first chapter provides a modern multidimensional approach to the assessment of young players playing in club youth teams, varying among numerous areas that impact the overall assessment of the young player. Each area of competence is paired with tests done by experts in the field, the results of which are reported as well as the methodology and techniques for conducting these tests.

The main objective is to clear customs of the traditional approach to youth player selection, making it partly more complex but certainly more comprehensive, effective, and suitable for the increasingly demanding requirements of large soccer clubs that are transforming the soccer team into a more corporate focus.

The chapter concludes with a mention of a new platform for contact between clubs and players that is becoming more and more preponderant given the onerous costs for clubs to carry out scouting activities.

The second chapter introduces how the way of selecting players is changing in the adult professional arena, i.e., already trained players who transfer from one club to another for large sums of money. The massive use of data and metrics is becoming common practice for scouting within top clubs, and the selection process is being completely revolutionized.

Some modern metrics are introduced in this chapter, which concludes with an analysis of a new metric on estimating market values.

Finally, in the third and final chapter I have carried out a performance analysis based on a plus/minus metric that aims to assess the contribution of each individual player in the overall performance of a club within a sports season.

The club considered is Ascoli Calcio 1898 FC, playing in the Italian Serie B in the season just ended.

The metric shows which players had the best impact in the team's success.

After performing this performance analysis, I conducted a regression analysis to understand if the values taken by the metric could be explained by some variables regarding the characteristics of the players.

1. TALENT IDENTIFICATION IN YOUTH SOCCER: A MULTIDIMENSIONAL AND DYNAMIC APPROACH

Talent identification (TID) in soccer is a process that involves identifying talented players with some prerequisites and potential to become a professional player based on several criteria.

In team sports, such as soccer, talent recognition is a tricky process due to the different qualities associated with performance, including physical, physiological, technical and tactical attributes, as well as psychological and sociological influences.

The challenge for scouts and recruiters during the TID process is that these qualities are dynamic, interact with one another, and are responsive to practice and training.

The process of Talent Identification has traditionally been based on coaches or scouts watching players in matches or training contexts over time who judge their performance and future potential to reach the elite level. The concept of talent and TID has usually been understood and used to identify and select players who have an above-average level of ability within a domain.

This mainstream approach is a process rarely based on objective criteria, but on the coach's subjective perception of the perfect player, his skills and/or potential, where the recruiter's previous experience and intuition affect the evaluation. Such a subjective assessment practice has been demonstrated by earlier research to be the norm in professional soccer around the world as well as a practice that can lead to repeated misjudgments and limited continuity in identifying talent.

The identifiers in the process, coaches and scouts, highlight technique as very important parameter, especially related to ball control, dribbling, first touch, passing/shooting, and technique under pressure.
Even perceptual–cognitive characteristics like decision making, positioning, and game understanding have been deemed as especially important by recruiters, while anthropometric, physiological, mental, and social factors have been considered less important by coaches and practitioners, even though in the recent study by Bergkamp et al. the anthropometric and physiological factors were highlighted as important as tactical skills by the participating scouts.

The coach’s role in relation to the identification of talent is thus only related to the coach’s perception of skills that are important to succeed at the elite level and awareness of how they train and implement them most effectively.

However, to guide the talent identification and recruitment process there is an extensive body of research exploring the skills and qualities that may discriminate skilled and less-skilled performance at a youth level, including anthropometric and physiological, perceptual-cognitive, and psychological factors.

Following the model on potential predictors of talent in soccer made by Williams and Reilly in their reviewed paper, research has tried to elaborate which predictors would be considered the most important. In 2000, they introduced the physical, physiological, sociological and psychological predictors, then Williams et al. reintroduced the potential drivers of adult high performance in soccer with four predictors: skill, physical, psychological and social. In the meantime, research on both the motorial and cognitive levels have highlighted several abilities that have shown to be of great importance for later success at the senior level.

In general, technical performance characteristics have proven to be important predictors of future success in elite-level soccer. Huijgen et al. showed that technique was a crucial discriminating factor already in youth sector and that it was a potential indicator for future professional soccer players.

Considering physiological factors, young elite athletes generally tend to reach higher values than their less skilled age mates, which fits with what one sees in senior football. Physical characteristics and anthropometric proportions are factors that the player can hardly improve on himself, such as height, growth, physique, and muscle composition.

In addition to physiological and technical attributes, researchers have also indicated skilled youth players possess greater domain-specific information processing abilities. This knowledge base emphasizes that skilled soccer players hold superior perceptual-cognitive abilities in comparison with less able players. Although this provides an indication of the qualities that may differentiate skilled performance, the coaches' understanding of the worth of these attributes and, if so, how they identify perceptual-cognitive skills in youth skilled soccer players is still restricted.

Further, researchers have indicated psychological attributes may predict elite level soccer career success. In addition, models that outline potential talent predictors in soccer underscore the necessity of considering sociological factors like parental support, educational background, and practice hours. Despite these outcomes, the recognition of these attributes within the talent development and recruiting process is yet limited, however, researchers indicates that the integration of psychological and sociological qualities into this process could provide a more comprehensive description of potential talent.

In soccer, coaches and recruiters are constantly looking for the attributes and qualities that can predispose individuals to a successful soccer career. Although it is recommended that coaches and recruiters consider a new and innovative approach to talent recognition, there is still limited understanding of the way they conceptualize the capability to identify future talents.

Thus, since successful soccer performance is a complex interaction of many skills and qualities, a holistic and multidisciplinary approach to talent recognition should be implemented, instead of isolated evaluations of individual skills and qualities.

This part of the thesis is aimed at analysing the recruitment process into a youth professional soccer sector by using a multidimensional approach based on the evaluation of players through four main aspects:

1. Technical and tactical
2. Physical and physiological
3. Psychologic and emotional
4. Perceptual and cognitive

The main objective will be to demonstrate how the selection of 'personnel' can also take place using methods based on objectivity and to propose some researches and types of tests that can be implemented and replicated in the field.

All the following analyses obviously have one main goal: to identify, from an early age, the future professional football player who can become an asset for the club.

In this session, we assume that the evaluation of young players takes place through an *audition* inside the club's facilities, since the proposed tests can only be carried out with the physical presence of the player.

A necessary premise to be made is that the selection process of a young player requires an extended period of time to observe, test and finally evaluate the player as a whole.

The younger a player is, the greater the difficulty in selection as well as the probability of making 'mistakes' will be.

1.1. TECHNICAL AND TACTICAL ASPECTS

Soccer technique is primarily classified according to the player's performance with and without the ball, the degree of difficulty of the technical element, the players' roles, and the actions of the player either on the spot or on the move.

The researcher Knapp (1963) established the original definition of skill, defining it as the learned ability to achieve certain predetermined results with maximum confidence, frequently with minimal time and/or energy consumption. Some examples of technical skills with the ball in football are passing, dribbling, tackling, crosses, headers, shooting, ball control, corner kicks, free kicks and throw-ins.

Technical skills assessment is a crucial element in identifying the most promising football players. These footballers generate not only millions in revenues for the club they are representing, but also contribute to the team's overall success. This makes player recruitment and evaluation an extremely important task for soccer clubs and associations.

In particular, specific technical skills seem to be essential, given the highly specialised demands required to deliver high quality performance in these sports, starting from the early stage of development.

Researches shows that specific technique tests in football can differentiate between low and high performance during both pre-adolescence and adolescence (10-16 years) and to predict better future performances in comparison with other indicators.

Taking into account that the technical skills (e.g. first touch, hitting the ball, one-on-one and technical ability under pressure (Larkin & O'Connor, 2017; Roberts, et al., 2019), tackling, heading, passing and crossing (Roberts, et al, 2019)) of young footballers are one of the preponderant aspects in their development and further success in football, it becomes crucial and necessary to evaluate the most optimal ways of assessing and subsequently implementing the methodology of technical selection of young footballers.

1.1.1. Two approaches: traditional and alternative

Traditional football practice is based on a linear approach to the selection process in which technical skills must be practised and mastered (Samur, 2019) before players can play a game against opponents (Harvey, et al., 2010). The traditional approach of football skills nowadays is about to be overtaken by what we can call a 'holistic approach' to the selection of technical skills in football, which simultaneously concentrates all skills together, creating a combination of several useful factors to assess a young footballer as a whole (Larkin & O'Connor, 2017).

In practice, the technical selection of young footballers mainly involves two approaches to assessing technical skills: the analytical/traditional approach, dominated by the repetition of technical exercises without the presence of any opponents, which contributes to achieving 'perfection' in the execution of the technical gesture, and the global/alternative approach, which emphasises the integration of technical exercises in tactical situations, i.e., with the presence of opponents. The global approach promotes sporting practice based on educational experience, allowing the player to form a creative practice on the playing field, playing autonomously and taking initiative and responsibility. This type of methodology stimulates real playing situations that arise in competitions. The use of the global approach leads to greater understanding, as the proposed exercises are tasks involving an opponent, a ball and one or more players.

Content of the Training Programmes for Analytic and Global Approach (modified according to Bernal-Reyes, et al., 2018)

Sessions	*10-11 years old*	
	Analytic approach	*Global approach*
1	Running	Moves without/with ball in the field
2	Pass	Collectives' games to 1 and 2 touches
3	Reception	Work with number superiority (2vs1) (3vs2)
4	Heading	Small sided games
5	Dribbling	Defence / Attack game transitions
6	Shooting	Free shots and corner shots as offensive plays
7	Control	Ball position
8	Running and shooting	Defence / Attack game transitions
9	Reception and pass	Game amplitude
10	Heading, dribbling and control	Collective games with definitions

Table 1: Content of the Training Programmes for Analytic and Global Approach, (TECHNICAL SKILLS DEVELOPMENT FOR YOUTH FOOTBALL PLAYERS: THEORY AND PRACTICE, 2021)

Table 1 shows the two different approaches for selection, analytical and global, and similar tools are used to analyse each element of football technique.

The results of the technical tests carried out on a number of footballers provide no clear evidence of the superiority of the global learning approach over the analytical one, where the former of the two was carried out and implemented without continuous repetition of the movements to be learnt and without error correction in the skill acquisition process, where young players independently and autonomously perform all the complex movements under conditions of constant change due to the presence of opponents, in contrast to the traditional approach, which was dominated by multiple standardised repetitions of movements.

Within an audition to select one or more young players, it is necessary to create practical activities in which coaches involve the players as much as possible in game situations where they have to make decisions and appropriate technical choices in the shortest possible time.

The selection process must consider the holistic approach to training and education activities, the stage of development of the young players and the learning objectives.

In the introductory phase of technical training (from 6 to 13), before a youngster's technical skills can be assessed, it is necessary to create and deepen a love of football through play and enable the player to best express his football technique, find his position on the pitch and understand the need to cooperate with teammates in order to defeat the opponent. Therefore, the global approach is predominantly recommended as teaching must strike a balance between specific technical exercises and free play, allowing creativity to come to the fore.

Basic technique in football is divided into two parts: technique without and with the ball. Some examples of movement technique without the ball are: walking, running, acceleration, sprinting, starting speed, running while changing direction and pace, jumping, ducking, standing up, falling, sliding. On the other hand, the movement technique with the ball is divided into 9 basic categories: shooting; ball conducting; controlling, changes of direction, 'shielding'; feints and movements; passing and catching; stealing and intercepting; throw-in (throw from the sideline); juggling; goalkeeper technique.

The assessment of elementary technique is dominated by the analytical approach in static or isolated dynamic conditions, while the acquisition of dynamic technique is dominated by the synthetic method in isolated dynamic conditions.

The *'Programma di sviluppo territoriale*" provided by the Italian federation is a useful tool for recruiters to offer good drills to young players, thus ensuring that the young player can express himself at his best.

Technical training in the first group (from 6 to 11) is based on the development of actions with the ball in all its forms, providing an intense experience. In turn, technical selection in the second band (from 12 to 16) takes place in two directions: 1) dominated by actions with the ball, which are designed to ensure activation at the start of training; 2) dominated by game situations, using combinations of technical elements (movement technique, functional technique).

The aim of training and the resulting technical selection is to provide young players with technical movements that are functional and adapted to changing situations; 'open' skills are defined as those that are developed in a constantly changing environment. The various fundamental technical methods such as ball control, conducting, etc. practically become functional units within an overall assessment. Football technique is considered to transfer player decisions into movements, so it can be assumed that the dominant approach to technique acquisition at this age is a global one.

1.1.2. A way to test: Small Sided Games

The term small-sided game (SSG) refers to a mini football game that provides greater validity to recruiters than isolated skill tests and is often considered a more feasible technical evaluation context than a full-scale game.

SSGs have gained popularity in recent years as they allow for the simulation of game situations while maintaining the most essential elements of football by allowing them to be reproduced on a smaller scale, such as in a 3v3 or 7v7 set-up.
Although SSGs have a faster pace than full-scale matches, research suggests that, especially when considering a relative field area per player, they are actually representative of 11-vs-11 matches.
Furthermore, by reducing the number of players, SSGs also allow individual players to be more involved in the game. For this reason, numerous researches have indicated their use not only for player selection but also for the improvement of technical, tactical and physical skills.

However, for SSGs to be considered a valid evaluation context, they should be structured and organised in such a way as to be able to discriminate players of different skill levels. That is, players with a higher level of play and who are older (thus participating in stronger competitions) should demonstrate relatively better performance in SSGs.

Even though this instrument can be applied to assess different performance characteristics, research shows that elite level players differ from less skilled players in particular in their technical-tactical skills.

Consequently, the results of recent studies suggest, just as in full-scale matches, that higher-level players show better technical-tactical skills in SSGs. For example, by studying the performance of footballers aged between 11 and 15 years old in a 4v4 SSG, Bennett et al. showed that the better players have greater skills in passing and ball control.

The study conducted by the Department of Human Movement Sciences at the University of Groningen analysed several key databases on the most important research sites focusing on SSGs in football.

Regarding the actual performance of SSGs, 3vs3 with or without goalkeeper was found to be the most common SSG mode in all studies (n = 10). Almost the same number of studies included SSG 4vs4 with or without goalkeeper (n = 8) among the most used methods. In general, the mode of SSGs varied considerably, mainly depending on the technical elements that were to be analysed. Other common tools were the 5vs5 and 6vs6 with goalkeeper, as well as conditional SSGs, such as superiority and numerical inferiority situations (e.g., 4vs3 or 5vs3).

When evaluating the technical-tactical skills of individual players, the results suggest that a similar analysis or scoring system, which combines individual skills (e.g., passing, shooting and defence) into a total performance score, might be feasible and more appropriate.

However, the choice of SSG formats can have a considerable influence on the results obtained and this should be taken into consideration.

For example, if the main evaluation is focused on passing skills, it might be more functional to structure the SGG with a reduced number of players and no goalkeepers. However, unbalanced modifications (e.g., more attackers than defenders) could allow players to showcase their tactical skills, such as spacing in attack or defence.

Finally, large-sized pitches could also be used since research has shown that SSGs with six to eight players per team are more representative of a full-sized game if the relative pitch area per player is similar to that of an 11v11 (i.e., 80 m × 56 m for a 7v7, resulting in a relative pitch area of 320 m^2).

In summary, we can argue that SSGs, in all its facets, is one of the best tools to analyse and evaluate the technical skills of a young footballer since all 'open' skills are highlighted. This does not detract from the fact that analytical methodology can also provide a useful additional tool for gaining a more complete overall picture of the young footballer.

1.2. PHYSICAL AND PHYSIOLOGICAL CHARACTERISTICS

Research on talent identification in soccer, among other sports, demonstrates a systematic selection bias in favor of early-born players (relative age effect) and mature players. From the studies that have examined the physiological attributes (e.g., power) of players of varying levels of maturity, early born footballers have tended to perform better in these tests and are thus more likely to be influential on the game and to be perceived as more talented.

When taking into account actual playing level and eventual future success, elite youth and future professional football players performed significantly better on physiological tests compared to amateur youth and future non-professional players, independently of maturity status.
However, these testing methods were not sensible enough to differentiate elite youths from sub-elite youths or future national team players from professional club players.

Studies have demonstrated the need to use estimations of maturity status and a further appropriate analysis of the data gained from physiological tests. If maturity is considered, these testing procedures can give an indication of the responsiveness of young players to the training load and an evaluation of the potential to be a successful football player. Nevertheless, these tests should not be utilized as selection indicators before reaching complete maturity and they should be included in a multidimensional approach to talent identification that takes into account the significance of other aspects of the game at the top level.

Soccer is characterized by intermittent, repetitive activities during which force and explosive actions are executed, such as sprinting, jumping, tackling, kicking, spinning and changing pace. These high-intensity activities critically affect match performance and must be developed from an early age. For this purpose, several national federations and pro clubs are investing considerable resources in identifying talented young players. Considering the importance of explosive repetitive actions and winning challenges in football, the talent identification process typically incorporates a battery of physical (anthropometry) and physiological (performance measurements: speed, strength, aerobic and anaerobic power) tests that are relevant to the requirements of the game.

However, a unidimensional approach to talent recognition focused only on physical and physiological measures can be misleading. Instead, a multi-disciplinary approach should be adopted considering physical, physiological, technical, sociological and psychological predictive factors.

An important issue is that excellence in a sport is not dependent on a standard set of abilities but can be achieved in unique ways through various combinations of skills. This effect has been termed the 'compensation phenomenon' and suggests that deficiencies in one area of performance can be compensated for by strength in other areas. Moreover, physically dominant players at junior level are capable of compensating for their performance and may not retain this advantage in adulthood.

The tracking of physical and physiological changes caused by maturation and training makes it possible to establish the player's progression and responsiveness to different training stimuli.

The evaluation of biological maturity status differs depending on the body system considered (e.g., skeletal maturity, sexual maturity). Performance spurts (e.g., speed, power, endurance) may occur at different chronological ages, depending on the time and timing of maturation.

Advanced age and/or maturity can create advantages in terms of strength, power and speed and lead to the systematic recruitment of more mature, older players (relative age effect) in the talent identification process.

In addition, the physical and physiological attributes of young players should be monitored in relation to the transitory nature of maturity associated with the changes. Considering that both game intelligence and technical skills could be linked to maturity status, it is interesting to link them to these physical and physiological factors. To validate the use of physical, and physiological tests, it is required to examine the sensitivity of these tests to determine future success (i.e., professional status) and give practical solutions for performance analysis.

1.2.1. Misconception in talent evaluation

Entrance into a professional soccer youth academy and the selection in national or state representative teams are quite often recognized as important milestones in the development of future professional players. Players recruited in these programs are exposed to both highly competent coaches and national and international tournaments.

This selection process frequently takes place from 8 years of age group. The 'coach-led' talent identification methodology is built on multifaceted intuitive knowledge that comprises socially constructed 'images' of the ideal player. When a talent is selected by a coach, he usually has the feeling of doing something evident, logical and unavoidable, since he differentiates among various talented players without being clear about the guiding principles of his selection. The selection is thus made based on personal preference, knowledge and experience, and this is considered a legitimate process by recruiters. However, this approach is extremely subjective and can lead to frequent errors in talent evaluation.

During infancy and adolescence, differences in maturity can be large, even between individuals of the same chronological age. While age differences of less than 12 months have minor significance on adult physiques, they can be meaningful in adolescents who undergo rapid growth and development rates. Players born at the beginning of the selection year frequently have the advantage of being bigger, stronger, faster and having greater endurance in their sport. Consequently, they can be more successful than their younger counterparts, resulting in higher motivation and effort. Younger, less mature athletes may be considered less talented during the recruitment process or drop out because of perceived lack of skill and lack of success. This phenomenon causes a distortion in the distribution of birthdates of recruited players and is known as the Relative Age Effect (RAE). In other words, children born in the first 3-4 months after their date of birth are over-represented in the selection of teams in various sports, as shown in Figure 1.

The recruitment process in soccer seems to create one of the highest RAEs among sports. The RAE is found in all youth teams, starting from club to national level, with a gradually increasing incidence with the level of excellence, as the table below shows. The latter situation can expose a problem associated with the selection process and the recruiters' view of talented players. Furthermore, although reduced, this bias tends to persist at senior level, which supports the assumption that early-born players have a greater chance of success thanks to their more advanced state of maturity during youth years. Early-born children were more represented in selected squads than normal or late-born 15–18-year-olds, and late-born players were less represented at club level as the age group increased. This tendency is observed especially between the ages of 13 and 16, when differences in maturity status are amplified by the timing and pace of adolescent growth. Therefore, adulthood can play a decisive role in recruiters' opinions on the potential of young players and the possibility of signing a pro contract. The physical advantages offered by advanced age and maturity in adolescence are largely transitory and are reduced or eliminated in young adulthood.

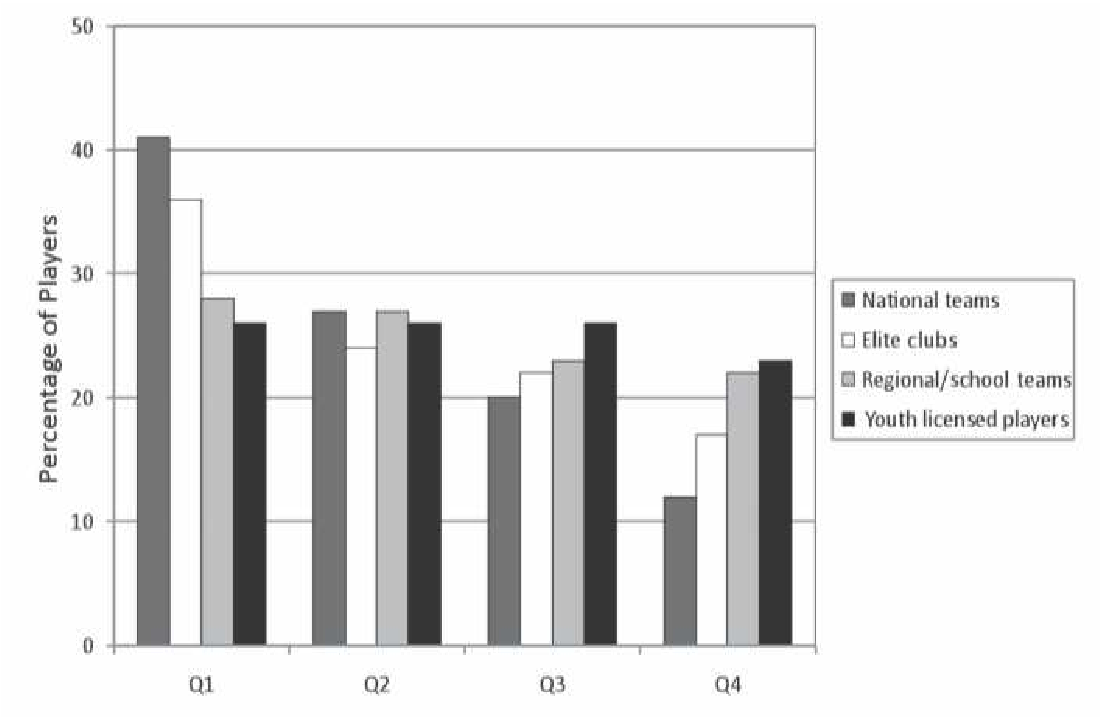

Figure 1: Summary of the Relative Age Effect in Youth Soccer Across Different Levels of Play (REVIEWS: TALENT IDENTIFICATION IN SOCCER: THE ROLE OF MATURITY STATUS ON PHISICAL, PHYSIOLOGICAL AND TECHNICAL CHARACTERISTICS, 2010)

1.2.2. Physical and physiological testing in youth soccer

Considering the differences in birth date distribution and maturity status among elite and non-elite youth football players, the purpose of this section is to investigate three main issues concerning the physical and physiological tests currently utilized in youth football for talent identification and estimation of higher soccer performance: (i) the impact of maturation time and timing on the physical and physiological characteristics of youth football players; (ii) the sensitivity of physical and physiological characteristics to determine actual (i.e. elite vs. non-elite) and future (professional vs. non-professional) success of youth football players; and iii) the role of youth players' physical and physiological profiles in coaches' tactical decisions regarding the game, elite vs. non-elite) and future (professional vs. non-professional) success of youth football players.

The articles quoted in this section reported on: a measure of maturity status (e.g., skeletal age); physical attributes (e.g., height, mass) and physiological performance (e.g., speed) of male youth football players. The studies that met the inclusion criteria are presented in Table 2.

Authors	Players	Groups	Maturity	Anthropo.	Physiological testing	Significant gradient (> = better; p > 0.05)
Carling *et al.*[32]	n = 160 U14 National level	Future national team vs. future professional club vs. future amateur	SA	Height Mass SSK	10 m sprint 20 m sprint 40 m sprint Max anaerobic power CMJ Isokinetic strength[†] Estimated VO_{2max}	**Height:** Q1, Q2, Q3 > Q4 (professional) **Weight:** Q3 > Q4 (professional) **Max. anaerobic power:** Q1 and Q3 > Q4 (professional) **Strength:** Q1, Q2, Q3 > Q4 (professional) **Estimated VO_{2max}:** Q1 and Q2 > Q3 (professional)
Figueiredo *et al.*[43]	n = 159; U13 (11.0- 12.9 yrs) U15 (13.1-14.9) Non elite club level	Late vs. average vs. early maturer	SA	Height Mass SSK Leg length	35 m sprint with slalom Shuttle run (5 x 10m) SJ CMJ Repeated sprints Yo-Yo test (level 1)	**Mass:** early>on time>late maturers (U13 & U15) **Height:** early>on time>late maturers (U13 & U15) **Leg length:** early>on time>late maturers (U13 & U15) **SSK:** early > on time >late maturers (U13) **SJ:** early>on time>late maturers (U15) **CMJ:** early>on time>late maturers (U15) **Yo-Yo test:** late >on time and early maturers (U13)
Figueiredo *et al.*[ɛ 18]	n = 159; U13 (11.0- 12.9 yrs) U15 (13.1-14.9) Elite to non elite club level	Future youth elite vs. future non elite vs. future drop out	SA	Height Mass SSK Leg length	35 m sprint with slalom Shuttle run (5 x 10m) SJ CMJ Repeated sprints Yo-Yo test (level 1)	**Maturity:** elite > non elite and drop out (U13, U15) **Mass:** elite > non elite (U13); elite > drop out (U15) **Height:** elite > non elite and drop out (U13, U15) **Leg length:** elite > non elite and drop out (U13, U15) **CMJ:** elite > non elite (U13); elite > drop out (U15) **35 m sprint with slalom:** elite > drop out (U13, U15); elite > non elite (U13) **SJ:** elite > drop out (U13, U15); elite > non elite (U13) **Shuttle run (5 x 10m):** elite > drop out (U13, U15); elite > non elite (U15) **Repeated sprints:** elite > drop out (U13, U15); elite > non elite (U15) **Yo-Yo test:** elite > non elite and drop out (U13, U15)
Le Gall *et al.*[9]	n = 161 U14, U15, U16 National level	Future national team vs. future professional club vs. future amateur	SA	Height Mass SSK	10 m sprint 20 m sprint 40 m sprint Max anaerobic power CMJ Isokinetic strength[†] Estimated VO_{2max}	**Maturity:** amateur> professional and international (U14-U16) **Mass:** professional > amateur (U14) **Height:** international and professional > amateur (U14, U16) **Anaerobic power**: international and professional > amateur (U14, U16) **Jump height:** international > amateur players (U14) **40 m sprint time:** international players > amateur (U14)

Authors	Players	Groups	Maturity	Anthropo.	Physiological testing	Significant gradient (> = better; p > 0.05)
Vaeyens *et al.*[49]	n = 232 U13, U14, U15, U16 Elite to non elite club level	Early vs. on average vs. late maturer Elite vs. sub elite vs. non elite	SA	Height Mass SSK Girth (limb) Breadth (bone)	SLJ Flying 30 m Shuttle run (5 x 10m) VJ ESHR STR	**All anthropometry variables:** early>on time>late maturers (U13-U16) **SLJ & VJ:** early>on time>late maturers (U13) **Flying 30m &shuttle run:** early>on time>late maturers (U13 & U14) **ESHR:** early>on time>late maturers (U15, U16) **SSK:** Elite and sub elite < non elite **SLJ:** Elite > non elite (U13, U14, U15) **VJ:** Elite > non elite (U13 and U15) **30 m :** Elite > non elite (U13, U14 and U15) **Shuttle run:** Elite > sub elite and non elite (U13, U14,U15) **ESHR:** Elite and sub elite> non elite (U13, U14); Elite > sub elite and non elite (U15, U16) **STR:** Elite and sub elite > non elite (U13, U14); Elite > sub elite (U15); Elite > non elite (U16)
Malina *et al.*[56]	n = 69 U15 (13.2 to 15.1 yrs) Elite club level	Early vs. on average vs. later maturer	PH	Height Mass	30 m sprint CMJ Yo-Yo test (level 1)	**Height:** PH5 > other PH **Mass:** PH5 > PH3 & PH4 > PH1 & PH2 **30 m sprint:** PH4 & PH5 > PH1 & PH2 **CMJ:** PH4 > PH2 & PH3 **Yo-Yo test:** PH2-PH5 > PH1
Hansen *et al.*[ɛ 46]	n = 110 U12 Elite and non elite club level	Elite vs. non elite	PH	Height Mass SSK	SLJ Isometric strength[¥]	**Height:** Elite > non elite **Mass:** Elite > non elite **SSK:** Elite < non elite **SLJ:** Elite > non elite **Isometric strength:** Elite > non elite

Key: Anthropo.: anthropometric measurements; [†]Peak concentric torque of leg extensor and flexors at angular velocities 1.05 and 4.19 rad/s; [ɛ] Longitudinal study over 2 years; [¥] leg extensor, trunk and grip; Q: quartiles of year; SA: Skeletal age; PH: Tanner stage of pubic hair; U: under (age category); n: sample size; SSK: sum of skinfold; CMJ: countermovement jump; SLJ: Standing long jump; SJ: squat jump; ESHR: endurance shuttle run; STR: shuttle tempo run

Table 2: Physical and Physiological Factors Used in Youth Soccer to Discriminate Between Early, On Average and Late Maturers, Elite, Sub-Elite and Non Elite Players; and, Future International, Professional and Amateur Players

1.2.3. The role of maturation in physical and physiological testing

The wide spread of biological age and the variation in developmental phases of single players make it very challenging to have trust in biological age parity within agonistic categories. Longitudinal and cross-sectional data have shown the changes in physiological performance that are associated with growth. On the basis of these observations, the physical evaluation of young footballers should be interpreted in combination with maturation status to carry out a more objective talent recognition process.

The initial classification between late, average and early maturation in the same age category is a valuable method to assure equity and has been conducted in football studies. Even though early maturity has not always been linked to better performance, it has usually been associated with larger body size (height and weight) and superior explosive performance (vertical and standing long jump), sprinting (30 m), agility (shuttle running) and endurance performance in several age groups (U13-U16 categories).

A multidimensional approach to talent recognition should incorporate a set of sport-specific skills (e.g., dribbling, shooting, ball control, passing, etc.) in combination with physical, physiological and psychological tests.

Sport-specific abilities have been utilized as predictors of success in soccer and other sports (e.g., tennis, handball and hockey) and were frequently more sensitive than physical and physiological parameters. However, neither of the previous studies determined the maturity status of players and it is also possible that elite or better players were biologically more mature than their counterparts.

This may have three main effects on the measured technical abilities. Firstly, mature players are probably older and therefore have more game experience and time to develop the skill. Second, they may be quicker, stronger and more powerful, which may affect the results of technical exercises in which these components play a role (e.g., fast dribbling). Thirdly, the fact of being more mature and older may result in greater neuromuscular control.

1.2.4. Determining biological maturity

Since the birthdate distribution and the relevance of maturation on body size and physiological performance have been shown to have an important influence on selection in youth football, it is required to reconsider the theoretical question of age grouping and comparison of young players based on the sole principle that they were born in the same year.

Coaches' awareness of Relative Age Effect and the role of maturity on physiological capabilities in youth football was perceived as a solution.

An estimation of biological maturity appears to represent the first step for a fair and efficient selection of talented players, taking into account its relevance in the game and the confounding effect on the recruitment process.

Biological age, determined by non-invasive or invasive measurements, can provide the coaches and medical staff an accurate indication of a player's maturity and show the timing and speed of maturity in comparison with peers.

It is further used to determine critical periods for training in long-term development planning.

The most popular clinical method to establish biological age traditionally utilizes a plain radiograph of the left hand, wrist or knee, and various methods are available to interpret these radiographs (e.g., the Fels, Tanner- Whitehouse, Greulich and Pyle methods). Skeletal age is an indicator of physiological maturity since it provides a continuous indication of growth until maturity. This method has been extensively used in football academies and institutes to categorize players according to their skeletal age with respect to chronological age.

1.2.5. Discussion

The talent identification and selection of players is a needed process, but it requires a remarkable understanding of the demands of the game and knowledge of human development and maturation. RAE is present in many sports, but it appears to be more prominent in sports like football, where the number of players and the level of competition is high.

It is probable that mature players dominate the game physically at the youth level through increased body size, strength, speed, power and endurance, but do not necessarily hold this advantage at the senior level. Non-invasive methods of estimating maturity status can enable youth programmes and coaches to better interpret physical, physiological and technical test data with a clearer understanding of human growth.

Players who are both technically proficient but less mature may be missed in the selection process due to limitations associated with their maturity in physical and functional abilities (e.g., reduced size or less strength, power and speed). By overlooking the difference in maturity, recruiters may favor the most competitive players at the moment of selection but may reduce the possibility of retaining players with the highest potential in the organization. Moreover, staff members should not base their tactical decisions (e.g., playing position) exclusively on physical or physiological attributes, since these characteristics may not be transferred to the highest level.

A long-term approach to player development should be aimed at retention of many talented players and give them the same opportunities and quality of training and competition, since younger players are just as successful, if not more so, when selected in a squad.

1.3. PHYCHOLOGICAL AND EMOTIONAL FACTORS

In the sports sciences, there is a complete lack of prospective studies on career success which indicate the outcome of performance. Psychological factors are acknowledged as critical for the acquisition of sports skills, but the relevance of these factors has not been proven in any studies using a prospective design.

Engagement in practice activities specifically designed to increase performance is known as *deliberate practice*.

Ericsson et al. (1993) assumed three types of constraints on deliberate practice. First, *motivational constraint* relates to the commitment to one's goals that is demanded to engage in deliberate practice. Second, deliberate practice and success in professional football as adults require physical and mental effort (such as the ability to deal with stressful situations effectively). Effortful activity can only be sustained for a limited time each day during prolonged periods, without causing exhaustion (i.e., *effort constraint*). Third, *resource constraint* relates to the resources that deliberate practice demands, such as the access to coaches and training structures and social support.

The aim of the presented research is to examine the significance of these three types of constraints for career success in professional adult soccer by statistically controlling for relevant variables.

1.3.1. <u>The three constraints</u>

The Motivational Constraint

Achieving difficult goals requires a high level of commitment, that is, the individual's determination to achieve the goals (Locke & Latham, 1990), which motivates them to engage in (further) deliberate practices. For example, Baker and Côté (2003) argued that commitment may be the most important attribute for the acquisition of competence in sport, because only individuals who are highly committed to their goals are willing to carry out the thousands of hours of deliberate practice required to become an elite athlete. Indeed, through interviews with teenage players and their coaches suggest that dedication, willingness to make sacrifices, and strong motivation are associated with success in soccer.

The Effort Constraint

The quest for excellence can be a strenuous activity that draws on limited physical and mental resources. Successful people must have the resilience to sustain a high degree of deliberate practice over long periods of time without succumbing to exhaustion, namely the feeling of being drained or depleted (Schraw & Ericsson, 2005). Exhaustion is linked to a decreased ability to solve challenging, new, or complex tasks, to overcome usual responses, and to identify and correct errors, all of which negatively influence performance improvement (e.g., Boksem, Meijman, & Lorist, 2006). Successful players may have experienced a better capacity to recover from training activity, so that they are less vulnerable to exhaustion and its deleterious performance consequences.

Even though the effort constraint in the original theory of deliberate practice (Ericsson et al., 1993) focused largely on physical effort, subsequent research has shown that effort also includes mental effort (Starkes, Deakin, Allard, Hodges, &

Hayes, 1996). Mental effort can be particularly relevant in stressful situations, both during training and competition. Coping refers to the thoughts and behaviours that people use to manage the internal and external demands of situations that are perceived as stressful (Lazarus & Folkman, 1984). Two fundamentally different types of coping have been distinguished. Problem-focused coping consists of proactively intervening in the stressful situation; emotion-focused coping is defined as the cognitive regulation of stressful emotions.

In general, it is advisable to rely more on problem-focused coping in situations where the possibility of changing the outcome exists, whereas it is appropriate to rely more on emotion-focused coping in situations where very little can be done to alter the outcome (Folkman & Moskowitz, 2004).

The Resource Constraint

Resource constraint has traditionally been measured as social constraint (Côté, Ericsson, & Law, 2005) and involves resources like access to coaches and support in school and homework.

Social support is defined as the perception or experience of being loved and cared for by others, esteemed and valued, and being part of a social network of mutual care and obligations.

1.3.2 The research

The current analysis has been made into a soccer academy and it consisted in interviewing 65 male pupils.

The primary goals of the youth players were: (1) Playing for a club in the Premier League, (2) Playing for a team in a European Premier League, and (3) Playing for a professional club (see “goal importance”). Hence, players were assumed to be successful if they met at least one of these goals. In particular, participants were placed in the successful group if they had had (or still had) a contract with a top league football team in a European tournament and if they had actually played (or still played) for at minimum ten years within the 15-year period after the data collection.

The measures utilized were:

- **Initial Performance Level**. The coaches of the teams were asked to evaluate the performance level of all the players in their squad.

- **Goal Importance and Goal Commitment**. To examine whether perceived goal importance could explain any differences in goal commitment, participants were asked to indicate how important each goal was to them (from 1 = not important to 6 = most important): (1) playing for a local

Premier League club, (2) playing for a European Premier League club, and (3) playing for a professional club. Subsequently, goal commitment was measured by using the reduced and improved version of the scale originally elaborated by Hollenbeck, O'Leary, Klein and Wright (1989; Klein, Wesson, Hollenbeck, Wright, & Deshon, 2001). The example items are "I am strongly committed to my goals" and "Honestly, I do not care whether I reach my targets or not" (reversed item). The answer categories ranged from (1) completely disagree to (5) completely agree. Exhaustion was gauged using a seven-item measure devised by Van Yperen (1997). The main stalk was: "Did it happen the previous year?". The sample items were: "I felt exhausted more than usual" and "I was fed up with everything to do with soccer". Five response categories were provided, from (1) never to (5) always.

- **Potential Stressors and Coping**. In order to test whether the perception of the stress factors could explain any differences in coping, the participants were asked to indicate to what extent a number of potential stressors had occurred in the past year. The general potential stressors (25 items) represented different content areas, for example disputes with others (relatives, friends), illnesses (of self and others), school difficulties and financial issues. Soccer-specific stressors (25 items) included pressure to perform, injuries, discussions and problems with others (coaches, teammates, management). The answer categories ranged from (1) does not occur or does not apply, to (5) occurs very often.

- **Seeking Social Support**. This measure, developed by Folkman and Lazarus (Folkman & Lazarus, 1985), asks interviewees to report their tendency to seek social support when they encounter the problems and inconveniences. Examples of items are "I seek the company of friends to have fun" and "I talk to someone to find out more about the situation". The answer choices ranged from (1) never to (5) always.

1.3.3. Discussion

By statistically controlling for the level of initial performance (reflecting, among other things, possible differences in innate talent and the amount of time and effort already spent on football and related activities) and other control variables, the outcomes suggest that psychological factors are important in predicting career success in football.

Ericsson et al. (1993) argued that the quest for excellence implies operating within three types of constraints on deliberate practice. Regarding the motivational constraint, the results show that the goal of breaking through in adult professional football was high and largely unchanged in the present sample. However, compared to their unsuccessful counterparts, those who were able to succeed in adult professional football felt more psychologically tied to their goals, such that their willingness to commit to the goal, their perseverance in pursuing their goals over time and their reluctance to diminish or give up their goals may have been stronger.

With respect to effort constraint, no differences in exhaustion were observed among successful and unsuccessful participants, which suggests that there were no differences between the groups in their capacity to recover from the high physical and mental requirements that are intrinsically associated with pursuing a career in pro soccer.

As expected, compared to unsuccessful participants, those who were successfully reported a greater engagement in problem-focused coping behaviours. Furthermore, with regard to resource constraint, they were also more inclined to seek social support if they encountered problems and inconveniences. This suggests that in comparison to the unsuccessful participants, those who were successful may have been capable of better adapting to the stressful situations they inevitably faced during their soccer career, possibly by utilising their coping skills and social resources more frequently and flexibly.

In other words, at the time of data collection, participants who successfully transitioned to adult professional football were judged by their coaches to have performed at a higher level than their unsuccessful counterparts. Especially in competitive contexts, a high value is placed on achievement, success and excellence, thus individuals perceived as high potentials may have received more focus and support, which may have facilitated further development.

Even more remarkable is the finding that, compared to the non-winning group, the successful participants had more siblings, were more often from an ethnic minority and more often had divorced parents. To hypothesise these extraordinary results, it is possible that siblings forming a sibling group bound by strong bonds of trust and support may increase social skills, especially useful for progressing in team sports. In addition, belonging to an ethnic minority and having divorced parents may contribute to the development of coping skills and attitudes useful for dealing with any kind of problem or inconvenience.

But the observed model also emphasises that success in sport is a complex and delicate process, influenced by a range of psychological, physical, social and organisational factors.

In conclusion, the most significant contribution of this prospective study is that it demonstrates that psychological factors like commitment to goals, engaging in coping behaviours and seeking social support differentiate, when statistically controlling for both initial performance and demographic characteristics, adolescent soccer players who ultimately successfully transitioned to adult professional football from those who did not. There is suggestive evidence that both commitment to goals (Raabe, Frese, & Beehr, 2007) and the tendency to engage in coping and social support-seeking behaviours (Taylor & Stanton, 2007) can change with psycho-social interventions, possibly as a function of deliberate practice.

1.4. PERCEPTUAL AND COGNITIVE SKILLS

This part of the research examines the relative contribution of visual, perceptual and cognitive skills to the development of football expertise. Elite and sub-elite players, ranging in age from 9 to 17 years, were evaluated using a set of multidimensional tests. Four aspects of visual function were assessed: static and dynamic visual acuity, stereoscopic depth sensitivity and peripheral consciousness.

Perceptual and cognitive abilities were measured through the use of situational probabilities and tests of anticipation and memory recall.

Anticipation tests and the use of situational probability were the best in discriminating ability groups. Memory recall of structured play schemes was found to be more predictive of age. By the age of 9, elite football players already showed higher perceptual and cognitive capabilities than their sub-elite counterparts. Implications for the training of perceptual and cognitive skills in sport are discussed.

This study shows that more expert athletes do not have superior visual function and that perceptual and cognitive factors are the main discriminators of skill performance in adults.

In comparison to their less able counterparts, skilled adults are better at predicting opponents' intentions on the basis of partial information or anticipated clues (Abemethy & Russell, 1987; Jones & Miles, 1978; Williams & Burwitz, 1993), are more consistently able to grasp the minimal essential information (e.g., relative movement) necessary for a successful anticipation (Ward, Williams, & Bennett, 2002); Williams & Davids, 1998; Williams, Davids, Burwitz, & Williams, 1994) and are faster and more accurate in recognising and recalling typical playing patterns from memory (Starkes, 1987; Williams & Davids, 1995; Williams, Davids, Burwitz, & Williams, 1993).

The relative contribution of visual, perceptual and cognitive skills to competence in sport during late childhood, adolescence and early adulthood has received scarce attention so far.

Our awareness and understanding of how motor and cognitive aspects of performance influence skill development during childhood and adolescence has been greatly enhanced by the work of Thomas and colleagues (Thomas, Gallagher, & Thomas, 2001; Thomas & Thomas, 1999).

It has been shown that children can develop chunking skills as early as the age of 5, when they are stimulated to adopt a modified strategy and at 9 years of age without external collaboration.

Early perceptive organisation and the domain-specific knowledge base associated with it have been hypothesised as crucial factors for chunking skill performance.

Researchers have also investigated how tactical and strategic decision-making develops in sport (French, Nevett, Spurgeon, et al., 1996; McPherson, 1999; McPherson & Thomas, 1989). These studies suggest that the knowledge bases and cognitive strategies underpinning effective performance gradually develop as a consequence of extensive task-specific practice.

As children gain more experience with age and task-specific training, rules-based problem representations of increasing complexity arise (action plan profiles). The capacity to accurately track the current task demands, to use tactical and strategic planning, to forecast probable outcomes with increasing sophistication and to anticipate the opponents' intentions (current event profiles) continues to evolve until early adulthood.

One of the most useful methods of assessing expert performance is to ask players to choose the next best move (de Groot, 1978). When determining the outcome of an evolving game plan, novices of any age are likely to use an inappropriate selection strategy and generate far less solutions to the problem. In football, experts are likely to discard many events as highly improbable and assign a hierarchy of probabilities to the remaining possibilities.
These strategies are probable to be refined with experience and age, as domain-specific knowledge and associated memory skills become more sophisticated.

1.4.1. The study

The following study is aimed at examining how visual and perceptual cognitive skills improve and develop in function of age and skill in football and, above that, to select the best players.

Number 137 male soccer players among elite academies and sub-elite from local elementary and secondary school were selected.

Following measures of visual function were recorded using standardized equipment:

1. **Static Visual Acuity**: A Bailey-Lovie logMAR eye chart was used for testing binocular static acuity at 6 meters
2. **Dynamic Visual Acuity**: The Sherman Dynamic Acuity Disc was used to assess the dynamic visual acuity levels of the players.
3. **Stereoscopic Depth Sensitivity**: A random dot stereogram (TNO test) was utilised to assess stereoscopic depth sensitivity.
4. **Peripheral Awareness**: The Wayne Peripheral Awareness Tester was used to assess the ability to react to peripheral stimuli.

To examine perceptual ability, film-based simulations have been utilised. Sequences of actions from professional and semi-professional matches were assembled and displayed on a large video screen. The participants answered with paper and pen in a time-limited context.

Then, participants were subjected to anticipation, memory recall and situational probability tests.

1. **Anticipation**: Participants were presented with soccer action sequences including 1 v. 1 (2-choice response), 3 v. 3 (4-choice response), and 11 v. 11 (10-choice response) simulations,
2. **Memory Recall**: Structured conditions included 11 v. 11 attack and defensive action sequences. Unstructured trials included periods of inactive play,
3. **Situational Probabilities**: Offensive 11 vs 11 patterns of play were filmed from an elevated perspective behind the goal.

1.4.2. Results

Even at 9 years of age, elite players were better at predicting the involvement of key players when they observed offensive plays and assigned appropriate probability values to each key player more accurately. They were also more successful in utilising the available anticipatory information from emerging patterns of play and postural cues. These results suggest that 9-year-old elite players possess comprehensive understanding of player relationships, readily perceive the relative significance of each player, and are able to capture their anticipated actions more accurately compared to sub-elite players.

It can be necessary to have a large amount of practice over several years (e.g., the 10-year rule) to completely acquire the domain-specific knowledge and memory abilities to become expert performers. However, the current study indicates that limited practice associated with an high-quality coaching may have a significant influence on the acquisition of perceptual and cognitive skills from an early age.

The results of the situational probability paradigm indicate that elite players demonstrated a higher degree of situational awareness from an early age. The number of key players highlighted was one of the most discriminatory ability factors. Regardless of age, elite players were relatively accurate in picking up task-relevant information while viewing each simulation and they were able to incorporate this information with their previous experience to predict the best available options for the player in ball possession. Moreover, the elite players aged 9 to 15 years improved their capacity to predict the next best move by assigning an adequate probability hierarchy to the most important players, thereby improving the probability of an event occurring. In other words, they were not only able to select the key players in the game but, with increasing odds, were able to use the threat level of each key player.

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In other words, they were not only able to select the key players in the game but, with increasing odds, were able to use the threat level of each key player as a relative attention allocation index.

Although sub-elite players aged 9-13 years improved their capacity to identify key players, the reduction in the production of task-irrelevant information (i.e., non-key players) by elite players suggests that skill level, rather than age, was a greater contributor to the switch from an over-inclusive to a selective attention strategy (Ross, 1976). By utilising a more refined selection strategy and hierarchy of probabilities, elite developing players can reduce the decision-making threshold required to predict the likely outcome of a situation.

The pattern of perceptual-cognitive skills highlighted in this study suggests that both information grasping (i.e., the appropriate use of contextual information) and knowledge of what might happen next (i.e., the integration of expectations stored in memory) in the macro-states of the game are key components of top performance.

Abemethy's assertion that experts do not develop superior anticipatory skills until early adulthood is refuted, as the elite players in the present study were able to anticipate and predict their opponents' intentions, particularly in 11 vs. 11 simulations, from the age of 9.

To summarise, the present research shows that elite and sub-elite youth football players are not meaningfully discriminated against in non-specific tests of visual function during late childhood, adolescence and early adulthood. In contrast, elite players develop superior perceptual and cognitive skills that allow them to perform better in each of their respective age groups than their non-elite peers. The perceptual and cognitive skills model indicates that, as early as 9 years of age, elite players are able to effectively use and integrate contextual information with expectations stored in memory in ways that systematically differ from those of their sub-elite counterparts.

1.5. A NEW OPPORTUNITY FOR THE IDENTIFICATION OF FOOTBALL PLAYERS?

As assumed at the beginning of this chapter, the initial selection of a young player takes place thanks to scouts and coaches who notice the player in training sessions, matches, tournaments, etc., and then invite him for a 'try-out' within the club structures in which a full evaluation of the player is carried out according to the criteria analysed so far.

The role of scouts and coaches at this stage is of fundamental importance in order to carry out an initial 'eye' screening of potential candidates, but this is only possible if there is a physical 'meeting' between the player and the scout/coach.

Several sports organizations almost exclusively rely on human experience for the talent scouting process. In disciplines such as soccer, especially in the Italian context, it is still believed that experts in the domain (coaches, managers and scouts) can effectively turn collected information into utilizable knowledge.

In the last few years, new technologies (location tracking, player analysis software, online multimedia databases, etc.) have provided additional benefits, such as the prediction of specific matchups between players and/or the prediction of how an athlete might perform under specific conditions.

Despite the increasing proliferation of new media tools in the sports sector, a scientific understanding of the role and impact of new technologies on the talent scouting process is still lacking.

Based on these premises, we can state that the use of digital technologies within the sports industry is becoming increasingly invasive. Specifically, the questions to answered are:

1. What are the most widespread new technologies in football talent scouting?
2. Are there professional football clubs using new media to identify and recruit young players? If yes, how?
3. What opportunities do these tools offer, both for athletes (demand) and for scouts (supply)?

Applications of digital technologies are permeating the world of football in many ways, such as the collection of data on the field to monitor athletes' actions, statistical analysis of opposing teams, etc. A recent and innovative trend concerns the use of social media (e.g., Twitter, Facebook, etc.) to 'observe' the behaviour of young athletes on the web. Sports professionals and club executives who gather each year at the MIT Sloan Sports Analytics Conference agree that social media has helped coaches and scouts to open a more efficient dialogue with recruiting targets (Trotter, 2012). Monitoring the social accounts of high school and college students allows for a deeper analysis of promising young athletes, uncovering their personal habits and attitudes in a way that would not yield the desired results even through face-to-face interaction.

Online exploration of football scouting sites and platforms and interviews with professionals working in Italian clubs and federations indicate that these new media generally pursue two main purposes:

a) to support traditional scouting activities 'on the field',

b) to discover young talents.

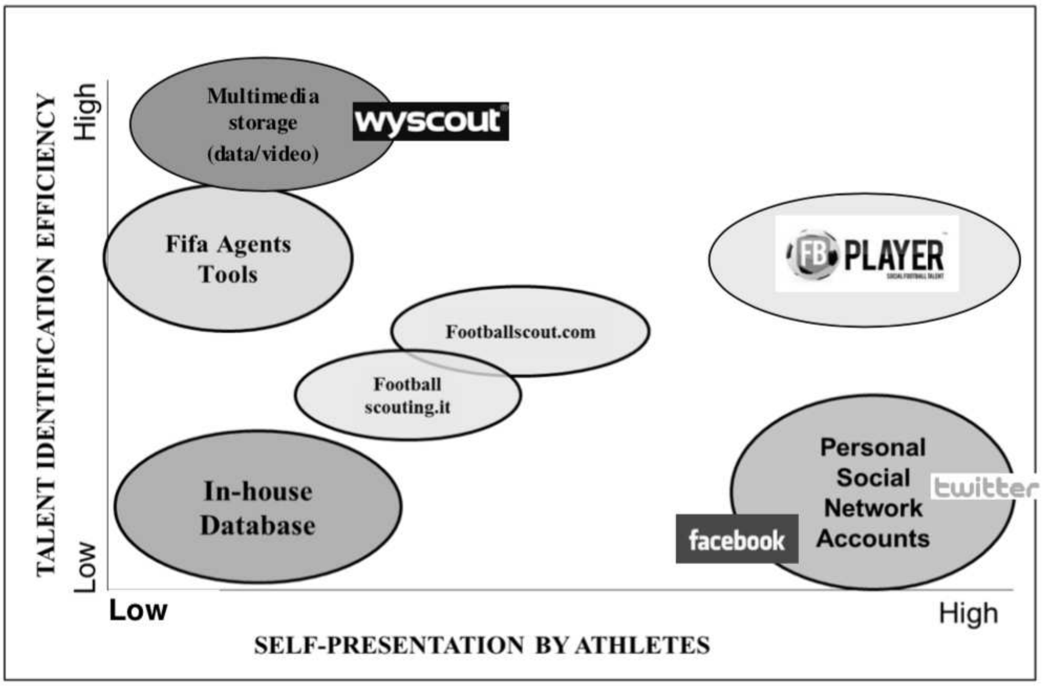

Figure 2: Digital and multimedia platforms for football talent scouting (SOCIAL TALENT SCOUTING: A NEW OPPORTUNITY FOR THE IDENTIFICATION OF FOOTBALL PLAYERS? 2016)

Figure 2 is a graphical representation of the most important digital and multimedia platforms used for talent scouting. The graph is constructed along two main dimensions. On the x-axis, the variable 'self-presentation by athletes' indicates the extent to which a platform allows athletes to co-participate in the talent scouting process. On the y-axis, the variable 'talent identification efficiency' assigns an efficiency ranking to each digital tool based on the extent to which the platform enables scouts to find new talent.

By correlating the different degrees of these variables, it is possible to gain an overview of digital and multimedia tools for football talent scouting.

At the top of the chart are innovative tools that scouts and coaches could use to maximise the efficiency of the talent selection process and discover new players. These types of platforms are multimedia archives for storing football-related video, audio and text files, which allow teams to access data collected by private companies that sell the right to access content to clubs and federations. Several professional sports organizations use these online tools. They are deconstructing the old, large and expensive internal scouting network by outsourcing part of the process to external private organisations. These companies, such as Wyscout, provide a 'common' database available via the Internet to clubs that subscribe to the service. In this way, "football clubs can apply an initial screening of players. Then they are able to contact and select only the most talented players.

Moving to the right (below), we find flexible platforms that allow users to sign up themselves and compile and publish their own profiles, adding information, photos and/or videos. The personal Facebook and Twitter accounts of junior players could be used by clubs as additional channels to obtain information and assess personal and interpersonal skills and qualities, such as values, emotion management, personal commitment, etc. On the other hand, players can use their social network pages to present themselves as talents, showcase their sporting performances by uploading photos and videos and keep in touch with a potential audience of coaches and scouts.

1.5.1. FB Player platform

Among the most popular web-based tools used for the collection and analysis of young footballers' profiles, there is a specific football-oriented social platform called FB Player - Social Football Talent, an Italian start-up founded in April 2014. FB Player is based on a completely innovative approach: this social platform aims to 'enable coaches and scouts to discover unknown football talents and champions'.

It also 'allows players to showcase their performances and stay in touch with other players, scouts, football clubs and fans around the world'.
Although this online community was designed to include everyone involved in the world of football (athletes, coaches, scouts, fans), the majority of users are players.
The main goal of the founders was to create a network, or better defined 'electronic marketplace', where demand (players) and supply (coaches and scouts) can meet, exchange information and keep in touch.
At the end of September 2015, FB Player had 6,671 members: most were registered as players, while few were registered as fans or as coaches and scouts.

By filling out a profile form, entering details such as age, gender, nationality and position on the pitch, and completing an online physical test, players can showcase their skills and get noticed by scouts, especially by uploading their own photos and videos of training sessions but especially of games played.

We can definitely say that recruitment processes are becoming increasingly complex and sophisticated as clubs exploit emerging communication technologies to gain more and more competitive advantages. Thanks to new and social media, the scouting process can start earlier and be completed in less time. The Internet is therefore becoming a valuable and essential tool for scouts to gather information on players, monitor their performance and 'screen' potential candidates. Thanks to the new media tools, travel costs can be reduced and the breadth and scope of scouting can be expanded, both quantitatively and geographically.

2. SCOUTING IN PROFESSIONAL ADULT SOCCER

Nowadays, football is the most played sport in the world with approximately 265 million players (men and women) and including referees and match officials brings the number of people actively involved to approximately 270 million, representing 4 per cent of the world's population. In addition to developing this large number of people, football consequently moves a multi-million-dollar market (Elferink-Gemser et al., 2012) and the economic benefits that a team can gain from being able to recruit talented players and develop them to their full potential are enormous. For example, the three most valuable teams currently, Manchester City, Chelsea and Bayern Munich, are worth EUR 1.05 billion, EUR 1.02 billion and EUR 995.72 million respectively, considering only the market value of the players (Transfermarket, 2023).

In this sense, the process of finding, selecting, identifying and developing talent becomes not only essential but also definitely profitable.

According to Williams, in the smallest clubs, players are identified and selected through scout reports based on performance during training and matches. This process is speculative, with the probability of success mostly based on intuition and not on objective criteria, which are necessary in modern football. Therefore, in the attempt to search for talented young players, scholars and scientists have an everincreasing task that requires joint work with coaches, scouts and 'administrators' to find key elements for the identification and development of young players.

The football industry has constantly faced several unique challenges and scouting has been one of them. The world of football is a very competitive environment in which numerous clubs compete to acquire top talent.

With the growth in the use of data analysis in football, one of the areas where there is the greatest impact is on players recruitment. Without the right players, a team will never be as successful as it hopes to be. Making the right recruitment decisions is difficult, especially in a sport as full of variability as football.

2.1. A NEW SCOUTING APPROACH: USE OF DATA

Gone are the days when football scouts, equipped with binoculars and notebooks, travelled miles to the most diverse football pitches to observe all kinds of players. Gone is the traditional process where scouts spent 90% of their time travelling and 10% scouting.

Usually, the traditional method involves the scout going to see the potential player, taking notes on his performance and presenting it to the club manager. Today, however, the recruitment process starts with the analysis of player data. Using the vastness and power of player data, analysts select a shortlist of players to view. Professional scouts then watch tons of videos showing the skills and talent of the selected players. Finally, they go on to see the potential player in action. If the scouts are positively impressed, they report back to the company management who will make an offer to sign the player to the team.

Increasing digitisation, combined with the pandemic, have led football clubs to rethink, digitise, streamline and consequently improve their scouting processes, thus making them more efficient. Thanks to the increasing amount of data and videos available today, it is possible, even with limited resources, to combine a systematic selection with a standardised scouting process.

The challenge, however, has not changed: finding the perfect player that no other club has on its radar. Only today it is much more difficult than it used to be. In the past, the biggest clubs were able to build a worldwide scouting network thanks to their investments, which could quickly point out many talents to choose from.
Today, thanks to simple and systematic data collection, an Asian player, for example, gets noticed in no time after a top performance in his first professional league game. The next day, at least half the football scouting world has already spotted him.

Data analysis has been becoming increasingly crucial in the football industry for more than a decade and now plays a significant role in scouting. Big Data allows clubs to obtain information that helps increase player performance, prevent injuries and improve a player's efficiency to gain a competitive advantage on and off the pitch.

DATA SCOUTING brings with it numerous advantages, including:

- The club can carry out the initial selection continuously and systematically according to its playing philosophy.
- The club already has many more players to consider from the beginning who, without the use of the platforms, would not have stood out. The clearer and more individual the search criteria related to the playing philosophy, the greater the chance of finding the most suitable player. Since the whole world does not look for club-specific criteria, this leads to savings in transfer spending. And in turn to higher profits in the event of eventual resale.
- The club and scouts save enormous amounts of resources and time that they can use for other purposes and are able to use their limited scouting resources more efficiently.
- The strict reliance on agents and other intermediaries proposing their players to clubs is reduced.

At the highest levels of the game, clubs recruit the best talents from around the world and also compete in a market where transfer costs for in-demand players can reach astronomical figures.

Data analysis is an invaluable tool for sifting through the hundreds of thousands of players worldwide, thus greatly increasing the range of players a club can consider and allowing the scouting team to focus on the players most likely to be a good fit for the club.

By working through data, clubs can discover players who will improve their team and who are available at an attractive price.

2.1.1. Clubs and data

Data is now commonly used in football and some clubs are at the forefront of data-driven recruitment, including Brentford. In recent years, the West London club has made significant profits in the transfer market by using its analytical model to compare the relative strengths of teams in different leagues. The club has been able to find talented players both in England's lower leagues and abroad, in countries such as France and Denmark, and after attracting Brentford's attention, signings such as Ollie Watkins and Neal Maupay have moved on to Premier League clubs for significant profits.

Another club that has been successful using data in the transfer market is Liverpool. Their transfer strategy has been very successful in recent years and thanks to the likes of Salah, Van Dijk and Alisson, they have managed to win the Champions League and the Premier League respectively in 2019 and 2020.

Ian Graham, head of Liverpool's data department, has developed a unique method of analysing player performance. For each play made by a player on the pitch, such as a tackle, a pass or a shot, Graham uses the data to assign a weight to how it affects the team's chances of scoring a goal. This metric is called 'goal probability added'.

Not only the biggest clubs use data for scouting. In the Championship even Derby County uses statistical analysis to help recruit players.

Head of recruitment, Joe McClaren, says that delving into and understanding the context of statistics is crucial when scouting players. Statistics such as total number of stats, such as aerial duels won or number of passes can be misleading. Looking at percentage statistics, such as the percentage of tackles won or crosses repelled, can be more meaningful in analysing a player's performance. This makes it easier to compare players whose teams play different styles or are at opposite extremes of the league table.

Furthermore, the club can assess whether a player is performing well despite being part of a team with poor performances, thus weighing the player's performance within an overall context.
Data analysis is useful to identify potential players who fit the way the manager wants the team to play. These players are then observed and their statistics are compared to those of other potential recruits and players the club owns.
The observation and evaluation of live players is always crucial for Derby, since there are important information about the players that is not and will never be covered by data.

2.1.2. Data companies

Not all clubs manage to have an in-house data analysis department and therefore many of them, especially the smaller clubs, collaborate with specialised external companies that provide tailor-made analysis to identify potential signings according to the club's needs.
Through the collection of data and thanks to professional data providers, the prerequisites for qualitative scouting are created. Today, clubs can access player statistics from all over the world by paying a simple subscription to one of the many platforms.

Even though smaller clubs have a very limited scouting budget, usually modern scouting departments often consist of only a few people. Everyone has access to cheap statistical data, but very limited resources for analysing and interpreting the data.

One such company is *Twenty First Group*. They have developed a tool for calculating the link between a player's performance and the team's overall performance, i.e., how much a player's performance affects the total, producing a rating for each player in the team. Following this model, clubs can use these numbers to determine whether a potential purchase would improve or weaken their team.

Another product available for modern clubs is *TransferLab* from Analytics FC. This software has numerous built-in metrics that make it easier for clubs to understand the data without the need for in-house experts. In addition, it uses future predictive algorithms to help clubs discover talented players who may not yet have reached their peak performance levels. Their database contains over 90,000 players in the men's sector and over 5,000 in the women's sector. Some of their clients around the world are Leeds United in England, Motherwell in Scotland and K.A.A. Gent in Belgium.

With the increasing popularity of the use of data, many companies now offer analysis for player recruitment. One of the most renowned brands in the field of football analysis is *Wyscout*. Founded in Italy back in 2004, the company offers services for various figures involved in football, including agents, coaches, referees and journalists. As the name suggests, scouting is the most important part of the service offered.

The Wyscout platform provides data on over half a million players and teams and contains over 100 filters that users can apply when searching the database. Visualisation tools can also be used to have counterevidence on the data analysis. In fact, the company also provides videos of more than 200,000 soccer matches so that, after sifting through the data, scouts can watch footage after footage without having to travel to remote corners of the world.

As mentioned, thanks to new technologies, scouts today no longer need to travel all the time to attend matches in person and a new type of scout is emerging.

Anyone can scout from anywhere. In addition to working with football clubs, databases like Wyscout are open to anyone who wants to subscribe while other companies, such as StatsBomb, provide football data freely available online.

This is leading online analysts to increase their popularity and build a portfolio of work that showcases their skills, sometimes managing to get hired by professional clubs.

2.1.3. The scouting process

Scouting is a classic human resources selection process, like what happens in companies. At each selection stage, the number of candidates is conspicuously reduced. Considering that 90 per cent of the players are 'eliminated' in the first two selections, it is crucial that they are carried out with the utmost care.

Figure 3: SCOUTING FUNNEL, www.soccerment.com

“Of course, I would say that you should never sign a player solely on the basis of data” these are the words of Dries Belaen, head of recruitment at Belgium's Anderlecht. “On the opposite, we cannot recruit a player based purely on video or live scouting. We require a complete picture.”

The use of data is definitely a way to make an intelligent decision and not left to pure subjectivity, which does not mean that the traditional scout who watches match after match and uses his own judgement to assess whether a player may turn out to be a good buy or not has been replaced.

In fact, the basic premise to be made is that data analytics is not intended to replace scouts. Rather, data analysis provides a valuable supplement to the talent identification capabilities of scouts.

The ideal scouting process consists of several steps and starts with data scouting.

In this way, the full potential of the player can be considered from the very beginning.

First of all, the club have to define the selection criteria based on its philosophy and playing principles.

Access to data is only the first step, especially since data alone is not enough to do any kind of work. Data does not automatically lead to insights. You need analytical skills and a data analysis platform to interpret the data, especially when we are overwhelmed by huge streams of numbers.

Copernicus had the same information and tools as everyone else, he saw, heard and learned the same things but came to completely different conclusions. This is because he questioned assumptions that were not in question for everyone else.

The creation of one's own Data Analytics area and platform can be described as a 'disruptive innovation' that many clubs struggle to initiate. However, this can create new potentials in the collaboration between football analytics and football expertise.

Next, an initial general selection of players is made based on performance values and statistics that can be analysed from the various platforms. This phase should already generate a fair number of players who would otherwise not have been considered.

At this stage, it is important to choose the right criteria, otherwise everything that follows may be useless. The difficult skills to develop are more important than the others since, with a good coach and staff, many dimensions of tactics and personality can be improved.

It is only after this initial 'skimming' that video scouting, on-field scouting (matches and training sessions) and player interviews take place. In addition to the football selection process, information on all psychological and mental aspects of the players must be obtained via the networks.

Summing up, it starts with data, proceeds to video and ends with the stadium.

2.2. METRICS

Statistics within a football game have moved from the simplicity of goals and assists, to expected goals and algorithms that collect and process data producing information relevant to coaches and technical staff. Amateur and professional scouts can examine the various free public data to make analyses on players and football teams.

Given the amount of data that is publicly available today, a football analysis can be done by anyone with patience and a keen eye for finding relevant numbers among the hundreds of websites and apps that deal with data.

Everyone visualises data differently and focuses on info that might be irrelevant to others, and navigating through the definitions can be just as complex a task as making sense of the numbers themselves, but with a combination of statistics and tactics and a visualisation of both in an understandable form, one can begin to draw some conclusions.

Statistics such as a goalkeeper's saves or a footballer's number of passes do not reveal much on their own, but when analysed together with the numbers that paint a player's role in the context of the team and the world of football in general, they are more useful and easier to understand.

One of the main objectives of data and performance analysis in football is to inform analysts of the most objective and unbiased way possible. Since football is a low-scoring sport with crucial events influencing the outcome of a match, metrics such as goals scored and assists made are often insufficient to evaluate players and teams. Leveraging detailed event data describing every single action on the pitch, machine learning tools are applied to create more objective performance metrics describing the offensive production of players.

In a sport like football where there are generally few goals and low scores, it is easy for player performance evaluations to be influenced by rare and valuable events such as goals or assists. Very often, and in Italy particularly, a player who scores an important goal immediately attracts the attention of journalists and fans, only to be forgotten after a few weeks if he does not score in subsequent matches. Discourses on football performances are often very volatile, with judgements turning at a frantic pace, based on results determined by rare and sometimes random events.

It is intuitive to understand why those in management positions in football, such as coaches or sports directors, need to structure their selection and evaluation process with performance metrics that are as objective as possible. For example, when choosing to sign a striker, a manager hopes to avoid signing a so-called 'one-season wonder', i.e., a player who particularly excelled in the previous season, only to see his performance plummet in the long run. Questions naturally arise: "Does the player score a lot of goals because he is favoured by his teammates?" or "Does he mostly attempt a lot of shots, many of which find the back of the net thanks to a good dose of luck?" and so on...

Football analytics seeks to answer these questions by exploiting detailed data from match events and providing positional and contextual information about everything that happens within a game. Thanks to new machine learning methods mixed with large datasets, it is possible to derive statistical models that transform binary outcomes of events such as goals and assists into probabilities of success that, when interpreted and combined correctly, provide more objective and, above all, comprehensive measures of footballers' performance.

Let us now introduce some advanced performance metrics that the biggest clubs use to assess performance and scout accordingly.

- Expected Goals (xG): quantify the quality of shots by attributing goal probabilities to each shot,
- Expected Assists (xA): credit creativity by assigning assist probabilities to passes,
- Expected Offensive Value Added (xOVA): isolating the players' offensive contribution,
- Expected Goals on Target (xGoT) / Goals prevented: measure the shooting ability of movement players and goalkeeper saves,
- Expected Passes (xPass): identify above-average passing skills.

2.2.1. Expected Goals (xG)

The most widely used and well-known metric among those listed is certainly Expected Goals, simply referred to as xG. Expected Goals measures the quality of the shot on goal by assigning each one a probability of turning into a goal based on information provided by the context and more specifically by the event data, the most important of which is the position from which the shot is taken. For example, a typical shot from the central area outside the penalty area is worth about 0.1 xG which, translating this into probabilistic terms, means that on average a player shooting from that position and in a similar game situation should score 10% of the times.

However, attention must be paid to the interpretation of the xG. It must be measured against a player's actual goals, as it only achieves significant predictive power when a huge number of shots are aggregated, e.g., over the course of an entire season in a league: only with these assumptions is qualitative scouting possible. For individual shots, the xG must be read as a measure of the quality of the chances created. Clearly, it is not certain that a team that consistently produces more xG than its opponents will win every game, but certainly its performance as measured by xG could mean that it should perform better in the long run.

Looking at individual players, the average xG per shot indicates how selective the player is in his shooting decisions. A lower-than-average xG per shot highlights a player who takes many shots from unfavourable distances. Conversely, a high xG per shot is typical of a striker who takes most of his shots close to the opponent's goal. These aspects also contribute to an overall picture of the player in the selection process.

The xG is calculated by applying a logistic regression model to hundreds of thousands of shots with contextual information provided by detailed Opta event data. As mentioned, the most important variable in the model is the position from which the shot starts, which is encoded as the distance to the goal and the angle of the goal (the angle at which the shooter is standing in relation to the goal). Other influencing factors are the type of assist (e.g., filtering pass, cross, etc.), the state of play, the part of the body that took the shot (e.g., right or left foot) and the pattern of play (e.g., open play, set piece, etc.). Penalties, on the other hand, are a special case, as they represent a rather simple event occurring under fixed conditions, so the value of xG is a fixed constant at the average conversion rate, which in many datasets is 0.78.

By analysing the Italian Serie A in the 2022/2023 season, it can be noted that the player with the highest xG number was V. Osimhen (24.48) with 26 goals scored (top scorer).

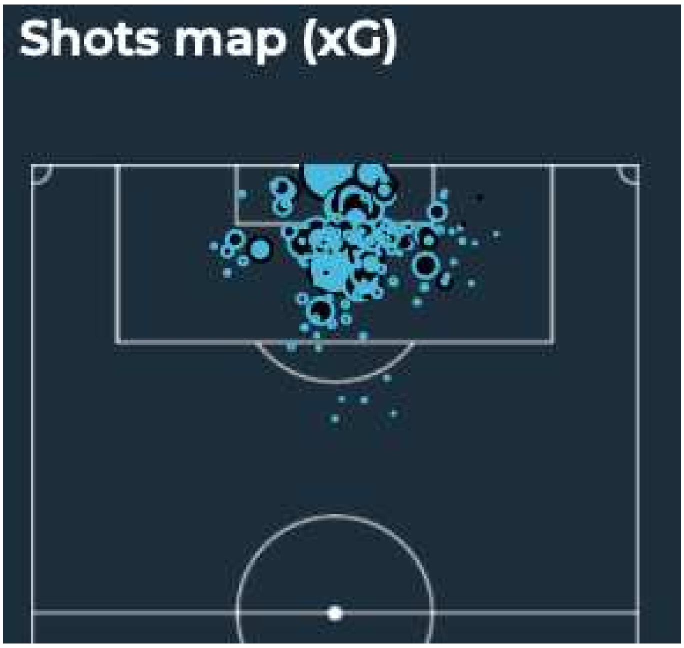

Figure 4: The Shots Map of V. Osimhen in 2022/2023 Serie A (www.soccerment.com)

2.2.2. Expected Assists (xA)

Expected assists, referred to as xA, measure the probability that each pass will be converted into an assist, i.e., that the player who receives the pass will score a goal. The main objective of this metric is to reward the most talented players who are able to create goal chances for their teammates.

In contrast with xG, for which the concept and objective of the metric is understood in the same terminology by all football analysts, there are two distinct schools of thought when it comes to calculating xA, which can be divided as 'shot-centred' or 'pass-centred'.

In the first and most widely used form, xA is only awarded to passes that lead to shots, crediting simply the xG value of the shot to the player who executed the previous pass, and therefore requires no further calculation.

In the second case, a separate model focuses on all the passes completed by each individual player, calculating the probability that each of them turns into an assist, regardless of whether the receiving player takes a shot or not.

Many analysts believe that the latter approach gives credit to creative players more fairly, separating their passing ability from the decision-making process and skill of the receiving teammate, and simply focusing on whether they can successfully and consistently pass the ball in dangerous positions and situations. It also prevents undeservedly awarding the player passing the ball a positive score for low risk passes that are followed by a difficult individual action from the player receiving the ball, resulting in a high xG opportunity.

In the 2022/2023 Serie A, T. Koopmeiners was the player with the highest xA (7.50), even though he made only 4 assists... maybe the strikers were not in the best condition this year.

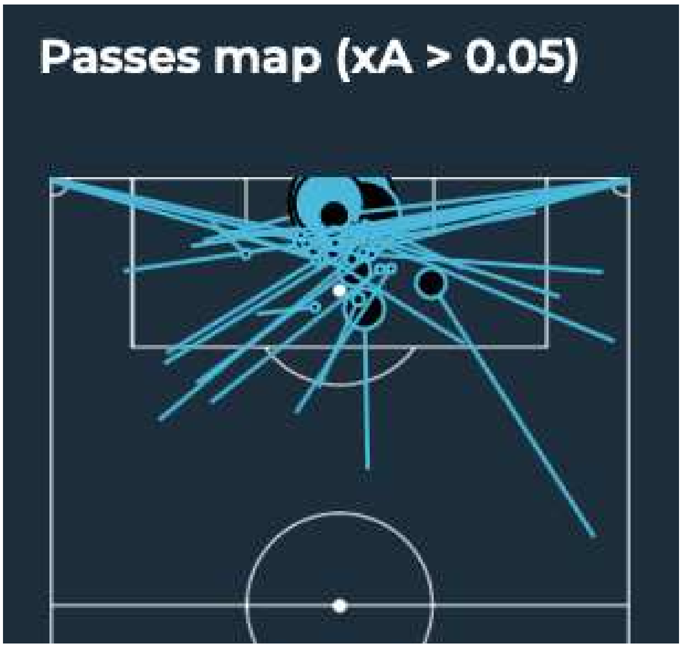

Figure 5: The Passes Map of T. Koopmeiners in Serie A 2022/2023 season (www.soccerment.com)

2.2.3. Expected Offensive Value Added (xOVA)

With this metric we measure the total offensive production of all players, evaluating both their shots and their creative passing, combining xG and xA. To comprehensively measure a player's individual contribution, the xA he received is subtracted from the total, thus measuring the added offensive value of the player in comparison with the value received by his teammates. This metric is defined as Expected Offensive Value Added, or xOVA:

xOVA = (non-penalty xG + xA) - xA received

With it, you easily obtain a solid overview of a player's ability to improve the team's chances of scoring a goal. After all, after receiving a pass, a player has several choices, including running with the ball or simply losing it; however, the player's expected end result is either to shoot or pass the ball to a better-positioned teammate. The quality of the shot and pass selection matches the sum of the expected goals and assists.

Two important points need to be emphasised: a) xOVA measures the creation of goal chances through shots and passes, not the actual result of such chances; and b) this metric can only be calculated with a 'pass-centric' approach to xA, while with the 'shot-centric' xA approach it would not make sense, which is one of the reasons why the former is more functional.

Rafael Leão had the highest number of xOVA in the last Serie A (13.48) and in fact is one of the best young players in the world and the MVP of the 21/22 league.

2.2.4. Expected Goals on Target (xGoT) and Goals Prevented

The xG model presented represents the probability of scoring before the shot, i.e., it does not consider the place on the net where the ball ends up after the shot. The value of xG is the same regardless of whether the ball is kicked into the centre between the goalkeeper's arms, or whether it is placed perfectly in the top corner. By construction, xG indicates the probability of scoring assuming an average shooting skill.

To assess a striker's goal-scoring ability, we can exploit the shot-goal mouth coordinates included in Opta's detailed goal-shot data to calculate the likelihood of goal after the shot, which we term Expected Goals on Target, or xGoT. Like xG, this metric is derived from a logistic regression on tens of thousands of shots on target in a dataset, but the prediction characteristics are simpler: the original value of xG, which codifies positional and contextual information, and the two coordinates of the goal mouth (horizontal and vertical).

The discrepancy between xGoT and xG measures the shooter's ability to score a goal, since it represents how much the player's shot increases the chance of a goal in relation to the initial xG. This metric is known as Shooting Goals Added, or SGA. One caution should be taken when interpreting this metric: the coordinates of the goal mouth are available only for shots on goal, while blocked shots are not included, therefore the model does not include all shots originally directed towards the goal mouth, but only the ones that arrived there and culminated in a save or goal.

The player with the best xGoT, always considering Serie A 2022/2023, was Lautaro Martinez (8.44) who was also the season's second top scorer.

The xGoTs have another very useful application in measuring perhaps the most important skill of a goalkeeper: parrying. If a goalkeeper concedes fewer goals than the number of xGoTs faced, it means that he is very adept at blocking direct shots in difficult-to-parry positions inside the goal and/or coming from very dangerous shooting positions (i.e., with a high initial xG). The difference between xGoT faced and goals is called 'goals prevented'.

Cremonese's goalkeeper I. Radu was the best in this statistic last season (4.33).

2.2.5. Expected Passes (xPass)

Using the pass dataset that feeds the xA model, a model of pass completion probabilities can be constructed, which is called Expected Passes or xPass. Again, the model is a logistic regression trained on millions of passes, using positional and contextual information analogous to that of the xA model, but taking as the target label not whether a pass is an assist for a goal, but merely whether it was successfully completed.

This metric reveals whether a player consistently executes risky and high-yield passes with a higher-than-average success rate, which would result in a positive difference between completed passes and total xPass.

Clearly, it is necessary to consider the level of the league, the teammates, the playing styles of the team and the opponents.

A combination of data, tactical analysis and traditional scouting is the way to go, especially when combined with effective analysis of all three. One without the other two may be missing, but thanks to the sites they are all available to everyone. Just remember to also watch the football matches and not just the data...

2.3. ONE STEP FURTHER: THE EXPECTED TRANSFER VALUE

As one can well imagine, after the process of scouting and identification of the player, the purchase negotiation between the two clubs takes place.

In this section we introduce a modern metric that allows clubs to evaluate a player economically, the Expected Transfer Value (xTV).

The xTV of a player is a prediction of how much it would cost to sign him outright, expressed as a range.

2.3.1. <u>How Expected Transfer Value (xTV) works</u>

Instead of being an indicator of the player's abilities alone, the xTV is a metric of the player's signing value for the club he currently plays for, in free market conditions. It is designed to capture the intersection between the price the selling club could obtain for the player and the price a purchasing club should expect to pay.

The elements that make xTV reliable can be divided into three areas:

1. Economic value assessment, based on factors other than playing ability,
2. Benchmarking against transfers of similar players,
3. Use of unique data to provide a picture of current market conditions.

Other information about the player is taken into account, such as playing ability, based on performance data and the level of the player's current club. Furthermore, xTV also uses mathematical values for further factors, including:

- Details about the player: age, position, national team appearances, etc.
- The financial strength of the club
- The remaining duration of the player's contract (including any options)
- The player's salary history
- The player's potential purchase market

To give a real insight into the value of players, xTV takes into account the factors that historically have clearly determined transfer fees, rather than having an opinion on which factors should or should not be important.

While xTV incorporates elements of traditional mathematical modelling, it is also based on an assessment of fees paid for 'similar' players, closely reflecting the way clubs make buy/sell price decisions by giving the numbers a more intuitive feel. For an xTV to be reliable and useful for decision makers, it must take into account historical agreements for players who had similar characteristics and were in similar situations at the time.

The xTV shows a comparative range that allows clubs to compare the value of their player with the market and helps them find an appropriate purchasing club by matching the xTV with the offer of potential purchasing clubs.

The xTV function provides both buying and selling clubs with the appropriate information to make an informed decision. Having access to reliable and correct player transfer values helps decision-makers at every stage of the process, from the initial assessment of the feasibility of a deal through to negotiations and setting terms. Clubs can also use xTV to track the economic value of their player assets and make sure they are protected and moving in the right direction.

Agents can also benefit greatly from the xTV function: by knowing the potential value of their clients and being able to compare it with similar players, brokers can make more informed decisions on which players to propose to which clubs.

The new xTV function provides the most credible data on the most fundamental consideration in a transfer transaction: how much a player is worth.

3. RESEARCH

The world of modern soccer has, in recent years, been invaded by what is commonly referred to as the "Digital Revolution," and in this part of the paper I can only contribute to this evolution: to try, through numbers and data, to explain and analyze what happens inside the green rectangle where everything, apparently, seems to be the result of an inexplicable science that has seen some predictions overturned in a striking manner and other outsiders triumph in unexpected ways.

Since the objective of this research is to unearth a player's potential and, more generically, to select the most valuable human resources that have not yet been "purchased" by competitors, the data analysis that follows is based on a metric that considers each player's contribution to the team's success and is carried out on the club Ascoli Calcio 1898 FC and players playing in the 2022/23 Serie B.

The analysis that follows is based on a +/- system for evaluating player performance, a decidedly daunting task because of the complex nature of the game. For example, one gives the fact that a team's success can be linked to the performance of a particular player over the course of a season, although it is not "noticed" enough. The +/- system shows whether a player's presence on the field is good or bad for his team, regardless of position, based only on actual minutes played. It makes it possible to compare a player's net impact on team performance to that of other teammates. This approach represents a significant advance in soccer statistics beyond just basic statistics such as goals, assists, or tackles. As such, the +/- system implements a quantitative view of a player's performance that leads to improved decision-making by coaches and managers in both coaching and, more importantly, scouting.

3.1. METHODOLOGY

The plus/minus metric is well established especially in field hockey and basketball and is also used for evaluating player performance in team sports. The basic idea is simple: whenever the team scores a goal, all players on the field at the time of the event receive positive points, while whenever the team concedes a goal, the players who are playing receive a negative score. Combining the negative and positive values over the time a player has been on the field results in the "plus/minus" metric calculation. Accordingly, players with positive scores in this metric were on the field when the team performed well (scoring more often than opponents), while players with negative values were on the field when their team was outscored by opponents. The plus/minus metric implicitly assumes that all players on the field contribute the same amount to the team's success. In sports with frequent formation changes, this metric can also be interpreted as an individual player's contribution to team success.

The simplest version of the metric (subtracting points/goals against from points/goals for) considers all scoring events (goals in hockey and baskets in basketball) in the same way, even when the 'weight' of the point is different. A strong objection against this assumption is that scores in games that have already been decided, such as a goal in favour when the team is winning 4-0 or in so-called 'garbage time', have less value than scores in hard-fought games or in 'crunch time'. A second objection is that wins against weak opponents do not have the same value as wins against big favourites.

The basic version of the plus/minus metric does not take either problem into account.

Although in football, line-up changes during a game are not as frequent as in hockey or basketball (mainly because substitutions are limited to five per game), they occur more and more frequently between games due to injuries, suspensions, a high number of close games, or simply due to coach's decisions. Goals also occur less frequently in football, but often enough to assume acceptable levels of statistical validity (on average about 100 events per team per season). What makes the following plus/minus metric unique and reliable is that it addresses the two objections mentioned above by analysing the importance of goals and the strength of the opponent. The plus/minus metric of each player for the entire season is calculated using the following formula:

$$pm_x(t, w) = \sum_{w=1}^{W} \sum_{t=1}^{T} \left\{ \left[\left(\frac{wp_w^{opp} - wp_w^{own}}{T_w} \right) + \left(\Delta goals_{t,w} - \Delta goals_{t-1,w} \right) \times \left(\frac{2}{1 + |\Delta goals_{t,w}| + |\Delta goals_{t-1,w}|} \right) \right] \times on_{w,t}^{x} \right\}$$

The variable *w* stands for the week of the game (the season has *W* weeks), *t* stands for the minute in the games (*T* is the total number of minutes for each game). This means that the calculation takes place on a per-minute basis. Summing up over all minutes in all games then yields the plus/minus score. The variable *wp* stands for "winning probability" according to the betting quotas of Bet365, a frequently used source for evaluating team strengths in econometrics (e.g., Franck et al., 2011). We subtract the player's team's winning probability from the opponent's winning probability to obtain the number of points that each player obtains if the game ended in a draw and if the player played the entire game. Dividing this number by the number of minutes the game lasted (90–95), yields a per-minute value.

One assumption is that betting odds provided by professional betting agencies are a valid factor in capturing the relative strengths of teams, as this source is expected to have a very high level of information on each match, incorporating not only quantitative data from previous matches, but also qualitative information, e.g., on injured players or particular events that have happened recently that could influence the match. A great deal of research has been conducted on the effectiveness of football betting markets in the sense that betting odds reflect available information (e.g., Croxson & Reade, 2014; Deschamps & Ger- gaud, 2007; Dobson & Goddard, 2011; Forrest et al., 2005; Goddard, 2005; Goddard & Asimakopoulos, 2004; Spann & Skiera, 2009) and consequently on the quality of information when using betting odds as a proxy for team strength. Betting odds for weekend matches are collected on Friday afternoon and Tuesday afternoon for midweek matches.

The second part of the equation accounts for the importance of goals. Subtracting the goal differential in a particular game one minute before the actual minute from the goal differential in the actual minute ($\Delta\ goals_{t,w} - \Delta\ goals_{t-1,w}$) yields “1” if the player’s team scored, “0” if no one scored, and “–1” if the opponent scored in the current minute. This part therefore determines whether scored goals count in favor or against the considered player. Most importantly, the following fraction takes the value of “1” if the goal is “point relevant”, meaning that the goal changes the outcome of the game from any of the three possible fundamental outcomes (win, draw, loss) to another. A goal that consolidates to an existing outcome (win or loss) is then only worth 1/2, 1/3, 1/4 and so on, depending on how large the goal differential already is. The last part $on^{x}_{w,t}$ simply takes the value of “1” if the considered player is on the pitch and “0” if he is not. This ensures that all the calculations mentioned above apply only to players who are on the pitch at the minute of the measurement.

While the 'goals part' of the equation supports the players of teams that outscore their opponents, the 'probability of victory' part incorporates a priori expectations into the metric. The favourites start, so to speak, with a disadvantage due to the expectation of victory. If the a priori favourites fail to overcome the underdog team, its players will end up with a negative +/- score for that match, because they have failed expectations. The players of the underdog team, on the other hand, receive a positive score because they exceeded expectations. Consequently, a team that exceeds expectations should have the majority of its players in the plus/minus range, while underperforming teams should have the majority of their players with a negative plus/minus value. Finally, a team that roughly meets expectations should have players with values around zero.

3.2. RESULTS

In conducting this research, I applied the formula to all players who played at least one minute on the field in the Ascoli Calcio jersey in the 2022/2023 Serie B, then considering only those who had a certain percentage of matches played compared to those in which they were registered for Ascoli Calcio (the January market window moved some players from one team to another).

With respect to the overall total results, I carried out a macro division between the 19 matches played at home, where generally Ascoli Calcio was favoured by the bookmakers, and the 19 away matches in which it is, according to predictions, more difficult to get points.

In addition, a further division was made between the roles to observe who had been the best (and the worst...) among the teammates.

At the end of the soccer season, Ascoli Calcio was ranked in 12° position with 47 points, getting 24 at home and 23 away: let us now assess whether the metric accurately reflects the results from the field.

Throughout the season, Ascoli Calcio used 33 players, divided into 3 goalkeepers, 10 defenders, 10 midfielders and 10 forwards.

For the truthfulness and reliability of the results, all players who played less than 33.33% of the matches in which they were registered for Ascoli Calcio were not taken into account in the individual or in the "by role" analyses and turned out to be

8 out of 33 for home matches, 10 for away matches, and 9 when considering the entirety of the matches.

3.2.1. Total Scores

The results that emerged from the analysis will be presented below.

METRIC SCORE RANKING	
Lungoyi C.	5,509
Caligara F.	4,023
Dionisi F.	3,504
Adjapong C.	1,418
Marsura D.	1,331
Giordano S.	1,012
Falasco N.	0,728
Quaranta D.	0,391
Donati F.	0,215
Collocolo M.	0,181
Simic L.	-0,539
Gondo C.	-0,845
Giovane S.	-1,129
Botteghin E.	-1,365
Leali N.	-1,502
Ciciretti A.	-1,784
Forte F.	-1,944
Eramo M.	-2,017
Bellusci G.	-2,711
Büchel M.	-2,924
Falzerano M.	-3,035

Proia F.	-3,413
Pedro Mendes	-4,579
AVERAGE	**-0,412**

Table 3: Total Scores, Source: my elaboration

Looking at the total scores, Ascoli Calcio's best player of the 2022/23 season was forward Lungoyi C. with a score of 5.509, while the worst was forward Pedro Mendes with -4.579.

Among the 24 players with at least 33.33% of the matches played, and who thus largely contributed to the team's seasonal performance, 10 of them had a value greater than 0 in the metric.

On the other hand, when considering all 33 players, only 14 contributed positively to the total team score.

Starting with the home games, those in which, in most cases, Ascoli was favoured, we note that the totality of the scores provides a negative result of more than -25 metric points, showing how the team's home performance has disappointed, and not a little, expectations.

In fact, focusing on the metrics of individual players, we note that only 6 out of the total 25 scored positively in the metrics: the best was Forte F. with about 2.44 points while the worst was Falzerano M. with over -5 points.

	N. game played	Percentage of game played	**TOTAL**
GOALKEEPERS			
Leali N.	13	68%	-0,190
Guarna E.	6	32%	-0,835
Baumann N.	1	11%	-1,480
DEFENDERS			
Donati F.	10	53%	0,652
Botteghin E.	19	100%	-2,505
Simic L.	12	63%	-1,677
Giordano S.	9	47%	0,909
Bellusci G.	9	47%	-1,117
Falasco N.	14	74%	-0,330
Adjapong C.	11	65%	-0,460
Salvi A.	4	40%	-3,632
Quaranta D.	8	42%	-2,910
Tavcar A.	1	5%	0,284
MIDFIELDERS			
Collocolo M.	18	95%	-0,280
Büchel M.	15	79%	-1,545
Proia F.	6	67%	-2,890
Eramo M.	12	63%	-0,465
Saric D.	1	5%	-0,539
Falzerano M.	13	68%	-5,328
Marsura D.	7	88%	1,823
Giovane S.	9	47%	-1,009

Caligara F.	17	89%	-1,111
Sidibe A.	0	0%	0
FORWARDS			
Ciciretti A.	7	37%	-1,250
Pedro Mendes	14	82%	0,329
Forte F.	8	89%	2,447
Dionisi F.	17	89%	-0,448
Gondo C.	17	89%	-2,919
Lungoyi C.	14	74%	1,239
Bidaoui S.	6	60%	-0,155
Re A.	1	5%	-0,008
Fontana A.	0	0%	0
Palazzino F.	0	0%	0
TOTAL SUM			-25,402

Table 4: Home games scores, Source: my elaboration

On the other hand, focusing on the total away performance, we get an overall team score of +7.5 and this is evidenced by the fact that as many as 12 players out of 23 considered got positive total individual scores.

Over 5 points were obtained by the second best of the team, Caligara F., while the lowest result belongs to Pedro Mendes with -4.9.

	N. game played	Percentage of game played	**TOTAL**
GOALKEEPERS			

Leali N.	12	63%	-1,312
Guarna E.	6	32%	2,802
Baumann N.	1	10%	-0,803
DEFENDERS			
Donati F.	10	53%	-0,437
Botteghin E.	18	95%	1,140
Simic L.	14	74%	1,139
Giordano S.	9	47%	0,103
Bellusci G.	9	47%	-1,595
Falasco N.	13	68%	1,058
Adjapong C.	12	67%	1,878
Salvi A.	2	22%	-0,939
Quaranta D.	10	53%	3,301
Tavcar A.	1	5%	-1,304
MIDFIELDERS			
Collocolo M.	18	95%	0,461
Büchel M.	13	68%	-1,378
Proia F.	4	50%	-0,522
Eramo M.	14	74%	-1,552
Saric D.	0	0%	0
Falzerano M.	9	47%	2,293
Marsura D.	6	75%	-0,492
Giovane S.	14	74%	-0,120
Caligara F.	16	84%	5,134
Sidibe A.	1	13%	-0,805
FORWARDS			
Ciciretti A.	6	32%	-0,533
Pedro Mendes	16	89%	-4,908
Forte F.	6	86%	-4,391
Dionisi F.	16	84%	3,951
Gondo C.	17	89%	2,074
Lungoyi C.	10	53%	4,270
Bidaoui S.	5	45%	-1,030
Re A.	1	5%	0,024
Fontana A.	1	9%	0,521
Palazzino F.	1	5%	-0,444
TOTAL SUM			7,582

Table 5: Away games scores, Source: my elaboration

The sum of total scores, however, gives a negative value of about -17.8, which is also given by the total sum of home and away games.

To sum up, following the metric, it can be said that Ascoli Calcio's season has partly mismatched the total expectations, particularly in the home games.

	Percentage of game played	**TOTAL**
GOALKEEPERS		
Leali N.	66%	-1,502
Guarna E.	32%	1,967
Baumann N.	11%	-2,283
DEFENDERS		
Donati F.	53%	0,215
Botteghin E.	97%	-1,365
Simic L.	68%	-0,539
Giordano S.	47%	1,012
Bellusci G.	47%	-2,711
Falasco N.	71%	0,728
Adjapong C.	66%	1,418
Salvi A.	31%	-4,571
Quaranta D.	47%	0,391
Tavcar A.	5%	-1,020
MIDFIELDERS		
Collocolo M.	95%	0,181
Büchel M.	74%	-2,924
Proia F.	58%	-3,413
Eramo M.	68%	-2,017
Saric D.	3%	-0,539
Falzerano M.	58%	-3,035

Marsura D.	81%	1,331
Giovane S.	61%	-1,129
Caligara F.	87%	4,023
Sidibe A.	6%	-0,805
FORWARDS		
Ciciretti A.	34%	-1,784
Pedro Mendes	86%	-4,579
Forte F.	87%	-1,944
Dionisi F.	87%	3,504
Gondo C.	89%	-0,845
Lungoyi C.	63%	5,509
Bidaoui S.	53%	-1,185
Re A.	5%	0,015
Fontana A.	5%	0,521
Palazzino F.	3%	-0,444
TOTAL SUM		-17,820

Table 6: Sum of home and away scores, Source: my elaboration

Focusing on the division "by roles" we note that the best defender in the season was Adjapong C. with about 1.5 points obtained, compared to the worst, Bellusci G. with a negative of about 2.7.

The best midfielder during this season, Caligara F. with 4 points, was one of the few with a positive score, while the worst turns out to be Proia F. with -3.4 points.

Finally, among the forwards only two had a positive value in the metric including the best of the team, Lungoyi C. with an impressive 5.5 points. Pedro Mendes with -4.5 points was the worst.

3.3. RELATIONSHIP BETWEEN MARKET VALUE AND TOTAL SCORES

The market value of a soccer player refers to the estimated financial worth of the player in the current transfer market. It represents the amount of money that clubs or teams might be willing to pay to acquire the player's services.

3.3.1. Which factors influence market value?

The market value of a soccer player can vary widely and is influenced by several factors, including:

- Performance and Skill: The player's current performance level, skill set, and potential for growth are significant factors in determining their market value. Players who consistently perform at a high level and possess exceptional skills tend to have higher market values.
- Age and Potential: Younger players with promising potential often have higher market values, as they are seen as long-term investments. Players who have already reached their peak and are closer to retirement age may have lower market values.

- Contract Situation: The length and terms of a player's contract can impact their market value. Players with long-term contracts remaining or those who have recently signed new contracts may have higher market values due to their increased stability and reduced risk for potential buyers.
- Reputation and Popularity: A player's reputation and popularity both on and off the field can influence their market value. Players with a strong fan base, significant social media presence, or international recognition may command higher market values.
- Transfer Market Activity: The overall state of the transfer market, supply and demand dynamics, and recent transfer fees for similar players can also impact a player's market value. If there is high demand for players in a specific position or if recent transfers have set new benchmarks, it can drive up market values.

It's important to note that market values are not fixed and can fluctuate over time based on various factors such as performance, injuries, team success, and player development.

Market values are typically estimated by sports agencies, specialized websites, and industry experts who analyze player attributes and market trends to provide valuations. These estimates are often subjective and can vary among different sources.

3.3.2. Market value/Metric score

To get a comparison between the plus/minus metric and market values, the site Transfermarkt was consulted, a popular online platform and database that provides comprehensive information on football (soccer) players, clubs, transfers, and obviously market values.

From the graph presented below, it can be seen that the market values of the players currently drafted for Ascoli Calcio range from 200,000 euros to 2.5 million.

In addition to the first division made between those with positive and negative metric scores, we analyze who is on the left and who is on the right side of the graph considering the market value.

Lungoyi C., the one who got the best score, has a market value close to the average, which shows that his season was definitely above expectations.
On the far right we find Collocolo M., the most desirable player on the market: although his score was positive, a better performance was probably expected.

Moving to the lower part of the graph, it turns out that Pedro Mendes, the worst player according to the metric, has a market value around average and therefore has undoubtedly disappointed expectations.
Similar discourse regarding, for example, Forte F.: although he is one of the most profitable players, his score did not reflect the club's hopes.

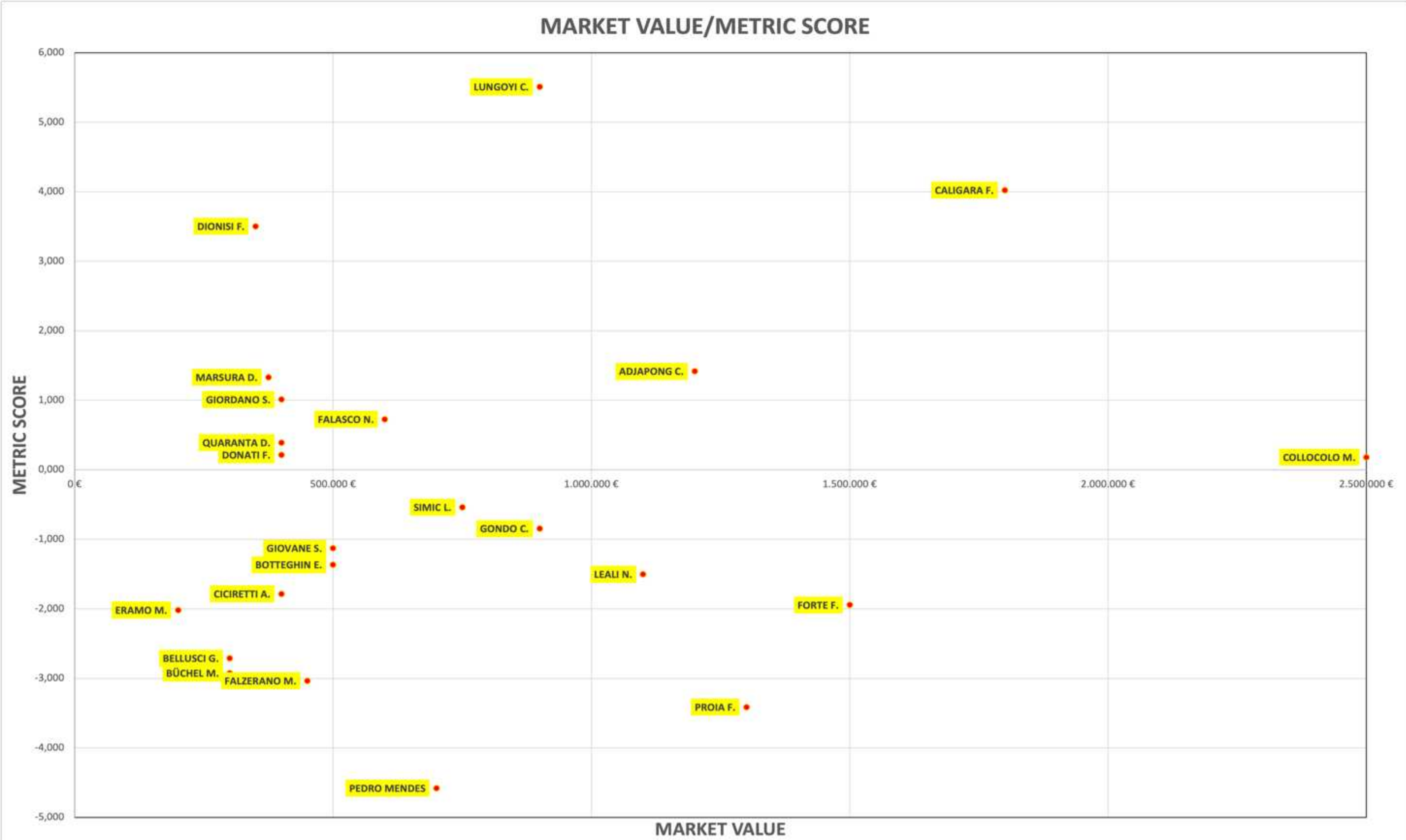
MARKET VALUE/METRIC SCORE
METRIC SCORE
MARKET VALUE
6,000
5,000
4,000
3,000
2,000
1,000
0,000
-1,000
-2,000
-3,000
-4,000
-5,000
0 €
500.000 €
1.000.000 €
1.500.000 €
2.000.000 €
2.500.000 €
LUNGOYI C.
CALIGARA F.
DIONISI F.
ADJAPONG C.
MARSURA D.
GIORDANO S.
FALASCO N.
QUARANTA D.
DONATI F.
COLLOCOLO M.
SIMIC L.
GONDO C.
GIOVANE S.
BOTTEGHIN E.
LEALI N.
CICIRETTI A.
FORTE F.
ERAMO M.
BELLUSCI G.
BÜCHEL M.
FALZERANO M.
PROIA F.
PEDRO MENDES

Figure 6: Relationship between Market Value and Metric Score, Source: my elaboration

3.3.3. Validation

The data analysis conducted makes the metrics scores jump out at you without providing an explanation of the factors influencing these data.

I conducted a regression analysis to try to explain what factors might account for the values taken by the metric.
Thus, the dependent variable is the metric score (“metric”) while the following were considered as independent variables: market value (“market”), player's age (“age”), consecutive years of militancy with the club (“legacy”), frequency of goals per player expressed in minutes (“scorfreq”) and accuracy in passing (“passaccuracy”) over the course of the season expressed in percentage values were taken into consideration.

Before beginning the regression, I found it appropriate and necessary to conduct a correlation analysis to gain a preliminary understanding of the relationships between the variables and the possible presence of correlations.

	metric	market	age	legacy	scorfreq	passaccuracy
metric	1					
market	0.183	1				
age	-0.280	-0.363*	1			
legacy	-0.063	-0.042	0.412*	1		
scorfreq	0.278	0.244	-0.143	-0.006	1	
passaccuracy	-0.065	-0.270	0.174	0.148	-0.020	1

Table 7: Correlation metrics, Source: my elaboration

The correlation made between the metrics and the above variables shows that:

- the metric has the greatest relationship in absolute value with the age of the players: it is an inverse relationship in that if age increases the value of the metric decreases and vice versa,

- the frequency of players' goals expressed in minutes (scoring frequency) positively influences the metric and it is reasonable since metric is favourably affected by the goals scored,

- market value is also negatively and significantly affected by age and this is coherent since as age increases the market value of players tends to decrease as they are less attractive in the market,

- there is a positive and significant relationship between years in the club (legacy) and age.

The significance level, represented with an asterisk, is 10% and it shows that the significant relationships are only between market value and age of the player and between years spent in the club and age, showing that there is no parameter that can explain the metric.

From Table 8 we can have a look at the regression analysis performed with 23 observations and 6 independent variables.

The F test shows that the model is not significant because P Value of F is equal to 0.78.

Source	SS	df	MS		
				Number of obs =	23
				F(5, 17) =	0.55
Model	18.9613727	5	3.79227455	Prob > F =	0.7344
Residual	116.657644	17	6.86221436	R-squared =	0.1398
				Adj R-squared =	-0.1132
Total	135.619017	22	6.16450076	Root MSE =	2.6196

metric	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
market	1.46e-07	1.12e-06	0.13	0.898	-2.21e-06	2.50e-06
age	-.1330968	.1418704	-0.94	0.361	-.4324172	.1662235
legacy	.1271859	.703883	0.18	0.859	-1.357877	1.612249
scorfreq	.0009901	.0009848	1.01	0.329	-.0010877	.0030679
passaccuracy	-.0049656	.0794501	-0.06	0.951	-.1725906	.1626593
_cons	2.866049	7.03194	0.41	0.689	-11.97005	17.70215

Table 8: Regression analysis model 1, Source: my elaboration

In fact, the results shows that none of the chosen regressors can explain the results of the metric.

Even considering the variables individually, looking at P Value none appears to be significant.

Following the model presented in Table 8, I decided to run the regression by rescaling the values of the variable "Market Value" by dividing all of them by 1000000. Next, I added the variable "Ruolo" by converting it to dummy by taking the role of striker as a reference. Compared to the model presented above, the new model will focus on the relationship between score, market value and role and weighting the entire model by the percentage of games played.

_IRUOLO_1-4 (_IRUOLO_1 for RUOLO==ATTACCANTE omitted)
(sum of wgt is 15.91350004914246)

Linear regression

Number of obs	=	23
F(5, 16)	=	.
Prob > F	=	.
R-squared	=	0.1944
Root MSE	=	2.6666

metric	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
market	.7935504	.8692782	0.91	0.375	-1.049237	2.636338
age	-.1688721	.1686177	-1.00	0.331	-.5263256	.1885814
legacy	1.188068	.7222093	1.65	0.119	-.3429474	2.719083
_IRUOLO_2	-2.401413	1.9149	-1.25	0.228	-6.46082	1.657994
_IRUOLO_3	-.7649648	1.887424	-0.41	0.691	-4.766125	3.236196
_IRUOLO_4	-5.085614	2.862691	-1.78	0.095	-11.15425	.983021
_cons	3.024367	5.503027	0.55	0.590	-8.641529	14.69026

Table 9: Regression analysis model 2, Source: my elaboration

I introduced weight in the regression since not all players present the same number of games played: again, none of the variables are significant. Interestingly, players' performances are not significantly associated with either age and consequently experience, market value or role.

Given that the sample analysed is reduced to a low number of observations, it is incorrect to generalize the final considerations to the entire soccer world, and surely this same analysis applied to all teams participating in the Serie B league would exhibit more reliable results.

However, the goal of the analysis is to determine a metric that can be a valid means of evaluating player performance for club Sporting Directors, i.e., those who make choices in the market and carry out the buying and selling process.

CONCLUSION

As is only to be expected given the history of the sport, the world of soccer is undergoing a profound transformation during the twenty-first century from so-called "street soccer" to one that can be called "business soccer."

This evolution, or better said revolution, is overwhelmingly taking over the scene of Italian soccer starting with youth soccer, and clubs are facing different challenges on a daily basis.

The ownership of football clubs in the 2020s are no longer the familiar ones that took the stage in the 1990s, but have been replaced by more mostly foreign entrepreneurs, investment funds or large holding companies that do not aim at the achievement of sports results as a pure taste and pleasure of success but as an opportunity for value creation and brand awareness and diffusion: all this leads to a general rethinking of the value chain aimed at the maximum enhancement of human resources and football brands and not only...

The thesis, which, not surprisingly, takes shape with the analysis of youth soccer, aims to show the change in the management of a football club in a vertical line.

Starting from the concept of a multidimensional approach, an attempt was made to highlight the complexity behind the selection of a young footballer. Given the high market value that soccer players manage to achieve today, it is crucial to analyze all the parameters that characterize the athlete's performance and how to assess potential.

The technical area, which is certainly one of the most important, is nothing if not supported by the other areas analyzed, and that is what this thesis aims to demonstrate when going to choose the human resources of the future.

Scaling the vertical line of a football club's human resources, the path was delineated by how data influence choices.

Although this is still a game, the selection of the modern footballer is influenced by what the numbers say, and numbers don't lie...

Data allows one to obtain a great deal of information on every footballer around the world and by analyzing it, one can make initial skims especially by evaluating and comparing modern metrics and calibrating them according to the difficulty of the match, the opponent and one can discover new emerging talents.

The valorization of the player undoubtedly passes through the scouting activity that clubs must maximize and that can be worth millions of euros.

The value that can be obtained from the metrics analyzed is certainly not very indicative if taken in isolation, as for example on XGs, and this is where the management's skill in understanding and attributing the correct market value to certain numbers must come into play.

The thesis concludes with the practical part of everything described so far.

Making the comparison with reality is, in most cases, very complex, especially in a field like football.

The data analysis carried out on the performance of players in the 22/23 season of Ascoli Calcio demonstrated how the management of a professional club can act to enhance the value of its players through the use and application of reliable and useful metrics.

The results obtained from the metrics have a twofold value: considering the purely technical side, they are useful tools for coaches to obtain information that, from the field, it is not easy to have; on the other hand, the sports management is able to have advantages in terms of evaluation of the players in the phase of valorization and/or sale of its own players and in the phase of purchase if applied to players of other teams.

In conclusion, the data validation carried out showed that there were no correlations with the metrics among the variables which allows us to say that expected performances are not always predictable a priori but, in a sport like soccer, nothing is taken for granted and that is where management's intuition and vision must make the difference, beyond the data.

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