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Thesis

Data Analytics and Match Analyst

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Chapter 1

Data, Decision-Making, and the Rise of the Analytical Function

The professional world of the twenty-first century is characterised by an abundance of data that would have been unthinkable even two decades ago. The emergence of digital networks, the miniaturisation of sensors, the proliferation of internet-connected devices, and the near-zero marginal cost of data storage have collectively produced what researchers and practitioners have come to call the *big data* era: an epoch in which the volume, velocity, and variety of available information exceed by several orders of magnitude the capacity of any individual to process it unaided (Mayer-Schönberger and Cukier 2013). This transformation is not merely technological. It has reorganised the cognitive architecture of professional decision-making, altered the internal structure of organisations, and given rise to an entirely new category of specialised worker – the data analyst, the data scientist, the intelligence officer – whose function is precisely to bridge the gap between raw informational abundance and actionable organisational knowledge (Davenport and Patil 2012).

The present chapter establishes the theoretical and empirical context within which the more specific questions of this thesis – concerning the match analyst in professional football – can be properly situated. The claim advanced here is that the emergence of the match analyst is not an idiosyncratic development specific to the sport, but a particular instantiation of a general organisational dynamic: the dynamic by which, as the data available to an organisation grows in volume and complexity, new professional figures are created to perform the specialised cognitive labour of interpretation, contextualisation, and translation that converts raw data into decision-relevant knowledge. Understanding this dynamic in its general form is a prerequisite for understanding its football-specific manifestation.

The chapter is organised as follows. Section 1.1 describes the empirical contours of the data revolution, situating it within the longer history of information management in organisations. Section 1.2 examines the theoretical foundations of decision-making under informational complexity, drawing on the canonical literature in behavioural economics and organisational psychology. Section 1.3 traces the emergence of evidence-based management as a professional norm in the business world and examines the organisational conditions under which data-driven decision-making is most effectively institutionalised. Section 1.4 analyses the structural response of organisations to data complexity: the creation of dedicated analytical functions and the emergence of new professional roles. Section 1.5 addresses the specific role of artificial intelligence as an amplifier of the data-driven transformation, and examines its implications for decision-makers at every level of the organisational hierarchy. Section 1.6 narrows the focus from organisations in general to the sport industry, reviewing the development of sports analytics in the big-data era and showing that sport reproduces – and in some respects anticipates – the general dynamics described in the preceding sections. Section 1.7 closes the chapter by drawing the conceptual bridge to the football context, showing how these organisational dynamics are reproduced, with domain-specific adaptations, in the world of professional football.

1.1 The Data Revolution: Volume, Velocity, and Variety

The concept of a data revolution is often discussed in purely quantitative terms: the exponential growth of data volume since the early 2000s, the doubling time of stored digital information, the number of connected devices projected to generate data over the coming decades. These figures are striking in their magnitude – International Data Corporation (IDC) projected the global datasphere to reach 175 zettabytes by 2025 (Reinsel, Gantz, and Rydning 2018) – but raw volume is not the analytically interesting variable. What matters is the ratio between data availability and the human capacity to use it, and it is this ratio that has undergone the most consequential change.

Mayer-Schönberger and Cukier (2013), in their foundational account of the big data phenomenon, identify three structural shifts that together define the present era. The first is the exhaustion of *sampling* as an epistemic strategy: when it was prohibitively expensive to collect and store large datasets, analysts were forced to work with samples – carefully selected subsets of the total population of relevant observations. The big data era makes it feasible, in many domains, to work with the *entire* dataset rather than a sample, dramatically altering the statistical properties of any analysis conducted on it. The second shift is the acceptance of *messiness*: in the era of small, carefully managed datasets, the premium was on data quality; in the era of large-scale, automatically collected data, the premium shifts toward volume and coverage, and some degree of imprecision is tolerated in exchange for breadth. The third shift concerns the move from *causality* to *correlation*: big data analysis is often agnostic about causal mechanisms, preferring instead to identify statistical associations of sufficient regularity to be actionable, regardless of whether the underlying causal structure is understood.

Each of these shifts has implications for the organisations that seek to exploit data as a strategic asset. The exhaustion of sampling as a strategy increases the computational and storage requirements for data management. The acceptance of messiness requires new quality-assurance practices adapted to high-volume, heterogeneous data streams. And the move from causal to correlational reasoning introduces new risks – particularly the risk of confusing spurious associations with genuine predictive signals – that require analytical expertise to manage. In each case, the practical response is the same: the organisation needs specialised human capital capable of navigating the new informational environment.

The data revolution has also dramatically reduced the barriers to entry for data collection itself. Historically, the capacity to generate and store proprietary data was a function of financial and technological resources available primarily to large corporations and national governments. Today, an organisation of almost any size can instrument its operations with sensors, log its transactions in cloud databases, and monitor its competitive environment through publicly available data streams. This democratisation of data access has had a paradoxical effect: by making data universally available, it has raised the bar for competitive advantage from data *possession* to data *interpretation*. The organisation that possesses data is no longer differentiated; the organisation that can extract insight from it, faster and more reliably than its competitors, is (Davenport and Patil 2012). This is the environment in which the demand for specialised analytical talent has grown most rapidly, and in which the structural pressure to create dedicated analytical functions within organisations has become most intense.

1.2 Decision-Making under Informational Complexity

The relationship between information and decision quality is not straightforward. A naive view would suggest that more information is always better: the decision-maker with access to a richer dataset will, ceteris paribus, make superior choices. The literature on decision-making under complexity tells a more nuanced and in many ways more sobering story.

The foundational contribution is Simon's (1955) concept of *bounded rationality*: the insight that human decision-makers do not optimise across all available information, as classical economic theory assumes, but instead *satisfice* – accepting the first option that exceeds a minimum acceptability threshold – because the cognitive costs of exhaustive information processing exceed the benefits in virtually all real-world decision contexts. Simon's model was motivated not by a normative argument about how decisions should be made, but by an empirical observation about how they actually are: human beings, including trained professionals, systematically short-circuit the formal optimisation process in favour of heuristic shortcuts that are faster and less cognitively demanding, at the cost of some degree of decision quality (Simon 1955; Simon 1979).

Kahneman (2011) extended this framework in two ways that are directly relevant to the present discussion. The first is the distinction between *System 1* and *System 2* cognition: fast, automatic, pattern-based intuition on the one hand, and slow, effortful, deliberate analysis on the other. In most professional decision contexts – including those faced by football coaches – the time pressure and attentional demands of real-time operation push decision-makers toward System 1, making their choices heavily dependent on pattern recognition, accumulated experience, and tacit knowledge rather than on explicit analytical reasoning. The second extension concerns the *systematic biases* to which System 1 cognition is prone: availability bias (overweighting recent or vivid events), anchoring (excessive reliance on initial reference points), confirmation bias (selectively attending to information that supports existing beliefs), and overconfidence (systematically underestimating uncertainty). Each of these biases degrades decision quality in proportion to the complexity of the decision environment, and the football context – with its continuous stream of novel match situations, its high emotional stakes, and its premium on rapid judgement – is precisely the kind of environment in which they are most likely to manifest.

The practical implication of the bounded rationality and dual-process literature is not that human intuition should be replaced by algorithmic computation, but that the two should be systematically combined in what Kahneman (2011) calls a *disciplined intuition* framework: a decision architecture in which the systematic, data-driven analysis provided by analytical tools and personnel pre-processes the information environment, reducing its complexity to a form that a human decision-maker's System 1 can engage with productively. The role of the analyst, on this account, is not to replace the decision-maker but to *extend* their cognitive capacity by performing the information-reduction tasks that their bounded rationality prevents them from performing unaided.

This framework has a direct operational implication for the design of analytical outputs. If the decision-maker's attention is limited and System 2 engagement is cognitively costly, then the analyst's deliverable must be simple, vivid, and rapidly digestible. A comprehensive statistical report that requires sustained deliberative engagement will not be used by a head coach preparing for a match in a time-pressured environment; a concise set of three to five targeted tactical observations will. The design constraint is cognitive, not computational: the analyst must translate complex data into a form compatible with the decision-maker's attentional architecture. This cognitive principle recurs, with domain-specific adaptations, throughout the empirical chapters that follow.

The information-overload literature provides an additional dimension. Eppler and Mengis (2004) document the phenomenon of *information overload* – the degradation of decision quality that occurs when the quantity of incoming information exceeds the decision-maker's processing capacity – and show that it is characterised by a non-monotonic relationship between information volume and decision quality. Beyond a certain threshold of informational complexity, additional data actually impairs the decision-maker's performance: it introduces noise, demands attention that would otherwise be devoted to processing already-available information, and can trigger the cognitive shutdown response in which the decision-maker reverts to a simple heuristic rule rather than attempting to integrate the full informational field. The practical design challenge for any analytical function – in business, in sport, or in any other domain – is therefore to calibrate the volume and format of its output to the decision-maker's cognitive capacity, not to the full complexity of the available data.

1.3 Evidence-Based Management and the Organisational Conditions for Data-Driven Decision-Making

The translation of data-driven decision principles into organisational practice is not automatic. The accumulation of data assets does not, by itself, produce evidence-based decision-making; it produces, instead, a potential that is realised only under specific organisational conditions. The literature on *evidence-based management* (EBM) – the application to management practice of the epistemic standards that characterise evidence-based medicine – is illuminating on this point.

Pfeffer and Sutton (2006) identify three main obstacles to evidence-based management in organisational settings. The first is the *dominance of experience over data*: managers rely on their own accumulated experience and on the experience of trusted colleagues far more than on systematically collected evidence, partly because experience is more cognitively available, partly because it is more consistent with the managerial identity as a practitioner rather than an analyst. The second is the *absence of an organisational culture of inquiry*: evidence-based decision-making requires an environment in which challenging existing practices with data is encouraged rather than penalised, and in which negative results are treated as informative rather than threatening. This cultural condition is fragile and easily undermined by hierarchical pressure, institutional conservatism, or individual status concerns. The third obstacle is *poor-quality evidence*: even managers who are epistemically well-disposed toward data are frequently confronted with evidence that is methodologically weak, contextually mismatched, or strategically framed by the interests of those who produced it.

The implications for the design of analytical functions are significant. An organisation can invest heavily in data infrastructure and analytical talent and still fail to achieve data-driven decision-making if the organisational culture does not support the use of analytical output. The literature on technology adoption in organisations (Davenport and Harris 2006) confirms that the successful integration of analytical capabilities requires not only the technical infrastructure to produce insights, but also the organisational architecture to use them: reporting lines that connect analytical teams to decision-makers, communication protocols that translate technical output into actionable recommendations, and a decision culture that treats data-informed arguments as legitimate inputs to the deliberative process.

Davenport and Harris (2006) identify five stages of what they call "competing on analytics": the first is the organisation that is analytically impaired, lacking both data and skills; the second is the organisation that has localised analytics, with isolated pockets of analytical activity but no strategic coordination; the third is the organisation with analytical aspirations, possessing the data infrastructure but not yet the cultural or structural conditions for systematic deployment; the fourth is the analytical company, which has integrated analytical capabilities into its core management processes; and the fifth – which they term the *analytical competitor* – is the organisation that treats its analytical capabilities as a primary source of competitive advantage and continuously invests in upgrading them. This taxonomy, developed in the context of large corporations, translates with reasonable fidelity to the football club context: the five stages correspond to the spectrum from the single-analyst Serie A club relying on a shared platform, through clubs with sophisticated in-house data teams, to the elite operations with dedicated analytics departments of a dozen or more professionals.

The critical variable in the transition from analytical aspiration to analytical competition is, in both the corporate and the football context, the quality of the interface between analytical teams and decision-makers – what Davenport and Patil (2012) call the "last mile" problem of analytics: the challenge of translating technically sophisticated output into the form and format that the decision-maker can actually use. The last-mile problem is not a technical challenge; it is a human one, requiring deep mutual understanding between analyst and decision-maker, combined with the communicative skill to present complex findings simply.

1.4 The Emergence of Dedicated Analytical Functions

The structural response of organisations to the data-driven transformation has been, almost universally, the creation of dedicated analytical functions: organisational units whose primary purpose is to transform raw data into decision-relevant knowledge, and whose personnel possess the technical skills – statistical, computational, and communicative – required to perform this transformation effectively.

1.4.1 The data scientist as an emerging profession

The emergence of the "data scientist" as a recognised professional category closely mirrors the dynamics described by Abbott (1988) in his account of how new professions crystallise out of complex work systems. Davenport and Patil (2012) trace the genealogy of the role to the confluence of three previously separate professional traditions: statisticians, who possessed the methodological tools for quantitative analysis; computer scientists, who possessed the technical skills for large-scale data management; and domain specialists, who possessed the contextual knowledge required to formulate and interpret meaningful questions. The data scientist is, in their account, the hybrid professional who integrates all three knowledge bases – and the rarity of this combination, rather than any single component of it, explains both the extraordinary demand for data scientists and their scarcity in the labour market.

The organisational position of the analytical function has itself been a subject of contested design. The early history of analytics in large corporations was characterised by *decentralisation*: analytical talent was distributed across business units, each of which maintained its own small team producing bespoke reports for its own management. This model has the advantage of contextual sensitivity but the disadvantage of duplication, inconsistency, and the inability to generate cross-unit insights. The subsequent trend has been toward *centralisation*: the creation of centres of excellence or chief data officer functions that consolidate analytical capabilities and establish methodological standards (Davenport and Patil 2012).

The most successful organisations have, in practice, adopted a hybrid model: a centralised data infrastructure maintained by a core team, combined with embedded analytical resources within each major operational unit who translate the central platform's capabilities into domain-specific outputs. This hybrid architecture is precisely the model that the most advanced football clubs instantiate – with a centralised data team providing the infrastructure and models, and embedded match analysts serving as translators within the operational football unit.

1.4.2 The Chief Data Officer and the governance of data as a strategic asset

The creation of the Chief Data Officer (CDO) role – now present in the majority of large financial institutions, pharmaceutical companies, and technology firms – marks the formal elevation of data governance to board-level strategic significance (Gartner 2019). The CDO's mandate is typically threefold: to ensure the quality, accessibility, and security of the organisation's data assets; to govern the policies by which data is collected, stored, and shared; and to drive the strategic deployment of analytical capabilities in pursuit of the organisation's competitive objectives. The CDO role is a signal that data management has crossed a threshold from operational to strategic significance. In the football context, the equivalent structural development – the creation of "Head of Data" or "Chief Analytics Officer" roles at leading clubs, explicitly separated from the traditional match analyst function – represents the same threshold being crossed, with a delay of approximately a decade relative to the corporate sector.

1.4.3 Organisational culture as a determinant of analytical effectiveness

The literature on analytical organisations consistently identifies cultural factors – rather than technological or structural ones – as the primary determinants of analytical effectiveness. Davenport and Harris (2006) note that organisations that compete most successfully on analytics are characterised by a distinctive set of cultural attributes: curiosity (a genuine interest in understanding why outcomes occur); openness (a willingness to challenge conventional wisdom with data, even when it contradicts senior individuals' judgement); rigour (a demand for methodological quality); and precision (a preference for quantitative specificity over qualitative generality). These cultural attributes are not randomly distributed across organisations: they cluster in particular ownership structures, industry sectors, and management traditions. The observation by one of the practitioners interviewed for this thesis – that the clubs most analytically developed in Italy are those under North American ownership – is consistent with this cultural analysis. The North American professional sports tradition, shaped by decades of sabermetric influence in baseball and quantitative innovation in basketball (Lewis 2004; Morgulev, Azar, and Lidor 2018), has institutionalised analytical curiosity as an expected competency of front-office leadership. Clubs with historically domestic Italian ownership structures have not been subject to this institutional pressure, and their analytical practices reflect this difference.

1.5 Artificial Intelligence as an Amplifier of the Data-Driven Transformation

The developments described in the preceding sections were largely in place before the current wave of artificial intelligence capabilities began to transform the organisational landscape. The emergence of large-scale machine learning models, neural networks capable of processing unstructured data (images, text, video), and – most recently – generative AI systems capable of producing human-quality natural language output represents a further amplification of the data-driven transformation whose first wave had already generated the dynamics described above.

1.5.1 Machine learning and the automation of analytical tasks

The most immediate organisational impact of machine learning is the *automation of analytical tasks* that previously required significant human labour. Pattern recognition – the identification of regularities in large datasets – has historically been the core function of the analyst; it is precisely the function at which machine learning models are most effective. The implication is a compression of the standard analytical workflow: tasks that previously required days of manual coding and statistical analysis can now be accomplished by trained models in seconds or minutes (Davenport 2018). This compression simultaneously reduces the cost of basic analytical functions and raises the bar for what counts as distinctively human analytical value-added.

In the football context, this dynamic is already visible in the automation of event tagging and video coding. Systems such as those developed by providers like Stats Perform and Metrica Sports can now produce reliable event-level codings of match footage without human intervention, at a fraction of the cost and time that manual coding requires. This automation does not eliminate the need for match analysts; it eliminates the portion of their work that was most repetitive and least analytically demanding, freeing them to focus on the interpretation, contextualisation, and communication tasks that require domain expertise and human judgement.

1.5.2 Predictive analytics and the shift from retrospective to prospective analysis

Traditional performance analysis has been predominantly retrospective: it describes what happened and identifies patterns in historical data. Machine learning enables a shift toward *predictive* analytics: models that estimate the probability of future events based on observed patterns, and thereby support prospective decision-making (Herold et al. 2019). In the football context, this includes predictive models for player performance and injury risk, probabilistic assessments of recruitment targets, expected goals as prospective valuation metrics, and models for opponent behaviour prediction.

The transition from retrospective to predictive analytics has profound implications for the role of the analyst. Predictive models introduce new forms of uncertainty that must be communicated to decision-makers: confidence intervals, out-of-sample performance degradation, sensitivity to distributional shift. The analyst who operates in a predictive analytics environment must therefore possess not only the technical skills to build and maintain models, but also the communicative skills to convey the limits of those models in ways that non-technical decision-makers can act on appropriately.

1.5.3 Generative AI and the transformation of the analytical interface

The emergence of large language models (LLMs) and generative AI systems since 2022 introduces a further dimension: the potential automation of the *communicative* layer of analytical work – the translation of quantitative findings into natural-language explanations, executive summaries, and personalised reports (Davenport and Mittal 2023). If the last-mile problem of analytics is fundamentally a communication problem, then tools that can automate this translation have the potential to dramatically increase the throughput and accessibility of analytical functions. The available evidence from analogous professional contexts suggests that the productivity-amplification effect is currently dominant: AI tools allow skilled professionals to work faster and at greater scale, but do not substitute for the domain expertise and contextual judgement that distinguish high-quality analytical work from generic output (Davenport and Mittal 2023). For the match analyst, this implies that the most defensible professional positions are those that combine technical proficiency with deep football knowledge.

1.5.4 The interpretability challenge and the human decision-maker

A structural tension that AI amplification introduces into the data-driven decision-making framework concerns the *interpretability* of model outputs. The most powerful machine learning models – deep neural networks, gradient boosting ensembles, large language models – are also the least transparent: their predictions are not easily explained in terms that a human decision-maker can interrogate, challenge, or contextualise. The organisational response has been the development of *explainable AI* (XAI) approaches: methodological tools designed to extract human-interpretable explanations from complex models. The more fundamental response – and more widely adopted in practice – is the maintenance of a *human interpreter in the loop*: an analyst who understands both the model's technical properties and the decision context well enough to flag situations in which the model's output should be treated with scepticism. This is precisely the function that the match analyst at the interface between a club's data team and its head coach performs: not to mechanically relay model outputs, but to contextualise, qualify, and translate them in light of the specific tactical situation.

1.6 Sports Analytics in the Big-Data Era

Before the conceptual bridge to professional football is drawn, it is useful to situate the sport industry as a whole within the data-driven transformation described in the preceding sections. Sport has not been immune to the explosion of data availability; on the contrary, it has proved one of the most receptive domains for data-driven analysis, to the point of generating a recognised interdisciplinary field – *sports analytics* – with its own conferences, journals, and professional community (Morgulev, Azar, and Lidor 2018). The reasons for this receptiveness are structural. Sporting competition produces, as a by-product of its normal operation, exactly the kind of data that analytical methods require: large numbers of repeated, comparable events; outcomes that are objectively measurable and publicly recorded; decisions taken by highly trained professionals under well-defined rules; and stakes – financial, competitive, and reputational – high enough to motivate sustained investment in any source of marginal advantage.

Morgulev, Azar, and Lidor (2018), in a survey of the field written from the perspective of data science, distinguish three types of data-driven analysis that the big-data era has made possible in sport. The first is *field-level analysis*: the study of the in-game behaviour of athletes, coaches, and referees. This strand has the deepest historical roots – it descends from the notational-analysis tradition inaugurated in football by Reep and Benjamin (1968) – and has expanded dramatically with the arrival of optical tracking systems and large event datasets. Its findings are not merely descriptive: a recurring result of this literature is the documentation of systematic departures from optimal behaviour even among elite professionals, such as goalkeepers' *action bias* in penalty situations (diving to one side when remaining central would be statistically superior), the misperception of random sequences underlying the long-running "hot hand" debate, and the susceptibility of referees' decisions to crowd pressure (Morgulev, Azar, and Lidor 2018). The second type is the *analysis of managerial and policy decisions*: the use of data to evaluate, and frequently to correct, the judgement of sporting executives – from the player-valuation inefficiencies made famous by the Oakland Athletics' "Moneyball" season (Lewis 2004) to pricing, resource-allocation, and contract decisions taken by clubs, leagues, and host cities. The third type is the use of *sports data as a laboratory for the social sciences*: because sport offers high-stakes, repeated decisions taken by experienced professionals under well-defined rules and complete observability, economists and psychologists have systematically exploited sports datasets to test theories of rational behaviour, incentives, and judgement that are difficult to test in conventional field settings (Morgulev, Azar, and Lidor 2018).

This taxonomy carries three implications that bear directly on the argument of this thesis. The first concerns the *location* of analytical production. A striking feature of the sports analytics literature is that a large share of it has been produced outside the organisations that actually compete on the field: by academic researchers using sport as a data-rich laboratory rather than by clubs seeking competitive advantage. The asymmetry between the abundance of available analysis and the scarcity of organisational uptake is the sport-sector manifestation of the "last mile" problem described in Section 1.3: the existence of rigorous, decision-relevant findings does not by itself ensure that the decision-makers to whom they are relevant ever encounter them in usable form. Bridging this gap is precisely the function around which the match analyst role, examined in the following chapters, has crystallised.

The second implication concerns the empirical standing of the bounded-rationality framework developed in Section 1.2. The field-level strand of sports analytics provides direct, domain-internal confirmation that elite experience does not immunise professional decision-makers against the systematic biases of System 1 cognition: the action bias of goalkeepers and the hot-hand misperception are textbook cases of heuristic judgement documented in the behaviour of world-class professionals operating within their own domain of expertise (Morgulev, Azar, and Lidor 2018). This evidence strengthens the case – advanced throughout this thesis – for analytical decision support in sport: if systematic biases persist at the highest levels of expertise, then the value of structured data analysis lies precisely in its capacity to surface the regularities that expert intuition mis-reads.

The third implication concerns the chronology and unevenness of analytical adoption across sports. Baseball's early lead in quantitative analysis – the sabermetric tradition that culminated in the Moneyball episode – reflected structural features of the game itself: a discrete, sequential structure that decomposes naturally into individually attributable events, making performance measurement tractable long before the big-data era (Lewis 2004; Morgulev, Azar, and Lidor 2018). Football presents the opposite profile: a fluid, low-scoring, continuously interacting game whose decisive events are rare and whose individual contributions are deeply interdependent. Quantifying football performance therefore had to await the technological developments – high-frequency tracking, large-scale event coding, machine learning – described in Section 1.5, which explains why the analytics revolution arrived in football roughly two decades after baseball, and why its arrival has been so closely tied to the emergence of new specialised professional roles rather than to the simple importation of established methods. The match analyst is, in this sense, a product of the specific moment at which football's informational environment became analytically tractable.

1.7 From the General Case to Professional Football: A Conceptual Bridge

The organisational dynamics described in the preceding sections – the data explosion, the bounded rationality of managers, the demand for evidence-based management, the emergence of dedicated analytical functions, the transformative impact of AI, and the rise of sports analytics as a recognised field – manifest, in the world of professional football, with a clarity and precision that makes the sport an unusually tractable case study for the general phenomena.

Professional football is, from an organisational-analytical standpoint, a domain characterised by the following features. First, it generates continuous, high-resolution data across multiple dimensions simultaneously: positional data at frame-level precision, event data coded at millisecond granularity, physical performance data from wearable sensors, and video data from multiple camera angles – all in real time, across an entire competition calendar. Second, it involves high-stakes decisions under conditions of extreme time pressure: the head coach must make tactical adjustments, substitutions, and strategic recalibrations in minutes or seconds, with large financial and reputational consequences attached to the outcomes. Third, it has historically been dominated by a culture of intuition, experience, and tacit knowledge – what practitioners call "football intelligence" – that is deeply resistant to the displacement of established authority by quantitative methods. And fourth, it is a domain in which competitive advantage is sufficiently consequential – both financially and symbolically – to motivate sustained investment in any method that credibly promises marginal improvements in decision quality.

These features make professional football a concentrated and revealing instance of the general organisational challenge of integrating data-driven decision support into a domain previously governed by expert intuition. The resistance to data in football is not irrational; it reflects genuine uncertainty about whether quantitative models can capture the contextual complexity of football decision-making, as well as a rational concern about the reputational costs of delegating authority to systems whose outputs cannot be explained post-hoc to sceptical stakeholders. Similarly, the enthusiasm for data in football's most analytically advanced clubs reflects genuine empirical evidence that structured data analysis generates decision-relevant insights that an unaided coach cannot reliably produce.

The match analyst is the organisational solution to the general problem described in this chapter, adapted to the specific constraints and opportunities of the football domain. The parallel with the corporate analytical function is instructive not only at the structural level – the emergence of specialised roles, the design of information flows, the cultural conditions for adoption – but also at the level of the specific professional challenges facing analysts in both contexts. In corporations, the central professional challenge for the analyst is the "last mile" problem: producing technically rigorous output that non-technical decision-makers can actually use. In football, this challenge is structurally identical, with the additional complication that the decision-maker typically operates under more extreme time pressure and with a stronger identity investment in their own intuitive judgement. The tools and workflows that professional football has developed to address this challenge – the opposition dossier, the team meeting presentation, the half-time clip package, the flash report – are, from an organisational standpoint, solutions to the same cognitive interface problem that corporate analytics departments address through executive dashboards and narrative reporting.

The following chapters examine this parallel in its football-specific detail: the structure and operation of the match analyst role (Chapter 2), the evidence gathered from key informant interviews with practitioners at the frontier of the Italian football analytics ecosystem (Chapter 3), and the synthesis of findings on how the coach's decision-making is shaped by data in the contemporary professional game (Chapter 4). The conceptual framework developed in the present chapter – bounded rationality, evidence-based management, the organisational conditions for analytical effectiveness, the transformative role of AI, and the position of football within the broader sports analytics movement – provides the interpretive lens through which that evidence will be read.

Chapter 2

The role of the match analyst in professional football

2.1 Scientific literature and press on the role of the match analyst

2.1.1 General framework: from *notational analysis* to *performance analysis*

The modern strand of *performance analysis* in football emerges in the 1970s and 1980s out of the English tradition of *notational analysis*, which introduced the systematic recording of match events; its founding document is conventionally identified in the statistical work of Reep and Benjamin (1968), whose analysis of passing sequences across decades of English football inaugurated the quantitative study of the game. Hughes and Bartlett (2002) were the first to propose a taxonomy of *performance indicators*, distinguishing between *scratch* (absolute) indicators and relative ones (normalised by opposition, match, and possession time): this is the point at which analysis ceases to be merely descriptive and becomes diagnostic.

Carling, Williams, and Reilly (2005), in the *Handbook of Soccer Match Analysis*, consolidate the state of the art and introduce, for the first time in an organic way, the figure of the *performance analyst* as a professional embedded within the technical staff, distinct from the scout and the fitness coach. Theirs is one of the earliest reference texts to describe the analyst's *workflow* explicitly: data collection, coding, feedback to the coach, and transfer to the players.

More recent literature has, however, exposed the limits of this classical strand. Mackenzie and Cushion (2013) identify three recurring weaknesses: an excessive emphasis on aggregate team-level data, insufficient situational contextualisation, and scant attention to how the head coach actually *uses* the analyst's output. This last point is central to the present thesis: data without professional interpretation risk remaining inert.

2.1.2 Systematic studies and field surveys

Sarmento et al. (2014) is the canonical reference for anyone framing the field: a systematic review of 53 studies showing that the vast majority of research clusters around four themes – offensive effectiveness, transitions, set pieces, and possession – while the *role of the professional* producing these analyses remains almost invisible in the academic record. This is the gap into which the present thesis can insert itself.

Memmert, Lemmink, and Sampaio (2017) mark the shift from event-based notational analysis to tracking-based spatial analysis: with the arrival of positional data (Hawk-Eye, Second Spectrum, ChyronHego), the match analyst also becomes a spatial-data analyst, and this introduces a new statistical and computational competence into the role.

Rein and Memmert (2016) offer what amounts to a manifesto for the *big data* era in football: they argue openly that the volume and complexity of available data have outstripped unaided human interpretation, and implicitly make the case for dedicated specialised figures – analysts, sports data scientists – to bridge that gap. Their argument is the football-specific instance of the cross-sport dynamic surveyed by Morgulev, Azar, and Lidor (2018) and discussed in Section 1.6: in every major sport, the big-data era has shifted the binding constraint from data acquisition to data interpretation.

2.1.3 Studies specifically addressing the analyst's professional role

Wright, Atkins, and Jones (2012) is the most important reference for the sociological and organisational angle of this thesis: an empirical study on a sample of elite-level coaches demonstrating that the coach's experience is the critical variable determining whether and how the analyst's output is actually used. More experienced coaches tend to integrate the analysis into their own vision; less experienced ones either passively absorb it or ignore it. It is one of the very few papers that explicitly addresses the *relationship* between analyst and head coach.

Wright, Atkins, Jones, and Todd (2013) extended this line of inquiry by showing that performance analysis has entered the decision-making cycle of English and other top-league technical staffs at very different speeds and in very different forms – from pure video support to a fully strategic role. Diffusion, in other words, is not uniform but depends on the technical culture of the individual club.

A more recent and methodologically important line of work involves the analysis of analyst *recruitment* based on job advertisements published by professional clubs. Francis, Kyte, and Bateman (2024) conducted a content analysis of 130 applied performance analyst job advertisements published in the United Kingdom and Ireland between 2021 and 2022, spanning 21 distinct role titles, and documented substantial variation in the roles, responsibilities, and skills requested – even between structurally similar first-team and academy positions. This approach allows the actual requirements of the role (degree, software skills, languages, prior experience) to be *objectified* without relying on self-reported interviews, and its finding of persistent heterogeneity in a mature market such as the British one is significant for the Italian case: if even the deepest analyst labour market in Europe has not converged on a standard professional profile, the heterogeneity documented for Serie A later in this chapter should be read as a structural feature of the profession rather than as a symptom of Italian backwardness. The job-advertisement methodology is also a model worth replicating for Italian clubs.

Herold et al. (2019) provides a survey of machine learning applications in men's professional football that captures the data-driven side of the industry: types of data collected, attacking-play applications, and future directions. Its findings should be cross-referenced with the Serie A proto-database attached to this thesis.

2.1.4 Italian specialised press and grey literature

On the Italian side, academic literature is sparse, but specialised press and professional bodies offer relevant material. The AIAPC (*Associazione Italiana Allenatori Preparatori Calcistici*, today also operating as *AssoAnalisti*) informally gathers Italian match analysts and has actively pushed for the official recognition of the role (AIAPC — Italian Association of Football Coaches and Trainers 2026).

The formal recognition of the role by the Italian Football Federation (FIGC) arrived in 2018 through the order issued by the Italian Competition Authority (Italian Competition Authority (AGCM) 2018), which had practical effects on the registration of the role within club staffs. This order represents the moment of *institutionalisation* of the role in Italy and constitutes a historical-normative milestone worth citing in any account of the profession's development.

Italian journalistic sources useful for the descriptive picture include articles in *L'Ultimo Uomo* (L'Ultimo Uomo 2026) and *Rivista Undici* (Rivista Undici 2026), alongside interviews and technical podcasts. These materials should be used as illustrations of practice and as sources of biographical information, not as scientific evidence.

2.1.5 Synthesis: what the literature says (and does not say)

Twenty years of research have produced a reasonably firm consensus on the importance of quantitative analysis in professional football. The technological evolution from event data to tracking to AI has dramatically increased data volume and complexity, making specialised figures necessary. Performance analysis has also begun to structure itself as a *discipline* with its own methodological standards (Hughes and Bartlett 2002; Sarmento et al. 2014; Memmert, Lemmink, and Sampaio 2017).

What the literature has not done, or has barely begun to do, is examine the organisational dimension: who the analyst is, how they are trained, how they communicate with the head coach, and what hierarchical position they occupy within the staff. Systematic Italian studies are absent. The role of coach experience as a *filter* on the use of data (Wright, Atkins, and Jones 2012) is mentioned but under-investigated, and the only systematic evidence on the actual labour-market requirements of the role comes from a single recent British study (Francis, Kyte, and Bateman 2024). The present thesis positions itself precisely within this gap.

2.2 How the match analyst operates during the week and on matchday

The description that follows draws on the available academic literature (Carling, Williams, and Reilly 2005; Wright, Atkins, and Jones 2012; Wright, Atkins, Jones, and Todd 2013; Mackenzie and Cushion 2013), on professional practice as documented by interviews and specialised press, and on the LinkedIn profiles of the Italian analysts surveyed in the proto-database. Practices vary significantly from club to club: what follows is the *modal model* observed across Serie A and the European top leagues, not a single universal protocol.

2.2.1 The standard weekly cycle (a 7-day microcycle with one match)

In the periodisation language commonly used in professional football, the weekly schedule is described in relation to the matchday (abbreviated MD). The days following a match are labelled MD+1, MD+2, and so on, while the days preceding the next match are labelled MD−1, MD−2, and so on. A standard microcycle with one competitive fixture per week therefore runs from MD+1 (the day after one match) through to MD (the next match). The analyst's work is structured around three parallel tasks that unfold across this cycle: self-analysis of the team's own performance, opposition analysis, and direct support to the training sessions.

MD+1: post-match analysis and individual feedback The day after a match is dominated by the systematic review of the team's own performance. The analyst begins by importing the match footage, typically from two or three sources: the television broadcast feed, the so-called *tactical camera* (a wide-angle, elevated camera that captures the full pitch and all 22 players simultaneously), and, where available, data from an optical tracking system such as Hawk-Eye, Second Spectrum, or Chyron-Hego, which records the positional coordinates of every player and the ball at high frequency (typically 25 frames per second).

The raw footage is then imported into the club's video analysis platform – most commonly Hudl Sportscode (Hudl 2026), though alternatives such as Wyscout (Wyscout 2026) and Metrica Play (Metrica Sports 2026) are also widely used – where it is *coded*: the analyst tags each relevant event (passes, shots, tackles, interceptions, fouls, offsides, set pieces) with metadata that allows the footage to be searched, filtered, and reorganised at will. From this coded footage the analyst extracts two types of output. The first is a *team-level report* summarising the match through a set of key performance indicators (KPIs): these typically include metrics such as expected goals (xG, a statistical estimate of the probability that a given shot results in a goal, based on the shot's location, angle, body part, and the preceding play), average team position, territorial dominance indicators, pressing intensity metrics, and a comparison of the actual performance against the pre-match tactical plan. The second output is a set of *individual player clips*: short video sequences isolating each player's key actions – both positive and negative – which are subsequently distributed to the players and the coaching staff for review.

MD+2 to MD−5: recovery phase and the start of opposition analysis During the recovery phase (typically one or two days after the match), the analyst distributes the individual player clips either through a digital platform (such as Hudl's player-facing interface) or in small group meetings organised by unit – defenders, midfielders, and attackers reviewing their respective clips together with the relevant assistant coach.

Simultaneously, the analyst begins the preparation for the next fixture by initiating the *opposition analysis*. This involves downloading and reviewing the footage of the upcoming opponent's most recent matches – usually the last four to six competitive fixtures, though the exact number varies with the analyst's and the head coach's preferences. The analyst codes this footage in the same event-based manner described above, but now with a different objective: identifying recurring patterns in the opponent's play. The concept of *patterns* is central to the analyst's work and merits clarification. In performance analysis, a pattern refers to a sequence of actions that an opponent repeats with sufficient regularity to be considered tactically predictable. For example, an opponent may consistently build up play through the left centre-back, who plays a diagonal pass to the right winger; or a full-back may habitually tuck inside during the attacking phase, leaving space behind for a runner. The analyst's task is to identify these regularities, quantify their frequency, and present them to the coaching staff in a form that is both accurate and actionable.

A particularly important category of patterns involves *transitions* – the brief, high-intensity moments when possession changes hands. In tactical analysis, the term "transition" refers specifically to the phase of play that occurs immediately after a change of possession: the *offensive transition* (also called *counter-attack* in common parlance, though the two concepts are not perfectly synonymous) is the phase in which the team that has just won the ball attempts to exploit the opponent's momentary disorganisation by attacking quickly, while the *defensive transition* (also called *counter-pressing* or *gegenpressing* in the terminology popularised by Jürgen Klopp) is the attempt to recover the ball immediately after losing it. Transitions are disproportionately important because a large share of goals in professional football are scored during these brief windows of tactical instability (Sarmento et al. 2014), and they are therefore a priority area of analysis for most clubs.

At this stage, the analyst also holds an initial briefing with the head coach to align on the interpretive direction: which aspects of the opponent's play does the coach consider most relevant? Which of the opponent's strengths should be neutralised, and which weaknesses exploited? This dialogue is critical because, as Wright, Atkins, and Jones (2012) have shown, the coach's experience and tactical philosophy determine how – and indeed whether – the analyst's output is actually integrated into the team's preparation.

MD−4 to MD−3: the tactical core of the microcycle The middle of the week constitutes the most analytically intensive phase. The analyst constructs the *opposition dossier*: a comprehensive document (typically delivered as a PDF, a Keynote or PowerPoint presentation, or a digital report within the club's internal platform) structured around a set of standard sections. These typically include: the opponent's behaviour in the *possession phase* (how they build up from the back, how they progress through the midfield, how they create chances in the final third); the *out-of-possession phase* (how they press, what defensive shape they adopt, how they deal with crosses and direct play); *transitions* (both offensive and defensive, as defined above); *set pieces* (corners, free kicks, throw-ins, analysed both in attack and in defence, with diagrams of the opponent's preferred routines); and *individual profiles* of the opponent's key players, highlighting their strengths, weaknesses, and habits.

During this phase the analyst also collaborates directly with the coaching staff in the design of training exercises. If the opposition dossier reveals, for example, that the upcoming opponent consistently leaves space behind the full-backs during the offensive transition, the analyst may suggest – and help design – a training exercise that replicates this situation, allowing the team's wide players to practise exploiting it in a controlled environment. This collaboration is one of the areas where the boundary between the analyst's role and the assistant coach's role becomes most blurred, and it depends heavily on the head coach's willingness to involve the analyst in the training process (Wright, Atkins, Jones, and Todd 2013).

MD−2 to MD−1: refinement and the team meeting The final days before the match are devoted to distilling the analytical work of the week into a form that can be communicated effectively to the entire squad. The centrepiece of this phase is the *team meeting*: a presentation, typically lasting 15 to 25 minutes, in which the analyst (or in some clubs, the head coach or assistant coach, using the analyst's materials) presents the key tactical messages for the upcoming match. The presentation is deliberately kept short and focused – usually three to five core messages – because the coaching staff's experience has shown that players absorb visual information best in concentrated doses rather than in exhaustive detail (Mackenzie and Cushion 2013).

In parallel, the analyst may conduct individual briefings for specific players – showing the centre-back a compilation of the opposing striker's movement patterns, or showing the set-piece taker the goalkeeper's positioning tendencies on free kicks. The analyst also prepares the technical infrastructure for matchday: setting up the workstation (laptop, coding software, communication devices), testing the connection with the bench or the press-box feed, and ensuring that the real-time tagging system is synchronised with the broadcast signal.

2.2.2 Matchday operations

Pre-match On the day of the match, the analyst's morning typically includes a brief refresh of the team meeting – a 5 to 10 minute slot in which any last-minute information is communicated to the squad. This may include the opponent's confirmed starting line-up (which often differs from the expected one and may require adjustments to the tactical plan), injury updates, and environmental factors such as pitch conditions or weather.

In-match: the analysis desk During the match, the analyst occupies a dedicated workstation. The choice of location – bench-level or elevated in the press stand – depends on the club's preference and on league and competition regulations. The UEFA Champions League Regulations (2024/25, Article 57) and the IFAB Laws of the Game define the boundaries of the technical area and limit the number of persons who may occupy the bench (UEFA 2024a). Many clubs prefer to station the lead analyst in the press stand, where the elevated and centred view of the pitch provides a much better perspective for tactical observation, while maintaining communication with the bench through a headset or a messaging application on a tablet.

From this position, the analyst performs *real-time tagging*: coding the match live as it unfolds, using the same software employed during the week but now operating in a time-pressured, abbreviated mode. The analyst is not attempting to code every event – that would be done post-match from the full recording – but rather to capture the most tactically significant moments as they happen: set pieces, dangerous transitions, systematic errors in the team's shape, and notable changes in the opponent's tactical approach.

The most time-critical task occurs at half-time. In the 15 minutes of the interval, the analyst must select, edit, and compile a short clip package – typically three to six clips, totalling no more than one to two minutes of footage – that the head coach can show to the players in the dressing room. These clips serve a specific purpose: they are not a comprehensive review of the first half but a targeted intervention, designed either to correct a recurring error or to reinforce a tactical instruction that is working well and should be continued. The ability to produce this clip package under extreme time pressure is one of the most demanding aspects of the analyst's job and requires not only technical proficiency with the software but also a deep understanding of the head coach's priorities and communication style.

After the final whistle, the analyst compiles a *flash report*: a concise summary of the match's key metrics, typically including expected goals (xG), territorial indicators, pressing data, and a brief list of the most significant tactical events. This report is delivered to the head coach before the post-match press conference, providing a data-informed basis for the coach's public statements and for the initial internal debrief.

Post-match and cycle reset In the hours following the match, the analyst backs up all materials – match footage, live codings, tracking data – and updates the club's historical database. This database, maintained over multiple seasons, serves both as a reference archive and as the basis for longitudinal analyses of the team's performance trends. With the backup complete, the analyst re-enters the MD+1 phase of the next microcycle, and the process begins again.

2.2.3 Recurring software tools

Without claiming exhaustiveness, the tools most frequently cited in interviews with Serie A analysts and in international surveys are: **Hudl Sportscode** (Hudl 2026), an event-based video coding platform that represents the de facto industry standard, used by the majority of clubs in both the Premier League and Serie A; **Wyscout** (Wyscout 2026), an Italian-founded platform (Chiavari) for video, data, and scouting, used transversally by analysts and sporting directors and relevant to this thesis also as an Italian case of a services industry that has grown around the analyst's role; **InStat**, **Stats Perform**, and **Opta**, providers of standardised event data covering all top leagues; **Metrica Sports** (Play, Nexus, Coach Paint) (Metrica Sports 2026), an Italian-Portuguese video analysis and tactical drawing software that is growing in market share; and the optical tracking systems **Hawk-Eye**, **Second Spectrum**, and **ChyronHego**, which generate the high-frequency spatial data that have opened the door to the spatial-analytics revolution described by Memmert, Lemmink, and Sampaio (2017).

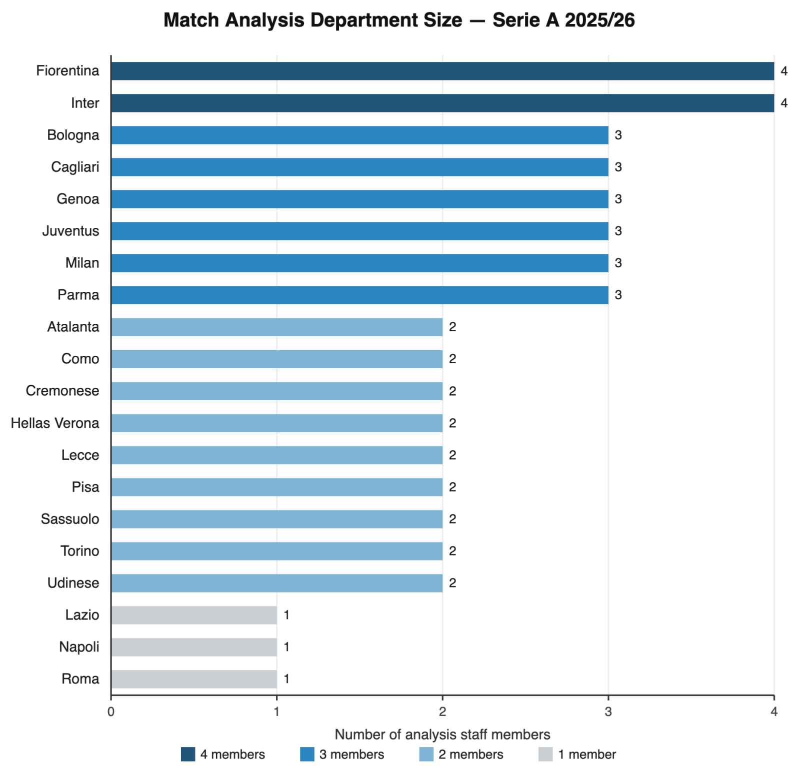

Figure 2.1: Match analysis department size across all twenty Serie A clubs (2025/26 season). Clubs are ranked by the number of identified analysis staff (match, video, performance and data analysts, and dedicated technical collaborators). Data source: Database compiled from official club staff pages and LinkedIn, verified against official 2025/26 club sources. See Appendix

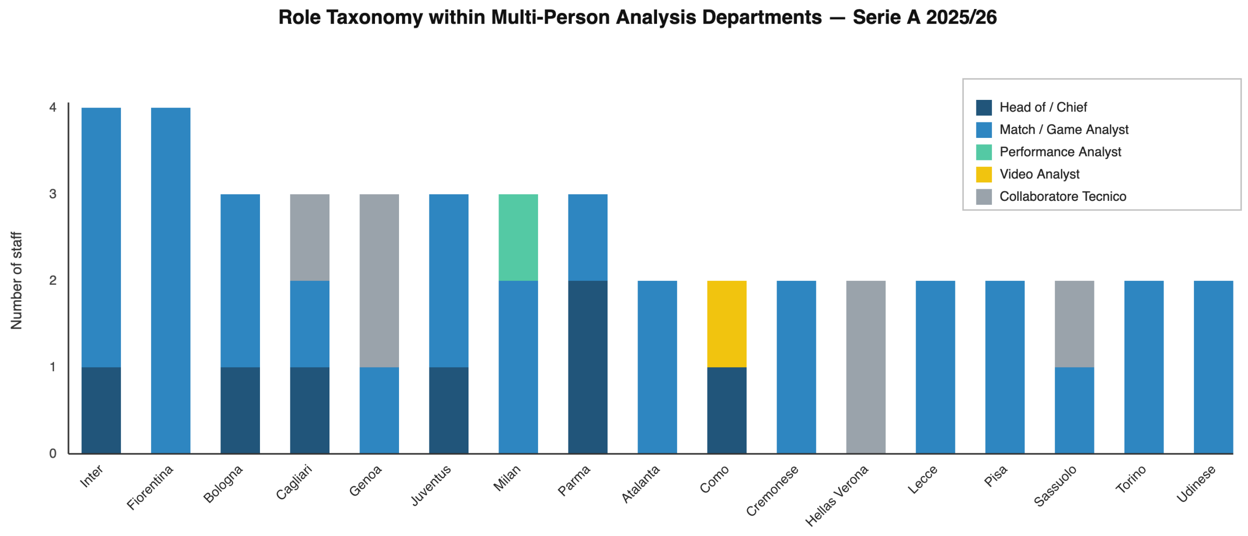

Figure 2.2: Role taxonomy within analysis departments with two or more members (Serie A 2025/26). Colour coding: *Head of / Chief* (dark blue), *Match / Game Analyst* (medium blue), *Performance Analyst* (teal), *Video Analyst* (yellow), *Collaboratore Tecnico – Match Analyst* (grey), *Data (Chief Data Analyst / Head of Strategy & Data)* (orange).

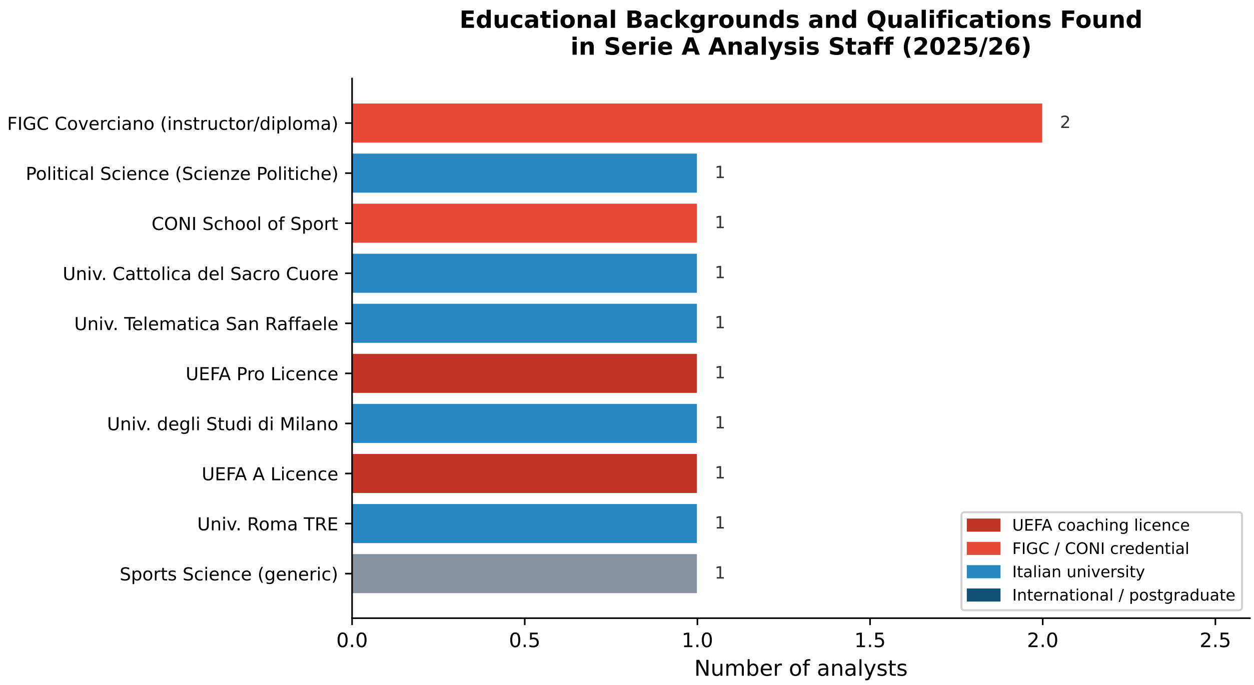

Figure 2.3: Educational backgrounds and qualifications identified among Serie A analysis staff (2025/26). The absence of a dominant pathway confirms the lack of a codified educational pipeline for the match analyst role in Italian football.

2.2.4 Position of the analyst within the staff and department size

The position of the match analyst within the organisational chart of a professional football club has changed considerably over the past decade. Historically, analysts operated as informal auxiliaries – often students or unpaid interns attached to the head coach's personal entourage rather than formally employed by the club. Today, the picture is markedly different. The data collected in the database (see Appendix) allow us to reconstruct the internal structure of the analysis departments across all twenty Serie A clubs for the 2025/26 season, revealing both the extent of formalisation already achieved and the substantial heterogeneity that still persists. A methodological note. The headcounts reported here follow a broad criterion: they include match and video analysts, performance and data analysts (including chief-data and head-of-strategy roles), and technical collaborators with an explicit analysis function, all verified against official 2025/26 club sources. Purely athletic or medical staff are excluded. Figures were cross-checked against each club's official staff page; where a club does not publish analyst roles (e.g. Inter, Milan), LinkedIn and specialised press were used and flagged accordingly.

The regulatory framework At the European level, the UEFA Club Licensing and Financial Sustainability Regulations (Edition 2024, Sporting Criteria, Article S.04) require each applicant club to employ qualified first-team coaching and technical staff, explicitly including "all sports scientists, analysts and performance staff" within this definition (UEFA 2024b). The regulation does not, however, prescribe a minimum number of analysts or specific qualifications for them – it merely establishes that they fall under the umbrella of licensed technical staff. The UEFA Champions League Regulations (2024/25, Article 57) govern the competition area and stipulate that a maximum of 23 persons – substitute players and team officials combined – may be seated on the bench during a match (UEFA 2024a). Among these officials, the analyst typically occupies one seat, although in practice many clubs station their lead analyst in the stand (*tribuna stampa*) rather than on the bench, in order to gain an elevated tactical view of the pitch.

In Italy, the formal institutional recognition of the match analyst came through the 2018 order of the Italian Competition Authority (AGCM, Order no. 27249 of 13 June 2018), which opened the way for the inclusion of the figure within the FIGC's internal regulations (NOIF – *Norme Organizzative Interne Federali*) and the club registration system (Italian Competition Authority (AGCM) 2018). Before this order, clubs could employ analysts de facto but could not formally register them as part of the technical staff submitted to the league.

Department size and hierarchical formalisation Across the twenty Serie A clubs surveyed, the size of the match analysis department ranges from a single analyst (in clubs such as Lazio, Napoli, and Roma**) to four-member departments at Inter and Fiorentina. (Monza, cited in earlier drafts, is not part of Serie A 2025/26.). The most notable pattern emerging from the proto-database is the adoption of *hierarchical titles* – specifically "Head of" designations – that signal the transition from an informal, coach-dependent role to a formalised organisational unit with its own chain of command. Four clubs display this pattern most clearly.

Inter Milan (4 members). The department is led by Filippo Lorenzon, whose title – Head of Football Analysis Department – is itself significant, but whose professional profile is even more so:

Lorenzon holds the UEFA Pro licence with a final mark of 110/110 (the highest coaching qualification, equivalent to that of a Serie A head coach) and serves as an instructor at the FIGC coaching school at Coverciano (FIGC — Settore Tecnico 2026). The person responsible for the analytical output at one of Europe's leading clubs thus possesses the same formal credential as the head coach himself – a finding that directly challenges the common perception of the analyst as a "low-level technician." Beneath Lorenzon, the department includes three match analysts – Salvatore Rustico, Giacomo Toninato, and Stefano Castellani – who work on the day-to-day coding, opposition reports, and individual player clips. The division of labour follows the standard pattern observed in multi-person departments: one analyst is typically assigned to self-analysis, one to opposition analysis, and one to set-piece and individual player analysis, although these boundaries are fluid.

Juventus (3+ members, multi-tier structure). Juventus operates a vertically integrated analysis structure spanning the first team and the youth academy. Riccardo Scirea, bearing the title Head of Match Analysis Office, leads the first-team unit. Scirea's background – a degree in Political Science (*Scienze Politiche*) and the CONI School of Sport diploma (2008) – illustrates a different pathway into the role: academic rather than coaching-based, with subsequent on-the-job specialisation within Juventus's own internal structures (AIAPC — Italian Association of Football Coaches and Trainers 2026). Below the first team, Juventus maintains dedicated analysts for the lower tiers: Matteo Poletti serves as Second Team (Next Gen) Match Analyst, having studied at the Università Cattolica del Sacro Cuore, while Alessio Varzi covers the U20 level, with a degree from the Università Telematica San Raffaele Roma. This pyramid structure – first team, second team, youth – is distinctive to Juventus and reflects the club's investment in continuity of analytical methodology across age groups.

Cagliari (3 members). The presence of a "Head of" title at a mid-table club is itself an analytically important finding. Davide Marfella serves as Head of Match Analysis Area, with Matteo Battilana as match analyst and Giovanni Venturelli as a technical collaborator responsible for tactical recordings. The Cagliari case suggests that hierarchical formalisation is not limited to the financial elite of the league but is spreading to the middle tier – a process that, if confirmed over time, would indicate a structural maturation of the role across Italian professional football.

Como (2 members, UK-style model). The Como case is particularly instructive because it represents the importation of an English front-office model into the Italian league. Chris Galley, a British professional, holds the title of Head of Strategy & Data Analytics – a role that explicitly combines strategy, data analytics, and recruitment, and is therefore *not* a traditional match analyst position. Transfermarkt listed Galley as "Video Analyst," but his LinkedIn profile reveals a substantially more senior and strategic function. Alongside Galley, Dani Suryadi serves as Video Analyst in the more conventional sense. The distinction is conceptually important: Galley's role belongs to the *front-office* data-analytics tradition (closer to the model pioneered in the Premier League and in American sports), while Suryadi's belongs to the *backroom* video-analysis tradition. Both coexist within the same club but serve fundamentally different purposes.

Other multi-person departments Several other clubs maintain departments of two or more analysts without the formal "Head of" designation observed above:

- **Milan (3 members):** Francesco Calone (Match Analyst, 1st team; Università degli Studi di Milano), Igor Quaia (Match Analyst), and Giorgio Tenca (Performance Analyst – a data-heavy, physical-performance orientation rather than a purely tactical one). The names Nélson Diogo Duarte and Roberto Ferrari, present in earlier compilations, belonged to the 2024/25 (Fonseca) staff and are not part of the 2025/26 department under Allegri.
- **Parma (3 members):** an unusually structured department for a promoted club, comprising Mathieu Lacome (Head of Performance & Analytics – a French academic with a PhD in sports science and a degree from HEC Paris, representing perhaps the most academically credentialled analyst in the league), Fabio Corradini (Head of Game Analysis), and Simone Salvo (Game Analyst). The dual-head structure – one for performance/data, one for game/tactical analysis – is a deliberate organisational choice that separates physical analytics from tactical analysis.
- **Fiorentina (4 members):** Simone Formica, Andrea Tordi, and Lorenzo Sandri at first-team level, with Lorenzo Pinzauti dedicated to the U18 – another example of vertical integration between the senior squad and the youth sector.
- **Bologna (3 members):** Stefano Firicano and Paolo Riela as match analysts, plus Yuri Dell'Atti as Chief Data Analyst. The Dell'Atti title implies a club-wide data function (scouting metrics, recruitment modelling, financial analytics) rather than the tactical analysis of the individual match.
- **Genoa (3 members):** Mirco Vecchi, Hacim Halim Ali M'Bae, and Lorenzo Folle, all carrying the title of *Collaboratore Tecnico – Match Analyst.* The persistence of the "Collaboratore Tecnico" prefix in Italian club nomenclature is itself an indicator of the role's transitional status: it frames the analyst as an extension of the coaching staff rather than as an independent professional category.
- **Roma (1 member):** under Gian Piero Gasperini (2025/26) the match analyst is Simone Beccaccioli (degree from Università degli Studi Roma TRE). Michele Salzarulo and the group Checcucci, Gallo, Iodice and Terrinoni belonged to Daniele De Rossi's personal staff (2024/25) and left when the coach was replaced – a vivid illustration of how, in Italian football, the analysis unit is often tied to the head coach rather than to the club.

Three professional profiles coexisting in the same league The evidence collected allows us to identify three distinct professional profiles operating under the broad label of "match analyst" in Serie A 2025/26.

The first is the *coaching-track analyst*: a figure who holds a high UEFA coaching licence (A or Pro), was trained at Coverciano, and has a career rooted in the football pitch. The paradigmatic case is Filippo

Lorenzon (Inter, UEFA Pro), but Giuseppe Maiuri (Napoli, UEFA A Licence) also fits this category; Maiuri's official title – *Assistant Coach & Match Analyst / Video Analyst* – makes the hybridisation between coaching and analysis explicit.

The second is the *academically trained analyst*: a figure who holds a university degree, typically in sports science, statistics, political science, or management, and entered the profession through academic rather than coaching pathways. Examples include Riccardo Scirea (Juventus, Political Science + CONI), Francesco Calone (Milan, Università degli Studi di Milano), Matteo Poletti (Juventus Next Gen, Università Cattolica), and Simone Beccaccioli (Roma, Roma TRE).

The third is the *data-driven, front-office figure*: a newer profile, inspired by the English and American sporting analytics tradition, that operates more on strategic decision-making (recruitment, squad-building, performance optimisation) than on the tactical analysis of the individual match. Chris Galley (Como, Head of Strategy & Data Analytics) and Yuri Dell'Atti (Bologna, Chief Data Analyst) represent this category.

The coexistence of these three profiles within the same league is perhaps the clearest indication that the role has not yet crystallised into a single professional identity – a finding consistent, as noted above, with the heterogeneity that Francis, Kyte, and Bateman (2024) document even in the far more mature British market. The thesis can contribute to this debate by mapping the trajectories, qualifications, and organisational positions of these figures more systematically than has been done to date.

Chapter 3

Qualitative research: practitioner evidence

3.1 Research design and methodology

The systematic review of the academic literature and the documentary analysis of the Serie A database assembled in the Appendix provide a structural portrait of the match analyst: what the role is formally called, how many people occupy it, under what institutional framework they operate, and across what weekly rhythm their work is organised. What this evidence cannot easily provide is a ground-level account of how the work actually unfolds in practice, how the Italian market for analytics is structured from the supply side, or how practitioners themselves understand the trajectory of a profession that the academic literature still treats as largely invisible.

To address this gap, the present chapter draws on qualitative primary data gathered through *key informant interviews* – a methodology well established in organisational and management research (Patton 2002; Creswell and Poth 2018; Miles, Huberman, and Saldaña 2014). Key informant interviews differ from standard semi-structured interviews in that respondents are selected not to represent a statistical population but for the depth and specificity of knowledge they possess by virtue of their professional position. The aim is not generalisability in the survey sense but *analytical insight*: access to operational, market, and contextual knowledge that documentary sources alone cannot yield.

3.1.1 Interview design

Interviews were designed around a thematic guide developed iteratively from the literature review and the database analysis. The guide covers five thematic clusters: (i) the informant's career trajectory and entry into the profession; (ii) the operational structure of the working week and the matchday; (iii) the organisation and size of analysis departments; (iv) the technology and data infrastructure currently in use; and (v) the international comparative landscape. The guide was treated as flexible – questions were adjusted in sequence and depth depending on the informant's area of expertise – and was shared with respondents in advance upon request.

All interviews were conducted in Italian, audio-recorded with the informant's consent, and subsequently transcribed. Direct quotations reproduced in this chapter are translated by the author; the translations have been verified against the original transcripts. Citations follow the format "(Informant name, personal communication, date)".

3.1.2 Sample

The first interview was conducted in April 2026 with **Stefano Ferrè**, Communication and Match Analysis Manager at mApp Sport. Ferrè was selected as the opening informant because his position – at the boundary between an analytics provider and the broadcasting and club markets – offers a panoramic view of the Italian professional football analytics ecosystem that a club-embedded analyst could not provide. He has direct professional relationships with the analysis staff of all twenty Serie A clubs.

The second interview was conducted in May 2026 with **Matteo Matteotti**, Head of Data at Parma Calcio. Matteotti was identified on Ferrè's recommendation as one of the most technically advanced practitioners in Italian professional football, and was selected to provide the club-embedded perspective that the first interview explicitly could not. Parma is one of the few Serie A clubs to have built a fully proprietary data infrastructure, making it an analytically extreme case – not representative of the Italian average, but illuminating precisely because of that distance from the norm.

A third informant, Giovanni Marchese (Inter Milan), has been identified and will be contacted in the next phase of the research.

3.1.3 Analytical approach

Interview data were analysed thematically following the procedure proposed by Miles, Huberman, and Saldaña (2014): initial open coding of the transcript, followed by focused coding into higher-order thematic categories, followed by analytic memo writing to link emergent themes back to the conceptual framework developed in Chapter 1. Quotations were selected to illustrate thematic categories with maximum representativeness; they are not intended as exhaustive documentation of the interview but as evidentiary anchors for the analytical claims advanced in each section.

3.2 Informant profile: career trajectory as evidence

Before turning to the substantive themes, it is worth dwelling briefly on Ferrè's career trajectory, because the trajectory itself constitutes evidence about the profession.

Ferrè holds a bachelor's degree in Economics and a master's degree in Marketing Management, both from Bocconi University. After graduating he joined Varese Calcio – then competing in Serie B – in a communications and press office role. When the club was relegated and career prospects contracted, he left football for the international tourism sector, where he worked for three years. The return to the sports industry came in 2020, via a post-graduate master's in Sport Business Management that provided the professional network and the sector-specific credentials necessary to enter a data analytics company operating in professional football. He joined Math and Sport initially as an intern; the collaboration became permanent when both parties concluded they were a productive match.

Three features of this path are analytically significant, and each connects directly to evidence presented in Chapter 2.

First, the *absence of a sport-science or statistics background* is consistent with the educational heterogeneity documented in Figure 2.3. The chart shows no dominant pathway: degrees in economics, political science, and sports science sit alongside UEFA coaching licences and FIGC credentials, with no single profile predominating. Ferrè's Bocconi-plus-sport-master trajectory is one of several equally plausible routes into the profession.

Second, the *pivot through a non-football industry* is consistent with the thesis that the match analyst role lacks a codified entry pipeline. In a profession with a clear and established pathway – medicine, law, engineering – a multi-year detour would represent a significant career interruption. In a profession still constructing its institutional identity, it is simply one of several paths.

Third, the *role of the specialist master as the key credential* confirms a pattern already noted in the organisational literature on emerging professions: when academic routes are absent or underdeveloped, post-graduate intensive programmes become the de facto gatekeepers (Abbott 1988). The 2020 master is not a substitute for a codified degree; it is a market response to the absence of one.

3.3 The analytics supply chain: mApp Sport's market position

mApp Sport is the commercial brand under which the Milanese company *Math&Sport* operates in the professional football market. Math&Sport was established in 2016 within the PoliHub innovation hub of the Politecnico di Milano, emerging from Moxoff – itself a Politecnico di Milano spin-off specialising in industrial mathematical modelling and consulting – and was co-founded by mathematician Alfio Quarteroni and entrepreneur Ottavio Crivaro, the firm's current Chief Executive Officer (Math and Sport 2025). In 2021, Math&Sport was acquired by Adriano Bacconi and relocated its headquarters to the joint premises of EMG and Infront in Milan; Infront is one of the leading sports marketing groups in European football, and integration into this operational environment substantially expanded the firm's institutional network across broadcasting and club markets simultaneously (Math and Sport 2025). The company's core product has evolved over time: presented to Lega Serie A in 2019 under the name *Football Virtual Coach* at the Barça Sports Technology Symposium in Barcelona, it was formally adopted by the Lega in the second half of the 2019/20 season (Calcionews24 2020; N3XT

Sports 2020) and is now distributed commercially as *IM Coach* – a product name that gives rise to the "mApp Sport" brand identifier used in the football market segment. Both denominations refer to the same legal entity; the divergence between the corporate name (Math&Sport) and the commercial brand (mApp Sport) is worth noting because the two appear in different source types, with academic and journalistic references employing the former while practitioners in the Italian football market – including the informant interviewed for this thesis – use the latter as the operative name.

The company operates simultaneously in two market segments: content production for broadcasting (it supplies data-driven analytical content for Lega Serie A media products, DAZN, and *Cronache di Spogliatoio*) and analytics and software provision for professional clubs. This dual positioning places the company – and Ferrè as its representative – at the intersection of the three main institutional actors in the Italian professional football analytics ecosystem: the governing body (the Lega), the clubs, and the media.

3.3.1 The Lega distribution arrangement and the democratisation of analytics

Math and Sport's distribution arrangement with Lega Serie A has notable structural consequences. The Lega purchases mApp's analytical platform and makes it available to all twenty Serie A clubs at no additional cost. Ferrè frames this as a deliberate equalisation mechanism:

> "This tool – a tablet application that offers real-time tactical and analytical insights – allows for a kind of democratisation of innovation: every club can make use of it according to their needs." (Ferrè, personal communication, April 2026)

The arrangement has a consequence that is not immediately obvious from the department size data in Figure 2.1: even clubs at the lower end of the resource distribution – those with single-analyst departments, such as Lazio, Napoli, and Roma – have access to the same analytical platform as the top clubs, because access is bundled into the league membership. The diffusion of basic analytics infrastructure across the entire Serie A is therefore partly an artefact of institutional design rather than purely of market forces.

The adoption of mApp Sport rather than a larger, internationally established analytics provider requires some analytical unpacking. Several structural factors help explain the choice. First, mApp Sport's origin within the PoliHub innovation network of the Politecnico di Milano confers an academic legitimacy that is particularly effective in persuading a heterogeneous set of member clubs – some governed by executives sceptical of quantitative methods – to adopt a shared platform: association with a leading technical university serves as an institutional guarantee of quality in a way that a purely commercial vendor cannot replicate. Second, the dual positioning described above means that a single partner simultaneously enriches the Lega's broadcast product and equips its clubs with analytical tools, addressing two strategic objectives that would otherwise require two separate contractual relationships.

Third, the relatively compact size of mApp Sport as a domestic SME makes the relationship more amenable to the co-design logic that the three-tier service model described in Section 3.4 requires: the iterative, dialogue-intensive interaction between provider and client at Tier 2 (customised service) and Tier 3 (live matchday support) is structurally more feasible with a domestically embedded company than with a large publicly listed corporation.

Finally, and perhaps most structurally, the choice to externalise reflects a capacity constraint of the governing body itself. LaLiga developed an equivalent capability entirely in-house over fifteen seasons (see Section 3.7.2 below), but doing so required treating technology as a core institutional competency – hiring engineers, data scientists, and product managers in permanent positions – a step the Lega Serie A has not taken. Externalisation to mApp Sport is therefore not only a pragmatic preference but also a reflection of an organisation that has historically managed technology as a procured service rather than a built capability.

This observation adds nuance to the diffusion story told by the department-size chart. What varies across clubs is not access to data per se, but the *human capacity to use it*: the number of analysts, their technical sophistication, and the degree to which the head coach is willing to integrate analytical output into decision-making. Rein and Memmert (2016) argue that the bottleneck in the big-data era is interpretation, not acquisition; the Lega distribution arrangement is a direct illustration of that argument in practice.

3.3.2 Tracking data and the second tier of the market

Beyond the platform made available through the Lega, Ferrè identifies a distinct second tier of the analytics market centred on *tracking data* – the high-frequency positional data generated by optical systems such as Hawk-Eye, Second Spectrum, and ChyronHego (described in Section 2.2.3). These data are not included in the Lega arrangement and must be purchased separately. Their cost places them out of reach for most Serie A clubs, reinforcing the stratification already visible in Figure 2.1:

> "There is also the question of the type of data available. It is not just about consulting: it is about buying the data itself – buying tracking data, which are the more valuable data that allow deeper analyses." (Ferrè, personal communication, April 2026)

The implication is that the between-club inequality documented in the database is not only a matter of headcount but of data quality. A department of four at a top club with access to tracking data operates in a qualitatively different analytical environment from a single-analyst department at a mid-table club working solely with event-based data.

3.3.3 The data rights landscape: three parallel flows

Three parallel data flows characterise the Serie A data economy in ways that do not emerge directly from the informant interviews, yet are central to understanding the sector. Each flow operates under a different commercial logic and is directed toward a different market.

The first is the mApp Sport platform itself: the Lega purchases the service and distributes it to all twenty clubs at no additional cost, in the equalisation logic described in Section 3.3.1. The second is the direct provision of raw tracking data from the optical cameras installed in Serie A stadia, distributed by the Lega to member clubs as a feed that – as Matteotti reports in Section 3.9.3 – arrives at a precision and cadence superior to anything available on the commercial market. Together, these two flows represent the Lega's investment in its member clubs' sporting performance, financed from collective league revenues and provided as an infrastructure service.

The third flow is entirely distinct in its logic. Between 2021 and 2024, Stats Perform held the exclusive rights to distribute official Serie A match data and low-latency video streams to the global sports betting market. Following a competitive tender process opened by the Lega in June 2025 – covering five packages encompassing international and domestic sports betting data, video streaming, and a tracking data package for betting applications – Genius Sports was awarded the exclusive official data and betting video streaming rights through the end of the 2028/29 season (Business Wire 2025; SBC News 2025). This arrangement inverts the logic of the first two flows entirely: rather than the Lega bearing the cost of providing data to clubs for sporting purposes, it monetises the data asset by selling exclusive distribution rights to a commercial intermediary, who then charges its global sportsbook clients for access.

The analytical interest of this three-flow model lies in what it reveals about the data ownership structure underpinning the Italian football analytics economy. The positional data generated by optical cameras in Serie A stadia appears to serve as the common input to all three flows simultaneously: it feeds the mApp Sport dashboard available to clubs, the raw tracking stream distributed directly to technically advanced clubs such as Parma, and the commercial betting data package licensed to Genius Sports. The contractual architecture that allows these three uses to coexist – and in particular whether Genius Sports' exclusive commercial rights constrain the Lega's ability to distribute the same raw positional feed to clubs for sporting purposes – is not determinable from publicly available sources. This ambiguity reflects a broader unresolved question in the political economy of sports data: who owns the data generated in a professional football match, and on what terms can it be simultaneously deployed for sporting and commercial ends. The question is not merely academic; as tracking data becomes the primary input to advanced club-level analytics, its governance has direct implications for the structural inequality between clubs that the mApp distribution arrangement was designed, at least in part, to address.

3.4 Three service tiers and the depth of analytical integration

Ferrè articulates a clear taxonomy of the services that mApp provides to clubs. The taxonomy is not merely a commercial description: each tier corresponds to a qualitatively different relationship between the external provider and the club's internal staff, and by extension to a different model of how analytical output is integrated into the coaching process. Wright, Atkins, and Jones (2012) identify the coach–analyst relationship as the critical variable in determining whether data actually influences decisions; this taxonomy operationalises that variable at the market level.

Tier 1: standard service The club purchases a predefined product – a set of reports (opponent analysis, individual player profiles, team-level KPI summaries) whose structure and content are fixed by the provider. The club's staff receive the output without having shaped its design. This is the most transactional form of the relationship and corresponds to what Wright, Atkins, and Jones (2012) term passive consumption: the analytical work is complete before the club engages with it. The head coach can use it, ignore it, or selectively reference it; the provider has no visibility into which of these outcomes occurs.

Tier 2: customised service Club and provider co-design bespoke reports or bespoke algorithms tailored to the club's specific strategic priorities, the head coach's tactical philosophy, and the analyst department's workflows. This tier requires iterative dialogue and commands a premium over the standard product. It corresponds to what Wright, Atkins, Jones, and Todd (2013) describe as the entry of performance analysis into the decision-making cycle: the analytical product is shaped by the coaching staff's priorities before it is produced, which makes it more likely to be actionable.

Tier 3: real-time matchday service An external analyst from Math and Sport, already proficient with the platform, operates alongside the club's internal staff on matchday: performing live tagging, monitoring tactical patterns as they emerge, and assisting in the compilation of the half-time clip package. This tier addresses a genuine resource constraint. As Ferrè explains:

> "During the match the resources we have are just sufficient, because one person must handle video cuts and another must monitor the live dashboard. Having an additional external resource who already knows the product and the tool is a significant advantage." (Ferrè, personal communication, April 2026)

The matchday tier is the highest-integration form of the relationship, and also the one where the distinction between internal and external analyst becomes most operationally blurred. An external provider performing live coding alongside the internal staff is functionally indistinguishable from an additional staff member for the duration of the match.

Taken together, the three tiers provide a market-level operationalisation of the analyst–coach integration spectrum that the literature (Wright, Atkins, and Jones 2012; Wright, Atkins, Jones, and Todd 2013) describes but rarely quantifies. They also suggest that the "depth of integration" is not a fixed organisational property but a variable that clubs can adjust by selecting a different service tier from the same provider.

3.5 The internalisation trend: from reports to API feeds

One of the most strategically significant observations in the interview concerns the direction of travel for the most analytically advanced clubs. Rather than purchasing finished reports from external providers, leading clubs are increasingly building proprietary data platforms into which they ingest raw KPI feeds from multiple providers, combining them with internally generated data and data from other commercial sources. Ferrè describes this shift in terms of what clubs are requesting:

> "Clubs want to develop and manage data in their own proprietary platform. The tendency will increasingly be to supply them with finished reports *or* with initial KPIs – indicators that we compute – which they can integrate into the data portfolio they already have on their platform." (Ferrè, personal communication, April 2026)

This is a significant structural change in the analytics supply chain, and it has direct implications for the profile of the in-house analyst. A role currently centred on video coding and the consumption of finished reports will need to evolve toward data-engineering and integration competencies: the ability to query and maintain databases, manage API connections, write data transformation scripts, and operate within proprietary analytical environments that aggregate feeds from heterogeneous sources.

This trajectory is not unique to Italian football. It mirrors the broader transition described by Herold et al. (2019) and by the systematic review of Goes et al. (2021): as the volume and variety of available data increase, the bottleneck shifts from data access to data architecture and interpretation, and the integration of position-based big data into tactical analysis becomes the field's central methodological challenge. Clubs that currently rely on a video analyst to read predefined dashboards will, on this trajectory, increasingly require someone capable of building and maintaining the dashboards themselves.

The internalisation trend also raises a question about the role of the external provider. If the value-added progressively migrates from finished products to raw data feeds, then the provider's competitive position rests less on the quality of its reports and more on the quality and granularity of its underlying data infrastructure – and specifically on access to tracking data, as discussed in Section 3.3.2.

3.6 Operational validation of the weekly cycle

Ferrè's account of the analyst's standard working week is substantially consistent with the reconstruction offered in Section 2.2 of Chapter 2, built from the academic literature and the LinkedIn profiles of Serie A analysts. He identifies the same three parallel axes of work – self-analysis of the team's own performance, opposition analysis, and direct training support – and confirms the same temporal logic:

- **MD+1:** post-match coding, initial KPI extraction, compilation of individual player clips.
- **MD+2 / MD−5:** distribution of individual clips to players and coaches; beginning of opposition analysis (downloading footage, initial coding).

- **MD−4 / MD−3:** construction of the opposition dossier; preparation of training-session clips; initial briefing with the head coach on opposition priorities.
- **MD−2 / MD−1:** refinement of the dossier; preparation of the team meeting presentation; individual briefings for specific players; technical set-up for matchday.
- **Matchday:** real-time tagging; half-time clip package; flash report.

The interview does not contradict any element of this reconstruction; it validates and densifies it with the authority of daily professional experience. What it adds, beyond confirmation, are two observations that the literature does not capture.

3.6.1 Compressed microcycles: specialisation over subdivision

When clubs have two competitive fixtures within a single week – a pattern increasingly common in Serie A with European competition and the Coppa Italia – the analyst's workload does not simply compress: the available time is approximately halved while the volume of required output remains essentially constant. Ferrè notes that in well-staffed departments this is managed through *parallel assignment by competition* (one analyst covers the Serie A fixture, another covers the cup fixture) rather than through a functional division of labour:

> "What I notice is more that work compresses – everyone does the same things they always do, just with less time. The real differentiation I see today is more linked to set pieces, which tend to be separated from the analyst's core work." (Ferrè, personal communication, April 2026)

This is an important qualification of the role taxonomy shown in Figure 2.2. The chart identifies distinct role titles – *Head of*, *Match Analyst*, *Performance Analyst*, *Video Analyst* – which might suggest a clean horizontal division of labour by function. Ferrè's observation suggests that in practice the division is more often by competition (which fixture you are responsible for) than by analytical function (what type of analysis you perform), at least at the current stage of departmental development in Serie A.

3.6.2 The set-piece exception

The one consistent functional differentiation Ferrè identifies is the delegation of set-piece analysis to a dedicated *collaboratore tecnico*:

> "You tend to delegate the set-piece component – both in possession and out of possession – in order to lighten the analyst's workload when there are many matches. If you also have to prepare every set-piece situation in attack and defence, it becomes too much." (Ferrè, personal communication, April 2026)

This delegation pattern deserves attention beyond its operational logic. Set pieces are among the most consequential and most analytically demanding phases of the game: they account for a disproportionate share of goals in professional football (Sarmento et al. 2014) and require detailed frame-by-frame video analysis, positional mapping, and tactical modelling. The emergence of a distinct *set-piece specialist* sub-role – visible in some of the role titles captured in Figure 2.2, where "*collaboratore tecnico*" appears in grey – marks an early phase of functional specialisation within departments that were previously organised around a single generalist analyst.

From a sociological standpoint this is consistent with Abbott's (1988) theory of professional systems: as the volume and complexity of work increase, a jurisdictional competition emerges within and between adjacent roles, and specialised sub-roles crystallise around those areas of work that are simultaneously high-stakes, time-consuming, and technically distinctive enough to justify a dedicated practitioner.

3.7 Italy in comparative perspective: England and Spain

Ferrè's comparative observations are based not on systematic research but on professional contacts and direct observation; they should be read accordingly. They are nonetheless analytically valuable as a practitioner's calibration of the Italian market relative to its European peers.

3.7.1 England: budget, institutional infrastructure, and the coaching degree

The primary structural difference between Italy and England, in Ferrè's account, is not technological but institutional. It is not that English clubs have better software or more sophisticated algorithms; it is that they operate within an educational system that has formalised the football coaching profession at the university level. England has a recognised undergraduate degree in football coaching; Italy does not:

> "In England there is a recognised university degree in football coaching. In Italy we make do: post-graduate masters or bespoke courses. The educational structure is quite different there – and that helps, because there is a market, and where there is a market everything flows more easily. In Italy there is no market, because the figure is still not widely recognised – except at the top, in Serie A and in a few Serie B clubs." (Ferrè, personal communication, April 2026)

The causal mechanism Ferrè identifies is a self-reinforcing cycle: without a formal degree, the profession lacks institutional recognition; without recognition, the labour market remains thin; without a thick labour market, there is no economic incentive to create the degree. The Italian situation is a low-equilibrium trap of the kind described in the literature on emerging professions (Abbott 1988).

A notable counterpoint is the international reputation of Italian football coaching: a significant number of Italian professionals now work as analysts for English Premier League clubs and for the Football Association. This suggests that the problem is not one of competence but of domestic institutional architecture – a distinction worth making in a thesis that is, in part, an argument for greater institutional investment in the role in Italy.

The structural argument about educational credentials is complemented by a data infrastructure that, at the league level, is substantially more developed than Serie A's. Premier League clubs benefit from a league-wide tracking provision through Second Spectrum, which supplies three-dimensional positional coordinates for all 22 players and the ball at 25 frames per second across all fixtures, supplemented by event data from Opta/Stats Perform; the league uses an Oracle Cloud infrastructure for advanced aggregate analytics, processing over 10 billion data points from a full season of 380 matches for statistical and award-related applications (Oracle 2024). At the club level, available evidence suggests that approximately 75 per cent of Premier League clubs maintained dedicated analytics teams as of the 2024/25 season, with average staffing growing from four to six personnel between 2020 and 2025; the most analytically invested clubs allocate between £1 million and £5 million annually to analytics functions (Sportblog-Online 2024). These figures define an investment range that is structurally unreachable for most Serie A clubs and that reflects not an absence of ambition but an absence of the revenue base – Premier League domestic television rights are approximately three times the Serie A equivalent – that would be required to finance comparable activity. The English case thus presents a double gap relative to Italy: an institutional gap (the presence of a recognised undergraduate pathway) and a financial one (the revenue differential), with each reinforcing the other in a way that makes the distance difficult to close through either measure alone.

3.7.2 Spain: accessible formation and the media visibility of data

LaLiga is described as broadly comparable to Serie A in terms of staff structures, but with two meaningful differences. The first is a lower barrier to entry into football education, which produces a larger pool of trained practitioners. The second is more surprising: the systematic on-screen integration of data during live match broadcasts.

> "In Spain they are ahead on the media side too: you watch a LaLiga match and you immediately notice how data is front and centre on screen. This helps the whole ecosystem: if you show it, you give it visibility; if you give it visibility it acquires notoriety; if it acquires notoriety it acquires credibility; and credibility means that not only the data but also the role of the person who works with it is recognised." (Ferrè, personal communication, April 2026)

This passage introduces a mechanism of professional legitimation that the academic literature on performance analysis has not explored: the role of *media representation* in constructing occupational credibility. The argument is that the public normalisation of data in football broadcasts – the on-screen display of xG, pressing intensity, or positional heatmaps – signals to viewers, club executives, and potential analysts alike that this type of knowledge is valued, credible, and professionally consequential. Over time this signal shapes hiring practices, educational investment, and public discourse in ways that reinforce the legitimacy of the role.

This is consistent with Abbott's (1988) account of how professions compete for jurisdictional control: visibility in public arenas is not merely a marketing outcome but a constitutive element of professional authority. The fact that Ferrè explicitly situates Math and Sport's broadcasting partnerships (with Lega Serie A, DAZN, and *Cronache di Spogliatoio*) within this legitimation logic suggests a deliberate institutional strategy: producing data-driven broadcast content is not only a revenue stream but a contribution to the professional ecosystem in which mApp operates.

The scale and technical depth of the Spanish platform also merit more precise documentation than the practitioner account alone provides. Mediacoach, operational since the 2010/11 season, captures data through 16 optical tracking cameras per stadium, generating approximately 3.5 million data points per match; it provides clubs with more than 6,400 unique metrics and produces in excess of 112,000 analytical reports per season across the 42 participating clubs in the first two divisions (LaLiga 2022). Its technical stack has progressively migrated to a cloud-native architecture centred on Microsoft Azure, with Azure Databricks processing advanced metrics and Power BI handling visualisation; the *Beyond Stats* collaboration with Microsoft has made more than fifty game-enhancing metrics available to clubs and broadcasters (LaLiga 2022). In July 2025, Mediacoach was rebranded as *Sportian Performance*, reflecting a deepened partnership with Sportian, the sports technology division of Globant, alongside the establishment of an internal LaLiga *Football Intelligence & Performance* unit that provides clubs with ongoing technical support and workshops (LaLiga 2025). A new advanced environment, *Mediacoach Sandbox*, allows clubs with in-house data engineering capacity to process raw positional data directly in a secure Databricks workspace. This last development mirrors, at the league level and for all technically capable clubs, the arrangement that Parma Calcio has negotiated individually with the Lega Serie A through the raw tracking feed described in Section 3.3.2: the frontier that Parma currently occupies as an outlier within the Italian market is, in Spain, the standardised provision that LaLiga extends to every one of its forty-two member clubs. The distance between the two leagues' institutional ambitions for their data ecosystems is measured precisely by this gap.

3.7.3 Germany: the broadcast-first analytics model

The Bundesliga, managed by the DFL (*Deutsche Fußball Liga*), offers a third European model worth examining. Its strategic approach to data and analytics differs in orientation from both the Serie A and LaLiga models: where the latter two have prioritised the provision of operational analytics tools to member clubs, the DFL has invested primarily in the broadcast and fan-engagement dimensions of data.

The DFL entered a partnership with Amazon Web Services (AWS) in 2020 and expanded it substantially in March 2024, when AWS became not only the league's official technology provider but also its official generative artificial intelligence provider (DFL Deutsche Fußball Liga 2024). The technical infrastructure captures approximately 3.6 million data points per match through up to 20 optical tracking cameras per stadium; these data are processed through AWS cloud infrastructure and delivered through the *Bundesliga Match Facts powered by AWS* product set, which provides metrics such as expected goals, pressing intensity, and match momentum indicators to broadcasters and digital platforms worldwide (DFL Deutsche Fußball Liga 2024). The Match Facts product is oriented toward fan experience and broadcast enrichment; it is not a club-facing operational analytics tool of the kind that Mediacoach or IM Coach represent. The DFL does not distribute a centralised performance analytics platform to its member clubs: Bundesliga clubs develop their own analytical capabilities autonomously, each engaging commercial providers on individual contractual terms.

For the comparative argument of this thesis, the Bundesliga model introduces a conceptually important distinction. The sophistication of a league's broadcast analytics product and the analytical development of its member clubs are not the same variable and need not move together: a league can invest heavily in real-time data visualisation for television audiences while its clubs remain analytically underdeveloped at the operational level, and vice versa. The DFL case suggests that the broadcast-facing and club-facing dimensions of the football analytics economy can be managed through fundamentally different institutional logics. Ferrè's observation that Spain is ahead "on the media side too" (Section 3.7.2) is consistent with this distinction: what distinguishes LaLiga from both Serie A and the Bundesliga is that it has invested in both dimensions simultaneously, building the only platform in European football that serves clubs operationally *and* enriches broadcast content from the same underlying data infrastructure.

3.8 The role today: a profession still in formation

Two observations from the final part of the interview bear directly on the long-run trajectory of the match analyst role.

3.8.1 The analyst as a stepping stone: the UEFA licence and career mobility

Ferrè notes that many Italian analysts pursue UEFA coaching licences concurrently with their analyst work. The motive is pragmatic: a UEFA licence is required to occupy a bench seat as a *collaboratore tecnico*, a position that is structurally closer to the head coach, more visible within the club, and more portable across employers – since coaches routinely bring their personal staff when they move between clubs, in a way they rarely do for analysts:

> "Being an analyst is a way to gain great experience, acquire knowledge, and have the possibility of a horizontal move – becoming a technical collaborator. When a coach joins a new club he typically wants to bring two people: his assistant and perhaps a fitness coach or a technical collaborator. He will rarely bring the analyst. It is difficult." (Ferrè, personal communication, April 2026)

This observation identifies a structural tension at the heart of the role. The analyst's professional value is largely relational and club-specific: it is embedded in knowledge of the club's data infrastructure, the head coach's preferences, and the team's tactical history – precisely the kind of knowledge that does not travel well when a coach leaves. By contrast, a *collaboratore tecnico* with a UEFA licence is portable by design: the licence certifies a set of competencies recognised across all clubs and competitions, and the coach–collaborator relationship is one of personal loyalty rather than institutional embedding.

The implication is a persistent *retention problem*: the analysts most likely to leave for coaching positions are precisely those who have accumulated the deepest institutional knowledge, because they are the ones good enough to be wanted as technical collaborators. This revolving-door dynamic helps explain the limited seniority visible in the educational profiles of Figure 2.3 and is consistent with the absence of recognised senior credentials in the current Serie A analyst population.

3.8.2 Video analysis versus data analysis: the current frontier

Ferrè's most direct assessment of where the role currently stands on the analytical sophistication spectrum is unambiguous:

> "The analyst role is gaining ground, it is growing – but it is still mainly a video-analysis role rather than a data-analysis role. It still has a long way to go." (Ferrè, personal communication, April 2026)

This statement provides a practitioner's anchor for the main conceptual axis of this thesis. The literature review in Chapter 2 documented the academic trajectory from notational analysis to big-data analytics – from Reep and Benjamin in the late 1960s (Reep and Benjamin 1968) to the spatial-analytics paradigm of Memmert, Lemmink, and Sampaio (2017) and the machine learning applications surveyed by Herold et al. (2019). That trajectory describes what the technology makes possible; Ferrè's observation describes what the profession, in the Italian context, actually does.

The gap between the two is the field this thesis inhabits. The Italian match analyst of 2025–26 is predominantly a video analyst who codes footage, builds clip packages, and presents findings in team meetings. He (and, as Figure 2.3 indicates, it is almost always a he) operates in an institutional environment where the role is only recently formally recognised, where the educational infrastructure is underdeveloped, and where the dominant career incentive is to *leave* the analyst role for a coaching role rather than to develop within it. In this environment, the transition from video analysis to data analysis is not simply a matter of technology adoption; it is a matter of institutional investment, labour-market development, and professional identity construction.

3.9 Second informant: Matteo Matteotti, Head of Data, Parma Calcio

3.9.1 Informant profile: an engineering pathway into professional football

Matteotti holds a bachelor's degree in Statistics and a master's degree in Computer Engineering from Politecnico di Torino. The contrast with Ferrè's economics and marketing background is immediate and analytically significant: two of the most technically accomplished practitioners in Italian Serie A arrived at the same destination via routes that share no academic common ground whatsoever. The observation reinforces the structural heterogeneity documented in Figure 2.3 and suggests that the role's entry conditions are currently governed by individual initiative and informal networks rather than by any canonical educational pipeline.

The entry itself is equally instructive. While completing his master's degree in 2022, Matteotti discovered football analytics through YouTube and subsequently identified an open data scientist position at Parma on LinkedIn. Unable to apply formally – he had not yet completed his degree – he contacted the hiring manager directly and proposed an unpaid remote internship of approximately 300 hours. The offer was accepted. After the internship he continued contributing voluntarily, completing his thesis on machine learning in the interim, and received a formal employment offer in July 2023. He joined as a data engineer – the most technically oriented profile in the department – and was promoted to Head of Data in April 2025 following the departure of his predecessor.

This trajectory contains two features that are analytically relevant beyond the biographical. First, the unpaid internship as the de facto entry mechanism confirms a pattern already noted in the literature on emerging professions and visible in Figure 2.3: in the absence of formal degree pipelines, aspirant practitioners absorb the cost of credentialling through volunteered labour. Second, the speed of progression from intern to departmental head – approximately two and a half years – is consistent with the shallow seniority distribution observed across Serie A analysis departments, where the absence of established career ladders compresses hierarchies and accelerates advancement for those with the right technical profile.

3.9.2 Organisational architecture: separating data from analysis

To understand the separation that follows, it is first necessary to establish the dual leadership architecture within which Matteotti's role is situated. The Performance & Analytics department at Parma Calcio is led by Mathieu Lacome, who holds the title of *Chief Performance & Analytics Officer* since August 2021. Section 2.2.4 of this thesis identifies Lacome, alongside Fabio Corradini (Head of Game

Analysis) and Simone Salvo (Game Analyst), as constituting Parma's unusually structured analytical department – described there as a dual-head architecture that explicitly separates performance science and data analytics from tactical game analysis. Prior to his arrival at Parma, Lacome served as Head of Research and Innovation at Paris Saint-Germain, and has maintained a parallel academic profile over the course of his practitioner career (Lacome 2023). He describes his mandate in terms that make the ambition of the project unmistakable: "My remit is to make sure the department is working well and serving scouts, coaches and management and that every decision has data embedded in the process" (Lacome 2023). When he arrived in 2021, he found "no data nor analytics capabilities on the sporting side of the club" (Lacome 2023); the infrastructure described in the present chapter was therefore built from zero over approximately four years.

Matteotti operates within this structure as Head of Data, a role focused on the technical data infrastructure – the pipelines, the models, the automated reporting architecture – rather than on performance science or match analysis. The separation between these two functions is not incidental but architecturally deliberate. Parma's most distinctive structural feature is the explicit institutional separation between the data team and the match analysis team: both units sit within the same Performance department, but they perform different functions, report through different lines, and interact with the coaching staff in qualitatively different ways.

The match analysts at Parma are permanent club employees. This is a deliberately chosen institutional design, and Matteotti articulates its rationale in terms of organisational continuity: in the sixteen months preceding the interview, Parma had employed three different head coaches. Had the data and analysis function been structured around coach loyalty – as Ferrè described for the analyst-as-*collaboratore-tecnico* pathway – the department's accumulated institutional knowledge would have turned over three times. By anchoring the analysis staff to the club rather than to any specific coach, the organisation preserves the analytical memory of previous match cycles, player profiling work, and tactical datasets across managerial transitions.

The communication architecture that follows from this design is equally deliberate. The data team's primary interlocutor is not the head coach but the match analyst:

> "Our point of contact is the match analyst. We have had three coaches in sixteen months – if every time we had to rebuild the communication channel with the coach it would be chaos. So we work with the match analyst and it is his job to interface with the coaching staff." (Matteotti, personal communication, May 2026)

This institutional arrangement has a direct implication for the conceptual map of the role drawn in Chapter 2. The literature and the Ferrè interview both treat the analyst–coach relationship as the critical variable in determining whether analytical output influences decisions (Wright, Atkins, and Jones 2012). At Parma, this relationship is deliberately mediated: the data team generates the output, the match analyst translates and contextualises it, and the coach receives a filtered and operationally framed version. The "analyst–coach relationship" is not a single dyadic link but a three-node chain. Ad hoc requests do occasionally bypass the match analyst and reach the data team directly – typically for one-off quantitative queries generated by the coach's tactical curiosity – but systematic analysis flows through the established mediation structure.

3.9.3 In-house philosophy and proprietary data infrastructure

Parma's data team operates on an explicit philosophical commitment to full internalisation: no finished products are purchased from external analytics providers, and all models and pipelines are built and maintained in-house. Matteotti is direct about the reasoning:

> "As a philosophy we have never relied on external companies. Everything is built in-house. This allows us to really understand the models." (Matteotti, personal communication, May 2026)

This position stands at the opposite pole of the market from the standard and customised service tiers described by Ferrè in Section 3.4. Where those tiers represent degrees of reliance on an external provider, Parma's model represents the terminal case of the internalisation trend that Ferrè identified as the direction of travel for the most sophisticated clubs.

The practical architecture of the in-house approach is built on three data inputs. The first is external event data, purchased from commercial providers and ingested into Parma's own database infrastructure. The second is raw tracking data supplied directly by Lega Serie A, which distributes positional data from the optical systems installed in all Serie A stadia to its member clubs. Crucially, Matteotti specifies that the club uses only the raw positional feed from the Lega, not any pre-calculated metrics:

> "Recently the Lega has been sending tracking data from stadium cameras with a precision and delivery cadence far higher than anything we can buy from providers. We use those – but only the raw data, nothing calculated by them." (Matteotti, personal communication, May 2026)

The third input is internally collected physical and athletic test data, which is the only category of data generated directly by the club without any external component.

On top of this data infrastructure, the team has built its own implementations of standard football analytics models – expected goals, expected corners, and pass options – following the definitions published in academic white papers and replicating them internally rather than consuming vendor-supplied versions. The motive is epistemological as much as operational: building a model from first principles allows the team to audit its assumptions, modify its parameters for Parma's specific playing style, and explain its outputs to non-technical stakeholders without reliance on proprietary black boxes.

The in-house philosophy extends to scouting tooling. The club previously used a commercial scouting software platform at a cost of approximately €30,000 per year; the data team rebuilt the equivalent functionality in-house at a running cost of under €10 per month. The rebuilt platform is not only cheaper but more flexible: it is tailored to Parma's specific scouting workflows, integrates directly with the club's data infrastructure, and is not subject to vendor lock-in or pricing volatility.

3.9.4 Automated reporting and the expansion of analytical scope

Perhaps the most consequential operational decision Parma's data team has made is the automation of its routine reporting pipeline. Both the pre-game and the post-game dashboards are generated and delivered automatically, without manual intervention:

> "We have built dashboards for the match analysts, both pre-game and post-game, that are generated and delivered automatically – without us doing anything. Our job ends there. My objective and my team's objective is to make sure the post-game data arrives one minute after the final whistle and the scouting report on the opponent arrives the day after the match." (Matteotti, personal communication, May 2026)

The post-game dashboard is delivered within sixty seconds of the final whistle; the opposition scouting report arrives the following day. Neither requires a human to trigger, compile, or format it. The match analysts receive operational-quality analytical output as an infrastructure service rather than as a manually produced artefact.

The strategic logic Matteotti articulates is explicit: the more the routine is automated, the more residual human capacity is available for novel, high-value analytical work. In practice, this has allowed the data team to extend its activities well beyond the match-centred cycle that dominates the academic literature's description of the analyst's role (Carling, Williams, and Reilly 2005; Mackenzie and Cushion 2013). The team regularly produces analytical work for the medical and sports science staff, the nutritionist, the youth academy, the scouting department, and occasionally the club's commercial and brand functions. The working week is not structured around the match cycle at all; approximately thirty per cent of capacity is reserved for maintenance of existing systems, and the remaining seventy per cent is directed toward new analytical projects that may have no direct connection to the upcoming fixture.

This finding adds a dimension to the role taxonomy presented in Figure 2.2 that the chart cannot represent. The formal title "Head of Data" at Parma designates not a senior match analyst but the leader of what is functionally a small in-house technology and analytics consultancy operating across all performance-relevant departments of the club.

3.9.5 Matchday as a closed system

Parma's data team produces no live or half-time dashboards. The analytical pipeline terminates at the pre-game report; what happens during the ninety minutes is outside the data team's scope entirely. Matteotti's account of why is notable because he explicitly rules out the head coach's individual preference as the explanation:

> "We haven't managed to do anything live, because the matchday is somewhat sacred, a hard wall to penetrate. And it isn't even a question of the coach – we've had three coaches who were completely different from one another, younger, older, more open, less open, and yet matchday has always been sacred for all of them." (Matteotti, personal communication, May 2026)

This observation is significant precisely because it rules out the idiosyncratic explanation. If the closure of matchday to external data input were a personal preference of a single coach, it could be attributed to generational conservatism or tactical philosophy. The fact that three successive coaches – differing in age, background, and tactical orientation – all treat the match itself as impermeable to data-team input suggests that the boundary is institutional and cultural rather than personal. It reflects a shared professional norm within Italian football coaching: the match is the coach's domain, a space of real-time judgment and interpersonal authority that does not admit algorithmic mediation.

This finding extends Ferrè's observation that real-time analysis is the highest-integration and most operationally demanding service tier. At Parma, even a club with one of the most technically sophisticated data operations in Serie A, that tier is effectively inaccessible – not for lack of technical capacity but because the norm of matchday closure is held consistently across coaching appointments. The implication for the diffusion of real-time analytics in Italian football is significant: technical capability is not the binding constraint.

3.9.6 The Italian market: a practitioner's audit

Matteotti offers the most explicit and granular assessment of the Italian football analytics market provided by any informant in this research. He organises it around a binary: clubs that are doing data well, and clubs that are not.

> "There are two ways to do what we do: well, or poorly. Doing it poorly means having a department where someone with the title of Head of Data is actually a match analyst, or works on Excel, or works without any procedural structure – only on tasks that arrive on the day. Doing it well means understanding that a data department is in fact a technology department: it needs a person responsible for setting priorities and a vision in the short, medium, and long term." (Matteotti, personal communication, May 2026)

His assessment of how many Italian clubs meet the "doing it well" threshold is stark: in his view, only three – Parma, Inter, and Milan. The remainder either do not have a dedicated data function at all or have one that is structurally misaligned, typically because the role has been filled by a match analyst with a data-adjacent title rather than by a technically trained data professional operating within a properly architected department.

Matteotti is careful to frame this not as a normative judgment about what clubs should do, but as a pragmatic observation about the conditions under which data investment generates value. A misaligned or purely cosmetic data function, he argues, is not merely ineffective – it is potentially damaging, because it consumes resources and management attention without producing reliable analytical output:

> "It isn't that there is a right answer and a wrong answer – but doing it badly is genuinely worse than not doing it. Rather than building something half-hearted, I would rather a club spend that money on scouting and take the data from a provider. That's perfectly fine." (Matteotti, personal communication, May 2026)

He is equally careful to note the limits of the performance argument: the correlation between analytical infrastructure and sporting results is not established, and the absence of a data department is not evidence of poor management. The empirical basis for this caveat acquired additional weight in the weeks immediately preceding the interview, when Napoli secured a fourth *Scudetto* in the 2024/25 season under Antonio Conte (Il Post 2025). Napoli has thus won two of the four most recent Serie A titles – the 2022/23 championship under Luciano Spalletti and the 2024/25 championship under Conte – without the type of structured data infrastructure that Matteotti defines as the condition for doing data "well": a record that his caveat explicitly acknowledges and that should give pause to any straightforward narrative equating analytical investment with competitive advantage in the Italian context. What differs between clubs, in his account, is not the likelihood of winning titles but the organisational philosophy of the ownership: Parma's American ownership brought a data-first culture from outside Italian football, whereas a historically Italian ownership structure would typically not have generated the same institutional appetite for quantitative analysis.

The ownership argument acquires broader analytical significance when set against the macrostructural pattern of foreign investment in Serie A. As of the 2025/26 season, nine of the twenty Serie A clubs are owned or co-owned by American or Canadian shareholders (Sportcal 2025); the group includes AC Milan (RedBird Capital Partners), Inter Milan (Oaktree Capital Management), and Parma (the Krause Group). The three clubs that Matteotti identifies as "doing data well" – Parma, Inter, and Milan – coincide precisely with this North American ownership cluster. This correspondence suggests a structural mechanism of cultural transfer: proprietors whose professional formation occurred in the North American sports environment bring institutional expectations about data investment that have been normalised in that context through decades of exposure to quantitative analytics in baseball, basketball, and American football (Lewis 2004; Morgulev, Azar, and Lidor 2018). Clubs with historically domestic Italian ownership structures have not been subject to the same institutional pressure toward quantitative formalisation, and their investment decisions reflect this difference. The implication for any forward projection of analytics diffusion in Serie A is that adoption is likely to proceed at a pace governed less by demonstrable competitive advantage – which, as the Napoli case illustrates, remains empirically ambiguous – and more by the rate at which foreign acquisition of clubs continues to import data-first management cultures from outside the Italian football tradition.

Turning to the international comparison, Matteotti's observation about England extends Ferrè's budgetary contrast to the level of organisational scale. Even Championship clubs – the second division of English football – maintain data departments of meaningful size and technical sophistication. He cites Leeds United, encountered when the club was still in the Championship, as an example of impressive analytical work produced with a limited budget through sound architecture and strategic focus. The lesson he draws is not about money but about institutional commitment: the English clubs he is aware of treat data as a core organisational function rather than as a support service, and they staff and resource it accordingly.

3.9.7 Demystifying data: simplification as a professional imperative

The final theme to emerge from the interview addresses a tension implicit throughout the thesis: the gap between how data-driven analysis is perceived by football's traditional power structure and what it actually consists of in daily practice. Matteotti argues that part of the Italian market's resistance to data investment is rooted in a systematic misrepresentation of complexity on both sides of the conversation.

> "The perception of what we do is that we're building NASA, that we're making algorithms and models and all sorts of things. In reality what we do is much simpler. When I was asked to analyse a player during the January transfer window, I didn't go looking for some exotic predictive model. I looked at how many of the available players were strong in the air and how many aerial duels they won, because we knew the kind of football we were playing and what we had asked of that position. I didn't do anything transcendental." (Matteotti, personal communication, May 2026)

The analytical output in this example – a one-page summary of a player's aerial contest record, calibrated against the team's stylistic requirements – is not technically demanding. Its value lies in the speed, consistency, and contextual fit with which it is delivered, not in its methodological sophistication. The infrastructure required to produce it reliably and at scale is complex; the output itself is not.

This distinction – between the complexity of the infrastructure and the simplicity of the deliverable – is central to Matteotti's vision of what data work in professional football should look like. It is also, he argues, the message that data professionals need to communicate more effectively to club directors and coaches: not "we build models" but "we answer your questions faster and more systematically than you can without us." The failure to simplify this message is, in his account, one of the reasons why data departments in Italian football are routinely under-resourced, misunderstood, and staffed with practitioners whose titles describe an ambition rather than a reality.

From a theoretical standpoint this observation connects to the interpretation bottleneck identified by Rein and Memmert (2016): the constraint on data-driven analysis in professional football is not computational but communicative. The challenge is not building the model; it is translating its output into a form that a head coach or sporting director can act on within the time and attention constraints of competitive football. Matteotti's emphasis on one-page deliverables, automated pipelines, and structured communication channels is, at the operational level, a direct response to that bottleneck.

3.10 Chapter summary

This chapter has reported and analysed two key informant interviews conducted with practitioners who occupy structurally distinct positions within the Italian professional football analytics ecosystem: Stefano Ferrè, operating from the supply side as Communication and Match Analysis Manager at the analytics provider mApp Sport, and Matteo Matteotti, embedded within a club as Head of Data at Parma Calcio. Reading the two interviews together produces a set of findings that neither could have generated alone.

The first concerns the structure of the Italian analytics market. The market is stratified across at least three dimensions simultaneously: by data access (event data versus tracking data, with tracking data commanding a significant price premium); by organisational model (external-provider reliance at one end of the spectrum, full in-house architecture at the other); and by the depth of integration between analytical output and coaching-staff decision-making. The Lega Serie A distribution arrangement provides a floor of analytical capability for all twenty clubs, but Matteotti's frank assessment – that only three clubs are currently operating effective data departments – suggests that the floor and the ceiling of Italian football analytics remain very far apart.

The second finding is an operational enrichment of the weekly cycle described in Section 2.2. Both informants confirm the same basic temporal structure: post-match self-analysis, opposition analysis across the midweek, and a match-preparation phase culminating in the team meeting. What the interviews add is an account of how this cycle is institutionally managed. At clubs with dedicated data departments, routine reporting is automated and delivered as infrastructure; the human analytical work is reserved for novel, higher-order tasks. The analyst's working week, properly understood, is not a cycle of manual report production but a rhythm of automated delivery punctuated by bespoke projects generated by the coaching staff's questions.

The third finding concerns the boundary of data-driven analysis at matchday. Both informants independently describe the match itself as a closed system into which quantitative input does not easily penetrate. Ferrè identifies real-time analysis as the highest-integration service tier, available only through external specialist provision; Matteotti reports that three successive coaches of different profiles and generations all treated matchday as impermeable to data-team involvement. Taken together, these observations suggest that the matchday boundary is not a coach-specific preference but a durable professional norm – one whose erosion, if it occurs at all, is likely to be slow and uneven.

The fourth finding is a comparative calibration of the Italian case against England and Spain. Italy lags England on budget, on the institutional infrastructure of professional football education, and on the absolute size of data departments. It lags Spain on the media visibility of analytical output, which both informants identify as a mechanism of professional legitimation whose absence in Italian broadcasts slows the public normalisation of data-driven work. These deficits are structural rather than cultural: they reflect institutional investment decisions that are, in principle, reversible.

The fifth finding, and the most theoretically consequential, is the organisational bifurcation between data teams and match analysis teams at the most analytically advanced clubs. At Parma, the data team does not attend analysis sessions, does not interact directly with the coaching staff except for ad hoc requests, and does not participate in the match-preparation communication chain. These functions belong to the match analysts, who are permanent club employees shielded from the turnover that accompanies coaching changes. This separation implies that the "match analyst" and the "data scientist" – roles that the literature often treats as points on a single continuum – may in practice be diverging into distinct professional identities with different educational profiles, different organisational positions, and different career trajectories. Whether this divergence will deepen as the Italian market matures, or whether a hybrid role will emerge that reintegrates the two functions, is among the most important open questions that the subsequent phases of this research will seek to address.

Chapter 4

The Coach and the Data: A Synthesis

The two preceding chapters have approached the match analyst role from complementary directions. Chapter 2 provided a structural portrait of the profession: its academic genealogy, its weekly operational rhythm, the regulatory framework within which it operates in Italy, and the heterogeneous organisational landscape of Serie A analysis departments. Chapter 3 enriched this structural portrait with practitioner testimony: two key informant interviews that together mapped the Italian football analytics ecosystem from both the supply side (mApp Sport) and the club-embedded perspective (Parma Calcio), surfacing findings about market stratification, technological trajectory, and the institutional norms that govern the integration of analytical output into coaching decisions.

The present chapter brings these two bodies of evidence together and reads them through the theoretical framework established in Chapter 1. Its central question is one that neither the structural analysis of Chapter 2 nor the practitioner interviews of Chapter 3 could address directly: how does the figure of the *head coach* – the primary decision-maker in a professional football club's sporting operations – relate to the data-driven analytical infrastructure that has developed around the match and the training week? How does data enter the coach's decision-making process, in what form, through what channels, and subject to what filters? And what does this relationship reveal about the general dynamics of data-driven decision-making in organisations, as theorised in Chapter 1?

The chapter is organised around four analytical themes. Section 4.1 examines the head coach as a decision-maker in organisational terms: the cognitive demands of the role, the information environment in which it operates, and the specific ways in which the dynamics of bounded rationality manifest in the coaching context. Section 4.2 traces, in integrated form, the pathways by which data enters the coaching process, distinguishing between the pre-match preparation phase, the in-match real-time phase, and the post-match review phase. Section 4.3 examines the structural and cultural barriers and enablers that determine the depth of data integration in the Italian professional context, drawing on both the interview evidence and the comparative European perspective. Section 4.4 addresses the organisational bifurcation between match analyst and data scientist roles that the most analytically advanced clubs are beginning to institutionalise, and considers its implications for the future development of the profession.

4.1 The Head Coach as Organisational Decision-Maker

The head coach of a professional football club occupies one of the most cognitively demanding decision-making roles in any contemporary organisational context. The structural features that make coaching decisions cognitively demanding are worth identifying precisely, because they determine the form in which analytical support can be most effectively provided.

4.1.1 Temporal compression and the decision horizon

The most immediately obvious feature of the coaching role is temporal: decisions must be made across a range of time horizons that span from the multi-year (squad-building, youth development philosophy, tactical style evolution) through the weekly (match preparation, training design, squad management) to the real-time (in-match substitutions, positional adjustments, set-piece targeting). Each of these horizons imposes different cognitive demands and different informational requirements. At the multi-year and weekly horizon, the coach operates in conditions that admit deliberate System 2 processing: the time available allows for the consultation of analytical reports, the review of video evidence, and the deliberate weighing of alternatives. At the real-time matchday horizon, however, the cognitive architecture of decision-making shifts entirely: the coach must read a continuously evolving tactical situation, identify relevant patterns from the dense stream of match events, form hypotheses about the opponent's adjustments, and implement responses – all within a time frame that admits only System 1 processing.

The vulnerability of System 1 processing to systematic error in sporting contexts is not merely a theoretical extrapolation: it is one of the most robustly documented findings of the sports analytics literature itself. Field-level analyses of elite professionals have repeatedly identified systematic departures from optimal behaviour – goalkeepers' action bias in penalty situations, the misperception of random sequences underlying the "hot hand" belief, referees' susceptibility to crowd pressure – among practitioners operating at the very highest levels of expertise in their own domain (Morgulev, Azar, and Lidor 2018). If world-class professionals exhibit these biases in the execution of their core tasks, there is no reason to expect the head coach's real-time tactical judgement to be exempt; and this is precisely the gap that pre-match analytical preparation is designed to narrow.

This temporal structure has a direct implication for the division of labour between coach and analyst. The match analyst's most consequential contribution occurs not during the match itself – where the time constraint reduces the cognitive accessibility of complex analytical output – but during the preparation phase, where the analyst's work converts raw information about the upcoming opponent into the pattern-recognition templates that the coach's System 1 can deploy during the ninety minutes. The opposition dossier, the team meeting presentation, and the individual player briefings described in Chapter 2 are, from a cognitive standpoint, *pre-loading* exercises: they install in the coach's working memory the tactical patterns most likely to be relevant during the match, so that when those patterns appear in real time the coach can recognise and respond to them with minimal deliberative effort. The analytical value of the pre-match preparation process is therefore not that it provides the coach with more information than they could otherwise access, but that it organises and distils available information into a form calibrated to the System 1 architecture that matchday decision-making demands.

4.1.2 The authority structure and the status of analytical knowledge

A second structural feature of the coaching role concerns its authority architecture. The head coach of a professional football club operates within an organisational hierarchy in which their authority over the technical domain – squad selection, tactical approach, training design – is both formally mandated and culturally reinforced. This authority is not merely administrative: it is constitutive of the coaching identity itself. The head coach's decisions are, in the dominant cultural framework of professional football, understood as expressions of a distinctive professional competency – "football intelligence," "tactical vision," "man-management" – that is qualitative, experiential, and personal rather than algorithmic.

This identity structure has predictable implications for the reception of analytical input. When the analytical team's output is consistent with the coach's existing tactical judgement, it is typically welcomed as confirmation: it provides evidential support for a conclusion already reached, and may be selectively communicated to players or the press as quantitative validation of the coach's approach. When the analytical output challenges or contradicts the coach's existing judgement, however, the reception is more complex. Wright, Atkins, and Jones (2012) document this dynamic empirically: more experienced coaches tend to integrate analytical output selectively, absorbing what confirms their vision and filtering out what does not; less experienced coaches may show greater deference to analytical evidence, but at the cost of a more passive relationship to the analytical process. In neither case is the analytical output simply adopted as an input to a neutral optimisation process; it is always interpreted through the filter of the coach's existing frame.

The implication for the analyst's communicative strategy is significant. Effective analytical communication in the coaching context is not simply a matter of producing accurate and methodologically rigorous output; it is a matter of presenting that output in a form that is navigable within the authority structure of the coaching relationship. The analyst who presents findings as challenges to the coach's judgement will be less effective than the analyst who presents them as resources that support and extend that judgement. This "framing constraint" is not a form of intellectual dishonesty; it is a necessary adaptation to the cognitive and social architecture of the decision environment.

4.1.3 The experience variable and the analyst–coach relationship

The evidence gathered in Chapters 2 and 3 consistently identifies the head coach's experience level as the primary variable determining whether and how analytical output is integrated into decision-making. Wright, Atkins, and Jones (2012) established this empirically: experienced coaches show a stronger tendency to use analytical output instrumentally – as a selective resource to be drawn on when it supports their own tactical conclusions – while less experienced coaches show greater openness to being guided by analytical evidence. Ferrè's observation that "being an analyst is a way to gain great experience... a horizontal move" toward the technical collaborator role implies, from the converse direction, that the analysts who succeed in penetrating the coach's decision process most effectively are those who have also developed a coaching-level understanding of the game – precisely the UEFA-licensed, Coverciano-trained analysts who occupy the most senior and coach-proximate positions in the Serie A landscape.

The experience variable also determines the stability of the analyst–coach relationship. Coaches with deep tactical convictions and a clear analytical vocabulary are more likely to develop a durable working relationship with the analyst that survives the inevitable mismatches between analytical recommendations and actual match outcomes. Less experienced coaches, or coaches in transitional phases of their career, may be more volatile in their use of analytical support – enthusiastic when results confirm the analytical predictions, dismissive when they do not. This volatility creates a structural risk for the analyst, whose professional credibility is partly a function of the perceived accuracy of their outputs and partly a function of the quality and stability of their relationship with the coach.

4.2 How Data Enters the Coaching Process

The pathways by which data enters the coaching process are not uniform across the weekly cycle. Three distinct phases can be identified – pre-match preparation, in-match real-time, and post-match review – each characterised by a different relationship between data availability, time constraint, and decision architecture.

4.2.1 The pre-match preparation phase: data as tactical scaffolding

The pre-match preparation phase, spanning from the day after the previous match through to the final hours before kick-off, is the phase in which data integration is deepest and most consequential. It is during this phase that the analytical output described in Chapter 2 – the opposition dossier, the individual player profiles, the set-piece analysis – is produced and communicated to the coaching staff, and that the coach's System 1 pattern-recognition templates for the upcoming match are formed.

The form of data integration in this phase is not the consumption of raw statistics but the translation of data into tactical narrative. The analyst does not present the coaching staff with a spreadsheet of passing completion percentages; they present a curated selection of video clips that illustrate specific tactical patterns, accompanied by a verbal or written commentary that connects those patterns to the team's tactical response. This translation is the core analytical task of the preparation phase, and its quality determines whether the data generates actionable coaching knowledge or remains inert informational noise.

The evidence from Chapter 3 reveals two additional dimensions of data integration in the preparation phase that are not visible in the academic literature's account. The first is the mediating role played by the match analyst in clubs with dedicated data teams: at Parma, the data team's automated dashboards and model outputs are not delivered directly to the head coach but are filtered and contextualised by the match analyst, who translates them into the tactical vocabulary of the coaching staff. This three-node chain – data team, match analyst, head coach – is a structural adaptation to the bounded rationality of the coach and to the authority dynamics described in the preceding section. The second dimension is the automation of the routine reporting pipeline: the fact that post-game dashboards and pre-game opposition scouting reports arrive automatically means that the match analyst's manual effort is reserved for the interpretation layer – the selection of relevant patterns, the construction of the tactical narrative, the identification of the specific details worth highlighting in the team meeting. Automation does not reduce the analyst's workload; it shifts it up the value chain, from data extraction to data interpretation.

4.2.2 The in-match phase: the matchday as a closed system

The in-match phase constitutes the most contested terrain in the entire data-coaching relationship. As documented in Chapter 3, both key informants – independently and from their respective positions within the Italian football analytics ecosystem – describe the match itself as a domain that is highly resistant to systematic data input. Ferrè identifies real-time analytical support as the highest-integration and most operationally demanding service tier, available only through the provision of external specialist staff. Matteotti reports that three successive Parma head coaches – differing in age, tactical background, and coaching philosophy – all treated matchday as impermeable to the data team's involvement.

The convergence of these two accounts is analytically significant. It rules out idiosyncratic explanation: the matchday boundary is not a product of any individual coach's conservatism but a durable professional norm. It can be explained with reference to the theoretical framework of Chapter 1 in the following terms. During the match, the coach operates in a high-stakes, real-time, socially observed decision environment in which the authority structure of the role is most publicly at stake. The introduction of external data input into this environment would not merely supplement the coach's decision-making; it would, in the cultural context of professional football, implicitly challenge their claim to autonomous expert authority over the match. The matchday boundary is therefore a boundary not of informational capacity but of professional jurisdiction – in exactly the sense described by Abbott (1988) in his account of how professions protect their jurisdictional claims from encroachment by adjacent knowledge systems.

The half-time clip package is the most striking illustration of this dynamic. The analyst can produce, under extreme time pressure, a precisely targeted video compilation designed to correct a specific tactical error or reinforce a specific tactical instruction; but the clip package is presented to the players not by the analyst but by the head coach, who selects from the analyst's materials what to show and frames the presentation within their own tactical authority. The analyst's contribution is substantively consequential but organisationally invisible: the decision-making credit, in the public and internal accounting of the match, belongs to the coach.

4.2.3 The post-match review phase: data as institutional memory

The post-match review phase – the MD+1 cycle described in Chapter 2 – is the phase in which data integration is most clearly institutionalised. The systematic archiving of match footage, performance data, and analytical codings constitutes the club's analytical memory: the longitudinal database from which trend analyses, player development trajectories, and tactical evolution studies can be constructed.

The institutional significance of this archiving function extends beyond its immediate operational utility. As Matteotti's account of Parma's organisational design makes clear, the anchoring of analytical staff to the club rather than to any individual coach is predicated precisely on the value of this accumulated institutional memory. When a head coach departs – as Parma's three coaches did in rapid succession over sixteen months – the analytical memory of previous tactical cycles, player performance histories, and opponent databases remains intact and available to the incoming coach. This continuity of analytical knowledge is, in an environment characterised by high coaching turnover, itself a significant competitive asset: it allows each new coach to begin their tactical preparation not from zero but from a rich historical baseline assembled by the club's analysis team.

The post-match phase also constitutes the primary occasion for the individual player feedback that Chapter 2 describes as central to the analyst's weekly cycle. The distribution of individual clip packages – curated video sequences illustrating each player's key actions from the previous match – is an exercise in data translation at the individual level: it converts the analyst's systematic coding into the form of evidence most directly usable by the player, whose improvement in the next match depends not on access to aggregate statistics but on the specific, contextualised visual evidence of their own actions. This individual feedback function is analytically important because it positions the analyst not only as a support function for the coaching staff but as a direct contributor to player development – a dimension of the role that is underrepresented in the academic literature and that gives the analyst a professional foothold independent of any individual coach's preferences.

4.3 Barriers and Enablers: The Italian Case in European Perspective

The evidence assembled in this thesis identifies a set of structural and cultural factors that determine the depth of data integration in the Italian professional football context. Understanding these factors, and their relative weight, is essential to any assessment of the trajectory of the match analyst role in Italy.

4.3.1 Structural barriers

Three structural barriers are clearly documented in the evidence. The first is the *educational deficit*: Italy lacks the formalised pathway for football-related analytical education that England possesses in the form of undergraduate degrees in football coaching and sports analytics, and that Spain has partially addressed through accessible post-graduation formation. The absence of a canonical educational pipeline means that the Italian match analyst labour market is thin, entry criteria are heterogeneous, and the professionalisation of the role proceeds more slowly than in markets where institutional credentials provide a clear selection mechanism. Ferrè's account of the low-equilibrium trap – no degree, no recognition, no market, no incentive for a degree – captures the self-reinforcing dynamics of this structural deficit.

The second barrier is the *revenue asymmetry*: the financial gap between the Premier League and Serie A – with English domestic television rights approximately three times larger than their Italian equivalent – translates directly into a gap in the resources available for analytical investment. Premier League clubs operate with analytics budgets that are structurally unreachable for the majority of Serie A clubs; the tracking data that is league-wide infrastructure in England remains a luxury purchase in Italy. This financial constraint shapes not only the absolute level of analytical investment but also the risk tolerance of Italian clubs: investment in analytical infrastructure requires a multi-year commitment whose returns are uncertain, and that uncertainty is more easily absorbed in an environment of financial abundance than in one of relative scarcity.

The third structural barrier is the *matchday norm*: as documented in the preceding section, the professional norm that treats the match itself as the coach's exclusive jurisdictional domain imposes a ceiling on the depth of real-time data integration that is independent of technical capability. This norm is not unique to Italy – the Bundesliga model described in Chapter 3 suggests a similar pattern – but it is particularly strongly entrenched in a football culture that has historically placed extreme premium on tactical intuition and personal authority as the markers of coaching excellence.

4.3.2 Structural enablers

Against these barriers, three structural factors operate as enablers of analytical adoption. The first is the *Lega Serie A distribution arrangement*: by purchasing the mApp Sport platform and distributing it to all twenty clubs, the Lega provides a technological floor of analytical capability that ensures even the least resourced clubs have access to real-time tactical metrics. As Rein and Memmert (2016) argue, the bottleneck in the big data era is interpretation, not acquisition; the Lega arrangement addresses the acquisition side, providing the raw material from which analytical knowledge can be constructed wherever the human capital to do so exists.

The second enabler is the *North American ownership cluster*: nine of twenty Serie A clubs are currently owned or co-owned by North American shareholders, and the evidence presented in Chapter 3 suggests a strong correlation between North American ownership and serious analytical investment. If this correlation holds over time, the continuing penetration of North American ownership into Italian football represents a structural vector of analytical adoption that does not depend on any change in domestic football culture.

The third enabler is the *generational transition* in coaching: as the cohort of coaches trained entirely in the pre-analytics era progressively gives way to a generation that has grown up with data as a normal part of football preparation, the cultural resistance to systematic analytical input is likely to diminish. This generational transition is visible in the structure of Serie A analysis departments: several head coaches in the 2025/26 season have explicitly incorporated data-informed processes into their preparation methodology, and the most progressive clubs have built analytical infrastructure that is now capable of informing decisions at every level of the coaching process.

4.3.3 The comparative benchmark: what Italy needs to do

The comparative evidence from England and Spain, assembled in Chapter 3, provides a clear benchmark against which Italian football's analytical development can be measured. The English case demonstrates that the combination of educational infrastructure (undergraduate degrees in relevant fields), revenue resources (television rights), and a thick labour market for analytical talent produces a self-reinforcing analytical ecosystem in which investment by any single club is amplified by the availability of trained practitioners, the competitive pressure from adjacent clubs, and the institutional support of a well-resourced governing body. The Spanish case demonstrates that league-level investment in an integrated platform – serving both clubs operationally and broadcasters commercially – can accelerate the diffusion of analytical practices even in a context where club-level resources are more constrained.

For Italy, the most actionable lessons from these comparisons concern the role of the governing body. The Lega Serie A's existing investment in the mApp Sport arrangement is a foundation; building on it to include tracking data provision for all clubs (as LaLiga does through Mediacoach/Sportian Performance), combined with institutional support for the development of formal educational pathways for the match analyst profession, would address the structural barriers most directly. The cultural barriers – the matchday norm, the authority structure of the coaching relationship, the preference for experience over data – are more slowly malleable, and are probably best addressed through the generational mechanisms already in motion rather than through top-down institutional intervention.

4.4 The Divergence of Match Analyst and Data Scientist: Implications for Professional Identity

Perhaps the most theoretically consequential finding to emerge from the evidence assembled in this thesis concerns the divergence between two roles that the academic literature and popular commentary frequently treat as points on a single spectrum: the match analyst and the data scientist in professional football. At the most analytically advanced clubs – exemplified in the Italian context by Parma, and visible in the English context in a more developed form – these two roles are not merely differentiated versions of the same function; they are institutionally separate professional identities with different educational profiles, different organisational positions, and different relationships to the coaching process.

The match analyst – defined by their daily operation within the football coaching cycle, their tactical vocabulary, their video coding skills, and their direct relationship with the head coach and assistant coaches – occupies a role that is fundamentally communicative and translational. Their primary competency is not statistical modelling but the conversion of complex performance data into the tactical narratives and visual evidence that the coaching staff can act on. Their career trajectory, as Ferrè's account illustrates, frequently leads toward coaching roles rather than toward data engineering roles: the UEFA licensing that enhances their bench-side access and portability with coaches values their football knowledge over their analytical skills.

The data scientist in professional football – defined by their technical infrastructure responsibilities, their model-building competencies, and their structural separation from the daily coaching cycle – occupies a role that is fundamentally engineering and quantitative. Their primary relationship is not with the head coach but with the match analyst (as at Parma) or with the sporting director (as at clubs where analytics is primarily deployed for recruitment rather than tactical preparation). Their career trajectory leads toward data engineering, sports analytics consulting, or the broader technology industry, rather than toward coaching.

The coexistence of these two roles within the same department – and, in the most advanced cases, their institutional separation into distinct reporting lines – is a structural marker of analytical maturity. It corresponds to what Davenport and Patil (2012) describe as the transition from "analytics as a support function" to "analytics as a core organisational capability": the moment when the organisation recognises that data-driven decision support is sufficiently complex and consequential to require a dedicated professional architecture, rather than a single generalist analyst who performs all analytical functions simultaneously.

For the future of the match analyst profession in Italy, this divergence raises an important question: which of the two professional trajectories will prove more durable? The evidence from the most advanced European and North American sports organisations suggests that both roles will persist, but will evolve in different directions. The data scientist role is likely to become increasingly technical as the data infrastructure of professional football clubs grows in sophistication – incorporating real-time tracking feeds, multi-source event data, predictive modelling outputs, and AI-augmented analytical tools – and will increasingly resemble the data engineering roles of the broader technology industry. The match analyst role, by contrast, is likely to become increasingly communicative and strategic: as automated systems take over the most repetitive coding and pattern-recognition tasks, the match analyst's distinctive value will lie in their ability to synthesise complex analytical output with deep football knowledge and to communicate it effectively to a coaching staff operating under extreme time pressure.

This trajectory implies that the most important professional development path for the Italian match analyst is not toward greater technical specialisation – which is better pursued by a different professional type – but toward a deeper integration of tactical football intelligence with the communicative and organisational skills required to navigate the authority structures of a professional coaching environment. The match analyst of the future is not a technician who happens to know football; they are a football professional who understands how to exploit the data infrastructure that the data scientist has built, and who can translate its outputs into the form that the head coach can use.

4.5 Chapter Summary

This chapter has developed a synthetic account of the relationship between data and the coaching decision-making process in professional football, drawing on the theoretical framework of Chapter 1 and the empirical evidence of Chapters 2 and 3.

Four main findings have been advanced. First, the head coach's decision-making architecture – characterised by extreme temporal compression, a dominant authority structure, and deep System 1 dependence at the moment of match execution – determines the form in which analytical input can be most effectively delivered. The analyst's most consequential contribution occurs not during the match but during the preparation phase, where data is converted into tactical narrative and pattern-recognition templates calibrated to the coach's cognitive architecture.

Second, the three phases of the coaching cycle – pre-match preparation, in-match real-time, and post-match review – exhibit qualitatively different relationships to data integration. Pre-match preparation is the phase of deepest data integration; real-time matchday is the phase of most resistant closure, governed by a professional norm that treats the match as the coach's exclusive jurisdictional domain; and post-match review is the phase of most institutionalised data collection, constituting the analytical memory that accumulates across seasons and coach changes.

Third, the Italian case is characterised by a combination of structural barriers (educational deficit, revenue asymmetry, matchday norm) and structural enablers (the Lega distribution arrangement, the North American ownership cluster, the generational coaching transition) whose relative weight will determine the pace of analytical adoption over the coming decade. The comparative benchmarks of England and Spain provide a clear trajectory of what sustained institutional investment at the league level can produce.

Fourth, the divergence between the match analyst and the data scientist roles at the most analytically advanced clubs is a structural marker of analytical maturity, corresponding to the transition from analytics as a support function to analytics as a core organisational capability. This divergence implies distinct professional development trajectories for the two roles, and suggests that the most valuable match analyst of the future will be defined by communicative and translational excellence rather than by technical data science competence.

Chapter 5

Conclusions

This thesis set out to examine the figure of the match analyst in professional football, using the Italian Serie A context as its primary empirical field. The inquiry was motivated by a double gap: a gap in the academic literature, which has extensively studied performance analysis as a methodology but has paid scant attention to the match analyst as an organisational and professional actor; and a gap in the Italian football landscape, where the role has been formally recognised since 2018 but has not yet been the subject of systematic empirical investigation. The thesis has addressed this double gap through a combination of documentary analysis, a database of all twenty Serie A match analysis departments for the 2025/26 season, and two key informant interviews with practitioners positioned at the boundary of the Italian football analytics ecosystem.

The structure of the thesis has moved through two levels of analysis. At the general level, Chapter 1 established the theoretical framework: the dynamics of the data revolution in organisations, the cognitive architecture of decision-making under informational complexity, the organisational conditions under which data-driven decision support is effectively institutionalised, and the position of sport – and of football in particular – within the broader sports analytics movement. At the domain-specific level, Chapters 2 and 3 applied this framework to professional football, mapping the operational structure of the match analyst role and documenting the Italian market through primary empirical evidence. Chapter 4 synthesised these two levels, examining how data enters the coaching process, what structural and cultural factors determine the depth of its integration, and what the emerging divergence between match analyst and data scientist roles implies for the future of the profession.

This concluding chapter draws together the main findings of the thesis and articulates their implications, first at the level of the football domain (Section 5.1) and then at the level of the general theoretical framework (Section 5.2). It then identifies the principal limitations of the research and charts directions for future inquiry (Section 5.3).

5.1 Conclusions: The Match Analyst in Professional Football

5.1.1 A profession in construction

The most fundamental conclusion this thesis can offer about the match analyst role in Italian professional football is that it is a profession in active construction. The descriptors of professional maturity – a canonical educational pathway, a recognised credential, a stable career ladder, a settled professional identity – are either absent or only partially established. What exists instead is a rich, heterogeneous field of practitioners approaching the role from multiple disciplinary backgrounds, operating under a variety of organisational models, and collectively working out, through practice rather than through institutional design, what the role should be and what competencies it should require.

The educational heterogeneity documented in the database – degrees in economics, political science, sports science, and engineering coexisting with UEFA coaching licences and FIGC credentials, with no single profile predominating – is not a transitional imperfection that will give way to a canonical pathway as the profession matures. It reflects, rather, the genuine multi-dimensionality of a role that requires fluency in at least three distinct knowledge domains: football tactics, statistical and data analysis, and organisational communication. The rarity of individuals who combine all three domains with equal competence is the primary constraint on the growth of the profession, and it is a constraint that no single educational programme can resolve without also constraining the diversity of the talent pool.

5.1.2 The three professional profiles and their trajectories

Chapter 2 identified three distinct professional profiles coexisting in the Serie A match analyst population: the coaching-track analyst (exemplified by Filippo Lorenzon at Inter), the academically trained analyst (Riccardo Scirea at Juventus, Matteo Matteotti at Parma), and the data-driven front-office figure (Chris Galley at Como, Yuri Dell'Atti at Bologna). The synthesis in Chapter 4 introduced a fourth analytical distinction: between the match analyst proper – whose primary function is translation and communication within the coaching process – and the data scientist – whose primary function is technical infrastructure and modelling.

These profiles are not competing alternatives but complementary nodes in an evolving professional ecosystem. The coaching-track analyst provides the bridge between analytical output and coach authority, using their tactical credibility to ensure that data-informed insights are listened to and acted upon. The academically trained analyst provides the methodological rigour and technical infrastructure that the coaching-track analyst's formation did not supply. The data-driven front-office figure provides the strategic and recruitment-oriented dimension of analytics that connects the sporting operation to the club's financial and organisational decision-making. And the distinction between match analyst and data scientist formalises the functional specialisation that clubs with sufficient analytical maturity have found it necessary to institutionalise.

The trajectory of the profession, extrapolated from the evidence assembled here, is toward greater functional differentiation: the three informal profiles identified in the database will, in the most analytically advanced clubs, progressively crystallise into formal roles with distinct titles, distinct educational expectations, and distinct career ladders. The clubs that are currently navigating this transition – Parma most visibly, but also Inter, Milan, and several others – are the leading indicators of a structural evolution that will, on this projection, diffuse more slowly through the remainder of Serie A over the next decade.

5.1.3 The Lega distribution arrangement and its strategic implications

The Lega Serie A's decision to purchase the mApp Sport platform and distribute it to all twenty member clubs at no additional cost is, from a strategic and institutional standpoint, one of the most consequential decisions the governing body has made in the analytical domain. Its effect has been to provide a technological floor of analytical capability across the entire league, ensuring that even clubs with minimal internal analytical resources have access to real-time performance metrics and post-match KPIs. This democratisation of access is structurally important: it has decoupled the availability of basic analytical tools from the size of the club's analytical budget, and has thereby altered the terms on which clubs compete analytically.

The limitation of this arrangement, as the evidence makes clear, is that it addresses the supply of data without guaranteeing the human capacity to use it. The bottleneck in the Italian football analytics market is not access to a platform but the availability of analysts with the technical and communicative competence to convert that platform's outputs into actionable coaching knowledge. The gap between the technological floor provided by the Lega arrangement and the analytical ceiling reached by the most sophisticated clubs – whose proprietary data infrastructure, ML-trained models, and dedicated data teams operate at a qualitatively different level – is therefore a human capital gap, not a technological one.

The strategic implication for the Lega and for Italian football's governing bodies is clear: investment in the educational and institutional infrastructure for the development of match analyst talent is more impactful, at the current stage of the market's development, than further technological investment. The Spanish model – in which LaLiga's institutional investment in Mediacoach has been complemented by the creation of a *Football Intelligence & Performance* unit offering clubs training, workshops, and technical support – provides a concrete blueprint for how a governing body can accelerate the diffusion of analytical practices by investing in human capital rather than solely in data infrastructure.

5.1.4 The matchday norm as a diagnostic marker

The finding that the matchday – the ninety minutes of competitive play – constitutes a closed system impermeable to systematic data input, confirmed independently by both key informants and consistent with the European comparative evidence, is a diagnostic marker of the current developmental stage of football analytics. It indicates that the data-driven transformation of professional football has so far been predominantly a transformation of the *preparation* phase of the coaching cycle, with limited penetration into the real-time decision environment of match execution.

This boundary is not immovable. The trajectory of sports analytics in North American professional sports – in particular in basketball, where the quantitative tradition documented in the sports analytics literature (Lewis 2004; Morgulev, Azar, and Lidor 2018) has extended into real-time statistical dashboards used by coaching staffs on the bench during time-outs – suggests that the matchday norm is a cultural and institutional constraint, not a cognitive one: there is no inherent reason why real-time analytical support cannot be integrated into in-match decision-making, provided that the trust between coach and analyst is sufficiently developed, the analytical output is sufficiently distilled, and the authority dynamics are sufficiently settled to allow the analyst's input to be perceived as supportive rather than usurping. The conditions for this evolution are not yet present in Italian professional football, but the direction of travel – faster communications between bench and stand, dedicated analyst positions in match-day logistics, tablet-based real-time platforms – points unmistakably toward the gradual erosion of the matchday boundary.

5.2 Conclusions: General Theoretical Implications

The football-specific findings reported in the preceding section carry implications that extend beyond the sport, and that speak to the general theoretical framework established in Chapter 1. Three implications deserve particular attention.

5.2.1 Professional football as a natural experiment in data-driven decision-making

Professional football is, as Chapter 1 argued, an unusually tractable case study for the general dynamics of data-driven decision-making in organisations. The football domain combines, in concentrated form, the features that make data integration challenging in any organisational context: extreme time pressure, a dominant expert-intuition culture, a strong authority hierarchy, and contested professional jurisdiction over the most consequential decisions. At the same time, it possesses features that make it unusually amenable to close empirical observation: the standardised, publicly documented nature of its data infrastructure; the explicit regulatory framework governing staff composition; and the availability of detailed documentary and interview evidence from practitioners who are, as a group, unusually willing to reflect publicly on their professional practice. These are the same structural features – repeated, observable, high-stakes decisions under well-defined rules – that have made sport a privileged empirical laboratory for the social sciences more generally (Morgulev, Azar, and Lidor 2018).

The thesis findings confirm, in the football domain, the core propositions of the evidence-based management literature as developed by Pfeffer and Sutton (2006) and Davenport and Harris (2006). The cultural conditions that enable or inhibit data-driven decision-making in organisations – leadership openness, ownership-level commitment to analytical investment, and the quality of the communicative interface between analytical and operational staff – are the primary determinants of analytical depth in professional football clubs, just as they are in corporations. The structural conditions – financial resources, human capital availability, institutional infrastructure – are necessary but not sufficient: clubs with limited structural resources that have found the cultural conditions for data integration (Parma's case is again instructive) outperform clubs with greater structural resources but weaker cultural conditions.

5.2.2 Bounded rationality and the cognitive architecture of expert decision-making

The match analyst's operational practice provides a detailed empirical illustration of the bounded rationality framework developed by Simon (1955) and extended by Kahneman (2011). The entire apparatus of the analyst's weekly cycle – the opposition dossier, the team meeting presentation, the individual clip packages, the half-time compilation – can be understood as an organisational response to the bounded rationality of the primary decision-maker. Each element of this apparatus is designed not to maximise the volume of information delivered to the coach but to minimise the cognitive load required to use it: three to five tactical messages in the team meeting rather than a comprehensive statistical report; a curated set of video clips at half-time rather than raw footage; a one-page player profile for recruitment rather than a multi-dimensional statistical profile.

This correspondence between the theoretical prediction of the bounded rationality literature and the operational practice of the match analyst is a validation of the theoretical framework in an empirical context far removed from its original formulation. It also has a normative implication for the design of analytical functions in any organisational context: the primary measure of an analytical function's effectiveness is not the technical sophistication of its outputs but their cognitive accessibility to the decision-maker they are designed to serve.

5.2.3 The data revolution and the emergence of new professional jurisdictions

The emergence of the match analyst as a professional figure is an instance of a general dynamic that Abbott's theory of professional systems (Abbott 1988) predicts: when the volume and complexity of a domain's informational environment crosses a threshold that makes unaided expert intuition insufficient, new professional figures crystallise to perform the specialised cognitive labour of information reduction and translation. This is the dynamic that produced the statistician, the management consultant, the data scientist, and the chief information officer in successive waves of organisational response to the data revolution; and it is the same dynamic that is producing the match analyst, the head of data, and the chief analytics officer in professional football.

The football case adds two observations to this general account. The first is that the emergence of these new professional figures does not displace the incumbent expert – the head coach – but operates in tension with their jurisdictional authority, particularly in the most consequential decision environments. The matchday boundary documented in this thesis is the most vivid illustration of this tension: the new analytical figure has extensive pre-match jurisdictional access but is excluded from the real-time decision environment that carries the highest reputational stakes for the incumbent. This pattern of partial access and jurisdictional contestation is likely to be a stable feature of professional ecosystems in which new analytical figures emerge alongside established expert authorities, and is not unique to football.

The second observation concerns the role of artificial intelligence in this jurisdictional dynamic. As AI tools automate the most routine analytical tasks – event coding, pattern detection, report generation – they simultaneously reduce the competitive advantage of the analyst who performs those tasks manually and shift the premium to the analytical competencies that AI cannot replicate: contextual judgement, communicative adaptation to a specific decision-maker, and the integration of tacit domain knowledge with quantitative output. The long-run trajectory of the match analyst role is therefore not threatened by AI but transformed by it: the analyst who flourishes in an AI-augmented analytical environment will be the one who has invested in the human competencies that AI complements rather than replaces.

5.3 Limitations and Directions for Future Research

This thesis has limitations. Each of them also points to a direction for future research.

The first concerns the geographic scope of the comparison. The European picture drawn in Chapter 3 rests on the accounts of the two informants and on documentary sources, not on primary research carried out in England, Spain, or Germany. A comparative study that applied the same methods in several national leagues would give the claims made here a firmer basis, and would place the Italian case more precisely among its European peers.

The second concerns time. The thesis captures the Italian football analytics market at one moment, the 2025/26 season, in a field that is changing quickly. The database of Serie A analysis departments was built from public sources in April 2026 and will be partly out of date within months: clubs hire and fire coaches, analysts move, departments are reorganised. Following the same database across several seasons would turn the patterns identified here, such as the spread of hierarchical titles, the separation of data and analysis functions, and the appearance of “Head of Data” roles, into trends that can be measured over time rather than read from a single cross-section.

The third concerns the part of the analytical function under study. The thesis looks at the tactical and performance-analysis side of the match analyst’s work, and sets aside recruitment and financial analytics, which at the most advanced clubs matter just as much. A complete account would have to include them: the statistical models used to recruit and value players, the use of data in contract talks and squad building, and the growing place of analytics in clubs' commercial and sponsorship work. These areas fall outside the present research, but the framework developed here extends to them.

5.3.1 From description to measurement: an empirical agenda on data and in-match decision-making

This thesis is a starting point, not a finished account. Its contribution is conceptual and descriptive: it has set out who the match analyst is, how the role is organised, and how analytical knowledge does or does not reach the decision-maker through a club's culture and institutions. It has not measured whether that analytical support actually changes the decisions taken on the pitch, or the results that follow, and the evidence gathered here is not enough to do so. The clearest next step is to move from describing the role to testing its effect: a study that asks whether data-informed decisions, taken at the decisive moments of a match, lead to a measurable improvement in results.

Such a study would rest on a match-level database covering several recent Serie A seasons, with each game broken down into the phases where in-match decisions concentrate. The dependent variables would describe how a match changes as it goes on: how goals divide between the first and second half, what share are scored in the closing minutes, and how the main performance indicators used in this thesis (expected goals, territorial control, and pressing intensity) shift between the two halves. The break between the halves matters most, because it is the one point at which the closed system of the match opens briefly. At half-time the analyst's observations, compiled quickly into the clip package described in Chapter 2, can be turned by the coaching staff into adjustments. Comparing performance before and after the interval is therefore a workable proxy for the analyst's contribution during the game.

The explanatory variables would measure how much, and what kind of, data-informed action takes place. Two are easy to work with. The first is the club's analytical maturity, which can be proxied by the departmental indicators in the database in the Appendix (department size, internal structure, and whether a dedicated data function exists), so that clubs can be ranked and their in-match behaviour compared. The second is substitution policy, which became far more informative after a specific, datable change: the permanent shift from three to five substitutions in 2020. That change is useful because it works as a quasi-natural experiment. It widened the choices open to the coach at exactly the tense, time-pressured moments where, as Chapter 1 argued, System 1 thinking takes over and pre-match preparation matters most. How substitutions are timed and sequenced under the five-substitution rule, and how this relates to later swings in momentum and to late goals, shows directly how far data supports decisions at the moments that decide matches.

Three hypotheses can organise the study. The first is that clubs with greater analytical maturity show different second-half and late-game patterns from clubs with weaker analytical functions, with a larger or more favourable swing in expected goals across the interval. The second is that the five-substitution rule strengthened the link between analytical capability and late-game results, because it widened the room in which better in-match information can be turned into action. The third is that the effect of data-informed decisions, once isolated, is positive but limited, which fits the main claim of this thesis: analytics does not replace the coach's judgement, it disciplines it.

Testing these hypotheses would need methods that separate the effect of analytical investment from squad quality and financial resources: club and season fixed effects, difference-in-differences designs built around the 2020 rule change, and controls for the structural drivers of results. The Napoli case noted earlier is a warning against reading too much into a simple correlation. A club can win without a structured data department, and a strong data department does not guarantee results. The relationship is neither absent nor automatic, and that is exactly why it deserves careful estimation rather than assertion. If such a study could isolate a credible effect, even a modest one, it would do what this thesis can only set up: it would move the case for the match analyst from a cultural and philosophical argument to an evidential one, and it would close the gap left open in Chapter 1 between the claim that data should improve decisions and a demonstration that, at the moments that decide a match, it does.

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Appendix A

Database of Serie A Match Analysts

The following table presents the database of Serie A analysts for the 2025/26 season, compiled from official club sources, LinkedIn and specialised press, and verified against the clubs' official technical-staff pages. The per-club count adopts the broad criterion (match analysts, video analysts, performance analysts, data analysts and technical collaborators with an explicit analysis function). The N column reports the overall size of each club's analysis department.

Table A.1: Database of Serie A's match analysts

Club	**Analista**	**Ruolo**	**Categoria**	**N**	**Fonte**
Inter	Filippo Lorenzon	Head of Football Analysis Department	Head/Chief	4	https://www.inter.it/it/teams/prima-squadra?role=staff
	Salvatore Rustico	Match Analyst	Match/Game		https://www.inter.it/it/teams/prima-squadra?role=staff
	Giacomo Toninato	Match Analyst	Match/Game		https://www.inter.it/it/teams/prima-squadra?role=staff
	Stefano Castellani	Match Analyst	Match/Game		https://www.inter.it/it/teams/prima-squadra?role=staff
Fiorentina	Simone Formica	Match Analyst (1^{a} squadra)	Match/Game	4	https://www.acffiorentina.com/en/news/lo-staff-di-mister-paolo-vanoli-1211252
	Andrea Tordi	Match Analyst (1^{a} squadra)	Match/Game		https://www.acffiorentina.com/en/news/lo-staff-di-mister-paolo-vanoli-1211252
	Lorenzo Sandri	Match Analyst (1^{a} squadra)	Match/Game		https://www.acffiorentina.com/en/news/due-nuovi-ingressi-nello-staff-tecnico-di-mister-vanoli-191125
	Lorenzo Pinzauti	Match Analyst U18	Match/Game		https://it.linkedin.com/company/assoanalisti-aiapc
Bologna	Stefano Firicano	Match Analyst	Match/Game	3	https://www.bolognafc.it/en/vincenzo-italianos-backroom-staff/
	Paolo Riela	Match Analyst	Match/Game		https://www.bolognafc.it/en/vincenzo-italianos-backroom-staff/
	Yuri Dell'Atti	Chief Data Analyst	Data		https://www.linkedin.com/in/yuri-dell-atti-22449612b/

following

Table A.1

Club	Analista	Ruolo	Categoria	N	Fonte
Cagliari	Davide Marfella	Head of Match Analysis Area	Head/Chief	3	https://www.unionesarda.it/en/cagliari-here-is-mister-pisacane-staff
	Matteo Battilana	Match Analyst	Match/Game		https://www.unionesarda.it/en/cagliari-here-is-mister-pisacane-staff
	Giovanni Venturelli	Collaboratore – registrazioni tattiche	Collaboratore		https://www.unionesarda.it/en/cagliari-here-is-mister-pisacane-staff
Genoa	Mirco Vecchi	Match Analyst	Match/Game	3	https://genoacfc.it/2025/07/21/lo-staff-tecnico-del-genoa-2025-26/
	Hacim Halim Ali M'Bae	Collaboratore Tecnico – Match Analyst	Collaboratore		https://genoacfc.it/2025/07/21/lo-staff-tecnico-del-genoa-2025-26/
	Lorenzo Folle	Collaboratore Tecnico – Match Analyst	Collaboratore		https://genoacfc.it/2025/07/21/lo-staff-tecnico-del-genoa-2025-26/
Juventus	Riccardo Scirea	Head of Match Analysis Office	Head/Chief	3	https://www.juventus.com
	Matteo Poletti	Next Gen Match Analyst	Match/Game		https://www.juventus.com/it/news/articoli/juventus-next-gen-staff-tecnico-stagione-2025-2026
	Alessio Varzi	U20 Match Analyst	Match/Game		https://www.linkedin.com/in/alessio-varzi-039787102/
Milan	Francesco Calone	Match Analyst (1ª squadra)	Match/Game	3	https://it.wikipedia.org/wiki/Associazione_Calcio_Milan_2025-2026
	Igor Quaia	Match Analyst	Match/Game		https://it.wikipedia.org/wiki/Associazione_Calcio_Milan_2025-2026
	Giorgio Tenca	Performance Analyst	Performance		https://it.wikipedia.org/wiki/Associazione_Calcio_Milan_2025-2026

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Table A.1

Club	Analista	Ruolo	Categoria	N	Fonte
Parma	Mathieu Lacome	Head of Performance & Analytics	Performance	3	`https://www.parmalive.com/news/una-squadra-alle-spalle-di-cuesta-lo-staff-gialloblu-al-completo-238223`
	Fabio Corradini	Head of Game Analysis	Head/Chief		`https://www.parmalive.com/news/una-squadra-alle-spalle-di-cuesta-lo-staff-gialloblu-al-completo-238223`
	Simone Salvo	Game Analyst	Match/Game		`https://www.parmalive.com/news/una-squadra-alle-spalle-di-cuesta-lo-staff-gialloblu-al-completo-238223`
Atalanta	Michele Orecchio	Match Analyst	Match/Game	2	`https://en.atalanta.it/news/coach-ivan-juric-s-technical-staff-2025-2026`
	Stefano Brambilla	Match Analyst	Match/Game		`https://en.atalanta.it/news/coach-ivan-juric-s-technical-staff-2025-2026`
Como	Chris Galley	Head of Strategy & Data Analytics	Data	2	`https://www.transfermarkt.it/como-1907/mitarbeiter/verein/1047`
	Dani Suryadi	Video Analyst	Video		`https://www.transfermarkt.it/como-1907/mitarbeiter/verein/1047`
Cremonese	Federico Barni	Match Analyst	Match/Game	2	`https://uscremonese.it/staff-tecnico-e-medico/`
	Vittorio Vona	Match Analyst	Match/Game		`https://uscremonese.it/staff-tecnico-e-medico/`
Hellas Verona	Alberto Nabiuzzi	Collaboratore Tecnico / Match Analyst	Collaboratore	2	`https://www.hellasverona.it/en/news/coach-zanettis-technical-staff`
	Nicolo Guberti	Collaboratore Tecnico / Match Analyst	Collaboratore		`https://www.hellasverona.it/en/news/coach-zanettis-technical-staff`

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Table A.1

Club	Analista	Ruolo	Categoria	N	Fonte
Lecce	Stefano Romano	Match Analyst	Match/Game	2	https://www.uslecce.it/groups/217254559378/staff-tecnico-2025-26
	Alessio Chiarin	Match Analyst	Match/Game		https://www.uslecce.it/groups/217254559378/staff-tecnico-2025-26
Pisa	Lorenzo Ferrari	Match Analyst	Match/Game	2	https://pisasportingclub.com/en/first-team/
	Francesco Ciulli	Match Analyst	Match/Game		https://www.linkedin.com/in/francesco-ciulli-9b51171aa/
Sassuolo	Mauro Carretta	Match Analyst	Match/Game	2	https://www.sassuolocalcio.it/prima-squadra/lo-staff-di-mister-fabio-grosso-per-la-stagione-25-26/
	Giuseppe Foti	Collaboratore (ex Match Analyst)	Collaboratore		https://www.sassuolocalcio.it/prima-squadra/lo-staff-di-mister-fabio-grosso-per-la-stagione-25-26/
Torino	Silvio Valanzano	Match Analyst (responsabile)	Match/Game	2	https://www.toronews.net/toro/torino-lelenco-ufficiale-dello-staff-tecnico-e-di-quello-medico-per-il-2025-26/
	Mattia Bastianelli	Match Analyst	Match/Game		https://www.toronews.net/toro/torino-lelenco-ufficiale-dello-staff-tecnico-e-di-quello-medico-per-il-2025-26/
Udinese	Michele Guadagnino	Match Analyst	Match/Game	2	https://www.udinese.it/news/squadra/lo-staff-della-prima-squadra-per-la-stagione-202526
	Mattia Mosanghini	Match Analyst	Match/Game		https://www.udinese.it/news/squadra/lo-staff-della-prima-squadra-per-la-stagione-202526

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Table A.1

Club	**Analista**	**Ruolo**	**Categoria**	**N**	**Fonte**
Lazio	Enrico “Billy” Allavena	Match Analyst	Match/Game	1	https://www.sololalazio.it/2025/06/02/lazio-ecco-chi-fara-parte-dello-staff-di-sarri/
Napoli	Giuseppe Maiuri	Assistant Coach & Match Analyst	Match/Game	1	https://www.calcionapoli24.it/ritiro_napoli/ssc-napoli-ecco-il-nuovo-staff-di-conte-tutti-i-nomi-e-n610671.html
Roma	Simone Beccaccioli	Match Analyst	Match/Game	1	https://www.sololaroma.it/gasperini-staff-roma/